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Estimating millet production for famine early warning: an application of crop simulation modelling using satellite and ground-based data in Burkina Faso

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Abstract

Early warning of impending poor crop harvests in highly variable environments can allow policy makers the time they need to take appropriate action to ameliorate the effects of regional food shortages on vulnerable rural and urban populations. Crop production estimates for the current season can be obtained using crop simulation models and remotely sensed estimates of rainfall in real time, embedded in a geographic information system that allows simple analysis of simulation results. A prototype yield estimation system was developed for the thirty provinces of Burkina Faso. It is based on CERES–Millet, a crop simulation model of the growth and development of millet (*Pennisetum* spp.). The prototype was used to estimate millet production in contrasting seasons and to derive production anomaly estimates for the 1986 season. Provincial yields simulated halfway through the growing season were generally within 15% of their final (end-of-season) values. Although more work is required to produce an operational early warning

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system of reasonable credibility, the methodology has considerable potential for providing timely estimates of regional production of the major food crops in countries of sub-Saharan Africa.

1. Introduction

The food security issue spans the ecological, biological, socioeconomic, political, and cultural dimensions. As pressure on the natural resource base increases, the assessment of those groups in society that are most at risk from food shortages will become increasingly important. Efforts to analyse the complex causes and effects of famine may revolve around the concept of vulnerability (Riely, 1993), the relative susceptibility of households to various levels of food insecurity. Vulnerability analysis can serve as a framework for the identification of susceptible sections of society; early warning is the mechanism for the monitoring of key indicators and conditions that may affect this susceptibility. The essential purpose of early warning is to give decision makers sufficient time to take action to avoid the worst effects of impending drought or poor harvests, for example, in an effort to protect or buffer the most susceptible households.

In most early warning systems, several indicators are monitored over time; the case for imminent action is heightened as the evidence from the various indicators converges to a single conclusion. A small but important component of any real-time monitoring system for early warning is the estimation (we deliberately avoid the term 'forecasting') of crop yields in a region for the current season in progress. Various methodologies for crop yield estimation may be used, ranging from surveys and crop scouting to the use of remotely sensed vegetation and water indices and, most recently, simulation models.

Rainfall in many environments in sub-Saharan Africa is highly variable and is a contributing factor to food insecurity. There are sites in the Sahel, for example, where the coefficient of variation in annual rainfall reaches 60% or more. Cereal production in a country such as Burkina Faso fluctuates wildly in response to such variation. In this paper we describe a highly preliminary prototype system that uses a detailed crop simulation model, real-time rainfall estimates obtained from satellite imagery, and a Geographic Information System (GIS) to store and georeference the input data required to run the model and to map the results. The outputs of the prototype include estimates of millet crop production at the provincial level in map and tabular form that could be used by decision makers. The use of the system in Burkina Faso is illustrated, and developments and refinements that could result in a credible tool for early warning purposes are listed.

2. The DSSAT crop simulation models

Many crop simulation models are now available to users; these range from multi-species models to suites of models with shared characteristics (Jones et al., 1995). A set of crop models that share a common input–output data format has been developed and embedded in a software package called the Decision Support System for Agrotechnology Transfer (DSSAT). The DSSAT itself (IBSNAT, 1989; Jones, 1993; Tsuji et al.,

1994) is a shell that allows the user to organize and manipulate crop, soils, and weather data and to run crop models in various ways and analyze their outputs. The models running under the DSSAT include the CERES cereal model for rice, wheat, maize, sorghum, pearl millet, and barley; the CROPGRO model for peanut, soybean, and *phaseolus* bean; and models for cassava and potato (Tsuji et al., 1994).

The CROPGRO and CERES models have much in common, notably the same input and output files and comparable levels of detail. Crop growth is simulated with a daily time step from sowing to maturity, based on physiological processes that describe the crop's response to soil and aerial environmental conditions. Phasic development is quantified according to the plant's physiological age. In CERES, for example, the crop growth submodels treat leaf area development, dry matter production, assimilate partitioning, and tiller growth and development. Potential growth is dependent on photosynthetically active radiation and its interception, whereas actual biomass production on any day is constrained by suboptimal temperatures, soil water deficits, and nitrogen and phosphorus deficiencies.

The soil water balance, nitrogen balance, and phosphorus balance submodels operate on the basis of soil layers. The soil water balance component simulates surface runoff, evaporation, drainage, irrigation, and water extraction by the plant. The nitrogen submodel simulates the processes of organic matter turnover with the associated mineralization and/or immobilization of nitrogen, nitrification, denitrification, hydrolysis of urea, and ammonia volatilization. The phosphorus component, still under development, simulates the processes of absorption and desorption of phosphorus, organic phosphorus turnover, and the dissolution of rock and fertilizer phosphate.

The input data required to run the DSSAT models include daily weather information (maximum and minimum temperatures, rainfall, and solar radiation); soil characterization data (data by soil layer on extractable nitrogen and phosphorus and soil water content); a set of genetic coefficients characterizing the variety being grown; and crop management information, such as emerged plant population, row spacing, and seeding depth, and fertilizer and irrigation schedules (Table 1).

The models can produce a large quantity of output data, including yield estimates, modified as appropriate by the stress factors noted above (water, nitrogen, and phosphorus limitations). There are other stresses that are not incorporated in the DSSAT crop models, such as the effects of weeds, disease, and pests. If a reliable submodel for insect or disease is available, it can be linked to the crop model and its effect on the plant can be simulated as a stress factor in terms of competition for light, reduction of leaf area, or interference with translocation (Boote et al., 1993).

A limited amount of validation work has been carried out with the CERES crop models in the Sahelian region. Validation involves collecting field trial data and setting up the input files required (weather, soil, genotype, and management) in an attempt to reproduce the historical field trial using the model. If the model can reproduce historical yields with tolerable accuracy over a range of different input conditions (different sites or nitrogen treatments, for example), the model can be applied to real-world problems with some degree of confidence. Validation work with CERES–Millet and CERES–Sorghum in the Sahel is described in Ritchie and Alagarswamy (1989), Ritchie et al. (1990), Fechter et al. (1991), and Ravelo and Planchuelo (1993).

Table 1
Data inputs needed to run the crop model CERES–Millet

Daily weather
· Maximum and minimum air temperatures
· Rainfall
· Solar radiation
Site
· Latitude
· Runoff and drainage characteristics
· Soil color/albedo
Soil properties (by layer)
· Sand, silt and clay content
· Moist bulk density
· Organic carbon content
· pH in water
· (Optional) soil water content in terms of the lower limit, drained upper limit, and saturation; rooting preference index; total N
Soil initial conditions (by layer)
· Soil water content
· Soil nitrate and ammonium content
Millet genotype data
· Heat units required for emergence, anthesis, maturity under nonlimiting conditions
· Yield components under nonlimiting conditions
Management data
· Planting date, plant population, and row spacing
· Irrigation and fertilizer scheduling (amount, date, type, method)

The crop models outlined above are being used in a wide variety of applications. Many of these applications are concerned with managing risk in agriculture, i.e., coping with production variability between years. Crop models are excellent tools for assessing production variability associated with weather. Model outputs can be used in a variety of ways; scenarios or strategies can be compared with one another using economic efficiency criteria (Anderson et al., 1977), and they can be analysed to investigate trends over time (Bowen et al., 1993) and for providing input to mathematical programming models (Veloso et al., 1994).

Simulations can also be carried out to update output distributions throughout a growing season, using the most recent weather data. What may be of interest to the analyst is the movement of the outcome distribution through time as more and more 'unknown' weather is replaced with historical, observed weather (or a suitable proxy). The closer to the end of a growing season the simulation date is, the less amount of uncertain weather there is. If this is translated into a yield distribution, as the end of the season draws near, the mean of the distribution should better approximate the yield actually obtained during the growing season. At the same time, the variability should decrease until the variance approaches zero, once all the unknown weather has been replaced by known, historical weather for the entire growing season. This process is

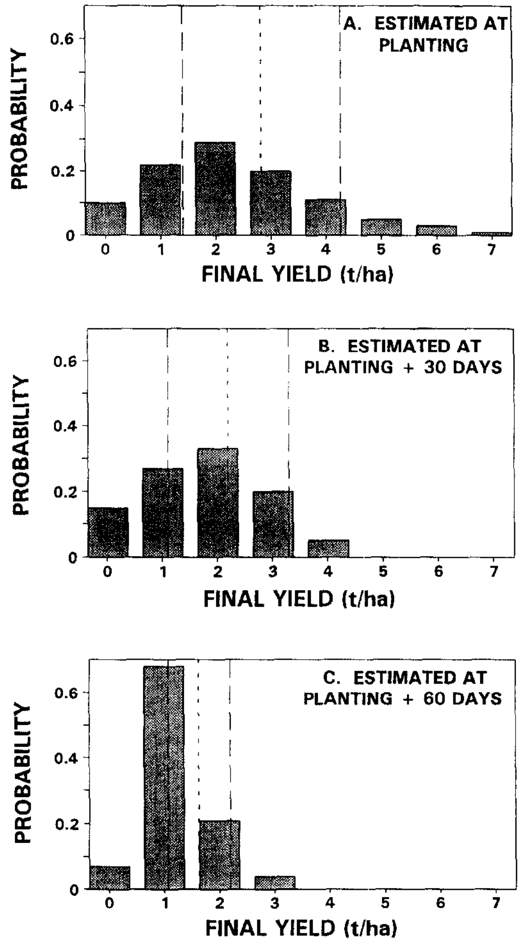

Fig. 1. Simulated yield distributions at planting (A) and 30 (B) and 60 (B) days after planting, reflecting the replacement of probabilistic weather records with observed weather data. The dotted lines represent the mean and one standard deviation on either side of the mean for each distribution.

illustrated for a hypothetical 120-day crop in Fig. 1; at planting, the simulated yield distribution has a high variance because the season's weather is as yet unknown (Fig. 1A). Corresponding yield distributions simulated 30 (Fig. 1B) and 60 (Fig. 1C) days after planting have progressively lower variances, because increasing proportions of the season's weather are now known.

In an early warning framework, modification of the yield distribution needs to be observed as early as possible in the season. If stable estimates of crop yield could be obtained perhaps two months before the crop matures, decision makers would have time to take any action that might be necessary. In a good season, with above-average yields, decisions might have to be made regarding disposal of a crop surplus; in a poor season, with below-average yields in some districts, it might be necessary to arrange for transportation of grain from surplus to deficit areas to alleviate localised food shortages.

3. A prototype yield estimation system for Burkina Faso

The prototype yield estimation system uses data from a number of sources:

- Weather data for the region, in terms of long-term means and real-time daily data, if available, or a proxy for real-time daily data, if not, for input to the crop model.
- Soils and crop data at a suitable scale for the region of interest, in the formats appropriate to the crop model.
- A land use map showing areas where millet is grown in the country.
- Historical production data, at a district or provincial level, that can be used to define the norm against which any particular season can be assessed, and for calibration and validation of the crop model.

3.1. Weather data

The usefulness of an early warning system is largely dependent on having up-to-date daily weather data to run the crop model. Given that the real-time collection of daily data from synoptic weather stations on the ground is not feasible in many developing countries, a fundamental problem is finding a suitable estimator or proxy for daily rainfall, because this is one of the principal determinants of agricultural production in the Sahel.

Two weather models, one for rainfall and one for maximum and minimum temperatures and solar radiation, were fitted to available data; the fitted parameters were then interpolated to a regular grid. Historical daily rainfall data were obtained for sites in Burkina Faso, Niger, and Mali from archives at the EROS Data Center in South Dakota. There were 231 sites that had at least 14 years' daily rainfall data since 1963 (data from earlier years were discarded because the isohyets in this region appear to have been shifting over the past 60 years). For these sites, daily rainfall data were used to estimate the parameters of a third-order Markov rainfall model (Jones and Thornton, 1993). The parameters of this model include monthly values of the average rainfall amount on a rainday, the gamma distribution shape parameter, the baseline probit of a wet day following three dry days, and the standard error of the baseline probit; and three lag coefficients that are used to adjust the baseline probit if rainfall occurs on any of the three preceding days. A triangular matrix of correlations of monthly raindays must also be estimated, although for much of the Sahel these correlations are only rarely statistically significant (i.e., there tends to be no persistence in rainfall amount from one month to another). Each Markov model coefficient was interpolated onto a 0.25 degree square grid from the 231 stations using an inverse distance algorithm with squared weighting.

The weather generator SIMMETEO (Geng et al., 1988) estimates daily air temperatures and solar radiation using monthly means and variances of these variables (there is generally much less variability in these variables than in rainfall). Maximum and minimum temperatures were estimated using monthly mean values from a subset of the 125 stations in Burkina Faso with rainfall data (Sivakumar and Gnoumou, 1987). These monthly means were interpolated to the 0.25 degree grid. For solar radiation, remotely sensed monthly average solar surface irradiance data were available from the Goddard

Institute for Space Studies, New York; these data are available at a resolution of 2.5° latitude by 2.5° longitude for the globe (Bishop and Rossow, 1991). These monthly values were converted to the 0.25 degree grid.

Parameters for generating stochastic weather records were obtained for each grid cell. METEOSAT-based rainfall estimates (RFEs) were used to incorporate the current season's rainfall data. These are estimates of current rainfall based on cold cloud duration as measured by thermal infrared radiometers on the METEOSAT satellite. The RFEs were calculated every 10 days by the Department of Meteorology at the University of Reading for a 7.6 km square grid. Cold cloud duration correlates well with the rainfall generated by convective activity and is thus suitable for use in the semiarid Sahel. The estimates work most accurately on level terrain, in the absence of rain shadows or local enhancements. At the dekadal (ten-day) scale, 80% of estimated rainfall amounts under 60 mm are accurate to within 10 mm, whereas estimated rainfall over 60 mm is accurate to within 20 mm. The method gives near-real-time coverage for large areas of the earth at reasonable accuracy and cost (Dugdale et al., 1991). The way in which dekadal rainfall totals are converted to daily data for input to the crop model is described below.

3.2. Soils data

A soils map at a scale of 1:500,000 was used as the basis of the prototype. Some 102 categories of soil exist in this classification (ORSTOM, 1976). Representative soil profiles were established for each soil type (the required variables are shown in Table 1). Soil profile characteristics were based on available pedon data. In terms of soils information for the crop models, the file formats provide for characteristics that pertain directly to a mapping unit and those that vary locally. A mapping unit might have a particular clay content; this can be kept constant for all occurrences of similar mapping units. The soil depth, however, may vary locally, as may the soil water content at any time. These initial conditions could be handled differently in the prototype system in the future, but at present there is a one-to-one correspondence between soil profile, mapping unit, and initial conditions. Important soils in Burkina Faso include Luvisols, Arenosols, Vertisols, Lithosols, and Cambisols, in the FAO description (FAO, 1988).

3.3. Land use data

A cropland use intensity (CUI) map for Burkina Faso was obtained from the United States Geological Survey (USGS, 1993) by interpreting and synthesizing Landsat imagery, soil maps, and meteorological data. This map was adapted to provide an estimate of the percentage of each pixel's area (7.6 km by 7.6 km) that was planted to millet. The CUI ranged from 0 to 26%.

3.4. Historical production data

Historical production data for the major crops in Burkina Faso are available through a database management system (FEWS, 1994). For millet, data are available by province for the years 1984 to 1992 and include area planted to millet and total production. From these data, the average provincial millet yield each year was calculated. The average provincial millet yield for the years in the sample was used as the norm against which yield anomalies in any season could be calculated.

3.5. Prototype description

The thirty provinces of Burkina Faso are shown in map form in Fig. 2. A schematic diagram of the prototype is shown in Fig. 3. The program is designed to be used every 10 days to update simulated millet yield distributions in response to the latest RFEs obtained for the region. For each simulation, a rainfall file that stores dekadal totals by grid cell for the entire region is updated (the proxy for real-time rainfall records) with the latest RFEs for the previous 10 days. The millet model is then run for each unique combination of soil type and weather grid cell. To obtain a distribution of outputs, each run is replicated ten times.

Once the simulations have been carried out, the provincial yield anomaly for the current season up to the date of simulation is calculated (Wilkens et al., 1995). To illustrate, consider a province for which average annual production over the past 12 years is 55,000 tonnes of millet; with an average area of 85,000 ha planted to millet each season, the long-term average yield is 650 $\mathrm{kg\,ha^{-1}}$. From the CUI coverage, the area sown to millet is calculated by summing for the province the area of each pixel multiplied by the proportion of the pixel sown to millet. Provincial production is then estimated by calculating the average millet yield over the province, weighted by area, and multiplying by the percentage of the area grown. The simulated production level is then compared with the provincial norm to produce a percentage anomaly for the province for the current season, using the most up-to-date dekadal rainfall estimates (Fig. 3).

The prototype estimation system is based on a software shell written in BORLAND PASCAL that issues calls to programs that run the crop model, draw maps, and perform analyses. These programs are written in FORTRAN, as is the crop model CERES–Millet. The GIS used is IDRISI (Eastman, 1993). The data structures of each coverage are IDRISI images, and IDRISI display modules are called as appropriate. Most of the coverage manipulation is performed using custom-built FORTRAN programs that operate on the IDRISI image files directly. The major components of the shell are shown in Table 2.

3.6. Real-time daily weather generation

For each weather grid cell (0.25° by 0.25°) there is a file that contains the parameters for the two weather models that are used. On any day for a particular grid cell, rainfall is generated first; SIMMETEO is then used to generate maximum and minimum temperature and solar radiation in response to the absence or presence of rainfall on that day. In the prototype system, there are programs to take the RFEs and calculate dekadal totals for each of the weather grid boxes (there is more than one satellite pixel in each of the weather grid cells). When simulations are carried out, the user can choose to generate the overall distribution of outputs (i.e., with no updating) or update yield estimates for a

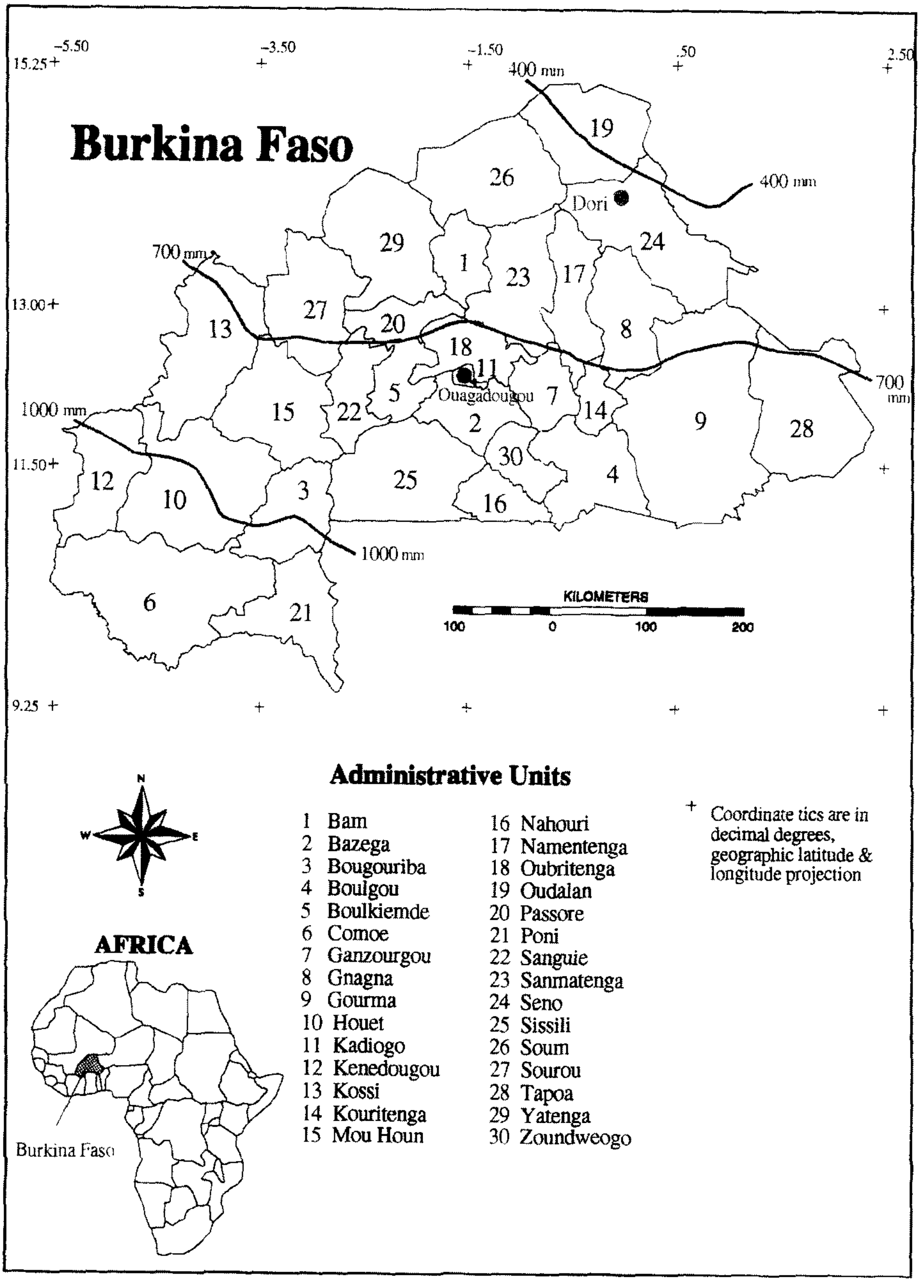

Fig. 2. Burkina Faso, showing provincial boundaries and selected isohyets.

particular season. In this latter case, weather files, generated for each grid cell, contain rainfall data that match the dekadal totals observed for that cell. Consider a cell whose centre is located at 2.75° W, 11.25° N. For dekad 16 of 1990 (1–10 June), assume that

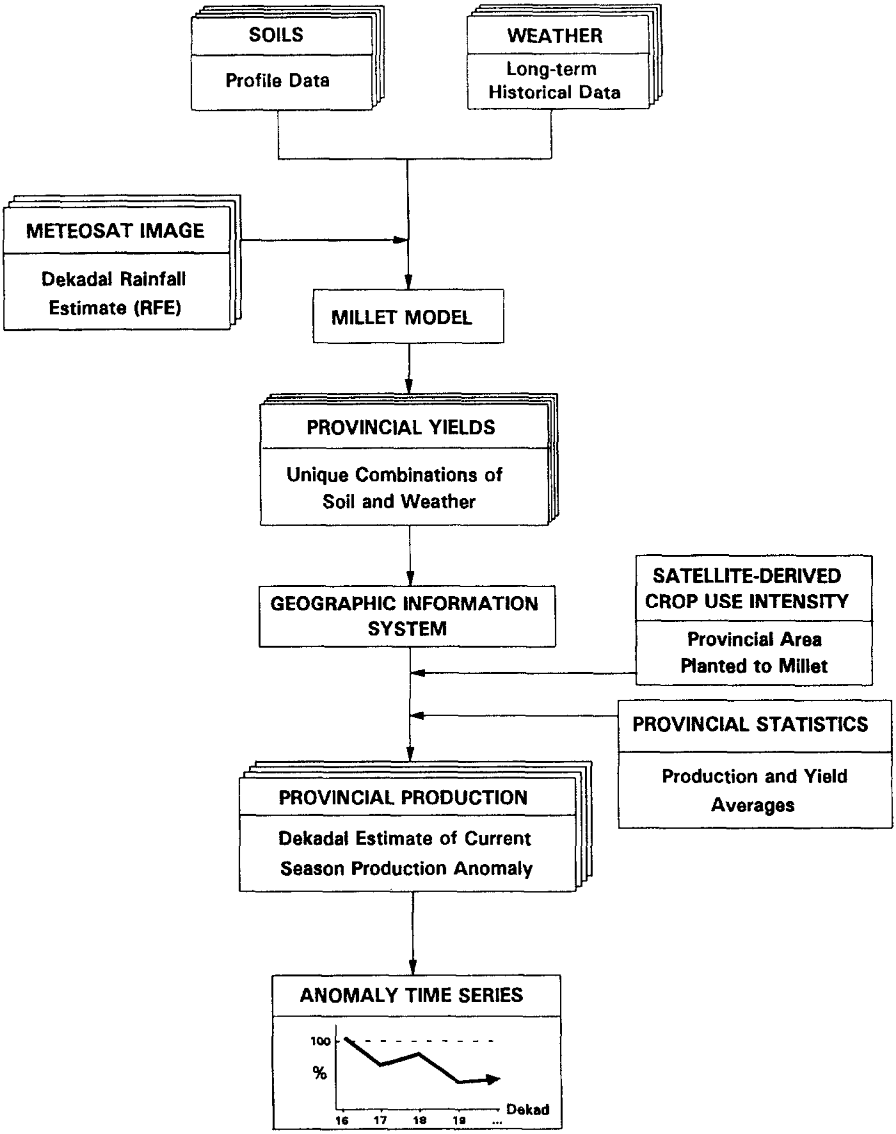

Fig. 3. Information flow in the prototype yield estimation system.

the RFE from the METEOSAT image shows a total of 38.1 mm of rain for the cell; this is the weighted average of all pixels from the METEOSAT image that fall in the quarter-degree grid box whose centre is at 2.75° W, 11.25° N. To convert this dekadal total to daily rainfall, the third-order Markov model is run, and the daily rainfall totals thus simulated are adjusted so that the dekadal total matches the RFE for the particular grid cell. The distribution of simulated rain days within the dekad is plausible because the probabilities of wet and dry days were derived from long-term historical data. This

Table 2
Components of the prototype shell

1. *Information — Coverages*
Map IDRISI raster images (with vector overlays if required) of soils, crop use intensity, provincial boundaries, etc.
2. *Information — Data*
Tabulate and plot provincial production data from 1984 to 1992 (millet area, production, and mean yield by province).
3. *Input METEOSAT Data*
Import ASCII data files of satellite data into the system and convert to an IDRISI rainfall estimate (RFE) image.
4. *Update RFE Data File*
Convert an RFE image to dekadal rainfall totals by grid cell for use by the crop model.
5. *Simulation*
Run the millet model in response to the user's choice of province, treatment, and weather overlays.
6. *GIS Analysis*
Map simulated outputs in terms of the mean, coefficient of variation, 10th and 90th percentile of the simulated distribution for each mapping unit (planting date, maturity date, yield, straw yield, seasonal rainfall, cumulative evapotranspiration, nitrogen leached, and nitrogen uptake).
7. *Tabular Analysis*
Examine the mean and variability of the simulated yield distributions over time for a season in one or all provinces.
8. *Run DSSAT3*
Access the detailed DSSAT3 crop modelling software (Tsuji et al., 1994) directly from the shell, if required.
9. *Configure system*
Configure the software shell and the system in terms of paths and hardware.

constitutes one replicate. There are of course other plausible ways in which the total dekadal rainfall could be distributed within the 10-day period. For this reason, the weather model is run for several replicates to produce ten rainfall files whose dekadal totals match exactly up to the day of simulation or updating but in which the distribution of rain within each dekad is different. If the Markov rain model simulates zero raindays in a dekad for which the RFE is greater than zero, the rainfall is assumed to fall on one randomly assigned rain day within the dekad.

An implication of this methodology is that there will still be some weather variation (and hence yield variation) when using dekadal totals for a complete growing season if the millet model is run with replication. This variation arises because of the probabilistic way in which dekadal rainfall totals are split up among the number of days in the dekad. The variation is generally much smaller compared with probabilistic runs of the model where no dekadal totals are used as a guide because they are either unknown or unavailable.

4. An illustrative example

The modification of a yield distribution through a growing season can be illustrated with reference to some simulations carried out using CERES–Millet at two sites in

Burkina Faso in two contrasting seasons (Table 3, and see Fig. 2). For all simulations, millet was planted on day 160 (9 June), reaching maturity in about 100 days. Dekadal totals were calculated for 1986 and 1990 from the historical rainfall records for each site. For each year, the millet model was run for 11 simulation dates (corresponding to the dates of updating the millet production estimates). Up to the day of simulation, dekadal rainfall estimates were used, divided up probabilistically according to which days within the dekad were simulated to be wet. From the day of simulation onwards, rainfall was simulated probabilistically until the end of the growing season. For several replicates, the result was that dekadal total rainfall for the start of the season was identical (its distribution within the dekad changed between replicates, but not the amounts), whereas rainfall from the date of simulation to the end of the season exhibited both different amounts and distribution between replicates.

The results of simulations replicated 20 times for each of the 11 simulation dates, corresponding to the start of dekads 17 to 27, are shown in Fig. 4, for the two contrasting seasons, 1986 and 1990. Yields are expressed relative to the mean of the yield distribution obtained when all the weather is generated probabilistically, corresponding to the pre-season expectation of yield, when nothing is known about the current season other than the average conditions. For Dori, as the simulation date progressed, the mean simulated millet yield decreased in 1986 but increased in 1990; the standard deviations of the yield distributions decreased in both years as the amount of purely probabilistic weather in the simulations decreased. The variation in yield obtained for the late-season simulation dates was due to the different distributions of rainfall within each dekad — the dekadal and seasonal rainfall total was unchanging between replicates for each year. For Ouagadougou, on the other hand, simulated mean yields increased with 1986 weather data to a level some 30% above the long-term mean but remained close to the long-term mean level with 1990 weather data.

Rainfall at Dori in 1986 was 67% of the long-term average. In Séno, the province in which Dori is situated, the observed average yield of millet in 1986 was 237 $kg\,ha^{-1}$, compared with an average of 355 $kg\,ha^{-1}$ (FEWS, 1994). The 1986 yield was thus only 67% of normal. The simulated yield anomaly (the deviation from the norm) agrees well with this value — final average yield at Dori was simulated to be about 70% of normal in 1986. (The provincial anomalies in Fig. 4 are included for illustrative purposes only.) From Fig. 4A, by the fourth simulation date (dekad 20, day 192), the simulated average deviation was already at the 60% level, giving early indications that the season was likely to be poor. This was indeed the case in 1986. In 1990, by contrast, rainfall was more plentiful although still less than average; the provincial yield was 28% above the average (454 $kg\,ha^{-1}$). By day 213 the mean simulated millet yield was 20% above the average, giving a reasonably early indication that the season was going to be better than average. For Ouagadougou, by contrast, seasonal rainfall in both 1986 and 1990 was close to the average (Table 3), and provincial production in these years was 111% and 102% of the average, respectively (Fig. 4B).

This example illustrates the movement of the mean and variability of the simulated yield distribution at a site level. The prototype system also allows simulations to be aggregated to the provincial level. To illustrate, some simulations were run for conditions in 1986. Nitrogen was assumed to be unlimiting, in order that successive yield

Table 3
Rainfall and millet production characteristics for two sites in Burkina Faso

Site	Province	Latitude	Longitude	Elevation (masl)	Soil type
Dori	Séno	14°2′ N	0°2′ W	276	Solodic Planosol
Ouagadougou	Kadiogo	12°21′ N	1°31′ W	303	Ultisol

Site	Rainfall (mm)			
	Average	Standard deviation	1986	1990
Dori	470	133	330	459
Ouagadougou	784	152	791	676

Province	1986				1990			
	Production (t)	Area (ha)	Yield ($t ha^{-1}$)	Relative yield[a]	Production (t)	Area (ha)	Yield ($t ha^{-1}$)	Relative yield
Séno	15,078	63,354	0.237	67%	29,056	64,000	0.454	128%
Kadiogo	3646	5610	0.649	111%	2380	4000	0.595	102%

[a]Provincial yield as a percentage of the average provincial yield, 1984–1992 (all data from FEWS, 1994).

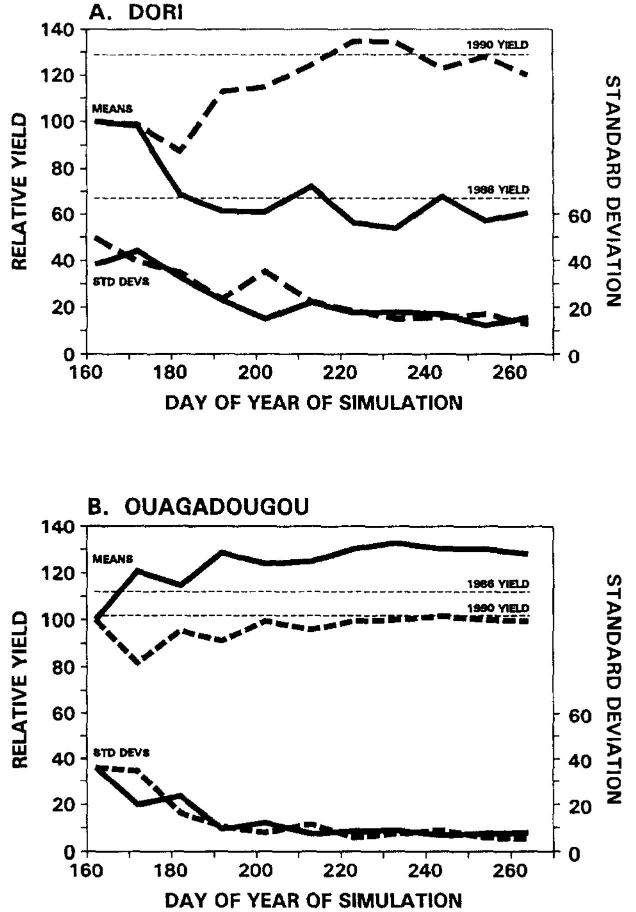

Fig. 4. Variation of the mean and standard deviation of simulated millet yield distributions for two sites in Burkina Faso over a series of simulation dates, using 1986 (solid lines) and 1990 (dashed lines) weather data.

estimates could be related solely to estimated rainfall. The millet crop was planted as soon as the soil profile to a depth of 30 cm was wetted to 20% of field capacity. Provincial mean millet yields per hectare for the 1986 season were calculated from statistics of total millet area and millet production (FEWS, 1994). These are tabulated in column 3 of Table 4 as percentage differences from the long-term provincial mean yield (i.e., historical yield anomalies). Thus in Bam province, the observed mean millet yield in 1986 was 105–125% of the mean yield (which in Bam was 520 $kg\,ha^{-1}$ for the period 1984–1992). Simulated anomalies for each province were generated using the METEOSAT dekadal RFEs for 1986. In Bam province, for example, there are 19 unique combinations of soil type and weather grid cell. CERES-Millet was run ten times for each combination, using the dekadal rainfall totals for the entire season, divided up into appropriate daily data as described above. For each province, the mean provincial yield was calculated by weighting simulated yield by the relative preponderance of that

Table 4
Categories of observed and simulated provincial millet yield anomalies in Burkina Faso, 1986 season

Province	Simulated		Observed (FEWS, 1994)
	Mid-season	End of season	
Bam	2[a]	3	3
Bazèga	4	5	3
Bougouriba	4	4	4
Boulgou	4	5	1
Boulkiemdé	4	5	4
Comoé	4	5	5
Ganzourgou	5	5	4
Gnagna	5	5	5
Gourma	5	5	2
Houet	4	4	2
Kadiogo	3	4	3
Kénédougou	4	4	4
Kossi	4	5	4
Kouritenga	5	5	2
Mouhoun	4	5	4
Nahouri	5	5	5
Namentenga	4	4	3
Oubritenga	4	5	4
Oudalan	1	1	4
Passoré	–	–	no data
Poni	4	4	4
Sanguié	5	5	4
Sanmatenga	4	5	3
Séno	2	2	1
Sissili	4	4	3
Soum	3	3	2
Sourou	4	5	3
Tapoa	5	5	5
Yatenga	3	4	5
Zoundwéogo	5	5	3
Chi-squared[b]	30.7***	38.1***	

[a]Categories as follows: 1, < 75% ('bad'); 2, 75–95% ('poor'); 3, 95–105% ('average'); 4, 105–125% ('good'); 5, > 125% ('excellent').
[b]Chi-squared statistic with 4 degrees of freedom calculated from contingency tables with frequencies in three classes ('poor' and below; 'average'; 'good' and above).

soil–weather combination and the crop use intensity coverage to produce the values shown in column 2 of Table 4. Thus for Bam province the simulated mean provincial yield anomaly was 105–125%. The first column in Table 4 shows the simulated yield anomaly using dekadal RFEs to half way through the season and probabilistic weather thereafter to crop maturity. The data in this column represent the situation in 1986 where half the rainfall data for the millet-growing season were known.

Two things may be noted. First, there is moderate agreement between the historical and simulated yield anomalies at the provincial level although there are large disparities for six provinces. For five of these provinces, simulated yield anomalies are greater than those observed; but only in Oudalan province was the yield anomaly grossly underestimated. The reasons for these discrepancies need to be investigated. The errors appear to be reasonably consistent, and could be related to the accuracy of the RFEs and the soil profile data. Second, there appears to be only limited change between the anomalies simulated at the end of the growing season and those simulated at the mid-point of the season (see the values of chi-squared at the end of Table 4). This suggests that by halfway through the millet-growing season, the model and the RFEs can provide fairly good estimates of what final yield is likely to be. There are exceptions; in Bam, for instance, the mid-season simulation shows that a poor season was in prospect; in fact the end-of-season simulation resulted in above-average millet yields.

5. Conclusions

Despite the crudity of some of the input data used in the examples above, there appears to be much potential in using crop models and satellite-derived estimates of real-time rainfall to calculate production anomalies during the growing season. An advantage of the prototype system is the relatively modest hardware requirement; with a reasonably fast personal computer and access to the internet to obtain the RFE images, a user can update the weather data files and run simulations for the entire country to provide production estimates in 3–4 h. Obtaining crop production estimates in real time in the countries where they are needed is thus perfectly practicable.

There are a number of areas where more work is needed, however. First, CERES–Millet needs further validation and calibration with field trial data from different sites in the region in different seasons. Second, the soils database needs refinement, particularly with regard to initial conditions and their spatial variability. The quantity of input data required to run models such as CERES–Millet is large, but some variables can sometimes be estimated satisfactorily from others that are more easily accessible (such as deriving soil profile water-holding capacity from percent sand, silt, and clay). There may also be some required input data to which the models are simply not very sensitive in Sahelian conditions, and sensitivity analyses could help identify these.

Third, further analysis of the weather data is required. In particular, a more extensive temperature and solar radiation database is needed for the interpolations. Perhaps most critically, the RFEs need to be checked against rainfall data recorded at the weather stations. We have not yet analysed years for which there are both daily historical weather data and dekadal RFE coverages. The accuracy of the RFEs is thus uncertain in these conditions.

Perhaps one of the most serious problems with the prototype system is that it represents a brute-force approach; because all plausible combinations of soil type and weather conditions are simulated for all mapping units that have at least some land area planted to millet, the burden of collecting and assembling the requisite input data is great. The prospect exists of using the statistical approach of a sampling frame; rather than run the models for every conceivable combination, a statistically valid sampling frame could be developed with a comparatively small number of segments; from this subset of segments, soils and weather information could be collected. The crop model would be run for only the segments sampled, and the area sampling frame would then be used to aggregate the simulation results to the regional and national levels. This methodology could have important implications for the amount of input data required.

In the future, continuing population growth and land degradation will increase the importance of the food security issue. Consequently, providing information to decision makers that can help, even in a limited way, to combat risk and ensure food security is a research area that warrants intense activity. The integrity of the information produced by crop models to study risk and food security depends on sound models, sound validation procedures, and sound input data. The input data required to run such models, and their objective testing, can pose substantial problems. However, the real potential of crop models in the study of food security issues has yet to be tapped.

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