Economic Impacts of Climate Variability in South Africa and Development of Resource Prediction Models

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ABSTRACT

An analysis of food and water supplies and economic growth in South Africa leads to the realization that climate variability plays a major role. Summer rainfall in the period of 1980–99 is closely associated (variance $= 48\%$) with year-to-year changes in the gross domestic product (GDP). Given the strong links between climate and resources, statistical models are formulated to predict maize yield, river flows, and GDP directly. The most influential predictor is cloud depth (outgoing longwave radiation) in the tropical Indian Ocean in the preceding spring (September–November). Reduced monsoon convection is related to enhanced rainfall over South Africa in the following summer and greater economic prosperity during the subsequent year. Methodologies are outlined and risk-reduction strategies are reviewed. It is estimated that over US$1 billion could be saved annually through uptake of timely and reliable long-range forecasts.

1. Introduction

Anticipating the swings of climate is important for sustainable economic growth in these times of increasing pressure on the earth’s limited resources. Recent improvements in the global climate observing system have been made with increasing in situ ocean data, satellite technology, and advances in climate modeling. Institutional systems are being developed to exploit these advances in support of sustainable development, through a reduction of risks associated with extreme climate events. Climate information is now being applied directly or indirectly in many developed countries to a wide range of activities, including agricultural practice, resource management, economic planning, international relations, hydrology, and health.

The improved understanding of climate variability is being exploited to provide seasonal climate forecasts through regional outlook forums. These activities have been instrumental in clarifying the requirements of both “producer” and “user” communities for adequate climate information and prediction services. Africa hosts three such forums, and climate scientists are actively involved in providing guidance to local users (Mason et al. 1999). This paper will cover one such effort to provide meaningful input to the southern African regional climate outlook forum (SARCOF), initiated in 1995 to create consensus predictions. An initial survey of mitigation strategies tailored to southern Africa is reported in Natural Resources Institute (1996). Harrison and Graham (2001) provide estimates of cost–benefits attributable to long-range climate predictions. The level of climate information uptake in southern Africa is growing in parallel with experimental risk-hedging operations, thus inhibiting a stable quantitative assessment. Hence, this study is limited to analyzing climate impacts on resources and development of predictive models.

a. Background

Southern Africa is dependent on subsistence agriculture to meet the basic needs of its population of more than 100 million. It is estimated that more than one-half of gross domestic product (GDP) and three-quarters of all jobs are attributable to rain-fed agriculture (Hulme 1996). South Africa exports a considerable volume of food stuffs and manufactured products to Africa, and its economy is interdependent with the rest of the continent. The work presented here will outline how South Africa’s GDP responds to rainfall variability. The impacts of this variability on crop (maize) production, the streamflow of major rivers, and overall economic growth are assessed in the context of the El Niño–Southern Oscillation (ENSO). The potential for predictability is explored, and statistical methodologies are provided. Southern Africa is particularly vulnerable to swings in climate owing to its location within the arid subtropics (Fig. 1) and the potential impacts of a warmer and drier future (Bohle et al. 1994).
The population of southern Africa is growing at a rate of 3% per year. The population of South Africa is one-half rural, and rates of urbanization outstrip population growth, implying a continual shift of people away from the land (Vogel 1994). The resulting decline in agriculture’s economic contribution could have a marked influence on regional energy consumption. Measures of production such as GDP indicate that many countries of southern Africa are poverty-stricken, with per capita annual incomes of less than U.S.$1000 (World Economic Forum 2000). In South Africa, the economy is diversified as shown in Fig. 2. Manufacturing and mining contribute about one-quarter of GDP; agriculture contributes less than 5%; and commerce, communications, and trade contribute more than 40% (South African Reserve Bank 1999, personal communication, hereinafter SARB99). This economic diversification has not reduced vulnerability to climate, as will be shown later.

Agricultural production has exhibited increasing fluctuations in recent decades. Following drought in 1992, the GDP of Zambia, Zimbabwe, and South Africa declined 9%, 8%, and 3%, respectively (Benson and Clay 1994), contributing to rising unemployment (>30%) and economic stagnation. Economic adjustments imposed by external creditors reduced consumptive demand, thus deflating national economies. Yet with increased political stability comes interdependence and the potential for overall growth in the region (Hulme 1996).

b. El Niño impacts on regional climate

An El Niño produces warm, dry conditions over southern Africa (Ropelewski and Halpert 1987; Janowiak 1988; Jury et al. 1994; Hastenrath et al. 1995; Shinoda and Kawamura 1996; Rocha and Simmonds 1997) via westerly winds that invade the more productive eastern highlands of southern Africa, increasing evaporative losses. Convergent subtropical jet streams are generated in the upper level of the atmosphere in

Fig. 1. Jan rainfall over southern Africa, illustrating semi-arid conditions (<4 mm day⁻¹ at the seasonal optimum) to the south of 20°S. The maize-growing region and Orange River are located near the “South Africa” label (analyzed from CRU rainfall climatology via the IRIDOE Web site).
response to the tropical warming associated with El Niño. The jet streams accelerate and swerve equatorward, producing subsidence over the interior (Mwafailirwa 1999). Rain-bearing troughs are carried eastward rapidly, and wet spells become short lived and patchy. Many of these atmospheric responses owe their origin to changes in tropical sea surface temperatures (SST) in the western Indian Ocean, which tend to warm in sympathy with the eastern Pacific (Cadet 1985). Together these factors displace cloud bands to the adjacent oceans in the November–March summer season, when the El Niño is at peak intensity (Meehl 1988; Jury 1995).

El Niño summers are characterized by two areas of opposing weather centered on Botswana (25°E) and Mauritius (55°E). Warmer sea temperatures in the tropical Indian Ocean enhance local winds and clouds, causing a surplus of rainfall over Mauritius and the surrounding ocean. Some 3000 km away, the plateau of southern Africa becomes moisture deficient. The zonal overturning circulation is often part of a stationary “wave train” in the subtropical westerlies (Kahn et al. 1996). Satellite normalized difference vegetation index images for composite El Niño years reveal that vegetation south of 15°S is water stressed and is considerably “browner” than usual. Jury and Lyons (1994) found that surface dewpoint temperatures decline below zero for extended periods during El Niño. Heat waves are produced when subsiding westerlies strengthen the Botswana high pressure cell, blocking the input of moisture from the Tropics.

The El Niño influence on southern Africa’s summer climate has been documented from historical observations (Vogel 1994). Since the 1950s, major El Niños have occurred in 1964, 1966, 1973, 1983, 1992, and 1998. Dry summers occasionally are unrelated to El Niño, for example in 1968 and 1970. Drought over southern Africa is characterized by rainfall of about 60% of normal, temperatures of about 5°C above normal, and evaporative losses of more than 10 mm day⁻¹ (Lema and Seely 1994). The percentage of land in southern Africa that can support crop production shrinks from about 30% to 5% of the total—an area too small to support a growing population. Maize yields decline below 1 Mg ha⁻¹, a fivefold reduction over the plateau. Yields for crops such as sunflower, sugarcane, and so on, show about a threefold decline. Annual agricultural income from dry-land crops valued at about U.S.$1 billion in South Africa, declines to about 30% of average (SARB99). The result for commercial farmers is a cash-flow crisis and bankruptcy, followed by a vicious circle of higher interest rates and shrinking profit margins. Even more serious is the impact of a failed crop on subsistence farming, which constitutes two-thirds of all jobs in southern Africa (Hulme 1996). Food shortages contribute to a high risk of malnutrition and starvation, affecting more than 30% of the population in southern Africa (Natural Resources Institute 1996). Comparable impacts are found across developing regions, in which strategies for coping with El Niño may benefit from the application of improved predictions (Nichols 1997).

c. Climate impacts on the economy

Although agriculture accounts for less than 5% of economic activity in South Africa (Fig. 3), its indirect influence is estimated to be about 25% (Lindesay 1990), attributable to the need for manufacturing and service
support in commercial farming operations. Agriculture’s share in export trade averaged over southern Africa is 36% (Rwelamira and Kleynhans 1996). Among the 15 countries of southern Africa, food stuffs are the largest single item of trade. The widespread nature of drought limits the potential for some parts of southern Africa to supply food to other parts during their time of need. Adding to the problem is a 30% coefficient of variation for summer rainfall, which plagues many of South Africa’s food and water resources. These variations appear to be growing over time, which suggests that the climate of southern Africa is becoming more extreme (Jury and Majodina 1997).

Maize contributes a large slice of agricultural GDP in South Africa. The timing of rainfall during maize growth in early February is critical to the food supply of southern Africa (Jury et al. 1997). Other factors that govern maize production include the amount of fertilizer used and the loan interest rates, which are tied to inflation and macroeconomics (Lindesay 1990). Interest rates in southern Africa are high by world standards. Over the past 25 yr, South Africa’s official rate of inflation has oscillated above 10%, with peaks in 1975, 1981, 1986, and 1991, following “good” rainfall years when consumption increases. However a weak quasibiennial cycle in southern African rainfall (Mason and Tyson 1992) means that a “negative cascade” often occurs. After a good rainy season for which inflation and interest rates are high, farmers must undertake crop preparation and planting with the prospect of a dry year looming.

Lindesay (1990) finds that the GDP in dry years is 83% of that in wet years. Rainfall departures of 10% lead to GDP changes of about 1%. In the 1983 El Niño year, the South African GDP dropped by about 7% (VanZyl et al. 1988). In other countries north of South Africa, agriculture makes a substantially larger contribution to GDP, as follows: Angola 46%, Botswana 3%, Lesotho 20%, Malawi 37%, Mozambique 61%, Namibia 11%, Swaziland 24%, Tanzania 63%, Zambia 11%, and Zimbabwe 20% (Rwelamira and Kleynhans 1996). It can therefore be expected that fluctuations in climate will have a proportionately larger influence on economic activity. Zhakata (1996) indicates how the extended drought of 1982–87 adversely affected crop production in Zimbabwe. Both the 1983 and 1984 harvests were about 30% of the long-term mean for maize, sorghum, and groundnuts. Ninety percent of the smaller inland dams dried up, and food supplies dwindled in urban centers. In the 1992 drought, 5.5 million communal farmers requested drought relief assistance, constituting say 10% of the rural population. Glantz et al. (1997) estimates that U.S.$60 million in foreign exchange losses occurred in Zimbabwe alone following the 1992 drought. Vogel (1994) indicates that 22% of agricultural debt can be traced directly to drought impacts. Multiyear droughts can lead to severe water shortages, as pointed out by Dilley (1996) in the case of the prolonged El Niño of the 1992–95 period. Vulnerability to climatic fluctuations is considerably greater in countries directly reliant on agricultural production to feed their people (VanZyl 1993).

Water is not a guaranteed commodity in southern Africa, mainly because evaporative losses are more than 2 times rainfall across most of the region. Water resources are depleted by prolonged dry spells; average runoff declines to about 1% of rainfall, and inflows to the Vaal River catchment, near Johannesburg, decline sixfold on average (Lindesay 1990). Limitations of water supply affect domestic and industrial activity in many areas, leading to quotas and consequent production losses across diverse sectors of the economy. Dam levels across South Africa drop to about 30% of capacity if drought is followed or preceded by another dry year (Vogel 1994).

Historical data extending back to 1900 indicate that the most severe and widespread drought was 1983, followed by 1992, both in association with a negative Southern Oscillation index (SOI). There conversely has been an increase in short-lived flood events, such as those associated with Tropical Cyclone Demoina in 1984, the September 1987 flood near Durban, those near Johannesburg in 1988, snowstorms over Lesotho in 1996, and widespread floods across east Africa in November of 1997 and southern Africa in February of 2000. These short-term flood events have more immediate and localized impacts, making the infrastructure more vulnerable to climate change. The current consensus of dynamical models on long-term trends is that evapotranspiration losses are likely to rise by about 20% over the next century (Hulme 1996), turning southern Africa into a water-scarce region. Schulze (1996) points out that seasonal and interannual changes in rainfall are significantly greater than long-term trends and decadal cycles; so efforts toward understanding and predicting hydrological impacts are critical to survival in the region. Rainfall during a dry year may be 50%–80% of normal, but runoff is typically 20%–50% of normal and is patchy in its spatial distribution. The compounding effect on resources is clear.

The forestry contribution to the economy of South Africa is important (~5%). Drought slows the growth rate of trees and contributes to fire hazard. Because climate fluctuations are integrated over a longer time period, say 10 yr for the average commercial pine or gum tree, it is likely that multiyear drought and decadal cycles of climate significantly impact this economic sector. In southern Africa, an 18.6-yr cycle of rainfall has been noted in the past century (Mason and Tyson 1992), so forestry production would have benefited in the wetter 1950s, 1970s, and 1990s, whereas slower growth and losses from fire would have occurred in the 1940s, 1960s, and 1980s. Fisheries are governed by shifts in ocean currents and by overexploitation. ENSO phase causes latitudinal shifts in upwelling and productivity in the Benguela Current along the west coast of South Africa. During El Niño, warmer waters near Cape Town modify the...
ecological environment through the food web, and a consequent shift in fisheries species, habitat, and abundance occurs. Fisheries management systems will be able to respond to predicted changes, thus reducing consequenc- es along the coast. Climate variability touches every facet of economic activity in southern Africa, particularly for the less-developed countries dependent on subsistence agriculture for food (Hulme 1996).

d. Resource prediction

Some of the year-to-year fluctuations in climate are the result of random sequences of events. A region may experience a dry spell simply because no storms happen to pass that way for some time. Prediction for these aspects of climate is unlikely. It is the climatic variations that are part of coherent large-scale patterns that are more predictable, especially where the “memory” of the initial state of the ocean plays an important role. If atmospheric circulation patterns are coupled to SST, then the observation and prediction of marine conditions can be used to forewarn of climatic consequences.

The demand for global long-range forecasts received impetus from the 1983 El Niño and its global consequences (>U.S.$10 billion damages; Glantz et al. 1997). The ability to model atmospheric responses to ENSO has grown such that ensemble numerical models are able to make skillful projections of rainfall and temperature in many parts of the world. However, the direct prediction of food and water resources involves complex interactions, which can be parameterized, albeit with compounding errors. Another approach is the statistical one, in which precursor “signals” are trained directly onto historical records of resources (e.g., Cane et al. 1994). This method requires a time series of high quality, relatively free of nonclimatic factors. South Africa is fortunate in this regard, with a long history of resource data available. The empirical technique attempts to replicate fluctuations in resources at a lead-time of 3–6 months over the past 25–40 yr using key indicators of the tropical ocean climate system (Jury et al. 1999).

2. Data analysis and model development

In this section, a statistical methodology is outlined to give insight to the predictability of resources influenced by climate. To formulate a statistical model, it is necessary to have a specific target in mind. After a decade of research, more than 20 target time series have been generated based on user needs, analyses of climatic data, and consideration of economic value. The targets consist of summer rainfall and temperature, yields for various crops based on quality-checked agricultural records, and naturalized catchment inflows to the major water supply dams of South Africa. The area averaging to state (provincial) level is guided by principal component analysis of gridded summer rainfall and temperature fields. For these climatic variables, dynamical model products are available. Reliable crop-yield data were available at provincial (state) level for maize, sug- ar, sorghum, sunflower, and so on. Analysis in the period of 1971–93 revealed increases due to improved farming practice, so linear detrending was applied. For the hydrological targets, specific catchments with highest water volumes were identified, including Gariep, Vaal, Pongola, and Hartebeespoort. The hydrological data derive from streamflow gauges, supplemented by daily catchment rainfall to interpolate missing records (typically <5%), and reduce anthropogenic effects (of dams built, etc.). For brevity, the analysis here is restricted to the national maize yield and the flow of the Orange River. GDP data were obtained from the Statistical Division of the South African Reserve Bank. The GDP is a useful measure of economic prosperity and depends on productivity, money supply, and other factors. To create a more stable, climate-oriented time series, year-on-year changes in the GDP (growth rate) are consid- ered. Hence, statistical models are trained directly onto food, water, and financial resource data.

A pool of candidate predictors is assembled from a subset of indices outlined in Jury et al. (1999). These include time series such as the SOI and quasi-biennial oscillation (QBO), SST in the tropical oceans, tropical air pressure and wind components, and indices of monsoon convection [outgoing longwave radiation (OLR)] averaged over areas of more than $10^5 \times 10^5$ (Table 1). The total number of predictors is 18. Two seasons are considered: July–September (JAS) and September–November (SON). The predictors have been identified on the basis of principal component analysis of the field parameters and by correlation and composite mapping with respect to summer rainfall (Jury et al. 1999). They reveal interactions between the regional and tropical cli- mate systems around Africa (Mason and Jury 1997). Models are formulated in stepwise fashion to a maximum of three predictors, and colinearity tests are applied to screen out adjacent variables with variance $r^2$ greater than 8%. Although ongoing research seeks to consoli- date predictors, the current formulation has a candidate pool nearly equal to the number of years trained (1971–93, or 22). Thus a “penalty” is needed to deflate the hindcast fit of the model, considering the candidate pool, the number of predictors utilized, and any autocorre- lation in the target series. In southern Africa, persistence of rainfall from summer to summer is negligible owing to an underlying quasi-biennial cycle (Mason and Tyson 1992). To evaluate the effect of candidate pool size, a Monte Carlo test was conducted by scrambling the exist- ing predictors into random sequences. The random numbers then were applied to the target time series to produce “optimal” three-predictor algorithms. The average hindcast fit was deemed to be artificial skill. The $r^2$ penalty, to account for a candidate pool of 18 with three predictors retained is 12%. To achieve 98% sig- nificance, the model $r^2$ fit should exceed 29%, after application of the penalty.
3. Results

The GDP response to rainfall over South Africa in the preceding summer is illustrated in Fig. 4. No clear relationship is evident in the 1960s and early 1970s, when the growth rate remained above 3% and the contribution of both gold mining and agriculture was greater. After the mid-1970s, summer rainfall and the GDP fluctuate together. Forty-eight percent of variance in the GDP growth rate may be attributable to rainfall in the second half of the record. It is not clear why the economy has become more vulnerable to climate in recent decades, given the levels of diversification. The withdrawal of government subsidies and high interest rates are contributing factors. It is also possible that the carrying capacity of this semiarid environment is nearing a population threshold. This increasing vulnerability arises despite the influences of internal political and external market forces.

In this section, statistical models are developed to predict the interannual variability. The first target for consideration is the detrended maize yield of South Africa. Much of the maize is grown in an east-west belt on the high plateau just to the south of Johannesburg. An adjusted fit of 38% is obtained by two predictors: OLR in the central Indian Ocean and the stratospheric QBO. Convection (OLR) is known to be influenced by ENSO through changes in the underlying SST (Cadet 1985) and monsoon circulation systems (Hastenrath...
A zonal overturning Walker cell is prominent during the SON season, with vertical motions over east Africa and Indonesia and zonal flow in between. As the ITCZ shifts south of the equator under the influence of the northeast monsoon, a dipole rainfall pattern is observed, with contrasting regimes over eastern and southern Africa (Goddard and Graham 1999). Reduced clouds over the western Indian Ocean and eastern Africa in the austral spring are consistent with wet conditions over southern Africa in the following summer, leading to increased maize yields. The stratospheric QBO acts to reinforce the zonal overturning in an unknown manner and favors increased maize yields during west phase. From this result, over one-third of the variability of maize yield can be predicted at a lead time of 6 months (e.g., November forecast for April harvest). The model predicts within the error bar 17 times in 22 yr (Fig. 5), and may be considered to be sufficiently reliable to adjust farming effort via exposure to credit.

The second target considered is the catchment inflow to the Gariep Dam (volume about $10^{11}$ m$^3$) on the Orange River to the west of Lesotho (30°S, 25°E). This reservoir is the largest water resource in South Africa, and its inflow is accumulated each year with a 1–2-month lag on rainfall. The model fitting the time series has three predictors: meridional wind in the tropical east Atlantic, pressure in the southeast Indian Ocean, and SST south of Africa. The southeast Indian Ocean pressure has the strongest influence and is closely related to ENSO (correlation coefficient $r = 0.83$ with Niño-3 SST for $N = 22$ cases). When pressure is low (La Niña), river flow is high. The lower pressure near 90°E heralds an alternating pattern of higher pressure at 60°E and lower pressure at 20°E (Rocha and Simmonds 1997), which contributes to southern African rainfall. The adjusted model fit for the Orange River flow is high at 59%, but the hindcast tercile “hit” rate is 15 of 22 and so offers a two-out-of-three reliability consistent with other prediction models.

The final target considered here is the GDP growth rate. The model uses predictors in the July–November period in the preceding year; a lead time of 6–9 months. The cloud depth (OLR) in the central Indian Ocean is the main determinant (same as for maize yield; see Table 2); SST in the west Indian Ocean provides a secondary input. With application of the penalty for artificial skill, the adjusted hindcast fit is 36%. The model suggests that, when clouds are reduced in austral spring (SON) in the area of 10°N–15°S and 45°–80°E, wet weather develops over South Africa during summer, leading to an increase in GDP the following year. Hence, improved knowledge of ocean–atmosphere coupling in the Indian Ocean will underpin long-range forecasts of climate-related economic activity in southern Africa. With a 1999 GDP valued at U.S.$168 billion and variations in growth rate of ±2% (e.g., U.S.$7 billion), a significant

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**Table 2. Multivariate models, where prefix o denotes SON and a denotes JAS.**

<table>
<thead>
<tr>
<th>Target</th>
<th>Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA.maize</td>
<td>+0.66(oOLR) - 0.34(oQBO)</td>
</tr>
<tr>
<td>Org. river</td>
<td>+0.39(aeAV) - 0.78(osetP) - 0.45(osocnS)</td>
</tr>
<tr>
<td>SA.GDP</td>
<td>+0.64(oOLR) + 0.53(awiST)</td>
</tr>
</tbody>
</table>
level of risk could be “hedged” through prediction and mitigation (Harrison and Graham 2001).

Validation tests have been conducted on the empirical formulations, as outlined in Jury et al. (1999), using independent periods for development and testing and using jackknife validation within the record. Given the low degree of persistence in the target data, it is found that both hindcast fit and tercile hit rate are reasonable measures of skill, consistent with more sophisticated performance checks. The inherent 2–5-yr variability also means that a 25-yr history will capture a sufficient number of interannual events to lend confidence in predictive applications. The statistical models are currently implemented, and results could be found online at the time of writing (http://weather.iafrica.com/forecasts/cip.seasonalOutlook.html). This site was receiving over 1000 hits per day during the peak season (October). Most of the users are from South Africa and are divided equally among financial analysts, commercial farmers, and other resource managers. According to response surveys conducted via e-mail, users prefer deterministic percentages to be listed together with error bars.

A validation of summer rainfall forecasts over eastern South Africa from predictive models based on similar techniques reveals hits in 1992, 1993, 1998, and 2000; near misses (e.g., within the error bar) in 1994, 1996, 1997, and 1999; and a complete miss (e.g., outside the tercile category) in 1995. In 4 yr out of 9 (44%), users were adequately forewarned and could gain a cost advantage. In another 4 yr, ambiguous forecasts suppressed potential benefits. The misleading forecast in 1995 may have incurred losses among users. Potential gains or losses affect many kinds of users, from institutions (banks, government departments) to donor agencies (financial and resource intervention) and individuals (commercial farmers, subsistence communities).

The cost–benefit of a forecast hinges on its uptake (Harrison and Graham 2001) and hence the level of confidence in its use. There is considerable scope for hedging losses, as outlined below.

Mitigation strategies

A reliable long-range forecast will have no value unless it is disseminated, taken up, and acted on. It may be relatively easy to develop predictive tools in southern Africa because of the known ENSO influence. Yet dissemination becomes difficult in some instances, particularly to small farmers without access to external media. A number of channels of communication need to be explored. SARCOF, which includes the region’s weather services and other agencies, is the main institution coordinating and disseminating long-range forecasts. The main response of users is to modify farming effort through exposure to borrowed finances, amounting to U.S.$1 billion per year. When a drought is forecast, farmers (and their bankers) in the maize belt of South Africa react by reducing debt to manageable levels, planting less acreage and utilizing drought-resistant varieties, purchasing less fertilizer, and deferring outlays on capital equipment (Natural Resources Institute 1996). Many subsistence farmers continue with “business as usual” in hopes of random rainfall on their plot, irrespective of the large-scale climate anomalies and forecasts thereof. Increasing sophistication with regard to forecasting the shift of seasonal rains (e.g., early in “dry” years, late in “wet”) enables farmers to adapt planting dates accordingly. Another potentially useful mitigation strategy would involve varying credit exposure east–west across the background gradients in rainfall. In this scheme, the level of financing made available for farming operations would shift east in dry years and west in wet years.

There is a system of rural extension officers who journey across the countryside every spring (October) to inform subsistence farmers and the rural public on the prospects for the coming season. This community approach to information transfer has worked very well in recent years. In other regions, early-warming systems are in place and involve in situ and satellite monitoring of resource status, analysis of household economic levels, nutritional analysis at rural schools, and administrative mechanisms to ensure that supplies are available. It is important that partnerships are forged among government departments, researchers, nongovernmental aid organizations, and commercial and industrial sectors of the economy, to make the most of the shifting and variable climate of southern Africa (Thomson et al. 1998).

Water resource managers act on long-range forecasts in a more conservative manner, mainly because of the longer lead times required in hydrological planning. Dam inflows and volumetric levels can be monitored, and shortfalls can be reduced through the imposition of quotas on domestic and industrial users. Yet, inefficient agricultural irrigation schemes near perennial rivers can evaporate large volumes of water, particularly during early summer (November–December). Water managers over the plateau of South Africa usually contain dam outflows except when levels are full and short-term flood warnings are issued. During drought, mitigating strategies are limited in the hydrological sector and involve supply quotas and incremental-use cost structures. Rural communities without formal water supplies rely on local access to streamflow. This dependence could explain the increasing sensitivity of South Africa’s GDP to rainfall.

4. Summary

A variety of economic outputs and resources in South Africa fluctuate according to climate. This study demonstrates that a reasonable percentage of this variability is predictable up to 6 months in advance. Statistical models, based on indicators of tropical ocean climate and ENSO, have been developed to anticipate shifts in economic prosperity, crop yield, and river flow in South
Africa. The most influential predictor for maize yield and GDP is the cloud depth in the central Indian Ocean. Air pressure in the southeast Indian Ocean is useful with respect to river flow. Both predictors are sensitive to the regional uptake of ENSO. Risk reduction based on projected earnings is an essential tool in financial management, which may be applied to forecast food and water supplies. The economic analysis suggests that swings of climate are manifested in GDP fluctuations on the order of U.S.$5 billion. With an ability to predict and to mitigate 20% of this variability through strategic planning, more than U.S.$1 billion could be saved annually in southern Africa, according to local user surveys (Harrison and Graham 2001). A cost–benefit ratio in excess of 20 is estimated, based on a government agency being employed to produce computer-intensive, numerical model forecasts of rainfall and so on. The cost–benefit ratio may be enhanced using statistical models trained directly on resources, as outlined here. Comparison of forecast products based on these two distinct techniques helps forums such as SARCOF gain an “ensemble” view of the expected climate. The result is better management of essential resources through long-range planning infused with relevant information.

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