Seasonal Maize Forecasting for South Africa and Zimbabwe Derived from an Agroclimatological Model

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(Manuscript received 4 September 1998, in final form 13 December 1999)

ABSTRACT

Seasonal maize water-stress forecasts were derived for area averages of the primary maize-growing regions of South Africa and Zimbabwe. An agroclimatological model was used to create a historical record of maize water stress as a function of evapotranspiration for 1961–94. Water stress, the primary determinant of yield in water-limited environments such as southern Africa, was correlated with two well-known indices of the El Niño–Southern Oscillation: the Southern Oscillation index (SOI) and the Niño-3 region of the equatorial Pacific. Forecasts for South Africa using only the SOI at a 4-month lead yielded a hindcast correlation of 0.67 over 17 seasons (1961–78) and a forecast correlation of 0.69 over 16 seasons (1978–94). Forecasts for Zimbabwe were less remarkable.

1. Introduction

Much of southern Africa is subject to climatic extremes that often result in poor crop yields. Maize is the most important crop grown in southern Africa, accounting for up to 70% of total human caloric intake (Byerlee and Eicher 1997). Most maize production is fed by rain. Even in South Africa, irrigated land is less than 1% of the cultivated area (Chenje and Johnson 1994). A strong dependence upon agriculture, high population growth rates, and unstable economic conditions compound the sensitivity to climatic extremes.

Variability in southern African interannual rainfall has been studied extensively (see reviews of Tyson 1986; Mason and Jury 1997). Statistical forecasts of interannual rainfall have recently become operational (e.g., Jury 1996; Mason et al. 1996; Mason 1998), using tropical circulation anomalies forced by sea surface temperature (SST) as the main predictors (Jury et al. 1994; Mason 1995).

Nearly all seasonal crop forecasts for southern Africa are inferred indirectly from rainfall forecasts. These forecasts do not capture fully the relationship between yields and other climatic variables such as temperature, humidity, radiation, and wind during the growing season. For example, warmer, less-humid conditions and increased solar radiation increase potential evapotranspiration (PET), exacerbating rainfall shortages during a drought.

As an alternative to developing crop forecasts from rainfall forecasts, historical crop yields have been related directly to predictors such as the Southern Oscillation index (SOI) (e.g., Nicholls 1985; Rimmington and Nicholls 1993; Meinke and Hammer 1997). Cane et al. (1994) achieved remarkable success in their assessment of forecasting both maize yield and rainfall in Zimbabwe using the Niño-3 index of the El Niño–Southern Oscillation (ENSO). In that assessment they actually reported a stronger correlation between maize yield and SST than between rainfall and SST.

The difficulties of linking historical yields directly to predictor indices are numerous, as alluded to by Mjelde and Keplinger (1998). Foremost is the unreliability of historical yields in southern Africa (Cane et al. 1994;

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TABLE 1. Classification of water-limited performance [adapted from FAO (1986)].

Expected percentage of max (potential) yield	Classification of crop performance	WRSI
>100	Very good	100
90–100	Good	95–99
50–90	Average	80–94
20–50	Mediocre	60–79
10–20	Poor	50–59
<10	Complete failure	<50

TABLE 2. Maize crop water requirement coefficients for each stage of the plant cycle (adapted from Doorenbos and Pruitt 1992). The development stage is estimated by interpolation between initial and middle phases.

	Phase			
	Initial	Development	Middle	Late
Length (days)	25	35	40	30
$k_c(t)$	0.45	0.8	1.1	0.55

Byerlee and Eicher 1997), especially for the small-farm sector.

Historical yields may be autocorrelated. Recovery from a bad year may take several years, specially in small-holder situations for which credit and commercial inputs may be unavailable (Scoones 1997). Conversely, a good year means that agricultural investment increases the likelihood of a higher yield the following year.

Socioeconomic and management factors complicate the relationship between yields and climate indicators. For example, over the past three decades, South African agricultural production has been influenced by a transfer of seed production to the private sector, release and dissemination of over 100 different hybrids, entry of multinationals, and exchange-rate reform. Maize production increased in the 1970s and early 1980s as a result of genetic improvements, intensive fertilization, crop protection, and more-timely crop operations (Byerlee and Eicher 1997). In Zimbabwe, the changing of land ownership from large commercial farms to small-holder farms since independence has decreased national yield averages as higher-yielding commercial farms were replaced (Muir 1994). Government promotion of fertilizer and the adoption of hybrid maize lead to a doubling of small-holder maize production (Byerlee and Eicher 1997).

In light of the difficulties of developing a prediction scheme from historical yield data or from rainfall forecasts, this paper presents seasonal forecasts for the primary maize-growing regions of South Africa and Zimbabwe. The maize agroclimatology is based on a simple crop water-balance model, the primary determinant of yield for these water-limited regions. Simulations were run for historical gridded climate data from 1961–94 for subequatorial Africa. Linear regression was used to relate the resultant water-stress record to ENSO indices at 4-month lead with respect to harvest.

Nicholls (1996) discusses the potential benefits of seasonal forecasts. At an early enough lead, they provide the opportunity to change the planting date, cultivar type, and whether to plan for fertilization or irrigation. South Africa and Zimbabwe are both traditional exporters of grain. Therefore, forecasts at shorter lead that follow planting, such as those given here, provide the opportunity for exports to be reduced in advance of crop failure, substantially decreasing the subsequent costs of imports (Betsill et al. 1997). Note, however, that regional forecasts are limited, because they do not necessarily represent the local weather variation representative of farm scale.

2. Maize water-stress model

The maize water-stress model was developed at the University of Oxford's Environmental Change Unit (ECU), where it has been used for climate change impact assessments in Europe and southern Africa (Harrison et al. 1995; Hulme 1996). Its accuracy was increased by incorporating a Penman adjustment in the evapotranspiration calculation. The model is described in more detail by Doorenbos and Kassam (1986), Doorenbos and Pruitt (1992), and the Food and Agriculture Organization (FAO 1986).

The model calculates water stress on a 0.5° × 0.5° grid for the region 0°–35°S by 9°–50.5°E from interpolated and gridded rainfall, temperature, soil water holding capacity, planting date, monthly average wind speed, monthly average number of hours of sunshine and cloud cover, and monthly average vapor pressure data provided by Hulme et al. (1996).

To categorize the effect of water stress, the maize water-stress model directly relates a water requirements satisfaction index (WRSI) to percent yield reduction from optimal conditions (Table 1). When water supply is limited relative to crop requirements, actual evapotranspiration (ET_a) is less than maximum evapotranspiration (ET_m), and the crop suffers water stress with corresponding yield reduction. Monthly calculations of water stress are subsequently summed over the season and subtracted from 100 to yield a seasonal WRSI,

$$\mathrm{WRSI}_{\mathrm{season}} = 100\left(1 - \sum_{\mathrm{planting}}^{\mathrm{harvest}} \frac{\mathrm{ET}_m - \mathrm{ET}_a}{\mathrm{ET}_m}\right). \quad (1)$$

a. Estimation of maximum evapotranspiration

Maximum evapotranspiration varies with the growth phase of the crop and with the climate characteristics of the region. During certain stages of growth, such as the development and middle stages, maize has high water requirements (FAO 1986). Empirically derived crop coefficients (k_c) represent this variation (Table 2), and

PET captures the seasonal agroclimatological characteristics in a monthly calculation,

$$\mathrm{ET}_m = k_c \times \mathrm{PET}. \tag{2}$$

Several different methods exist to estimate PET (Hulme et al. 1996), of which the Penman and Thornthwaite methods are considered. The Penman method (Penman 1948) is a function of temperature, humidity, wind, and daylength. In contrast, the Thornthwaite method (Thornthwaite and Mather 1957; Supit et al. 1994) is a function of only daylength and temperature,

$$\mathrm{TH}(t) = 3.65 \times 10^{-4}\, d(t) I^{-1} [10T(t)]^a, \tag{3}$$

where TH(t) results from the monthly Thornthwaite calculation, $d(t)$ is the total monthly daylight in hours, and $T(t)$ is the monthly mean temperature in degrees Celsius. The two variables a and I are empirically derived functions of mean annual temperature. Although less accurate than the Penman method and known to underestimate ET_m in dry or windy climates (Hulme et al. 1996), the Thornthwaite method requires less input data.

A combination of the two methods was used to correct for the general evapotranspiration underestimation of the Thornthwaite method by scaling the results with the Penman average:

$$\mathrm{PET}(t) = \frac{\mathrm{TH}(t)}{\mathrm{TH}_{\mathrm{Ave}}} \mathrm{PEN}_{\mathrm{Ave}}. \tag{4}$$

b. *Estimation of actual evapotranspiration*

Actual evapotranspiration (ET_a) is determined from the difference between plant available soil water and ET_m. If the amount of plant available soil water is less than ET_m, then ET_a is equal to that difference. Otherwise ET_a equals ET_m.

Plant available soil water is defined as the quantity of water in the soil that is greater than the available soil water at wilting point. The soil is treated as a single layer that fills through precipitation, empties through evapotranspiration, and produces runoff or becomes groundwater if it saturates. The monthly average available soil water is calculated from the recorded averages of precipitation, ET_a, and temperature for the region.

Planting was assumed to occur at the start of November, the average planting time for South Africa and Zimbabwe. The available soil water and initial evapotranspiration were initialized to zero, representative of conditions at the end of October. Over the subsequent 130 days, a water balance is computed from the previous month's soil water content and the current month's precipitation, PET, and runoff. If the soil water content is greater than 100% for the given month, the excess water is not available the following month.

c. *Evaluation and validation*

The water-stress model was evaluated with the more dynamic Agricultural Catchments Research Unit (ACRU) model of the University of Natal (Schulze et al. 1993, 1996), a model that treats the soil as multilayered, includes water infiltration and extraction rates, and operates at a higher temporal and spatial resolution. The spatial distribution of WRSI from the water-stress model related well to that of yield in the ACRU model (Martin 1998), with the most significant difference stemming from temperature thresholds in the Lesotho highlands that are not represented in the water-stress model.

The water-stress model was validated by comparing the annual WRSI to historical yield records. Although the accuracy of historical yield records is poor, they indirectly provide the best available record of actual crop water stress. Water-stress time series were derived by averaging WRSI for the regions representing the primary maize-growing regions of South Africa (FAO 1999a) and Zimbabwe (FAO 1999b) as specified by the FAO (Fig. 1). The upward trend from improving technology and management practices (e.g., Byerlee and Eicher 1997) was removed with linear regression.

Figure 2 illustrates the resultant relationship between detrended historical yields and water stress, both normalized to a standard deviation of one and a mean of zero. The correlation between historical yields and water stress is 0.61 (number of data points, $n = 33$, confidence level $p < 0.005$) for South Africa and 0.63 ($n = 33$, $p < 0.005$) for Zimbabwe.

Note that the correlation between water stress and historical yields is similar to the respective correlation between historical yields and seasonal rainfall for South Africa and Zimbabwe, respectively, of 0.58 ($n = 33$, $p < 0.005$) and 0.65 ($n = 33$, $p < 0.005$) because of the high correlation between water stress and rainfall ($n = 33$; correlation coefficient $r = 0.95$ and 0.82, respectively; $p < 0.005$). Although this correlation implies that seasonal rainfall could be used as a proxy for water stress, the following section suggests that water-stress forecasts are of higher skill.

3. Water-stress seasonal forecast

a. *Methodology*

Annual water-stress time series (Fig. 3) for South Africa (STS) and Zimbabwe (ZTS) over the period 1961–94 were created from area averages of gridded water stress for the primary maize-growing regions (Fig. 1). Although it is difficult to determine normality with certainty from only 33 yr, both water-stress time series fit a normal distribution ($p < 0.01$).

The water-stress time series were related to two well-recognized ENSO indices. The SOI is the standardized difference between sea level pressure in Tahiti (17.5°S, 149.6°W) and Darwin (12.4°S, 130.9°E) and is also used as an indicator of ENSO (Jones 1991). The Niño-3 index was calculated by spatially averaging SST anomalies over the region (5°S–5°N, 90°–150°W) to create an in-

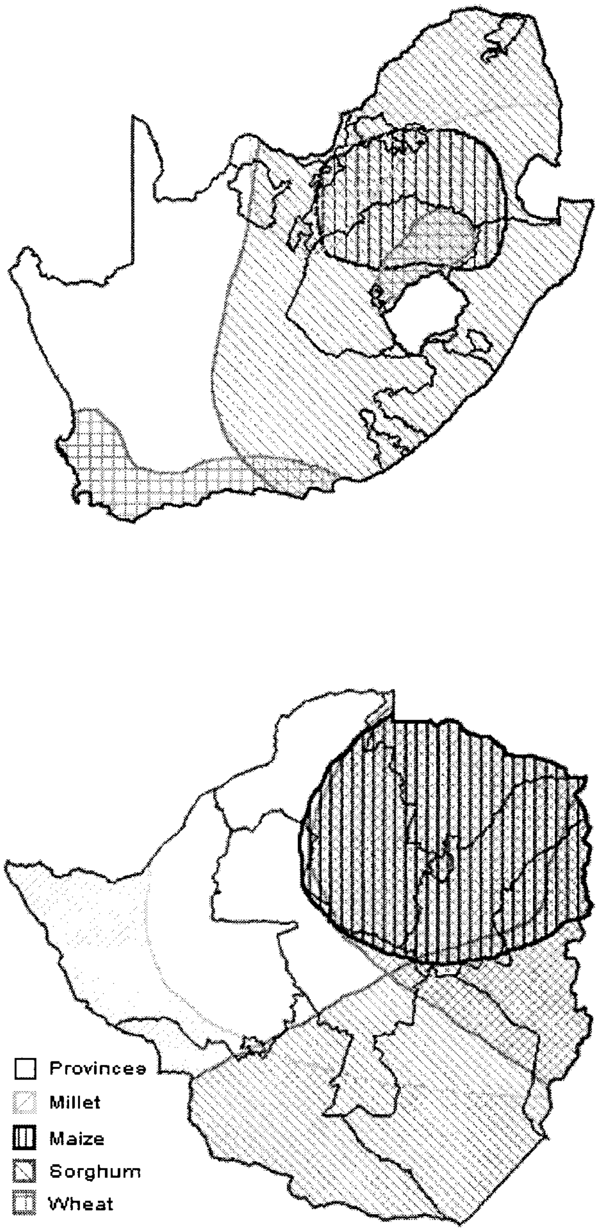

FIG. 1. Primary crop-growing regions in South Africa and Zimbabwe. Area averages of water stress in the maize-growing regions were used to validate the water-stress model and to develop the seasonal forecasts (FAO 1999a,b).

dex of the Niño-3 region, one previously recognized for its relationship with southern African climate (e.g., Cane et al. 1994). The SST dataset was calculated from the 1951–80 reference period on a $10° \times 10°$ grid from the Global Sea Ice and Sea Surface Temperature Data Set (Parker et al. 1994), a result of over two decades of research and extensive quality control by the United Kingdom Meteorological Office (The Met. Office) (Bottomley et al. 1990; Folland and Parker 1995). To reduce temporal noise, both ENSO indices were averaged over

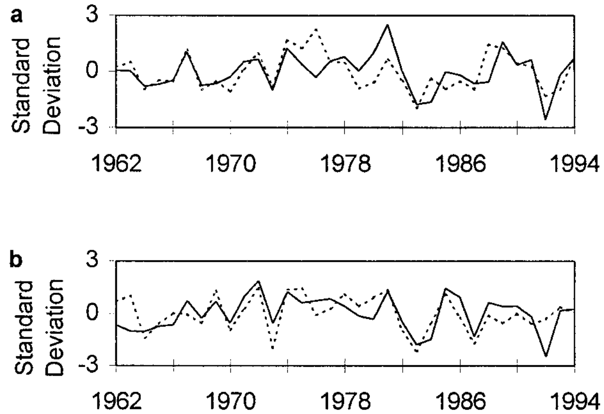

FIG. 2. Detrended annual variations in historical yield (solid lines) and WRSI (dashed lines), normalized to a standard deviation of one and a mean of zero for (a) South Africa, $r = 0.61$ ($n = 33$, $p < 0.005$) and (b) Zimbabwe, $r = 0.63$, ($n = 33$, $p < 0.005$).

the 3-month periods of July, August, and September (JAS); August, September, and October (ASO); September, October, and November (SON); October, November, and December (OND); and November, December, and January (NDJ).

The water-stress time series were divided into completely independent training (1961–78) and validation (1978–94) datasets. The water-stress time series from the training period were correlated with the two ENSO indices. Linear regression was used to develop a forecast from the ENSO indices.

b. Results

Correlations between the water-stress time series and the ENSO indices were highest at a 4-month lead (OND) with respect to a May harvest. At a 4-month lead, the STS training time series ($n = 17$) related best with the SOI ($r = 0.67$, $p < 0.005$). ZTS was better represented by the Niño-3 region ($r = 0.38$, $p < 0.1$). The following model results from linear regression with these two indices:

$$\mathrm{STS}_{\mathrm{predicted}} = 64.9 + 8.8\mathrm{SOI} \tag{5}$$

$$\mathrm{ZTS}_{\mathrm{predicted}} = 86.6 - 5.0\text{Niño-3}. \tag{6}$$

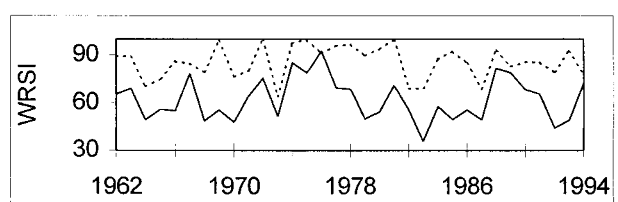

FIG. 3. WRSI time series for South Africa (solid) and Zimbabwe (dashed) calculated over the period 1961–94 (“1962” denotes the 1961–62 growing season, Nov 1961–May 1962).

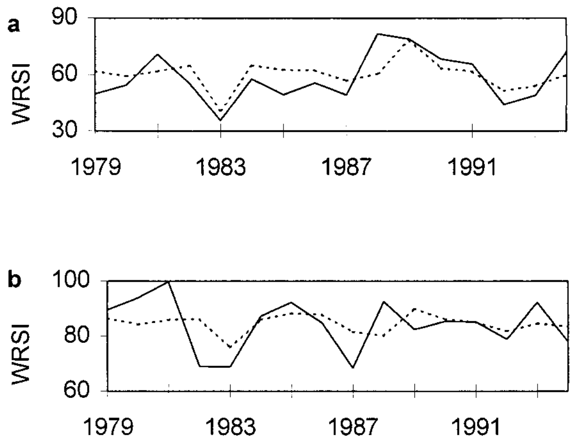

FIG. 4. Performance of the model (solid) against validation data (dashed): (a) STS, $r = 0.69$ ($n = 16$, $p < 0.005$); (b) ZTS, $r = 0.40$ ($n = 16$, $p < 0.05$).

TABLE 3. Error between the predicted and actual WRSI for the validation dataset.

	STS	ZTS
Mean error	−1.6	−0.3
Rmse	9.5	8.7
Mean WRSI	58.6	84.3
WRSI std dev	13.0	9.5

c. *Model performance*

Figure 4 illustrates the model performance against validation data for STS ($r = 0.69$, $n = 16$, $p < 0.005$) and for ZTS ($r = 0.40$, $n = 16$, $p < 0.05$). Table 3 quantifies the model error. The mean errors are close to zero. Although ZTS has a lower correlation between predicted and actual WRSI for the validation data, it also has a lower rmse, probably owing to smaller standard deviation of the Zimbabwean time series.

d. *Comparison with rainfall*

For comparison, rainfall forecasts have also been developed using the same methodology as with water stress. Rainfall time series were created by temporally averaging rainfall over the growing season and spatially averaging them over the primary maize-growing regions. As with water stress, the SOI over the months OND better represented seasonal South African rainfall and the Niño-3 index better represented seasonal Zimbabwean rainfall.

Forecasts for South African seasonal rainfall from SOI yielded a correlation of 0.53 ($p < 0.02$) with the training data and a forecast correlation of 0.60 ($p < 0.005$) with the validation data. Respective performance for Zimbabwe with Niño-3 was 0.40 ($p < 0.1$) and 0.34 ($p < 0.1$). These results suggest that water-stress forecasts relate more strongly to ENSO than does seasonal rainfall alone. The teleconnection between ENSO and southern Africa is captured better by incorporating several climatological variables into a water-stress forecast.

4. Discussion

The high correlation between SOI and South African water stress may be explained by the increased (decreased) PET from sunny (cloudy) conditions associated with the reduced (enhanced) rainfall characteristic of El Niño (La Niña) events. The resultant effect of drought upon water stress and maize yields will be magnified. A second factor accounting for the greater correlation with water stress and seasonal rainfall may stem from the strength of ENSO in the January–March period that corresponds to the flowering, tassling, and yield formation stages of maize growth during which water requirements and the potential for water stress are greatest.

The decreased skill in forecasting Zimbabwean water stress relative to STS is difficult to explain, especially since the relationship between ENSO and maize yields has been previously noted (Cane et al. 1994). Additional work, beyond the scope of this paper, is required here.

On a cautionary note, these forecasts are highly dependent upon ENSO. ENSO has evolved throughout the century and, in particular, has increased in both frequency and intensity in the last few decades. If ENSO weakens again as in the middle of this century, forecasts skills described here would be expected to decline.

Furthermore, farm-scale variability may be greater than regional variability, because local weather variation can lead to dry spells at a higher spatial and temporal resolution than is captured in these area-averaged regions. Thus individual farm-scale yields are expected to be of lower forecast skill.

The forecasts have purposely been left as water-stress forecasts rather than yield forecasts, because general water-stress forecasts should be more widely applicable. The teleconnections linking global conditions to water stress incorporate fewer assumptions than one for yield. Additionally water-stress forecasts should be useful for irrigation planning. If approximate yield forecasts are desired, WRSI can be related to yield using Table 1.

A stronger relationship with yield could be derived from a more dynamic crop model, such as the ACRU model (Schulze et al. 1993, 1996). Such a model, more finely tuned to both the climatic and management characteristics of the region, would more accurately represent crop yield. Of the many factors to include in the water-stress model discussed in this paper, probably the most critical omission is soil fertility (Jackson 1989). In many regions of Africa, nutrients are often an important constraint on plant growth.

These forecasts have been left purposely as simple linear models, so that the value of using an agroclimatological model is not shrouded by more-complicated forecast techniques.

5. Conclusions

Seasonal crop forecasting to date has been either derived from seasonal rainfall forecasts or from correlations between historical yields and global indices. Both techniques are limited. Many climatic variables influence crop yields. Historical yields are compounded by nonclimatic factors. Forecasts derived from historical yields are hindered by poor time series and socioeconomic variability. It has been suggested that forecasts of simulated water stress may provide a useful indication of climatic fluctuations, especially for the primary maize-growing region of South Africa.

Simple water-stress forecasts derived from a single index, the SOI in the case of South Africa, have been shown to perform well. These forecasts pioneer a new methodology for regional crop forecasting in arid and semiarid climates. Similar forecasts should also be possible for other crops and regions. The critical factors are that climate is an important limiting factor of crop yields and that seasonal climatic variations derive from persistent ocean anomalies.

Acknowledgments. We thank Gavin Kenny, Paula Harrison, John Orr, and David Blackwell for contributions to the crop-model development. The crop-model data were received by ECU from the Climatic Research Unit of East Anglia as part of a project funded by the World Wildlife Fund for Nature (Hulme 1996). This work was sponsored in part by the National Science Foundation (NSF) through an NSF Graduate Fellowship.

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