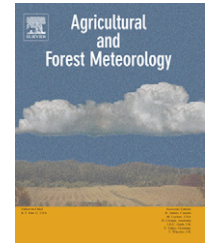


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Sorghum yield prediction from seasonal rainfall forecasts in Burkina Faso

Ashok Mishra^a, James W. Hansen^{b,*}, Michael Dingkuhn^c, Christian Baron^c, Seydou B. Traoré^d, Ousmane Ndiaye^b, M. Neil Ward^b

^a Agricultural and Food Engineering Department, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721302, India

^b International Research Institute for Climate and Society, The Earth Institute, Columbia University, Palisades, NY 10964, USA

^c Ecotrop, CIRAD-AMIS, TA40/01 Av Agropolis, 34398 Montpellier Cedex 5, France

^d AGRHYMET Regional Center, BP 11011 Niamey, Niger

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ABSTRACT

The high variability of rainfall, from interannual to multi-decadal time scales, has serious impacts on food security in the West African Sahel. At five locations in Burkina Faso, we explore the potential to improve model-based prediction of sorghum yields at a range of lead-times by incorporating seasonal rainfall forecasts. Analyses considered empirical and dynamic rainfall forecasts, two methods (regression and stochastic disaggregation) for linking rainfall forecasts with crop simulation, three levels of production technology and four forecast dates (15 May, June, July and August) based on predictors observed from the preceding month, for the period of available data (1957–1998). Accuracy of yield forecasts generally decreased with lead-time. Relative to forecasts based solely on monitored weather and historic climatology, incorporating rainfall forecasts resulted in modest improvements to yield forecasts made in May or June. The benefit from seasonal rainfall forecasts tended to increase with northern latitude. Statistical and dynamic rainfall forecast systems captured much of the multi-decadal variation apparent in historic rainfall and in yields simulated with observed rainfall. This multi-decadal component of rainfall variability accounts for a portion of the apparent predictability of sorghum yields. Correlation between point-scale crop yield simulations and district-scale production statistics (1984–1998) was weakly positive late in the season, and suggest that a dynamic crop model (SARRA-H) has potential to contribute to regional yield prediction beyond what the best linear regression can provide from seasonal rainfall or its predictors. We discuss avenues for further improving crop yield forecasts during the growing season.

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1. Introduction

Food and livelihood security in Sahelian West Africa are highly sensitive to precipitation. As is the case for most Sahelian countries, about 90% of the population of Burkina Faso depends on rainfed subsistence cereal production (Ingram et al., 2002). Some cash crops, such as cotton,

peanut and sesame, are also grown under rainfed conditions. Small dams that support irrigated rice and vegetable production during the dry season also depend on rainfall. Extensive livestock systems, which depend on the same dams and reservoirs, are an important source of income particularly in the drier northern areas of Burkina Faso.

* Corresponding author. Tel.: +1 845 680 4410; fax: +1 845 680 4864.

E-mail address: jhansen@iri.columbia.edu (J.W. Hansen).

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Sorghum is Africa's second most important cereal crop after maize, but the most important cereal in the Guinea savannah (800–1100 mm rainfall) and Sudan savannah (600–800 mm rainfall) regions of West Africa. From a food security standpoint, sorghum is by far the most important crop in Burkina Faso, accounting for 44% of the country's cereal production (1997–2006 mean, data from FAOSTAT) and 28% of caloric food intake (2001–2003 mean, [FAO, 2006](#)). Sorghum yields have been stagnant across West Africa since the late 1970s ([FAO, 1997](#)), but have shown a positive trend in Burkina Faso. Although breeding has increased yield potential of available cultivars, production continues to be dominated by traditional cultivars characterized by strong photoperiod sensitivity, drought tolerance, long stalks, high-quality grain and low harvest index. These traditional cultivars are well adapted to the rainfall variability that characterizes the dryer regions of West Africa ([Dingkuhn et al., 2006](#); [Kouressy et al., 2008](#)). Their extreme photoperiod sensitivity gives farmers the flexibility to adjust planting dates to take advantage of early rains while still getting a modest crop when rains are delayed, with little variation in time of flowering and maturity ([Dingkuhn et al., 2008](#)). Farmers in the Sahel and Sudan savannah plant as early as possible to take advantage of the flush of available nitrogen associated with early rains ([Blondel, 1971a,b,c](#)) and avoid weed pressure ([Stoop et al., 1981](#); [Vaksmann et al., 1996](#)), even though such early planting increases risk of failed establishment and re-sowing ([Sultan et al., 2005](#)). Planting dates in Burkina Faso typically range from May to early July, and tend to be later in more northern latitudes. Harvest maturity ranges from September to November, depending on latitude.

The West African Sahel region experienced catastrophic droughts during the early 1970s and 1980s that had tremendous consequences for its population and ecosystems. This led to the establishment of CILSS (French acronym for Permanent Interstate Committee for Drought Control in the Sahel) and the AGRHYMET Regional Center (www.agrhy-met.net), Niamey, Niger. Since 1974, AGRHYMET has been responsible for crop and pasture monitoring as part of an integrated early warning system for the nine member countries (Burkina Faso, Chad, Cape Verde, The Gambia, Guinea Bissau, Mali, Mauritania, Niger and Senegal) of CILSS.

A tendency toward aridification in the West African Sahel during the 1970s and 1980s has raised concern about the region's long-term ability to meet its food needs, and complicated the challenge of anticipating and responding to drought-related food crises. [Jensen \(1990\)](#) noted a long-term (45–78 years, depending on record length) negative trend averaging 10 mm year^{-1} (1960–1983) in rainfall records in northern Nigeria, shortening of growing seasons and southward movement of agroecological zones. Subsequent studies showed the same pattern throughout the Sahel ([Sivakumar, 1993](#); [Hulme and Jones, 1994](#); [Fontaine and Janicot, 1996](#); [L'Hôte and Mahé, 1996](#); [Diouf et al., 2000](#); [Traoré et al., 2000](#)). [Nicholson et al. \(2000\)](#) found that a substantial decrease in 1968–1997 mean rainfall, relative to the 1931–1960 mean, was particularly noticeable for August, when the decrease in mean rainfall amounts were 55%, 37% and 26% in the Sahelo-Sahara, Sahel and Sudan zones, respectively. [Lebel and Lebarbé \(1997\)](#) found that the decrease of the rainfall amount in the core of

the rainy season (July–August) was related to the number of rain events, while mean intensity of rainfall events remained unchanged. Most annual crops in the region are particularly sensitive to dry spells in August, when they undergo the processes of stem elongation, panicle differentiation and seed set.

The downward trend in Sahelian rainfall since the early 1960s must be considered in the context of dramatic multi-decadal fluctuations that have occurred repeatedly over longer timescales (e.g., [Brooks, 2004](#)), reflecting the fragile nature on the Sahelian climate located in a zone of tight precipitation and vegetation gradients. Several authors have noted that a number of relatively wet years have been observed since the 1980s, leading to average conditions that have been less severe in the last 15 years than in the previous two decades ([Nicholson, 2005](#); [Anyamba and Tucker, 2005](#); [Olsson et al., 2005](#)), yet mean precipitation is still far below the levels of 1950–1970. It is generally considered too early to assess whether the recent 15–20 years represents a temporary respite or the start of a major shift toward wetter conditions. There is also not yet a consensus about how anthropogenic global warming will affect rainfall in the region. Recognition of strong multi-decadal variations in the West African monsoon system and the increasing uncertainty associated with climate change call for food security early warning and response systems that are effective and robust in the face of climate variations at interannual and longer time scales.

Crop monitoring activities of AGRHYMET begin with the assessment of the start of the season, and continue throughout the season with the analysis of the crop water requirement satisfaction, available soil moisture, crop pests and diseases, and yields forecasts. The current yield forecasting system (described in [Traoré et al., 2006](#)) uses 10-daily observed rainfall data or rainfall estimates from METEOSAT infrared imagery, with a simple water balance simulation model, DHC ([Samba, 1998](#)). A water satisfaction index – the seasonally integrated ratio of actual to potential evapotranspiration – is used to estimate cereal yields statistically, based on surveys in six West African countries ([Girard et al., 1994](#); [Samba, 1998](#); [Dingkuhn et al., 2003](#)). Yields are first estimated at the end of August and updated at the end of September. Comparison with the average expected yield indicates whether a region is at risk of food insecurity. The skill of the current methodology is considered acceptable to disseminate to food security stakeholders only starting the end of August.

Any delay in identifying and initiating response to emerging food crises greatly increases the humanitarian and livelihood impacts and the cost of aid ([Haile, 2005](#)), as World Food Program data from the 2004–2005 Niger food crisis demonstrates for the West African case ([Barrett et al., 2007](#)). Increasing the lead-time of probabilistic staple crop production estimates would therefore potentially enable action to protect rural populations to be taken earlier.

The ability to predict rainfall at a seasonal lead-time raises the prospect of increasing accuracy (at a given lead-time) and lead-time (at a given accuracy) of crop production forecasts. The potential improvement from incorporating seasonal forecasts is expected to be greatest early in the growing season. Evidence of teleconnections between rainfall in the West African Sahel and temperatures of the oceans has been

established both at the near-global scale (Folland et al., 1986), and particularly for the tropical Atlantic (Lamb, 1978; Hastenrath, 1990) and the El Niño/Southern Oscillation (ENSO) in the equatorial Pacific Ocean (Janicot et al., 1996; Ward, 1998). These teleconnections influence rainfall at both interannual and multi-decadal timescales (Ward, 1998; Giannini et al., 2003), and provide a basis for forecasting precipitation at a seasonal lead-time, either through direct statistical relationships or dynamic general circulation models (GCMs). Several promising methods are available (reviewed in Hansen et al., 2006) for incorporating seasonal climate forecasts into crop simulation to predict yields.

This paper presents a study of the predictability of sorghum yields, using a dynamic crop simulation model driven by a combination of monitored rainfall and seasonal rainfall forecasts, at five locations in Burkina Faso. Our objective is to enhance the accuracy and lead-time of staple crop production forecasts that are produced operationally to inform food security interventions. Current crop production forecasts are based on monitored weather (through the forecast date) and historic climatology (for the remainder of the growing season). We consider the influence of lead-time, production system, seasonal forecast system and method on predictability, emphasizing the climate component of uncertainty rather than crop model error (Hansen et al., 2006). We then address the influence of multi-decadal fluctuations of the West Africa monsoon system on crop yield prediction. Finally, we compare simulated and forecast yields with historic yield records from the corresponding crop reporting districts (corresponding to administrative regions). The use of seasonal forecasts for crop yield forecasting is one of several components of ongoing research work by AGRHYMET and partner institutions aimed at improving food crop monitoring and early warning in West Africa.

2. Methods

2.1. Data

The study used 42 years (1957–1998) of daily weather data (rainfall, minimum and maximum temperature, relative humidity, solar irradiance and wind velocity) from five stations selected to represent the north–south rainfall gradient across Burkina Faso (Table 1, Fig. 1). A complete set of daily rainfall observations for the full period were available from all the stations from the National Meteorology Department (Direction de la Météorologie Nationale) of Burkina Faso. Measured temperatures, relative humidity, solar irradiance

and wind velocity were available from the National Meteorology Department through 1980, and were collected from the NOAA NCDC Daily Global Historical Climatology Network (GHCN) for the remainder of the study period. Satellite estimates of daily solar irradiance for 1985–1998 are from the Solar radiation Data website (SoDa, http://www.soda-is.com/eng/services/meteo_eng.html). Daily average relative humidity was estimated from minimum, maximum and dewpoint temperatures using the FAO56 method (Allen et al., 1998).

Temperature, relative humidity and wind velocity records were complete for 1950–1980, and roughly 85–95% complete for 1981–1998. There was a gap between National Meteorology Department records and SoDa estimates of solar irradiance from 1981 to 1984. Missing weather data were estimated using a modified stochastic weather generator (Hansen and Mavromatis, 2001) that maintains dependence on the occurrence of precipitation and controls auto-correlation, cross-correlation with available observations as it samples missing records stochastically. To meet the data requirements of the SARRA-H crop model, we extended the stochastic weather generator to include mean daily wind speed and dewpoint temperature (used to estimate relative humidity). Following the approach of Parlange and Katz (2000), we sample dewpoint temperature, and a square root transformation of wind speed, from a multivariate lag-1 auto-correlated normal distribution conditioned on the occurrence of precipitation. Fixed simultaneous and lag-1 cross-correlation matrices are based on data for Eugene, Oregon, USA, reported in Parlange and Katz (2000).

2.2. Seasonal rainfall prediction

We considered two seasonal forecast methods (Table 2): statistical prediction from a set of sea surface temperature (SST) indices, and statistical downscaling from wind fields from a GCM forced with predicted SST boundary conditions. We evaluated both forecast methods for the main July–September monsoon rainfall season, for forecast dates on 15 May, 15 June and 15 July, and August–September rainfall for a 15 August forecast date. Each forecast used SST observations from the preceding month. Based on processing time at the IRI and other operational climate forecasting centers, we assumed that 15 days is sufficient to incorporate observations into SST forecasts, run the GCM, process its output, and run the crop models in an operational crop forecasting system.

The statistical prediction method applied multiple linear regression to four SST indices: an index representing ENSO in the tropical Pacific (10°N–10°S and 150°W–90°W), an index in the northwestern subtropical Atlantic (20°N–40°N and 30°W–10°W),

Table 1 – Stations used in the study

Station	Longitude (°E)	Latitude (°N)	Elevation (m)	Annual rainfall ^a (mm)
Dori	0.1	14.0	277	491
Ouahigouya	–2.4	13.6	329	624
Ouagadougou	–1.5	12.4	306	735
Fada N'gourma	0.4	12.1	292	866
Bobo-Dioulasso	–4.3	11.2	432	1049

^a Mean of 1957–1998.

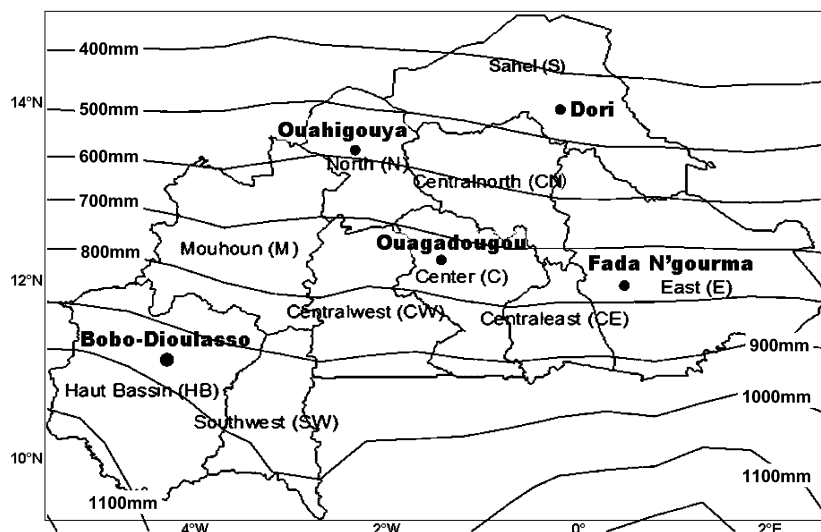


Fig. 1 – Stations and crop reporting districts in Burkina Faso used in this study. Rainfall isohyets are interpolated from 1971 to 2000 mean annual precipitation from the University of East Anglia, Climate Research Unit TS2.1 gridded precipitation data set (courtesy of Michael Bell).

an index in the equatorial southeastern Atlantic (0°S–10°S and 20°W–10°E), and a more global index primarily describing the contrast between SST anomalies in the northern and southern hemispheres, as represented by the third principal component (PC) of global SSTs. These indices, which build on the known teleconnection relationships, have been used for operational seasonal forecasts of rainfall by national meteorological services at the West Africa regional climate outlook forums (PRESAO) since 1998 (CLIPS, 1998).

The GCM used in this study was ECHAM v. 4.5 (Roeckner et al., 1996), developed at the Max-Planck Institute. It was run at a T42 (approximately 2.8°, or 280 km at the equator) horizontal resolution, with 18 vertical levels. Hindcasts were based on the mean of an ensemble of 24 GCM integrations (Li and Goddard, 2005), each run with different initial atmospheric conditions but the same SST boundary conditions predicted over the tropical oceans (30°N–30°S) using constructed analogs (van den Dool, 1994). Over the extra-tropical oceans, the damped persistence of the preceding month's observed SST anomalies were added to the climatological annual cycle of SSTs from each starting month through the following 6 months.

To downscale from the GCM to the study locations, we used the first principal component (PC1) of GCM output fields of low-level (925 hPa) zonal winds across the tropical Atlantic and West Africa (60°W–10°E, 40°S–30°N), based on the work of Ndiaye et al. (2001, submitted for publication). Ndiaye et al. found that ECHAM driven with observed SSTs simulated an index of Sahelian rainfall (1968–2002) poorly (cross-validated $r = 0.07$), but that prediction from PC1 of GCM zonal wind fields over this region improved skill dramatically (cross-validated $r = 0.56$). The choice of GCM wind field as the predictor for statistical downscaling was guided by the knowledge that in West Africa, the low-level wind is one of the major features of the rainfall dynamics, carrying moisture from the ocean in the monsoon flow to constitute precipitable water over land. ECHAM simulates low-level circulation over the tropical Atlantic in response to SST forcing particularly well. Simulation of rainfall in the Sahel is known to be problematic in GCMs, with many challenges such as the representation of convection at the coarse spatial scale of the GCM. The use of the GCM's wind field as a statistical predictor is a compromise, which nonetheless maintains the potential advantage of the GCM to respond physically to the full detail of the prevailing

Table 2 – Sorghum yield prediction scenarios

Scenario	Climate input	Method
Baseline ^a	Observed weather	Direct input
Climatology ^b	Sampled weather	Simple average
SST-regression	Seasonal hindcasts from SST indices	Multiple linear regression
SST-disaggregation	Monthly hindcasts from SST indices	Stochastic disaggregation
GCM-regression	Seasonal hindcasts from GCM fields	PC regression
GCM-disaggregation	Monthly hindcasts from GCM fields	Stochastic disaggregation

^a Yields under the Baseline scenario are simulated with weather observed throughout the season.

^b Predicted yield under the Climatology scenario is the mean of yields simulated with antecedent weather observed for the current year, and weather from all other years from the forecast date through end of season.

SST pattern in each year. In contrast, statistical climate forecast models are constrained to the predictability that can be extracted from the relatively short historical period of data. On the other hand, because statistical forecast methods can often simplify relationships very effectively and prove to be very robust, it is generally held that information from the two approaches should be considered complimentary.

We consistently applied leave-one-out cross-validation to statistical forecasting from SSTs and to the statistical transformation of GCM wind fields to reduce the danger of artificial skill by ensuring that observations from the forecast period did not directly influence forecasts (Michaelsen, 1987).

2.3. Crop model description

SARRA-H (Dingkuhn et al., 2003; Sultan et al., 2005; Baron et al., 2005) is a simple, deterministic simulation model for cereals. It was developed from SARRA, a dynamic soil water balance model developed for zoning and risk analysis (Affholder, 1997; Baron et al., 1999) and for sorghum and millet yield forecasting (Samba, 1998). SARRA-H simulates yield attainable under water-limited conditions by simulating the soil water balance, potential and actual evapotranspiration, phenology, potential and water-limited C assimilation, and biomass partitioning. The model requires latitude, daily weather data (minimum and maximum temperature, potential evapotranspiration, rainfall and solar radiation), soil depth and soil water holding capacity, mulches if any, and sowing density and depth as inputs.

The daily water balance component simulates runoff using an empirical rain event threshold of 20 mm (Baron et al., 1996), soil evaporation, storage, deep drainage, and extraction by transpiration and soil surface evaporation. To represent a typical sandy Alfisol for the West African Sahel, we set available water holding capacity (between wilting point and field capacity) to 100 mm m^{-1} , and maximum root depth to 1.8 m. The fraction of ground cover, based on simulated LAI and a Beer–Lamberts extinction coefficient of 0.49, is used to partition evaporative demand between the soil and plant. Water-limited transpiration is calculated from relative soil water content, scaled between wilting point and field capacity (Sinclair and Ludlow, 1986), and a genotype-dependent depletion factor set to 0.55 for sorghum, following FAO guidelines (Allen et al., 1998). Maximum evapotranspiration, achieved at full ground cover, is calculated with a crop coefficient set to 1.15, following FAO guidelines (Doorenbos and Pruitt, 1977; Doorenbos and Kassam, 1979).

Potential C assimilation rate is obtained by multiplying intercepted photosynthetically active radiation, with an empirical conversion efficiency coefficient that is analogous to radiation use efficiency (Sinclair and Muchow, 1999) but based on assimilation before subtracting respiration losses. Water-limited assimilation rate is then obtained by multiplying by the ratio of water-limited to potential transpiration. After subtracting maintenance respiration (Penning de Vries et al., 1989), biomass during vegetative growth is partitioned among root, stem and leaves (Samba et al., 2001). Leaf biomass is converted to area from dynamically simulated specific leaf area (Penning de Vries et al., 1989). To capture the influence of environment on harvest index, grain filling is simulated by

determining sink capacity during pre-floral stages and inducing leaf senescence after flowering when sink capacity exceeds current assimilation rate.

Phenology is driven by temperature for all stages and by day length during the photoperiod-sensitive phase (Dingkuhn et al., 2008). Relative development rate follows a trapezoidal function of temperature, with no development below 11°C (Lafarge et al., 2002; Clerget et al., 2004) or above 44°C (Ritchie and Alagarwamy, 1989), and maximum development rate in the optimal range of $26\text{--}34^\circ\text{C}$. Daily observed minimum and maximum temperatures are interpolated to hourly values for the calculation of thermal time (Dingkuhn et al., 1995).

2.4. Crop production scenarios

We calibrated SARRA-H v. 3.1.4 for three levels of sorghum production technology (denoted here “Traditional,” “Improved” and “Hybrid”) with associated varieties, based on experimental field data described by Kouressy et al. (2007) and parameterization procedures described by Dingkuhn et al. (2008). The field data originated from experiments conducted in 2004–2005 at the Sotuba agricultural research station of the Institut de l’Economie Rurale (IER) near Bamako in Mali ($12^\circ39'\text{N}$ and $05^\circ56'\text{W}$).

Traditional technology is based on a tall, traditional, highly photoperiod-sensitive Guinea landrace collected in southern Mali, with a grain yield potential of about 2.0 Mg ha^{-1} . Its local name is *Kendé Ngou*, its international password is SGO5015 IRD and its code in the ICRISAT germplasm collection for sorghum is IS 25975.

Improved technology is based on a dwarf breeding line sharing 75% of the Traditional cultivar’s genome as well as its photoperiod sensitivity (Kouressy et al., 2007). Despite virtually unaltered phenology, it produces less biomass but more grain (up to 3.5 Mg ha^{-1}) than the Traditional cultivar. It is thus an Improved cultivar that fits into traditional cropping calendars, generally based on sowing early in the season. Both Traditional and Improved cultivars enable flexible cropping calendars because their photoperiodic response triggers flowering at roughly the optimal time (end of the rainy season) regardless of sowing date.

Hybrid technology is based on a dwarf, early-maturing, photoperiod-insensitive, high-yielding (5.0 Mg ha^{-1}), *Caudatum* hybrid developed by the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT), coded ICSH89002. The hybrid must be sown at a specific date in order to synchronize flowering with the end of the wet season (to avoid drought, pest and disease problems during grain filling) and requires fertilizer inputs. It is thus a “modern” technology so far adopted only by a minority of farmers.

Since farmers generally use crop varieties whose phenology is specifically adapted to the local latitude and seasonal rainfall patterns, we adjusted the model’s phenological parameters for each of the three varieties to give optimal agronomic fit for the Ouagadougou site, while maintaining their inherent level of photoperiod sensitivity (phenological response to sowing date and latitude). Among the five reference sites, the latitude of Ouagadougou is intermediate in terms of latitude and rainfall. This choice was considered an appropriate compromise between the objective of

transparency (using the same model for the entire study) and site specificity of the simulated agronomic technology (genotypic parameters of crop variety).

To approximate the behavior of farmers in the West African Sahel, who generally sow only after a major rainfall event wets the soil, simulated germination was triggered the first time after planting when at least 15 mm water was available in the top (wetted) soil layer. Although simulated sowing dates were fixed at 15 May for the Traditional and Improved technologies, and 22 June for the Hybrid, triggering germination based on soil moisture captures the effect of farmers' typical sowing rules. The initial soil water profile was simulated by running the model's soil water balance for each year and location from 1 April until the sowing date, starting off with a dry soil profile. Simulated germination dates ranged from late May to late July. Harvest maturity was generally reached in October to early November.

2.5. Yield prediction

We evaluated two methods for incorporating seasonal precipitation forecasts into simulation of sorghum yields in Burkina Faso (Table 2): stochastic disaggregation of predicted monthly precipitation, and statistical prediction of simulated yields as a function of seasonal predictors.

The statistical approach assumes that robust predictors of local seasonal rainfall are potential predictors of crop response. In this case, the predictand used to train a linear regression model was yields simulated with observed weather. For each hindcast year i , SARRA-H simulated yield y_{ij} with observed daily weather up to the forecast date, then with every year j of historic weather (1950–1998) for the remainder of the growing season. Predicted yield for year i was then estimated by a linear regression model, fit by ordinary least squares to the simulated yields y_{ij} and corresponding seasonal rainfall predictors (GCM wind field PCs or SST indices) from each year $j \neq i$ as outlined in Hansen et al. (2004).

Stochastic disaggregation involves using a stochastic weather generator to generate synthetic daily rainfall that exactly matches predicted monthly totals. The method (Hansen and Ines, 2005) maintains consistency between the parameterized precipitation occurrence and intensity components of the parameterized weather generator by repeatedly generating a month of stochastic rainfall until the total is sufficiently close (i.e., within 5%) of the target, then using a multiplicative shift to exactly match the target. It used the same extended stochastic weather model described earlier (Section 2.1) for filling gaps in observed weather records. For each year, SARRA-H ran with observed daily weather up to the forecast date, then with ten realizations of synthetic weather from the stochastic model for the remainder of the growing season. We repeated the process for each of the four forecast dates.

We also estimated district-scale yield as a cross-validated linear regression function of seasonal rainfall and its predictors, to serve as a benchmark for assessing the ability of model-based yield simulations and predictions to represent historic production statistics. To approximate the model-based forecast system, we used observed rainfall total from June through the end of the month prior to the forecast date,

and SST indices from the month prior to the forecast as regression predictors.

2.6. Analyses

Analyses of predictability were based on 1957–1998 simulations, and used yields simulated with observed daily weather as a proxy for actual yields. They therefore represent only the climatic component of uncertainty, and not crop model error. We also compared crop simulations model-based yield predictions with historic yield statistics in the reporting districts containing the five study stations (Fig. 1), through the 1984–1998 period when available weather data and crop statistics overlap. We considered results for individual stations, and simple averages across all five stations. We applied a spectral smoothing filter (Press et al., 1989) with a 15-year smoothing period to separate the multi-decadal and the interannual components of variability, and compared goodness-of-fit measures for the raw results with residuals about the smoothed trend to estimate the influence of multi-decadal variations on predictability of rainfall and yields.

Pearson's coefficient of linear correlation between observations and cross-validated predictions served as a descriptive pair-wise measure of goodness of fit. We also evaluated mean bias error (results not shown), and found that it contributed only a small proportion of the overall prediction error when comparing yield predictions to simulations with observed weather. Consistent use of leave-one-out cross-validation minimized the potential for artificial prediction skill (Efron and Gong, 1983; Michaelsen, 1987).

3. Results and discussion

3.1. Rainfall prediction

We present a summary of predictability of July–September rainfall – the main monsoon period when there is established predictability – at the five study locations primarily to inform interpretation of yield prediction results. This study uses seasonal rainfall prediction methods that are published elsewhere, and focuses instead on prediction of sorghum yields.

When averaged across stations, empirical forecasts based on SST indices performed moderately better than forecasts from GCM wind fields, especially for the longest-lead forecasts (available in May from predictors observed in April (Table 3)). Statistical prediction methods can be more robust than GCM response to the substantial error of projections of SST forward through the rainfall season, as Ward et al. (1993) found for the Sahel based on a smaller set of experiments. Predictability of averages across stations was roughly the same for frequency (i.e., number of days with ≥ 1 mm rainfall) as for the seasonal rainfall total. However, for individual stations, correlations tended to be higher for rainfall frequency than for seasonal totals. Mean intensity showed no predictability from the GCM, and only weak predictability from SST indices. This indicates that the predictability of seasonal rainfall total is due more to the predictability of the number of rainy days than to the intensity of daily rainfall. For Senegal, Moron et al. (2006, 2007)

Table 3 – Correlation between observed July–September precipitation total, frequency and mean intensity, and predictions from GCM wind fields and SST indices, 1957–1998

Station	May		June		July	
	GCM	SSTs	GCM	SSTs	GCM	SSTs
Cumulative rainfall						
Dori	0.17	0.41**	0.42**	0.28	0.33*	0.26
Ouahigouya	−0.19	0.24	0.25	0.23	0.20	0.39**
Ouagadougou	0.09	0.43**	0.32*	0.34*	0.36*	0.40**
Fada N’gourma	0.47**	0.43**	0.21	0.37*	0.30	0.44**
Bobo-Dioulasso	0.21	0.13	0.19	0.20	0.37*	0.34*
Average	0.38*	0.56***	0.50***	0.51***	0.56***	0.65***
Rainfall frequency						
Dori	0.39*	0.38*	0.27	0.31	0.41**	0.44**
Ouahigouya	−0.51	0.18	0.05	0.25	−0.12	0.09
Ouagadougou	0.33*	0.51***	0.30	0.58***	0.42***	0.57***
Fada N’gourma	0.48**	0.57***	0.41**	0.45**	0.56**	0.47**
Bobo-Dioulasso	0.19	0.56***	0.26	0.50***	0.39*	0.46**
Average	0.40**	0.58***	0.40**	0.55***	0.55***	0.57***
Mean rainfall intensity						
Dori	−0.62	0.01	0.22	−0.05	−0.44	−0.30
Ouahigouya	−0.28	0.54***	0.30	0.43**	0.22	0.49**
Ouagadougou	−0.16	0.02	−0.05	−0.01	−0.12	−0.12
Fada N’gourma	0.16	0.12	−0.63	0.18	−0.07	0.16
Bobo-Dioulasso	−0.01	−0.04	−0.15	0.06	0.03	0.18
Average	−0.32	0.39*	0.15	0.38*	0.11	0.43**

Frequency and intensity are based on a 1-mm occurrence threshold. Asterisks indicate significance at the 0.05 (*), 0.01 (**) and 0.001 (***) levels.

also observed that frequency of rainfall is predictable, but that mean intensity is not, and attributed the difference in predictability to the moderate spatial coherence of rainfall occurrence and absence of correlation of intensities between stations.

Predictability tends to weaken substantially with increasing lead-time (Table 3). The difficulty of predicting Sahelian rainfall at a long lead-time is widely recognized, and is attributed to the relatively rapid changes in the key SST anomalies for Sahel rainfall: in the eastern and central tropical Pacific associated with the transition of ENSO states typically between March and June, and changes in the tropical Atlantic during this period. Ward et al. (1993) observed a substantial drop in GCM prediction skill when using SST projects based on May vs. June SST observations. Ndiaye et al. (submitted for publication) found that cross-validated correlations between an observed Sahelian rainfall index and predictions based on ECHAM wind fields dropped from 0.56 with constructed analogs based on June SSTs, to 0.35 and 0.30 with constructed analogs based on May and April SSTs observations, respectively. The GCM pattern of predictability for the Burkina stations also shows much better skill from June SST compared to April SST. For the empirical prediction models, the change in skill as a function of lead-time is less substantial. Indeed, predictions from April SST are slightly more skillful than those from May SST, though the difference is likely attributable to sampling.

The GCM-based forecast system used in this study should be taken as illustrative but not definitive of the potential performance of GCM-based seasonal forecasts for the Sahel. There are options that may provide modest increases in the skill of seasonal rainfall forecasts. The constructed analog method used in our study is likely not the best method to

forecast SSTs, particularly for the tropical Pacific. Improved SST forecasts would benefit both GCM-based and statistical seasonal rainfall forecasts. Furthermore, while we used a single GCM, the best predictive information often results from combining more than one GCM (Robertson et al., 2004; Hagedorn et al., 2005; Doblus-Reyes et al., 2006). Operational forecasts already routinely employ these enhancements. Yet combining multiple GCMs has not shown large improvements in skill for this region, and is not likely to lead to major improvements in the near future, at least with the current suite of GCMs available to the international community. On the other hand, the fact that the SST indices and GCM wind fields both provide substantial prediction skill suggests that it may make sense to consult predictions from both approaches when producing operational forecasts. Although the statistical SST-based forecasts are normally more skillful, the GCM is able to physically respond to the prevailing pattern of global SSTs and therefore potentially better able to handle unusual SST patterns.

3.2. Rainfall-based sorghum yield prediction

In general, the accuracy of yield forecasts decreased with increasing lead-time, regardless of the predictor or method (Fig. 2). This is expected because an increasing proportion of weather is observed rather than estimated or sampled from the climatological distribution as the growing season progresses. Decreasing skill of seasonal rainfall forecasts at the longer lead-times also contributed to the drop in predictability in May and June. In several instances, yields were slightly more predictable in May (based on April predictor observations) than in June, consistent with the slight increase in apparent predictability of rainfall.

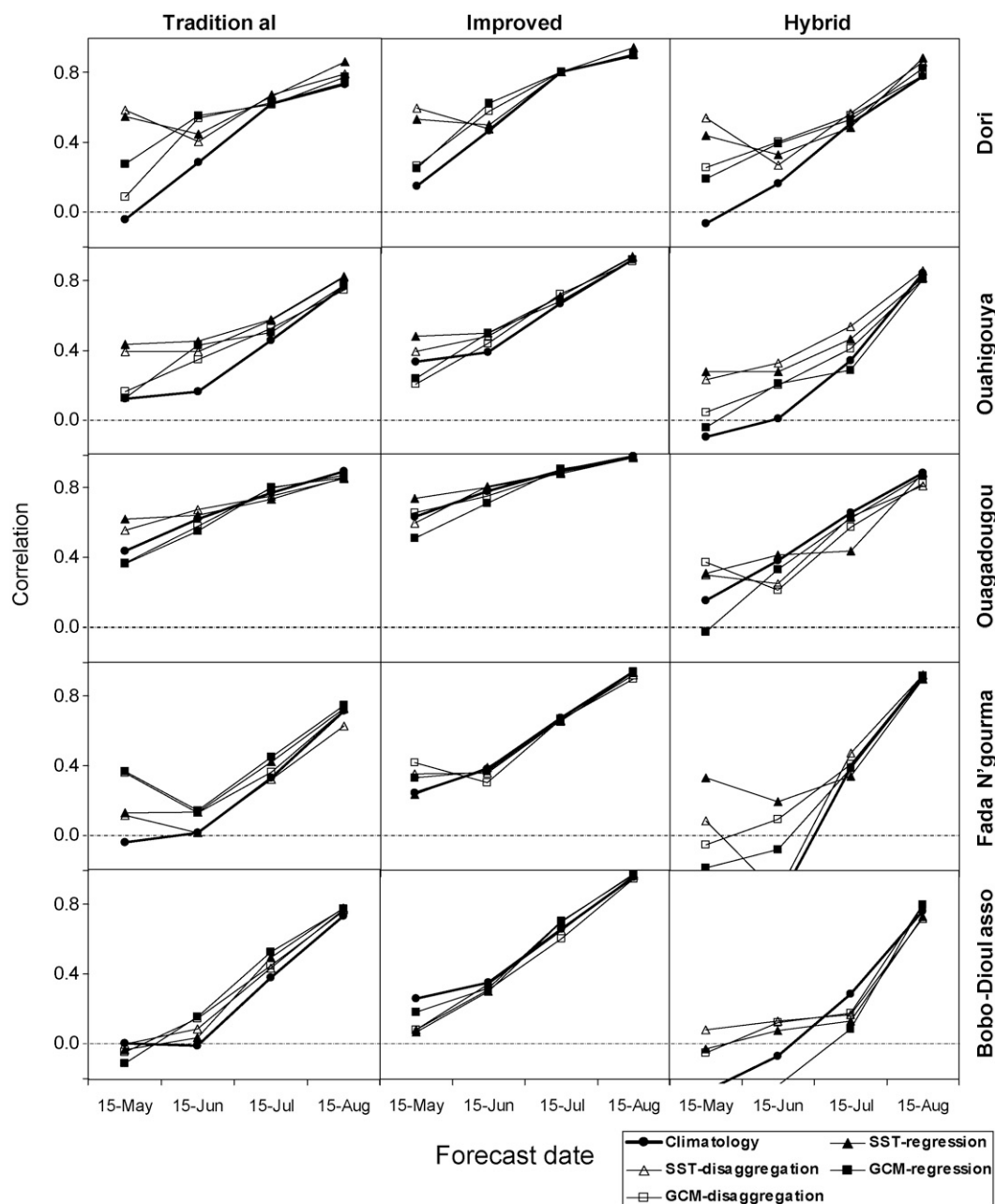


Fig. 2 – Correlation between predicted sorghum yields and baseline yields simulated with observed weather, 1957–1998.

With few exceptions, incorporating seasonal rainfall forecasts improved yield predictions made early in the season (Fig. 2). The benefit from seasonal rainfall forecasts was greatest at the earliest forecast date, and largely disappeared by July.

The Improved production technology showed the greatest predictability at all lead-times (Table 4). The Hybrid showed substantially weaker predictability than the Traditional and Improved technologies for forecasts made through July. Differences among technology scenarios diminished at later forecast dates. These observations are consistent with the physiological and phenological characteristics of the cultivars. The Traditional and Improved cultivars are sown earlier than the Hybrid and have longer duration, allowing more time to

integrate the effects of early rainfall anomalies on growth and yield (Kouressy et al., 2007). They produce a variable amount of biomass and number of tillers and panicles during pre-floral stages. However, the Hybrid produces a single stem per plant. Its grain yield is determined largely during panicle differentiation and grain filling, which occur relatively late in the season. Among the three, the Improved cultivar shows the highest potential number of tillers and the greatest yield response to resources (Kouressy et al., 2007). Although the crop model does not simulate tillering explicitly, it does capture the response patterns of each of the cultivars (Dingkuhn et al., 2008).

Crop response to rainfall is mediated by interactions between the timing of rainfall, the soil water balance and crop development. An important component of dryland cereal

Table 4 – Correlation between baseline sorghum yields, simulated with observed weather and yields predicted by regression from SST indices, 1957–1998

Station	May	June	July	August
Traditional technology				
Dori	0.55***	0.45**	0.67***	0.87***
Ouahigouya	0.44**	0.45**	0.58***	0.82***
Ouagadougou	0.62***	0.64***	0.73***	0.85***
Fada N'gourma	0.13	0.13	0.42**	0.73***
Bobo-Dioulasso	−0.03	0.03	0.49***	0.77***
Average	0.55***	0.52***	0.70***	0.90***
Improved technology				
Dori	0.54***	0.50**	0.81***	0.95***
Ouahigouya	0.48**	0.50**	0.71***	0.93***
Ouagadougou	0.73***	0.80***	0.88***	0.97***
Fada N'gourma	0.24	0.39*	0.66***	0.93***
Bobo-Dioulasso	0.07	0.30	0.69***	0.97***
Average	0.64***	0.62***	0.83***	0.98***
Hybrid technology				
Dori	0.44**	0.33**	0.49***	0.89***
Ouahigouya	0.27	0.28	0.46**	0.81***
Ouagadougou	0.31*	0.41**	0.43**	0.88***
Fada N'gourma	0.33*	0.20	0.34*	0.90***
Bobo-Dioulasso	−0.03	0.08	0.13	0.73***
Average	0.39*	0.38*	0.54***	0.91***

Asterisks indicate significance at the 0.05 (*), 0.01 (**) and 0.001 (***) levels.

response to drought is variability of crop physiological sensitivity among phenological phases. Although drought during the crop cycle generally has cumulative effects on yield (van Oosterom et al., 1996), accurate yield prediction requires weighting of phenological phases. The least sensitive period occurs during vegetative development, after crop establishment and before panicle initiation (roughly weeks 2–9 for Traditional and Improved cultivars, weeks 2–5 for the Hybrid).

Table 5 – Correlation between observation and predictions of precipitation and simulated sorghum yields (Improved technology, regression-based), 1957–1998

Station	GCM winds		SST indices	
	May	June	May	June
Sorghum yields				
Dori	0.26	0.63***	0.54***	0.50***
Ouahigouya	0.24	0.50***	0.48**	0.50***
Ouagadougou	0.51***	0.71***	0.73***	0.80***
Fada N'gourma	0.33*	0.37*	0.24	0.39*
Bobo-Dioulasso	0.18	0.32*	0.07	0.30
Average	0.50***	0.54***	0.64***	0.62**
July–September precipitation				
Dori	0.17	0.42**		
Ouahigouya	−0.19	0.25	0.24	0.23
Ouagadougou	0.09	0.32*	0.43**	0.34*
Fada N'gourma	0.47**	0.21	0.43**	0.37*
Bobo-Dioulasso	0.21	0.19	0.13	0.20
Average	0.38*	0.50***	0.56***	0.51***

Asterisks indicate significance at the 0.05 (*), 0.01 (**) and 0.001 (***) levels.

The most sensitive period is the subsequent reproductive phase, from panicle initiation through flowering (about 4 weeks) (Premachandra et al., 1994). The flowering period, which lasts only a few days, is particularly sensitive to drought. During the later grain fill and maturation period, tolerance to drought is intermediate for the Traditional and Improved cultivars, but quite high in the case of the Hybrid due to its stay-green traits (Premachandra et al., 1994; Borrel and Hammer, 2000). The SARRAH model reproduces these patterns of drought sensitivity (Heinemann et al., 2008).

At the longer lead-times, the SST indices were better on average than GCM wind fields as predictors of sorghum yields, using regression (Fig. 2, Table 5). This is consistent with the previously recognized tendency for the Sahel for rainfall predictability to be greater from SST indices than from the GCM, most clearly at the longer lead-times. In most instances, the best May or June predictor of sorghum yields was also the best predictor of July–September precipitation (Table 3). The advantage of SST indices over the GCM predictors tended to be greatest for forecasts available in May.

Differences in yield predictability due to method (regression vs. stochastic disaggregation) were generally smaller than differences due to predictor (Table 6). The direction of the difference was not consistent among forecast dates, locations, production technologies or seasonal rainfall predictors. These results therefore do not provide a basis for preferring one method over the other.

The results suggest that latitude may influence the contribution of seasonal rainfall forecasts to yield predictability early in the growing season. May and June yield

Table 6 – Correlation between baseline sorghum yields, simulated with observed weather and yields predicted from SST indices, 1957–1998

Station	Regression		Disaggregation	
	May	June	May	June
Traditional technology				
Dori	0.55***	0.45**	0.59***	0.41**
Ouahigouya	0.44**	0.45**	0.40**	0.40**
Ouagadougou	0.62***	0.64***	0.56***	0.67***
Fada N'gourma	0.13	0.13	0.12	0.02
Bobo-Dioulasso	−0.03	0.03	0.00	0.09
Average	0.55***	0.52***	0.54***	0.49**
Improved technology				
Dori	0.54***	0.50***	0.60***	0.48**
Ouahigouya	0.48**	0.50***	0.40***	0.48**
Ouagadougou	0.73***	0.80***	0.59**	0.81***
Fada N'gourma	0.24	0.39*	0.36*	0.36*
Bobo-Dioulasso	0.07	0.30	0.08	0.34*
Average	0.64***	0.62***	0.62***	0.60***
Hybrid technology				
Dori	0.44**	0.33*	0.55***	0.27
Ouahigouya	0.27	0.28	0.23	0.32*
Ouagadougou	0.31*	0.41**	0.30*	0.25
Fada N'gourma	0.33*	0.20	0.08	−0.33
Bobo-Dioulasso	−0.03	0.08	0.08	0.13
Average	0.39	0.38*	0.54***	0.34*

Asterisks indicate significance at the 0.05 (*), 0.01 (**) and 0.001 (***) levels.

Table 7 – Mean and standard deviation of simulated sorghum yields and rainfall through and after 1970

Station	Mean			S.D.		
	1957–1970	1971–1998	% change	1957–1970	1971–1998	% change
Yield—Traditional technology (kg ha⁻¹)						
Dori	416	225	-46.0	165	99	-39.8
Ouahigouya	670	462	-31.0	138	195	41.9
Ouagadougou	876	637	-27.3	175	279	59.7
Fada N’gourma	1017	847	-16.7	133	158	19.1
Bobo-Dioulasso	951	805	-15.4	123	195	59.3
Average	786	595	-24.3	65	123	90.1
Yield—Improved technology (kg ha⁻¹)						
Dori	1047	555	-47.0	561	322	-42.5
Ouahigouya	1832	1210	-33.9	427	587	37.3
Ouagadougou	2353	1616	-31.3	590	836	41.7
Fada N’gourma	2563	2272	-11.3	586	503	-14.3
Bobo-Dioulasso	2426	2118	-12.7	615	621	1.0
Average	2044	1554	-24.0	259	348	34.4
Yield—Hybrid technology (kg ha⁻¹)						
Dori	2233	1590	-28.8	605	674	11.3
Ouahigouya	3314	2503	-24.5	574	1197	108.7
Ouagadougou	2780	2613	-6.0	413	957	131.9
Fada N’gourma	2814	3025	7.5	367	471	28.4
Bobo-Dioulasso	3413	3433	0.6	413	696	68.7
Average	2911	2633	-9.5	220	523	138
July–September rainfall (mm)						
Dori	437	349	-20.3	75	71	-5.4
Ouahigouya	526	434	-17.6	74	119	61.6
Ouagadougou	592	480	-18.9	133	128	-3.8
Fada N’gourma	706	523	-25.9	142	133	-6.0
Bobo-Dioulasso	789	625	-20.8	144	114	-21.2
Average	610	482	-21.0	41	74	79.2

forecasts that incorporated rainfall forecasts tended to be better at the northern than the southern locations (Fig. 2). For forecast dates up to July, predictability of yields was weakest for the two southern-most locations, regardless of production technology, predictor or method (Fig. 2, Tables 4–6). This appears to be due to greater sensitivity of yields to rainfall in

the dryer north, as predictability of rainfall at these lead-times does not show a corresponding north–south trend (Table 3). Furthermore, Baron et al. (2005) showed a substantial north–south gradient in the relative influence of precipitation and solar irradiance on yields across a network of 30 stations across the Sahel and savannah zones of West Africa (10–18°N

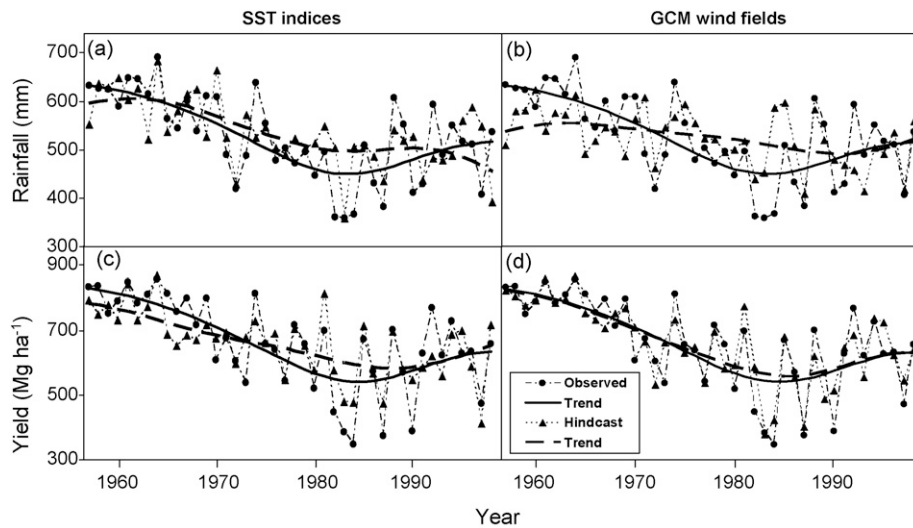


Fig. 3 – Observed (simulated for yields) and (a and b) July predictions of July–September precipitation and (c and d) sorghum yields simulated with Improved production technology, and multi-decadal variation trend estimated by a spectral smoothing filter with period of 15 years, average among stations, 1957–1998.

Table 8 – Correlation between predicted (by SST regression) and baseline sorghum yields simulated with observed station weather under Improved technology, raw results and residuals about a trend estimated by a smoothing filter, 1957–1998

Station	May		June		July		August	
	Raw	Residual	Raw	Residual	Raw	Residual	Raw	Residual
SST regression								
Dori	0.54***	0.16	0.50***	0.20	0.81***	0.77***	0.95***	0.94***
Ouahigouya	0.48**	0.27	0.50***	0.38*	0.71***	0.64***	0.93***	0.93***
Ouagadougou	0.73***	0.57***	0.80***	0.70***	0.88***	0.80***	0.97***	0.95***
Fada N'gourma	0.24	0.16	0.39*	0.37*	0.66***	0.61***	0.93***	0.93***
Bobo-Dioulasso	0.07	0.03	0.30	0.31*	0.69***	0.70***	0.97***	0.97***
Average	0.64***	0.29	0.62***	0.39*	0.83***	0.73***	0.98***	0.97***
GCM regression								
Dori	0.26	–0.09	0.63***	0.39*	0.81***	0.82***	0.91***	0.90***
Ouahigouya	0.24	0.17	0.50***	0.40**	0.68***	0.70***	0.92***	0.93***
Ouagadougou	0.51***	0.06	0.71***	0.63***	0.90***	0.86***	0.97***	0.95***
Fada N'gourma	0.33*	0.29	0.37*	0.39*	0.67***	0.62***	0.94***	0.94***
Bobo-Dioulasso	0.18	0.20	0.32*	0.36*	0.70***	0.74***	0.96***	0.96***
Average	0.50***	0.23	0.54***	0.37*	0.84***	0.79***	0.95***	0.95***

Asterisks indicate significance at the 0.05 (*), 0.01 (**) and 0.001 (***) levels.

latitude). Precipitation accounted for the greatest portion of simulated millet yield variability north of about 13°N, but solar irradiance has the dominant influence in the wetter region to the south. Fada N'gourma and Bobo-Dioulasso lie in the region where yield variability is controlled more by solar irradiance than by rainfall. Predictability of sorghum yields based on antecedent rainfall and climatology does not continue to increase toward the north of the country, but is greatest in Ouagadougou. This is likely a result of calibrating the phenology of each of the three cultivars to the latitude of Ouagadougou. At the dryer locations to the north, cultivars calibrated for Ouagadougou would be subjected to additional, unrealistic water stress at the end of the season.

3.3. Yield prediction and multi-decadal variations

Mean rainfall decreased substantially at every location and in several cases its variability increased after 1970 (Table 7). Simulated yields showed a similar mean reduction associated with the shift in rainfall regime. Although the percent reduction in precipitation after 1970 was fairly consistent across locations, impact on yields was greater for the dryer northern locations. In the three southern locations, the shift in rainfall regime did not reduce the yields simulated for the

Hybrid technology, but did substantially increase their year-to-year variability. This can be explained by the nonlinearity of crop response to rainfall; grain yields are more sensitive to a given change in rainfall where the average rainfall is below the optimum than where it is near or above the optimum. This is also the case when comparing wet and dry locations (Baron et al., 2005). We speculate that, because the Traditional and Improved cultivars were planted substantially earlier than the Hybrid, they were also more affected by variation in the rainfall onset date that tends to be associated with changes in seasonal total rainfall.

Both empirical SST indices and GCM wind fields captured a substantial proportion of the multi-decadal component of variability observed in the rainfall record, as estimated by a spectral smoothing filter, although predictions based on SST indices appear to follow the multi-decadal variations more closely (Fig. 3a and b). Yields predicted from the two sets of seasonal rainfall predictors captured most of the influence of observed multi-decadal rainfall variability on simulated yields (Fig. 3c and d).

The presence of multi-decadal variations in West African monsoon precipitation and in resulting yield simulations complicates the evaluation of predictions. Trends that appear in both predicted and observed time series can account for a

Table 9 – Mean and coefficient of variation (CV) of reported (Rep.) regional yields, and baseline yields simulated with observed station weather based on Traditional (Trad.) and Improved (Impr.) production technologies, 1984–1998

Station	District	Mean (kg ha ⁻¹)			CV		
		Rep.	Simulated		Rep.	Simulated	
			Trad.	Impr.		Trad.	Impr.
Dori	Sahel	671	230	519	0.340	0.528	0.686
Ouahigouya	North	634	479	1270	0.254	0.459	0.473
Ouagadougou	Center	768	540	1222	0.220	0.384	0.354
Fada N'gourma	East	851	820	2127	0.159	0.205	0.244
Bobo-Dioulasso	Haut Bassin	1160	854	2242	0.297	0.243	0.302
Average		824	584	1476	0.185	0.225	0.237

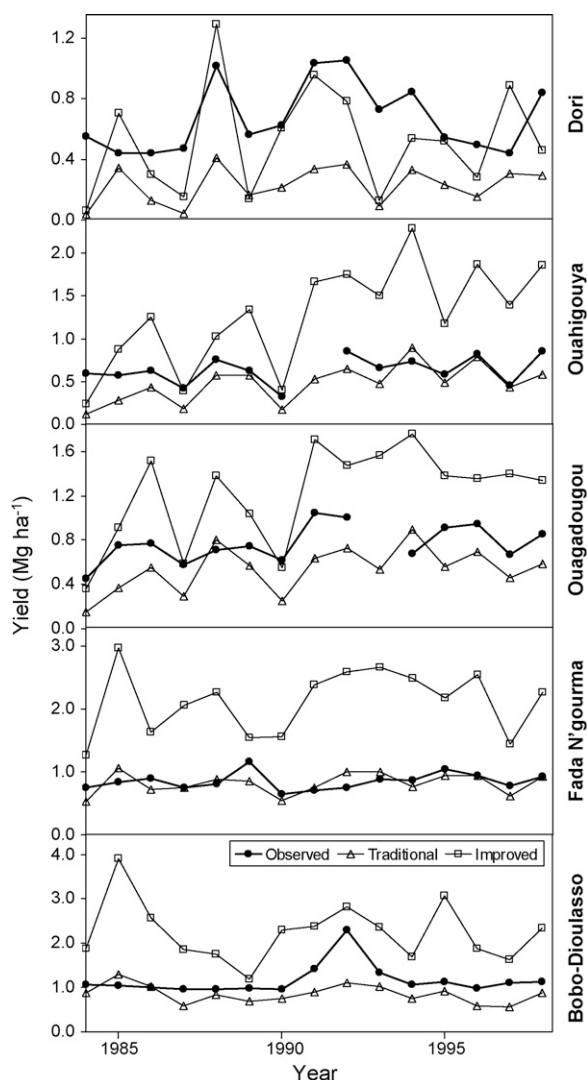


Fig. 4 – Sorghum yields simulated for Traditional and Improved production technology, and reported regional yields for the corresponding district, 1984–1998.

substantial portion of the correlation between the two series. Removing the multi-decadal component of variability in simulated and predicted yields reduced correlations between them, indicating that multi-decadal accounts for a substantial portion of the predictability (Table 8). The influence of multi-decadal rainfall variability diminished with decreasing forecast lead-time.

Multi-decadal rainfall variability has several important implications for food security early warning and response. On the one hand, it suggests that predictability early in the growing season is weaker at an interannual time scale than simple measures of goodness of fit might suggest. On the other hand, awareness of shifts between wetter and dryer climate regimes and the possibility that West Africa might be returning to a wetter regime have major implications for the region’s ability to meet its food needs. It is currently not possible to predict accurately how long a phase of multi-decadal variability will persist. However, rainfall and yield forecasts for the current season, based either on GCM output

or on statistical prediction from SST indices, appear able to capture the immediate effects of such shifts. Furthermore, monitoring global ocean temperatures that are associated with multi-decadal rainfall variations in the Sahel (Giannini et al., 2003) might provide opportunity for improving operational crop forecasts by shifting the weight given to predictors from the Pacific and Atlantic basins. During the wetter period (approximately 1950–1969), Sahel rainfall showed a much stronger linkage with tropical Atlantic SST, whereas ENSO has had stronger influence during the drier post-1970 period (Janicot et al., 1996; Ward, 1998; Ndiaye et al., submitted for publication). This pattern is also apparent in records from the first half of the twentieth century, when the tropical Atlantic dominated variability during wetter decades and the tropical Pacific dominated during drier periods (Ward, 1998).

3.4. Reported regional yield statistics

We compared simulated yields with reported regional yields to get an idea of how they relate in magnitude and variability. The results should not be interpreted as an evaluation of predictability of regional crop yields, as the point scale of our analyses does not match the regional scale of historic production statistics. Furthermore, we did not attempt to calibrate model simulations, or to incorporate any information (e.g., soils, germplasm or management) from crop reporting districts beyond weather data from a single station.

Regional yields reported for the districts that contain the study locations generally fell within the range of yields simulated with Traditional and Improved production technologies (Table 9, Fig. 4). Mean reported yields were closer to simulations for the Traditional technology except for the northernmost Sahel district where mean yields exceeded the mean for the Improved scenario by 29%. This suggests that average simulated yields were realistic for the expected level of technology that farmers employ. While there is some use of

Table 10 – Correlations of simulated and predicted (by SST regression) sorghum yields with reported regional average yields, 1984–1998

District	Simulated	Forecast	
		July	August
Traditional technology			
Sahel	0.60*	-0.03	0.52*
North	0.76***	0.12	0.64**
Center	0.60*	0.27	0.64**
East	0.46 [†]	-0.27	0.14
Haut Bassin	0.42	0.18	0.18
Improved technology			
Sahel	0.55*	0.16	0.54*
North	0.73**	0.47 [†]	0.66 [†]
Center	0.70**	0.38	0.68**
East	0.03	-0.32	-0.07
Haut Bassin	0.30	0.33	0.25

Symbols indicate significance at the 0.1 ([†]), 0.05 (*), 0.01 (**), and 0.001 (***) levels.

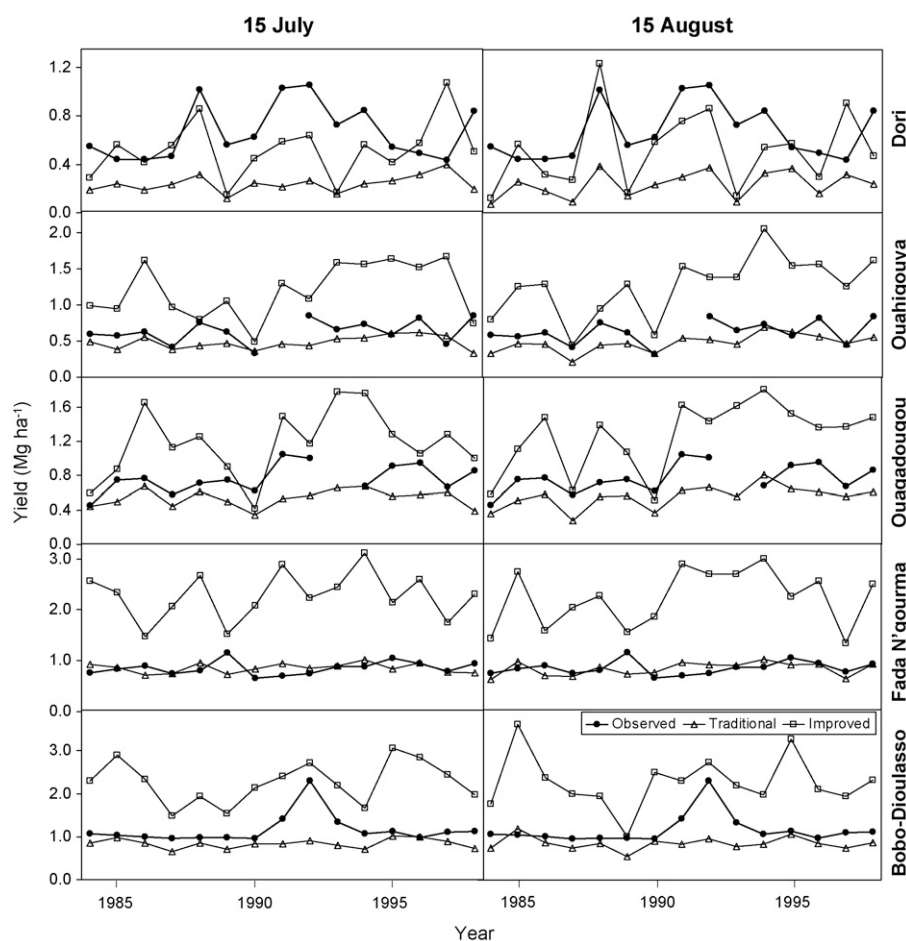


Fig. 5 – Sorghum yields predicted for Traditional and Improved production technology, and reported regional yields for the corresponding district, 1984–1998.

high-yielding hybrids and varieties, and intensive management, adoption has generally been low in part because traditional land races with high photoperiod sensitivity are well adapted to the high variability of seasonal rainfall and growing season length that characterize Sudano-Sahelian West Africa.

Observed variability was greater for simulated yields than for reported yields (Table 9). This bias is a predictable and often-reported result of the difference in scale between reported and simulated yields (Hansen and Jones, 2000). The imperfect correlation of yields in space causes the year-to-year variability of regional average yields to be substantially lower than the average yield variability within the many individual plots that comprise the district. The one exception to this tendency was Haut Bassin, in the southwestern part of the country, where the reported 1992 yield is unrealistically high—3.3 standard deviations higher than the average.

Positive correlations between reported and simulated yields were significant at $p < 0.05$ for the three northern districts (Table 10). These districts also show significant correlations with 15 August forecasts, but not with forecasts made at earlier dates (Fig. 5). The low correlations between model-based yield predictions and reported yields are likely

due to a combination of rainfall forecast uncertainty, crop model (including calibration and aggregation) error, poor representation of the crop reporting district by a single station, and the small number of years of overlap (15) between available production statistics and available daily weather data for crop simulations.

Cross-validated linear regression estimates of reported regional sorghum yields (Table 11) provide a benchmark for

Table 11 – Correlations of reported sorghum yields with estimates from a linear regression function of observed seasonal rainfall (May–September), and of a combination of observed antecedent rainfall total and forecasts through the remainder of the growing season, 1984–1998

District	Observed	Forecast	
		July	August
Sahel	0.48 [†]	0.20	0.07
North	0.61 [*]	0.23	−0.52
Center	0.27	0.10	0.07
East	0.29	−0.50	−0.87
Haut Bassin	−0.03	0.01	−0.06

Symbols indicate significance at the 0.1 ([†]) and 0.05 (^{*}) levels.

evaluating whether the use of a dynamic crop model adds value beyond simpler statistical forecasts based on cumulative precipitation. Correlations between reported yields and regression estimates from observed seasonal rainfall were significant at $p < 0.05$ only in the North district, and were not significant for July or August forecasts at any location. Comparing results in Tables 10 and 11, SARRA-H driven with daily weather data appears to follow reported regional yield response to rainfall variability more closely than a linear regression model that uses seasonal totals of the same precipitation inputs. This was true both for concurrent relationships based purely on observed precipitation, and for forecasts that combined observed antecedent rainfall with SST predictors of rainfall for the remainder of the growing season.

Given that the crop simulations and model-based predictions did not attempt to represent soils of each location, calibrate crop cultivars or practice to local environments, or correct aggregation bias, the prospect of simulating regional yields given the presence of significant positive correlations with reported yields in two of the districts (Table 10). There are several avenues, in addition to potential improvements in seasonal rainfall forecasts discussed earlier (Section 3.1), for improving sorghum yield forecasts at a district scale. First, crop model error can be reduced through local calibration of cultivars, the use of measured soil hydrological properties and better accounting for the spatial distribution of management practices. Our crop simulations were not tailored well to local conditions. Second, simulations need to be scaled up from individual stations to regions. Aggregation error can be reduced either by calibrating simulations to reported yields or by sampling the heterogeneity of the environment (Hansen and Jones, 2000). If the spatial distribution of weather, soil properties and management is known or can be estimated, sampling environmental heterogeneity in simulation inputs has the advantages of being less dependent on the quality and consistency of historic yield statistics, better representing average climatic conditions, and less constrained to the boundaries of crop reporting districts. Finally, we incorporated only rainfall forecasts into our yield predictions, but sorghum yields are sensitive to other meteorological variables (e.g., temperatures, solar irradiance, humidity and wind) that might have some predictability from the same large-scale atmospheric forcing that provides the basis for forecasting precipitation. Solar radiation, for example, is believed to become more important and precipitation less important in the higher-rainfall region toward the south (Baron et al., 2005), although solar radiation tends to be correlated with rainfall.

4. Conclusions

Our results show that seasonal precipitation forecasts can reduce the climatic component of uncertainty and thereby provide modest increase in the accuracy of crop forecasts based on monitored weather alone, in the semiarid rainfed environment of the West African Sahel, particularly at longer lead-times. This raises the prospect of providing probabilistic

forecasts of crop production early in the growing season. However, incorporating seasonal forecasts was not sufficient to provide estimates in July that have the same accuracy that climatology-based forecasts have in August, roughly the time that they are currently issued to inform food security interventions.

Although we did not attempt to simulate yields at a reporting district scale, our results provide some encouraging evidence. First, despite the scale mismatch and absence of local calibration, simulations using a single station explained a significant proportion of year-to-year variability of reported yields for the surrounding districts at two of the five study locations. Second, the assumptions in the Traditional and Improved technology scenarios resulted in average simulated yields that appear reasonable for the low levels of production technology (i.e., predominantly traditional landraces with limited adoption of improved varieties and hybrids) that regional yield statistics reflect. Third, stronger correlations of historic yields with simulated yields than with regression-based predictions suggests that a dynamic, process-oriented crop model run with daily rainfall is likely to perform better than the best linear statistical model driven by cumulative rainfall. Finally, the reduction in climatic uncertainty from incorporating seasonal forecasts into simulations, demonstrated at the scale of individual stations, should benefit regional yield simulations even more than point-scale simulations, as rainfall forecast skill tends to improve with scale of aggregation (Gong et al., 2003).

We discussed several promising avenues that may further increase accuracy (at a given lead-time) and lead-time (at a given accuracy) of crop yield forecasts: improvements to seasonal rainfall forecasts, better local calibration of soil and management inputs, capturing more of the observed variability of the environment (weather, soils, management) in space, and incorporating monitoring and forecasts of additional meteorological variables. We conclude that there is a good prospect for providing useful food security early warning information, incorporating climate-based yield forecasts, earlier in the growing season than is currently available. Whether this would translate into earlier response to emerging food crises depends in part on whether food security institutions, which traditionally require a high degree of certainty before taking action (Broad and Agrawala, 2000; Haile, 2005), have the flexibility to respond to earlier, probabilistic information.

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