Linking Seasonal Climate Forecasts with Crop Simulation to Optimize Maize Management

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Introduction

Rainfed maize a primary source of food, income for many in eastern and southern Africa. Climate variability creates a moving target for management and disincentive to sustainable intensification. Timely advance information about climatic conditions and crop response provides opportunity to improve management. As part of a broader effort to support farmers' risk management in Kenya and Zambia, we use crop simulation models linked with seasonal rainfall forecasts to translate forecasts into agricultural terms and assess outcomes of management alternatives.

Supporting Farmers' Use of Climate Forecasts

Our modeling work is designed to provide evidence and insight leading to sustained operational support for farmers' climate risk management.

In Kenya, our work provides insight into how to package and communicate forecast information, has led to interest in equipping the agricultural extension to support climate risk management.

In Zambia, our work has led to increased awareness and demand for climate information, and changes in the way forecast information is produced and communicated.

Conclusions

Smallholder farmers see opportunity to improve management in response to seasonal forecasts.

Linked modeling translates seasonal rainfall forecasts into crop yields.

Crop models can represent some of the management responses that farmers hope to change in response to forecasts.

Appropriate maize management – N fertilizer, planting density, use of conservation tillage – changes from year to year as a function of rainfall.

Ongoing analyses seek to evaluate potential income and food security benefits of maize management and a broader set of livelihood decisions in response to seasonal climate forecasts.

References

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Predicting Maize Response to Climate

Predicting response to fluctuations is complicated by dynamic, nonlinear crop response to environment, and mismatch between scales of crop simulation models and operational climate forecasts.

We use a multivariate statistical procedure to downscale seasonal forecasts based on GCMs (Kenya) and statistical relationships with sea surface temperatures (SSTs) (Zambia).

A stochastic weather model disaggregates monthly rainfall forecasts into the daily realizations that crop models require.

Simulated yields with APSIM (Kenya) and CERES-Maize (Zambia).

Initial assessment of predictability from climate forecasts relative to yields simulated with observed weather data.

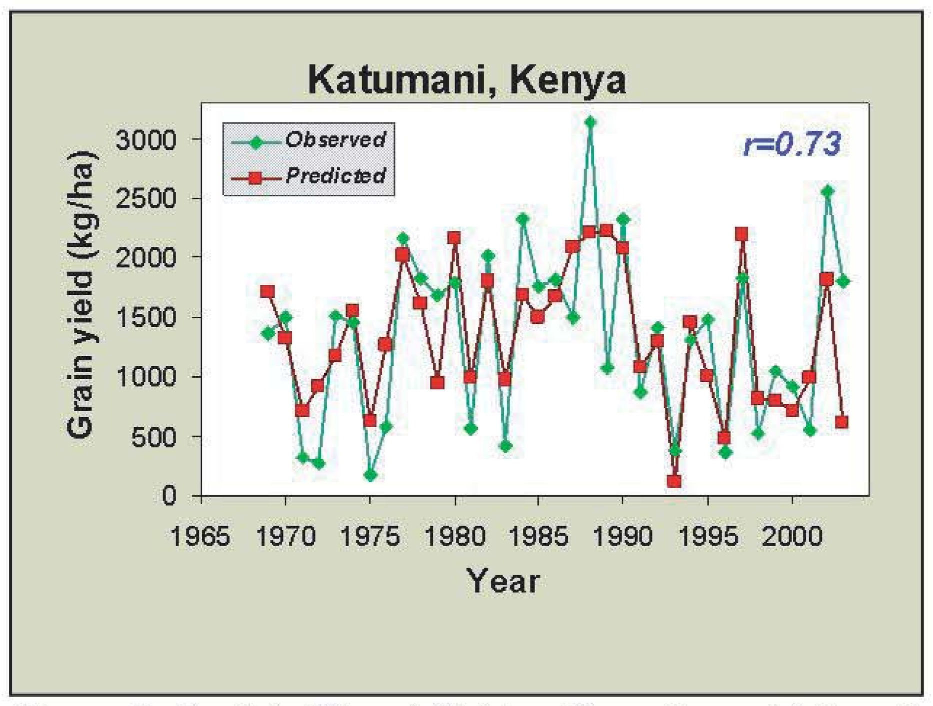


Figure 1. Predictability of October-December rainfall and resulting maize yields is relatively high in Eastern Province, Kenya. Rainfall forecasts are based on the ECHAM v. 4.5 GCM simulated with observed SSTs.

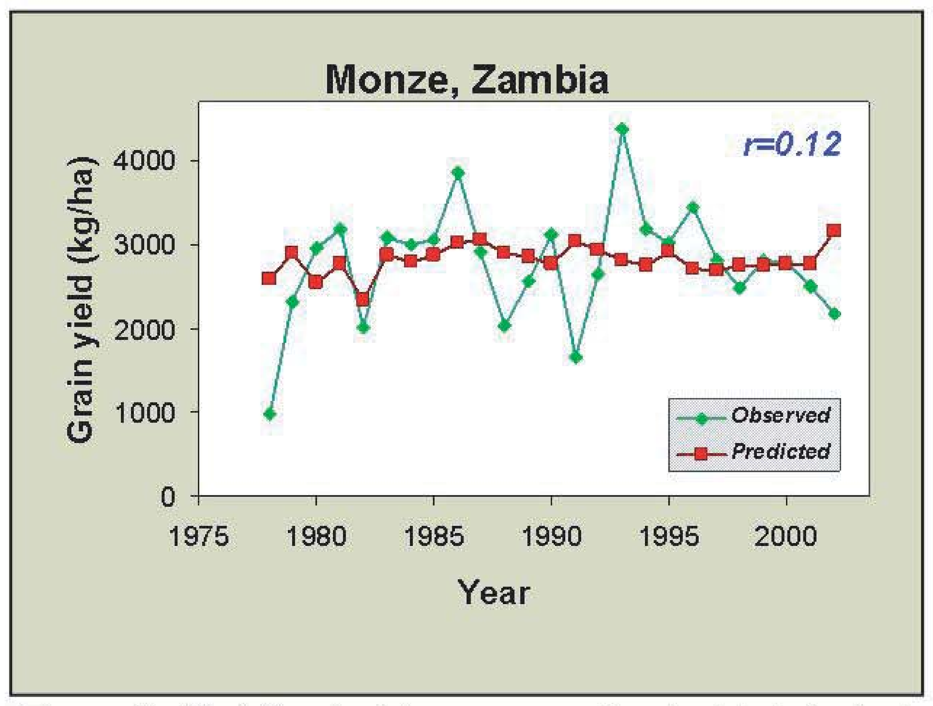


Figure 2. First 2 principle components of global tropical SSTs provide modest predictability of November-March rain in southern Zambia. Predictability is weak in January when maize is most susceptible to water stress, leading to weak yield predictability.

Modeling Maize Management Response to Forecasts

In workshops in Eastern Province, Kenya, farmers demonstrated interest and understanding of seasonal forecasts, identified viable management responses:

land preparation timing & method	area cultivated
crop & cultivar selection	terrace maintenance
planting strategy	labor procurement & allocation
weeding	fencing & cover for livestock
soil fertility	forage management
pest management	grain & fodder storage

We simulate a subset of potential management responses to seasonal forecast:

- Kenya: N fertilizer management, planting strategy, cultivar
- Zambia: Conservation vs. conventional tillage, fertilizer, planting strategy, cultivar

Optimal management can be identified by:

- Selecting best among a discrete set of strategies,
- Fitting to a differential analytical production function
- Constrained optimization whole-farm planning model.

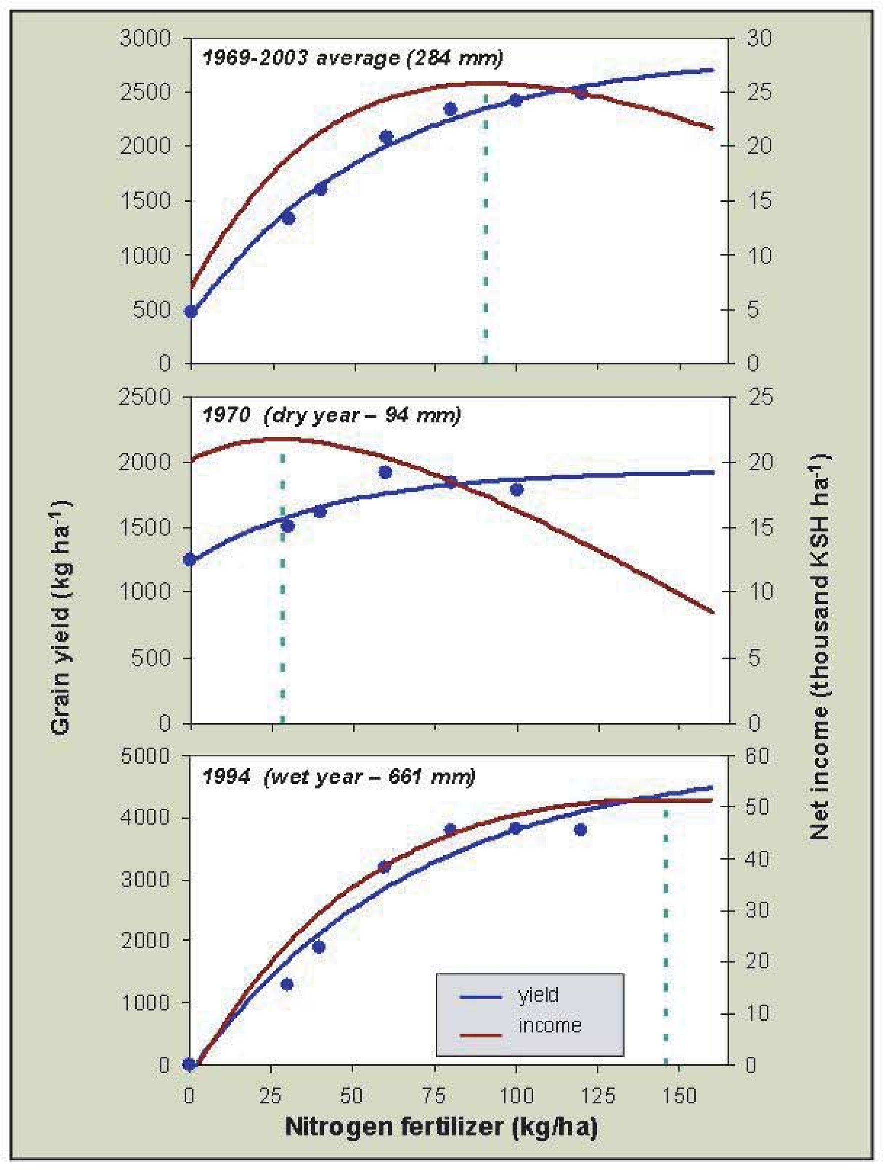


Figure 4. Simulations indicate that optimal N fertilizer amount tends to increase with increasing rainfall. The optimum was found by fitting yield response to N to a Mitcherlitch production function, incorporating into gross margin calculations, and differentiating.

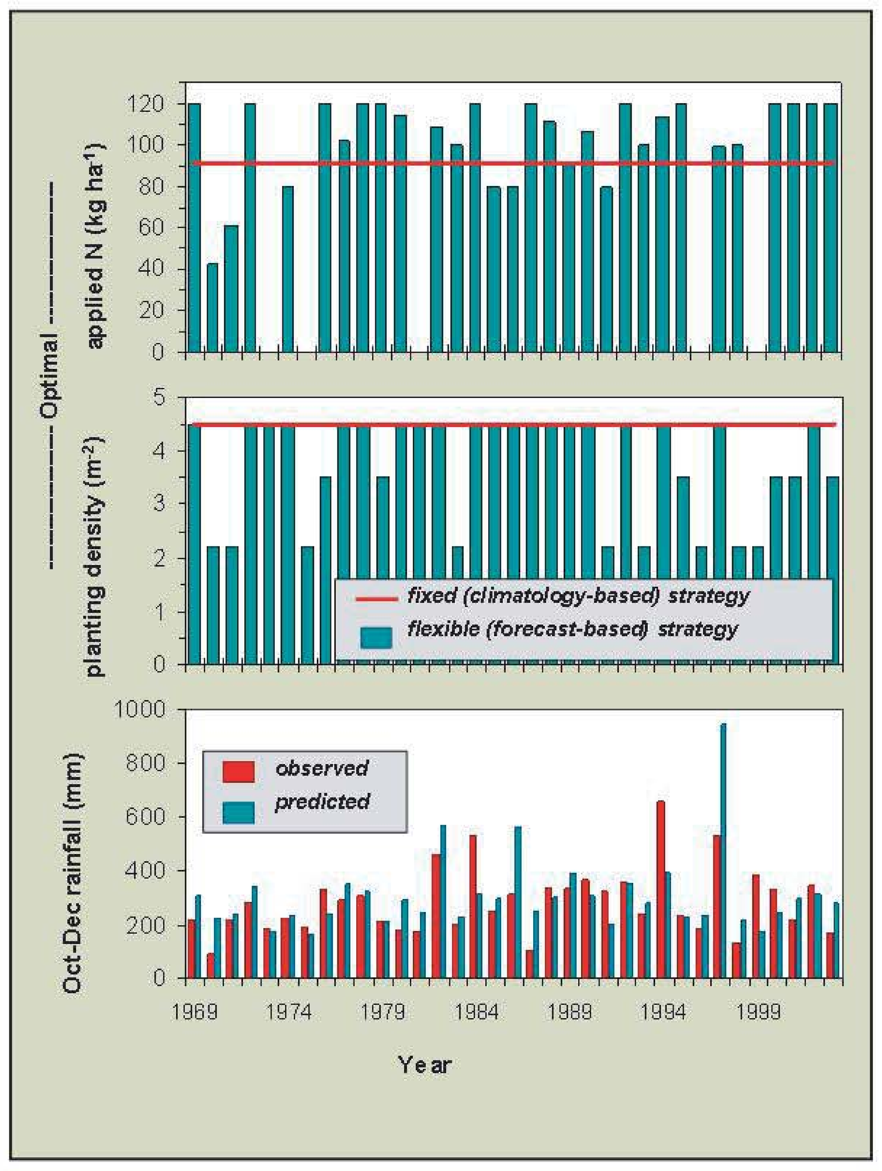


Figure 5. Seasonal rainfall forecasts change the optimal (profit maximizing) amount of fertilizer from year to year. The fertilizer strategy that is optimal on average is generally not optimal in particular years.

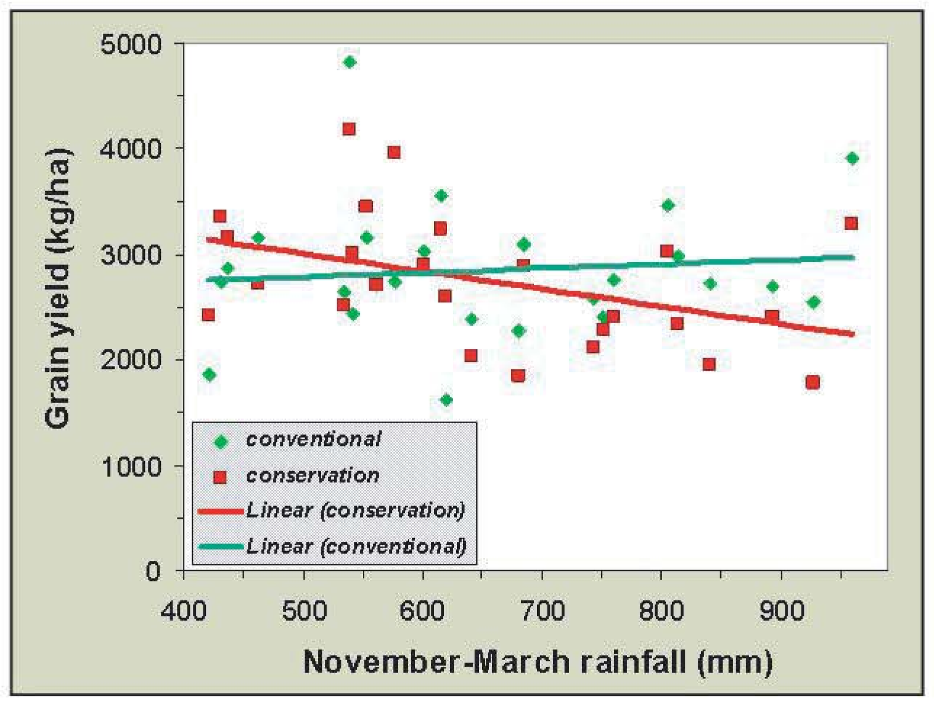


Figure 3. We simulated reduced runoff and water harvesting effects of conservation tillage on soil water balance. CERES-Maize simulations suggest that conservation tillage using basins and mulch may improve yields only in low rainfall years. Model predictions of reduced yields from excessive N leaching under conservation tillage in high rainfall years need further evaluation.

Estimating Forecast Value

Value of information: Expected outcome of best response to new information minus expected outcome of best response to prior information:

$$V_F = \mathrm{E}\{U(\Pi(\mathbf{x}^* \mid F))\} - \mathrm{E}\{U(\Pi(\mathbf{x}^* \mid C))\}$$

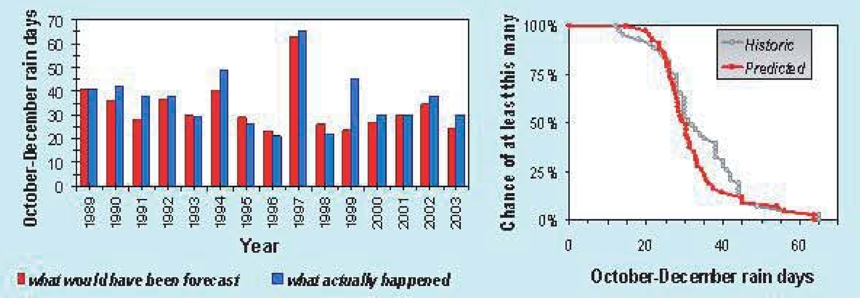
We simulated maize management optimized for all years, and for each year's predicted yields, then applied the optimal management to yields simulated with observed rainfall:

$$V_F \cong n^{-1}\sum_{i=1}^{n}\left(P_T\, y(\mathbf{x}^* \mid F_i; \theta_i, \mathbf{e}_T) - C_{\mathbf{x}^*|F_i}\right) - n^{-1}\sum_{i=1}^{n}\left(P_T\, y(\mathbf{x}^* \mid \Theta; \theta_i, \mathbf{e}_T) - C_{\mathbf{x}^*|\Theta}\right)$$

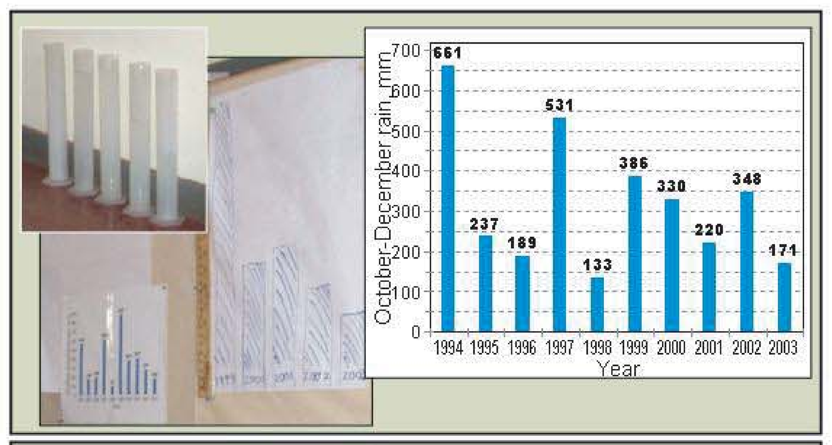
Analyses are ongoing, final results not yet available.

Communicating Forecasts to Farmers

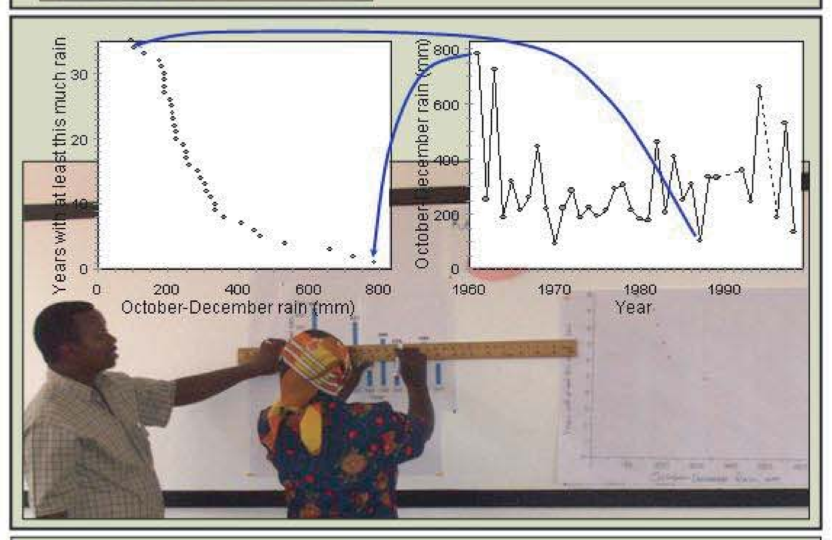
- Relate objective time series to farmers' experience.
- Convert time series to frequencies, then probability of exceedance. Explain and discuss interpretation.
- Use, e.g., El Niño or La Niña years to illustrate concept of forecast as shifted probability distribution
- Packing forecasts as (a) time-series of observations and predictions, and (b) shifted probability of exceedance:



1. Relate variability to memory



2. From time series to probability



3. Shifted distribution in e.g. El Niño years