Estimating the Potential Economic Value of Seasonal Forecasts in West Africa: A Long-Term Ex-Ante Assessment in Senegal

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ABSTRACT

Recent improvements in the capability of statistical or dynamic models to predict climate fluctuations several months in advance may be an opportunity to improve the management of climatic risk in rain-fed agriculture. The aim of this paper is to evaluate the potential benefits that seasonal climate predictions can bring to farmers in West Africa. The authors have developed an archetypal bioeconomic model of a small-holder farm in Nioro du Rip, a semiarid region of Senegal. The model is used to simulate the decisions of farmers who have access to a priori information on the quality of the next rainy season. First, the potential economic benefits of a perfect rainfall prediction scheme are evaluated, showing how these benefits are affected by forecast accuracy. Then, the potential benefits of several widely used rainfall prediction schemes are evaluated: one group of schemes based on the statistical relationship between rainfall and sea surface temperatures, and one group based on the predictions of coupled ocean–atmosphere models.

The results show that forecasting a dryer than average rainy season would be the most useful to Nioro du Rip farmers if they interpret forecasts as deterministic. Indeed, because forecasts are imperfect, predicting a wetter than average rainy season exposes the farmers to a high risk of failure by favoring cash crops such as maize and peanut that are highly vulnerable to drought. On the other hand, the farmers’ response to a forecast of a dryer than average rainy season minimizes the climate risk by favoring robust crops such as millet and sorghum, which will tolerate higher rainfall in case the forecast is wrong.

When either statistical or dynamic climate models are used for forecasting under the same lead time and the same 31-yr hindcast period (i.e., 1970–2000), similar skill and economic values at farm level are found. When a dryer than average rainy season is predicted, both methods yield an increase of the farmers’ income—13.8% for the statistical model and 9.6% for the bias-corrected Development of a European Multimodel Ensemble System for Seasonal-to-Interannual Prediction (DEMETER) multimodel ensemble mean.
1. Introduction

Climate has a strong influence on agricultural production, and is considered to be the most weather dependent of all human activities (Oram 1989; Hansen 2002), and it has socioeconomic impacts whose magnitude varies greatly from one region to another (Ogallo et al. 2000). The severity of climate impacts is particularly strong in the Sahel, where rain-fed agriculture is the main source of food and income and where the means to control the crop environment (irrigation, mechanization, fertilizers, and other off-farm inputs) are largely unavailable to small-scale farmers (Ingram et al. 2002). Dealing with the uncertainty of climate variability is a challenge for agriculture as farmers need to make critical climate-sensitive decisions months before the actual rainy season takes place (Meza et al. 2008). Therefore, forecasts about future climate might help African farmers take crucial strategic decisions to reduce their vulnerability and increase farm profitability.

Good predictability of seasonal climate fluctuations has been achieved for many parts of the world (Hansen 2002) by using comprehensive coupled models of the atmosphere, oceans, and land surface (Palmer et al. 2004) or regional statistical schemes (Ward 1998; Fontaine et al. 1999; Ogallo et al. 2000; Ward et al. 2004). In addition, the general circulation models are now able to produce plausible long-run climate change scenarios in response to various evolutions of greenhouse gas concentrations. Improved climate prediction capability might provide an opportunity for farmers to adapt their current management to a highly variable present climate (Ingram et al. 2002) as well as to future climate change (Lobell et al. 2008). However, obtaining these potential benefits is not straightforward because forecasting is imperfect and its application to management issues has not been developed and tested extensively (Hammer et al. 2001). Meza et al. (2008) provide an exhaustive review of such approaches assessing the economic value of seasonal forecasts. Here, the authors distinguish ex-ante evaluation (i.e., assessing the benefits of forecasts in advance of their adoption by society) from ex-post evaluation, which seeks to assess observed outcomes following adoption of actual forecast schemes. Even if seasonal forecasts are made routinely in sub-Saharan Africa (as in other parts of the world), adoption by farmers is too low to provide any reliable ex-post evaluation (Meza et al. 2008; Roncoli et al. 2000). Ex-ante approaches remain the best way to evaluate the forecasts, and they also present several advantages. They provide quantitative arguments which are often necessary to mobilize funds and institutional partners and to focus on where the benefits are likely to be the greatest (Thornton 2006; Meza et al. 2008). The review of Meza et al. (2008) presents 58 assessments of the economic value of seasonal forecasts for agriculture based on 33 scientific papers. However, none of the referenced studies considers sub-Saharan Africa or even subsistence agriculture. This paper is an attempt to fill this gap.

The aim of the present study is (i) to develop a methodology to assess the usefulness of seasonal forecasts in West Africa, by taking into account both climatic and economic evaluations, and (ii) to apply this methodology to state-of-the-art climate predictions that are or can be made routinely in the subcontinent. To be consistent with the existing categorical climate prediction systems in West Africa (Prévisions Climatiques Saisonnières en Afrique de l’Ouest, le Tchad et le Cameroun, PRESAO; see http://www.acmad.ne; Hamatan et al. 2004; Ward et al. 2004), we will focus on forecasts of total seasonal (July to September) rainfall amount categories according to the terciles of the expected distribution of values: wet (upper tercile), normal (middle tercile), and dry (lower tercile). However, although PRESAO and major forecasting centers provide probabilistic information (e.g., as probability shifts of the climatological tercile categories), this study will mostly examine the deterministic case (i.e., farmers supposing the next rainy season will be in the most probable tercile category). This allows us to document which management changes would be needed with a perfect knowledge of the coming rainy season to optimize farmers’ income and what would be the economic value of these changes. We thus refer to the potential economic value since we take into account neither the probabilistic nature of forecasts nor dissemination, acceptance, and adoption of forecast within local knowledge frameworks, which would define the real economic value of the forecasts. Moreover, we understand that forecasting total rainfall is of limited usefulness for farmers since it is the timing of the onset and end of the rainy season and the distribution of rainfall within the season that are the more salient parameters that may influence farmers’ cropping decisions (Ingram et al. 2002).

For our purpose, we developed a simple bioeconomic farm model based on a typical smallholder farm in the Sahelian zone of Senegal. This kind of model has already been used to estimate the value of forecast information (Wilks 1997). While farm-level models can be enhanced to take into account climatic risk (Cocks 1968; Hazell and Norton 1986), we prefer, like Cabrera et al. (2006), to estimate risk by running simulations with actual climate data. The model, described in section 2, is used to simulate the farmers’ response to the adoption of categorical forecast. By looking at the differences between the simulated farmers’ income with and without a priori information on probable future rainfall amounts, it is
possible to evaluate quantitatively the value of that kind of climate forecast.

By solving the farm model we obtain the farmer’s different optimal management strategies in response to the use of a forecast, as well as his resulting income. This allows us to make an ex-ante assessment of the economic value of the forecasts and its sensitivity to the forecast accuracy (or skill). Finally, we evaluate two state-of-the-art climate prediction methods: a statistical forecast based on the well-documented link between rainfall and sea surface temperature (SST) and a dynamical forecast system based on the outputs of seven comprehensive European global coupled atmosphere–ocean models from the Development of a European Multimodel Ensemble System for Seasonal-to-Interannual Prediction (DEMETER) project (Palmer et al. 2004). This evaluation is done over a 31-year hindcast period from 1970 to 2000.

2. Materials and methods

a. Rainfall data in Senegal

Mitchell and Jones (2005) have produced a global climate observations database including 1224 monthly grids of observed climate for the period 1901–2002 and covering the global land surface at 0.5° resolution. This database is known as the Climatic Research Unit (CRU) TS 2.1 and is publicly available (http://www.cru.uea.ac.uk/cru/data/hrg/cru_ts_2.10). There are nine climate variables available: daily mean, minimum and maximum temperature, diurnal temperature range, precipitation, wet day frequency, frost day frequency, vapor pressure, and cloud cover. In this study, we use rainfall data for the period 1970–2000. We compute a Senegal rainfall index by averaging rainfall data over the grid points from 11.5° to 16°N in latitude and 16° to 11.5°W in longitude and computing the mean July–September (JAS) rainfall amount (mm month$^{-1}$). The Nioro du Rip region, where the bioeconomic model has been calibrated, is located near the center of the Senegal rainfall index domain (Fig. 1). The area covered by the rainfall index is much larger than the Nioro du Rip region since the choice of the domain size is motivated by the spatial resolution of the climate models’ predictions (see section 2c). However, when averaging JAS rainfall, there is good agreement between the large scale of the index and the farm scale. This agreement is assessed by comparing the CRU data and nine local rainfall stations located at Nioro du Rip with 31 years of data. We first transform the Senegal rainfall index from CRU data into

FIG. 1. Map of the studied area in Senegal. The area delimited by the thick black line represents the Nioro du Rip department where the bioeconomic model was calibrated. The thick gray box represents the area for which rainfall indexes were computed. The thin grid corresponds to the 2.5° DEMETER model outputs.
binary time series in which only three outcomes are possible: an occurrence of a "wet," "normal," or "dry" year, according to whether the rainfall of the year is above the upper tercile, between the upper and the lower tercile, or below the lower tercile of the 31-yr rainfall distribution. Since the JAS Senegal rainfall data are normally distributed, it permits classification of the years according to tercile groups that divide the sorted dataset into three equal parts so that each part represents 1/3 of the sampled population. For each category defined from CRU data, we look at the fraction of wet, normal, and dry situations depicted from local data from 279 situations (31 years and 9 locations in Nioro du Rip). Figure 2 shows that a dry (wet) year depicted by the Senegal index from CRU data corresponds to a dry (wet) or a normal situation in about 90% of the cases and corresponds to a strictly dry (wet) situation in around 60% of the cases. The normal year as depicted from the Senegal rainfall index is less discriminate at the local scale because it corresponds to a normal situation in only 40% of the cases.

b. Seasonal rainfall hindcasts

1) Statistical techniques

A number of empirical studies have been made using prerainy season SST to predict the summer Sahelian rainfall total (Folland et al. 1991; Ward 1998; Ward et al. 2004), which helped us in building our own simple statistical model to predict Senegal total summer rainfall. This model is based on SST data from the monthly extended reconstructed sea surface temperature (ERSST; see http://www.ncdc.noaa.gov/o/a/climate/research/sst/ersstv3.php), which is built using the most recently SST data available from the International Comprehensive Ocean–Atmosphere Dataset (ICOADS) and improved statistical methods that allow stable reconstruction using sparse data (Smith et al. 2008). Only the SST data over the 1970–2000 period are used in this study. We first compute lagged correlation maps between the JAS Senegal rainfall and SST in each of April, May, and June (Fig. 3). First, there is a positive correlation between tropical Atlantic SST and West Sahel rainfall, implying that wetter years are associated with warmer SST in this basin through a northward migration of the intertropical convergence zone over the tropics. Second, West Sahel rainfall has a strong connection with Pacific SST in which a warm phase of El Niño–Southern Oscillation is associated with reduced precipitation in the Sahel (Janicot et al. 2001). The correlation maps are then used to select a set of predictors that are box averages of SST over specific regions known to be linked with the West African monsoon (Ward 1998; Giannini et al. 2003), where the highest significant correlations are found (Fig. 3). Three sets of predictors are selected independently, corresponding to the three considered months. These predictors are then used to build a stepwise multivariate linear regression model to predict the JAS Senegal rainfall. The equation of the multivariate model is

\[ Y = \alpha + \beta_1 X_1 + \cdots + \beta_p X_p, \]

where \( Y \) represents the predicted JAS Senegal rainfall value, \( \alpha \) is a constant, and each \( \beta \) term denotes a regression coefficient for the corresponding SST predictor \( X \) for
FIG. 3. Correlations between JAS rainfall in Senegal and SST in (top) April, (middle) May, and (bottom) June. The black boxes indicate the regions where SST was averaged to be included in a statistical predictive model of JAS Senegal rainfall.
a given month. Once a first model is built with all predictors, we reduce the number of predictors by minimizing the variance inflation factor to reduce collinearity among predictors in the model. In the same way, we also apply ascendant and descendant methods to choose the best set of predictors among the initial set. We built three different models by using separately the April, May, and June sets of predictors to explore three different prediction lags where 30 April, 31 May, and 30 June are the last days of observed data of the April, May, and June models, respectively.

2) The DEMETER Hindcasts

Seasonal forecasts were also computed from the DEMETER project (Palmer et al. 2004), whose objective was to develop a well-validated European coupled multimodel ensemble forecast system for seasonal to interannual prediction. The use of a multimodel ensemble system based on seven comprehensive European global coupled atmosphere–ocean models allows for uncertainties in model formulation to be included in the estimation of seasonal forecast probabilities and is thought to produce the most reliable seasonal climate forecasts possible. By the end of the project, an extensive set of 6-monthly hindcast ensemble integrations had been generated using the DEMETER system. These were run four times a year starting on the first of February, May, August, and November over a period of about 40 years. Each model produced nine members of the multimodel ensemble corresponding to nine different ocean initial states (see Palmer et al. 2004). In this study, we obtained hindcasts of monthly rainfall from the online data retrieval system installed at the European Centre for Medium-Range Weather Forecasts (ECMWF; see http://www.ecmwf.int/research/demeter/data/index.html) from 1970 to 2000 (Table 1). We select the integration starting on the first of May, which gives a JAS rainfall prediction with the same lag as the April statistical model [see section 2b(1)]. The outputs are provided at 2.5° × 2.5° resolution. We compute the same JAS Senegal rainfall index as for observation data (section 2a), but for DEMETER hindcasts it is done by (i) averaging the 63 model outputs (seven models and nine initial ocean states) from June to September over the 11.5°–16°N, 16°–11.5°W domain, (ii) computing the seven individual model ensemble means by averaging separately the nine runs of each model, and (iii) computing the multimodel ensemble mean (MMEM) by averaging the seven individual model ensemble means.

c. The climate evaluation

The forecast skill of the hindcasts was assessed using two standard methods: (i) the correlation between observations and predictions by cross-validation and (ii) the relative operating characteristics (ROC) scores.

The leave-one-out cross-validation method (Michaelsen 1987; Wilks et al. 2006) was used to document the stability of the statistical SST models: model parameters were computed from a portion of the data (called the training period) composed by all years minus one, and we looked at the prediction of the remaining data not used for training. The cross-validated correlation is a realistic representation of the skill of the model for “unseen” years. Particularly adapted to small datasets, it partly reduces distortion in skill estimates and protects against overfitting (Bouali et al. 2008). For DEMETER hindcasts we computed a simple Pearson correlation coefficient between DEMETER rainfall outputs and the observed JAS Senegal rainfall.

ROC is a mean of testing the skill of categorical forecasts (Mason and Graham 1999; WMO 2006). It is based on contingency tables giving the hit rate (HR) and false alarm rate (FAR). To be consistent with actual forecast schemes in West Africa, we first transform our data and forecasts according to the terciles. We then compute a contingency table based on these three categories and calculate the HR and FAR, which are simply percentages that tell us how well the forecast did when a wet, normal, or dry year was observed and, likewise, how well the forecast did when a wet, normal,
or dry year was not observed. An illustration of how the contingency table is used, in the case when we are interested in predicting wet years, is given in Table 2. The “hits” category represents the number of wet years that have been forecast as such. The “false alarms” category represents the number of normal or dry years that have been forecasted as wet years. The HR for the prediction of wet years is defined as

\[
HR = \frac{\text{hits}}{\text{hits} + \text{misses}}.
\]

It ranges between 0 and 1, 1 meaning that all occurrences of wet years were correctly forecast as so. The FAR is defined as

\[
FAR = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}}.
\]

The value can range between 0 and 1, 0 meaning that all forecasted wet years were observed as so. The ROC score is a measure of the hit rate to the false alarm rate. It is recognized that the ROC score as applied to deterministic forecasts is equivalent to the scaled Hanssen and Kuipers score (HKS; WMO 2006), which is defined as

\[
HKS = \frac{HR - FAR + 1}{2}.
\]

The range of possible values goes from 0 to 1; a perfect forecast system has a value of 1 and a forecast system with no information has a value of 0.5 (HR being equal to FAR). The same skill scores can be computed for the prediction of normal or dry years.

In our study, these standard forecast skill methods are also applied to a reference forecast method based on persistence (the JAS rainfall of one year belongs to the same tercile as the previous year). Indeed, it has been noticed by Ingram et al. (2002) that most farmers in Burkina Faso make decisions about planting based on what happened during the previous season.

d. The bioeconomic model

We designed a simple bioeconomic model based on mathematical programming model of a typical farm in Nioro du Rip in central Senegal using the General Algebraic Modeling System (GAMS) software. The region is under a semi-arid climate regime and gets around 700 mm yr\(^{-1}\) of rainfall in one short rainy season. With more than 100 inhabitants per square kilometer, the Nioro du Rip area experiences high population pressure. New land is scarce and fallow has almost disappeared. The cropping intensity over arable land is close to 1 but agriculture remains of low intensity and is part of a heterogeneous landscape. Inputs are expensive, organic matter application is rare, and crop yields remain low. The use of animal traction with horses or donkeys is widespread. Under the Food and Agriculture Organization (FAO)—United Nations Educational Scientific and Cultural Organization (UNESCO) soil classification system, Nioro du Rip soils were classified as predominantly dystric nitosols, tropical ferruginous soils with various degrees of leaching. Farmers—who usually make a good connection between the extremely variable soil texture and expected yields—distinguish three types of soils: lowlands, clayish soils (called deck locally), and clayish soils with organic matter and sandy soils (called dior). Farmers perceive important differences in yields depending on the soil types cropped. Sandy soils are easy to till but are permeable, making crops sensitive to dry spells. They cover 38% of the province and support mainly millet and peanut. Clayish soils (38% of the province) are richer in micronutrients and organic matter but harder to till. They are more suited to maize and sorghum. Mixed soils (deck dior) cover 10% of the area and are suitable for most crops. Lithosols, which cover 6% of the area, are generally under pasture. Lowlands (6% of the area) are suitable for rice, sorghum, and vegetables during the dry season. Saline soils (3% of the area) are unsuitable for agriculture. Overall, the major crops are peanut and millet. However, maize area is increasing fast because of a perceived recent increase of rainfall, new policy incentives, and the increasing use of fertilizers. Rice and sorghum are limited to lowlands.

The aim of the farm model is to find the conditions that maximize the farmers’ global net income generated by cropping activities for various types of rainy seasons weighted by the probability of the occurrence of each type of rainy season (i.e., wet, average, and dry). At this stage, it is important to keep in mind that such a simple model is not designed to help farmers, agricultural extension agents, or even decision makers directly, but
rather to illustrate farmers’ opportunities to mitigate climatic risk. All parameters and variables are derived from interviews with farmers and observations of traditional farming systems in the Nioro du Rip region. We analyzed agricultural censuses for the region (2005–06) and conducted several interviews with local farmers and agronomists (in the period 2005–06) to get the socioeconomic data needed to build the model. Four crops are included in the model: maize, peanut, millet, and sorghum. Consistent with the strategies of farmers in the area, two input levels were considered for maize and one for peanut. The model distinguishes three types of soils: lowlands, deck, and dior. Net income maximization is made under several constraints (land, labor, capital, crop rotations, grain consumption, and minimum income during dry years).

The model maximizes the farm net cash income \( I \) from cropping activities for three types of rainy seasons \( y \) according to their quality: dry, normal, and wet years. The objective function is

\[
\text{Maximize } I = \sum_{y}^{3} P_{y} \times I_{y}, \tag{1}
\]

where \( P \) represents the ex-ante decision of the farmer regarding the probability of occurrence of each type of rainy season and \( I \) is the net cash income per type of rainy season:

\[
I_{y} = \sum_{c} \left( \text{pri}_{c,y} \times \text{sale}_{c,y} - \text{bpri}_{c,y} \times \text{purch}_{c,y} \right) - \sum_{s} \left( \text{inp}_{c} \times X_{c,s} + \text{rpri}_{c,s} \times \text{yield}_{c,s,y} \times X_{c,s} \right), \tag{2}
\]

where \( \text{pri}_{c,y} \) are sale prices (Table 3), \( \text{sale}_{c,y} \) are number of sales, \( \text{bpri}_{c,y} \) is the purchase price of grains for family consumption, \( \text{purch}_{c,y} \) is the quantity of purchased grains, \( \text{inp}_{c} \), the input price (Table 3), \( X_{c,s} \) the cropped area of the crop \( c \) under the soil type \( s \), \( \text{rpri}_{c,s} \) the sale price of crop residues, and \( \text{yield}_{c,s,y} \), the yield of crop residues. Crop residues are only considered for peanuts.

The production is allocated to sales and to family grain consumption:

\[
\sum_{c,s} \left( \text{yield}_{c,s,y} \times X_{c,s} \right) = \sum_{c} \left( \text{cons}_{c,y} + \text{sale}_{c,y} \right) \quad \forall \ y, \tag{3}
\]

where \( \text{yield}_{c,s,y} \) is the expected yields for crop \( c \) during year \( y \) on the soil type \( s \). Yields are a compilation of farmers and agronomists’ observations and local statistics (Table 4). Yields and prices vary according to these three types of years. Production is allocated to consumption \( \text{cons}_{c,y} \) and sales \( \text{sale}_{c,y} \). Different optimal management solutions can be obtained by varying the farmer’s ex-ante decision about the probability \( P_{y} \) of occurrence of each type of rainy season.

Purchase of grains (purch) and the consumed farm production (cons) have to satisfy the family needs (need):

\[
\sum_{c} \text{purch}_{c,y} + \text{cons}_{c,y} \geq \text{need} \quad \forall \ y. \tag{4}
\]

The optimization is made under several other constraints. The land constraint is the maximum area available for

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**Table 3. Prices (CFA francs) for the considered crops according to the category of the rainy season (1 USD = 507 CFA francs).**

<table>
<thead>
<tr>
<th>Crop</th>
<th>Dry</th>
<th>Normal</th>
<th>Wet</th>
<th>Input costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peanut1</td>
<td>160</td>
<td>160</td>
<td>160</td>
<td>0</td>
</tr>
<tr>
<td>Peanut2</td>
<td>160</td>
<td>160</td>
<td>160</td>
<td>32 000</td>
</tr>
<tr>
<td>Maize1</td>
<td>120</td>
<td>100</td>
<td>90</td>
<td>0</td>
</tr>
<tr>
<td>Maize2</td>
<td>120</td>
<td>100</td>
<td>90</td>
<td>21 500</td>
</tr>
<tr>
<td>Maize3</td>
<td>120</td>
<td>100</td>
<td>90</td>
<td>42 000</td>
</tr>
<tr>
<td>Millet</td>
<td>100</td>
<td>90</td>
<td>75</td>
<td>0</td>
</tr>
<tr>
<td>Sorghum</td>
<td>120</td>
<td>100</td>
<td>90</td>
<td>0</td>
</tr>
<tr>
<td>Peanut1 residues</td>
<td>100</td>
<td>75</td>
<td>60</td>
<td>0</td>
</tr>
<tr>
<td>Peanut2 residues</td>
<td>100</td>
<td>75</td>
<td>60</td>
<td>0</td>
</tr>
</tbody>
</table>

---

**Table 4. Expected yields (kg ha\(^{-1}\)) for the considered crops according to the type of soil and the category of the rainy season.**

<table>
<thead>
<tr>
<th>Crop</th>
<th>Rainy season</th>
<th>Deck Dior</th>
<th>Lowlands</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peanut1</td>
<td>Dry</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Peanut2</td>
<td>Dry</td>
<td>200</td>
<td>300</td>
</tr>
<tr>
<td>Maize1</td>
<td>Dry</td>
<td>200</td>
<td>150</td>
</tr>
<tr>
<td>Maize2</td>
<td>Dry</td>
<td>300</td>
<td>200</td>
</tr>
<tr>
<td>Maize3</td>
<td>Dry</td>
<td>300</td>
<td>200</td>
</tr>
<tr>
<td>Millet</td>
<td>Dry</td>
<td>400</td>
<td>500</td>
</tr>
<tr>
<td>Sorghum</td>
<td>Dry</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Peanut1</td>
<td>Normal</td>
<td>300</td>
<td>600</td>
</tr>
<tr>
<td>Peanut2</td>
<td>Normal</td>
<td>300</td>
<td>900</td>
</tr>
<tr>
<td>Maize1</td>
<td>Normal</td>
<td>400</td>
<td>175</td>
</tr>
<tr>
<td>Maize2</td>
<td>Normal</td>
<td>1000</td>
<td>450</td>
</tr>
<tr>
<td>Maize3</td>
<td>Normal</td>
<td>1000</td>
<td>600</td>
</tr>
<tr>
<td>Millet</td>
<td>Normal</td>
<td>600</td>
<td>600</td>
</tr>
<tr>
<td>Sorghum</td>
<td>Normal</td>
<td>500</td>
<td>350</td>
</tr>
<tr>
<td>Peanut1</td>
<td>Wet</td>
<td>500</td>
<td>1000</td>
</tr>
<tr>
<td>Peanut2</td>
<td>Wet</td>
<td>500</td>
<td>1500</td>
</tr>
<tr>
<td>Maize1</td>
<td>Wet</td>
<td>900</td>
<td>200</td>
</tr>
<tr>
<td>Maize2</td>
<td>Wet</td>
<td>1600</td>
<td>600</td>
</tr>
<tr>
<td>Maize3</td>
<td>Wet</td>
<td>2200</td>
<td>700</td>
</tr>
<tr>
<td>Millet</td>
<td>Wet</td>
<td>800</td>
<td>700</td>
</tr>
<tr>
<td>Sorghum</td>
<td>Wet</td>
<td>700</td>
<td>400</td>
</tr>
</tbody>
</table>
cropping activities. We fixed this maximum to 10.5 ha with 5 ha of *deck* soil, 5 ha of *dior* soil, and 0.5 ha of lowlands. The capital constraint fixes the maximum amount of capital available for purchasing inputs. The capital is fixed to 50 000 CFA francs (~$98 USD).

The farm is also constrained by the amount of labor dedicated to sowing and harvesting. Although farm size in the Nioro du Rip region is roughly related to the number of family workers (one worker cultivates one hectare on average), we had to be more specific to get all the scenarios right. We thus obtained the required labor for each crop and soil type according to farmer interviews (Table 5) and we estimated a number of working days available for the major labor bottlenecks of the cropping season (planting and harvesting).

The rotation constraint specifies that a peanut crop cannot follow a previous peanut crop because it generates agronomic problems. Indeed, peanuts are susceptible to a host of foliar and soil-borne diseases and should be rotated with other crops to reduce diseases, weeds, and insect susceptibility and to improve yields. In the model this is translated into a constraint that peanut cannot cover more than half the total cropped area for each type of soil.

In the model, risk is taken into account as a constraint on income, as in the target minimization of total absolute deviations (MOTAD) formulation (Tauer 1983) or as developed by Jacquet and Pluvinage (1997). It sets a minimum income *mi* has to be reached under all conditions, even during the worst type of harvest. It is defined in the model as

\[
\sum_{c,s} \left( gm_{c,y,s} \times X_{c,s} \right) \geq mi, \quad (5)
\]

where a minimum income *mi* is fixed and the gross margin \(gm_{c,y,s}\) is

\[
gm_{c,y,s} = \text{pri}_{c,y} \times \text{yield}_{c,y,s} + \text{rpri}_{c,y} \times \text{yield}_{c,y,s} - \text{inp}_c. \quad (6)
\]

A low value of *mi* would characterize farmers with a low risk aversion whereas a high value would lead to high risk aversion. In this study we set a medium risk aver-

### Table 5. Labor time required for crop planting (person-days ha⁻¹).
The last column gives the labor time required for harvesting.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Deck</th>
<th>Dior</th>
<th>Lowlands</th>
<th>Harvest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peanut1</td>
<td>18</td>
<td>15</td>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>Peanut2</td>
<td>20</td>
<td>16</td>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>Maize1</td>
<td>24</td>
<td>19</td>
<td>29</td>
<td>22</td>
</tr>
<tr>
<td>Maize2</td>
<td>25</td>
<td>21</td>
<td>30</td>
<td>24</td>
</tr>
<tr>
<td>Maize3</td>
<td>28</td>
<td>22</td>
<td>31</td>
<td>26</td>
</tr>
<tr>
<td>Millet</td>
<td>18</td>
<td>16</td>
<td>21</td>
<td>18</td>
</tr>
<tr>
<td>Sorghum</td>
<td>18</td>
<td>16</td>
<td>21</td>
<td>18</td>
</tr>
</tbody>
</table>

### e. The economic evaluation

The bioeconomic model provides a plan (area cropped by crop type, labor, etc.) that maximizes the farm income according to the farmer’s ex-ante decision on the probability *P* of occurrence of each of the three year types (*P* represents the a priori information on climate used to establish the farmer production strategy). The year types are called PD, PN, and PW for the probability *P* of a dry, normal, and wet year, respectively. We first run the model by prescribing an equi-probability of each year type *P* = (PD = 0.33; PN = 0.33; PW = 0.33), which means that the farmer does not know about the rainfall amount of the coming rainy season. This simulation provides a control strategy (C) with three values of income: CD, CN, and CW for a dry, normal, and wet year, respectively. Then we define three strategies that maximize the income according to the adoption of climate forecast by the farmer—that is, *P* = (PD = 1; PN = 0; PW = 0), *P* = (PD = 0; PN = 1; PW = 0), *P* = (PD = 0; PN = 0; PW = 1), respectively called the dry, normal, and wet strategies—which are the strategies with perfect knowledge of the upcoming rainy season. Each strategy corresponds to the farmer’s response to the adoption of a forecast of a given type of rainy season (dry, normal, or wet). This corresponds to an extreme situation since it considers that forecasts are deterministic or interpreted as such whereas forecasts produced by PRESAO and by major forecasting centers provide probabilistic information (e.g., as probability shifts of the tercile categories). Intermediate strategies in the context of the use of probabilistic forecasts can be obtained by varying the values of PD, PN, or PW from 0 (deterministic forecast) to 0.33 (no forecast).

One of the model outputs is the farm income according to each adopted strategy and each type of coming rainy season (see the income matrix of Table 6). By looking at the differences between the income obtained by a farmer adopting one of the three strategies and the one obtained with the control strategy, it is possible to evaluate the economic value of using that climate information. This value of the forecast (VOF) varies whether the deterministic forecast is right or wrong. For instance, the VOF in case of a dry forecast for one specific year can take three values:

1. **Case 1: Perfect forecast.** The season is dry and forecast as such.

\[
\text{VOF} = \frac{\text{IDD} - C_D}{C_D} \times 100
\]
2) **Case 2: Imperfect forecast, type 1.** The season is normal and forecast as dry.

\[
\text{VOF} = \frac{\text{IND} - C_N}{C_N} \times 100
\]

3) **Case 3: Imperfect forecast, type 2.** The season is wet and forecast as dry.

\[
\text{VOF} = \frac{\text{IWD} - C_W}{C_W} \times 100,
\]

where IDD, IND, and IWD correspond to the income obtained with the dry strategy when the year is respectively dry, normal, and wet (see Table 6), computed from Eq. (2) where \(y\) corresponds to a dry year and the values of \(X_{cs}\) are based respectively on the dry, normal, and wet strategy.

A similar procedure can be applied to compute the VOF in case of a wet or normal forecast. Since the computation of the VOF concerns a single year, we then calculate the economic value (EV) of adopting a forecast system in Senegal during 1970–2000 by summing up the VOF of each year. The EV can be computed by adopting only dry, normal, or wet forecasts or by adopting all the forecasted categories.

### 3. Results

#### a. Farm model’s optimal allocation according to the quality of the rainy season

Without knowledge regarding the coming season (i.e., control C), the model (and hence the income-maximizing farmer) chooses to plant millet on the sandy soils, maize and peanut on the clayish soil, and sorghum in the lowlands (Fig. 4). In the dry strategy, the model replaces the risky crops such as maize and peanuts with millet on all types of soils, except in the lowlands, where sorghum remains in all cases. In the normal strategy, the model makes the same choice as without forecast, which means that forecasting a normal year has no value for agricultural strategy. In the wet strategy, the model chooses to plant more peanuts and maize because these crops display better yields when the water deficit is minimal. However, the model chooses to plant also a small area of millet because the farmer lacks the capital to plant the more expensive crops, maize and peanut, because their production costs are high, and it therefore produces some of its self-consumption crop (millet) instead of purchasing it at the local market. In all cases sorghum is the crop of choice in the lowlands. These results reflect what is observed in the field. However, farmers tend to plant more peanuts and less maize than what is predicted by the model.
because peanut prices are guaranteed by the state whereas prices for the other crops are not regulated. In the model, the strategies are mainly driven by the yields and gross margins of each crop (Fig. 5). If the gross margins of maize and peanuts are large when the rainy season is wet, they are very small for a dry rainy season, even smaller than the gross margins of millet or sorghum. The risky character of maize and peanuts is also illustrated by comparison of the standard deviation for each crop. The standard deviation is computed from the values of Table 4 with nine values per crop, corresponding to the three considered types of soil and the three considered types of rainy season. Maize and peanuts show large standard deviations of yields compared to millet or sorghum (Fig. 5).

To assess the importance of the effect of risk aversion in driving the farmers’ strategies, we performed three simulations of the model by varying the value of \( m_i \) [see Eq. (5)] to define high, low, and medium risk aversion categories. When computing income per type of year and per risk aversion (Fig. 6), one can notice that income for dry years increases with high risk aversion whereas income for wet years decreases. It leads to a high variability of low risk aversion incomes whereas a high risk-averse management tends to smooth income differences from one type of year to another. The variability of incomes with a low sensitivity to risk is due to a variety of management options chosen by the model that are close to the ones described above (corresponding to the intermediate case of Fig. 6), with basically an competition between cash crops for wet years and food crops for dry years. On the other hand, the low variability of income and the low mean income over the three types of years for the high-risk aversion simulation comes from the predominance of food crops (sorghum and millet) every year to prevent risks of a bad year.

b. The economic value of using seasonal forecasts: Sensitivity analysis

To document the economic value of the use of seasonal forecasts, we compare the income obtained with no a priori information on the coming rainy season to that obtained when the farmer adapts his strategy to a priori information on the coming season. This value is
defined by the VOF (see section 2e) which is computed separately for dry- and wet-year forecasts (Table 7) in order to assess which type of rainy season farmers may find the most useful to know in advance. The VOFs for dry and wet year forecasts show very different values. The VOF of a dry year forecast is very high, up to 80% in case of a perfect forecast. The losses resulting from an imperfect forecast represent 9% or 28% of the income obtained using the control strategy respectively in case of a normal or a wet year. In contrast, the VOF of a wet year forecast is low (7% respect to the control strategy) and the cost of the error is high, with a loss of income of 11% with the occurrence of a normal year and 70% with the occurrence of a dry year. It means that predicting dryer rainy seasons is much more useful than predicting the wetter ones. Indeed, on the one hand the response to a wet year forecast introduces a high risk with the increase of areas planted with cash crops such as maize and peanuts that are highly vulnerable to drought. On the other hand, the response to a dry year forecast minimizes the climate risk by favoring robust crops such as millet and sorghum.

Since forecasts are often probabilistic, we examine the variations of the VOF of dry and wet years by varying respectively the value of PD and PW from 1 (the deterministic case) to 0.33 (no forecast). Figure 7 shows that forecasts have an economic value when the probability of being in a particular tercile category reaches 0.4 for wet year forecasts and 0.5 for dry year forecasts. The maximum economic value of dry (wet) year forecasts is obtained with a probability greater than 0.6 (0.8) of being in the lower (upper) tercile category, which is a very strong probability shift when considering the outputs of the actual seasonal forecast products.

We now examine the sensitivity of the economic value of the use of seasonal forecasts according to the accuracy of the forecasts. To do so, we generate random forecasts of the JAS Senegal rainfall index such as

$$X = Y + \xi \times k,$$

where $X$ is a random forecast, $Y$ the JAS Senegal rainfall index, and $\xi$ a white-noise process that represents the uncertainty of the forecast whose amplitude is defined by a scale factor $k$. We then generate 10 000 random factors by varying the value of $k$. A value of 0 for $k$ indicates a perfect forecast; the skill score decreases with the increase of $k$. We then evaluate the performance of these random forecasts $X$ by computing the correlation with $Y$, ROC scores, and the economic value (see sections 2d and 2e). Figure 8 shows the EV of dry year forecasts according to four measures of skill prediction of dry years: the HR, the FAR, the HKS, and the correlation. Several threshold values of the forecast skill can be defined from Fig. 8. Forecast systems of dry years would lead to benefits (e.g., only positive EV) with an HR, HKS, and correlation with observations respectively greater

\begin{table}[h]
\centering
\caption{The value of forecast (see section 2e) of the use of dry, normal, and wet year forecasts. The VOF of the use of a dry year forecast varies from +79.7% if the year is dry (perfect forecast) to -9.4% and -27.7% if the year is respectively normal or wet (wrong forecast). The VOF of the use of a wet year forecast varies from +6.5% if the year is wet (perfect forecast) to -10.8% and -70.1% if the year is respectively normal or dry (wrong forecast). The prediction of a normal year shows a VOF of zero.}
\begin{tabular}{lccc}
\hline
 & Predicted & \\
 & Dry year & Normal year & Wet year \\
\hline
Observed & Dry year & +79.7 & 0 & -70.1 \\
Normal year & -9.4 & 0 & -10.8 \\
Wet year & -27.7 & 0 & +6.5 \\
\hline
\end{tabular}
\end{table}
than 0.6, 0.7, and 0.6. In the same way, the FAR should be lower than 0.2. These levels for skill scores are promising: a forecast system that is able to predict only 6 dry years out of 10 would still be quite beneficial for farmers. To expect only benefits from the adoption of the wet forecasts (Fig. 9), the forecast system needs to be more skilful than the dry one, with an HR greater than 0.7, an HKS greater than 0.75, and a correlation with observations greater than 0.8. The FAR should be lower than 0.15.

**FIG. 7.** Value of the forecast (VOF) of dry years (black circles and full line) and wet years (white circle and dashed line) with respect to the control strategy (%) according to the forecasted probability of being in the lower (for dry year forecasts) or upper (for wet year forecasts) tercile category.

**FIG. 8.** Relationships between the forecast value of a dry year (%) and the skill of the forecast. The skill of the forecast is assessed by the hit rate (HR), the false alarm rate (FAR), the Hanssen and Kuipers score (HKS) and the correlation coefficient (COR). Results are based on the generation of 10 000 virtual forecasts of the JAS Senegal rainfall index, where the uncertainty of the forecast is modeled by adding noise to the rainfall time series.
c. Skill and economic value of actual statistical forecasts

Seasonal forecasts are performed by national meteorological and hydrological services and are included as a part of the West Africa Climate Outlook Forum (PRESAO; see http://www.acmad.ne; Hamatan et al. 2004; Ward et al. 2004), which has produced seasonal rainfall outlooks for the region for the JAS season each year since 1998. To evaluate the skill and the economic value of such forecast system over a long-term period, we built our own simple deterministic statistical model to predict Senegal rainfall (section 2b), based roughly on the main assumptions of the statistical forecasts included in the PRESAO system. Our objective was not to build the best predictive model but to make an illustrative and simple one and so we used a multiple linear regression model with SST predictors instead of more sophisticated methods such as principal component analysis (PCA) and/or canonical correlations analysis. Each model gives a JAS rainfall prediction for each lag month; since the correlation values decrease rapidly with the lag, there is a decrease of the forecast skill from June to April (Table 8). The cross-validated correlation value is the highest (weakest) for the June (April) model, up to 0.66 (0.41), which means that 44% (17%) of JAS rainfall variance is captured by the June (April) model. However, although the skill of April model is the lowest, it remains far greater than the persistence one. HR is higher for wet year forecasts up to 0.73. The HR for dry year forecasts, which is the most salient parameter to forecast according to the model results described in section 3a, is lower (up to 0.6 with the June model), which means that 6 dry years over 10 years are predicted as dry.

We now compute EV for each model over the 1970–2000 period (Table 8; see section 2e for details on the computation of EV). The June model has the greatest EV for dry year forecasts with an increase of 15% of the farmer’s income. However, although it is the most accurate forecast, the lead time is very short and one cannot expect the farmers to wait for the first of July to establish their strategy. Indeed, most of the irrevocable decisions are taken before the onset of the rainy season. Ingram et al. (2002) and Mjelde et al. (1988) have already investigated the balance between the end users’ needs for forecast accuracy and timeliness in Burkina Faso and the United Sates, showing that a less accurate forecast with sufficient lead time would be more valuable than a highly accurate forecast that arrives after farmers have made irrevocable decisions. In Burkina Faso as well as in the studied Senegal region, most farmers requested that a forecast of seasonal precipitation arrive 1–2 months...
before the expected onset of the rainy season—that is, by late April or early May. This lead time would enable them to optimize land allocation, to obtain seed of different varieties, and to prepare fields in different locations (Ingram et al. 2002). This lead time corresponds to the April model in the present paper. Even if the correlation between predicted and observed rainfall is worst from the June model, the April model shows a good ability to predict the dry years (HR = 0.5) and it thus presents a promising EV with an increase of about 14% of income with respect to the control strategy (i.e., with no a priori information). One can notice a non-intuitive difference in EV for dry year forecasts between the April model (EV = 14%) and the May model, which shows a weaker EV (EV = 8.5%) although the lead time is weaker, while the HR for dry year forecasts is the same (HR = 0.5). This difference results in the fact that HR does not discriminate between the two types of error in the case of an imperfect forecast (see section 2e), and in the computation of VOF (and probably in reality) the occurrence of a normal year or a wet year when the year is forecast as a dry one does not have the same impact at farm level.

d. Skill and economic value of DEMETER dynamical forecasts

We now evaluate the value of DEMETER dynamical forecasts, which are based on seven coupled model simulations from a climate and an economic point of view (Table 9). The lag of these simulations is comparable to the one of the April statistical model in the section above and corresponds to the ideal timing for forecast as stated by Senegal farmers. The skill scores are very low, with most of the correlation coefficients with negative value and ROC scores lower than the persistence ones. As a matter of fact, EV is negative for all forecasts, which means that no benefits can be expected by using them. The inability of the DEMETER direct rainfall outputs to reproduce the year-to-year variability of rainfall in the western and central Sahel regions has already been documented by Bouali et al. (2008). Since variables relative to the atmospheric dynamics are much more predictable and reproducible than rainfall in a coupled GCM (Philippon et al. 2008, manuscript submitted to Climate Dyn.), an alternative approach is to combine in a statistical model predictors computed from GCM outputs (Bouali et al. 2008; Mo and Thiaw 2002; Paeth and Hense 2003, Rogel et al. 2006). Such statistical adaptations give very promising results, greatly increasing the forecast skill of July-to-September rainfall in comparison with models’ direct rainfall outputs (Garric et al. 2002; Bouali et al. 2008). To restore the true potential of dynamic models, we will therefore apply a correction to the rainfall DEMETER outputs. This correction, much simpler than the one of Bouali et al. (2008), is based on the assumption that the large-scale variability is much more predictable than the whole signal. The basic idea is that the first modes of a PCA on JAS rainfall, which contain the large-scale variability, are likely to be more predictable than a local rainfall average (such as the JAS Senegal rainfall index used in this study) and thus the partial reconstruction of the JAS Senegal rainfall index with only these first modes would improve its predictability. We apply PCA separately on both observed and simulated JAS rainfall over a large African domain (10°S–30°N, 20°W–30°E; see Fig. 10).

The spatial structure of the first principal component (PC) shows similarities in most of the simulations and in the MMEM simulation, with a zonal maximum of covariance between 5° and 10°N (Fig. 10). This structure is shifted southward compared to the observations showing a zonal maximum located between 10° and 15°N. This difference can be attributed to the southward bias in the location of the ITCZ in most of the coupled models (Bouali et al. 2008; Cook and Vizy 2006). The correlations between the PC time series in the observations and in the models are generally significantly positive,

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**Table 8. The skill scores and economic value (EV) of statistical forecasts based on the June, May, and April SST and based on persistence. The skill of the forecast is assessed by the hit rate, the false alarm rate, and the Hanssen and Kuipers score over the 1970–2000 period. Positive EVs are in bold.**

| Lag  | COR | HR  | FAR | HKS | EV  | COR | HR  | FAR | HKS | EV  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| June | 0.7 | 0.6 | 0.2 | 0.7 | 15.0| 0.7 | 0.2 | 0.8 | 3.0 |
| May  | 0.6 | 0.5 | 0.2 | 0.6 | 8.5 | 0.7 | 0.2 | 0.8 | 2.1 |
| April| 0.4 | 0.5 | 0.2 | 0.6 | 13.8| 0.6 | 0.3 | 0.7 | −0.8|
| Pers | 0.3 | 0.3 | 0.4 | 0.5 | −1.6| 0.4 | 0.3 | 0.6 | −6.9|

**Table 9. The skill scores and economic value of DEMETER dynamical forecasts. The skill of the forecast is assessed by the HR, the FAR, and the HKS over the 1970–2000 period. The skill scores and EV are given for each model and for the the multimodel ensemble mean (MMEM).**

| Lag  | COR  | HR  | FAR | HKS | EV  | COR  | HR  | FAR | HKS | EV  |
|------|------|-----|-----|-----|-----|------|-----|-----|-----|-----|-----|
| CNRM | −0.3 | 0.2 | 0.4 | 0.4 | −11.2| 0.3  | 0.4 | 0.4 | −16.5|
| CRFC | −0.5 | 0.1 | 0.4 | 0.4 | −18.7| 0.0  | 0.5 | 0.3 | −29.7|
| LODY | −0.3 | 0.2 | 0.4 | 0.4 | −11.4| 0.2  | 0.4 | 0.4 | −12.3|
| SCNR | −0.4 | 0.1 | 0.4 | 0.3 | −21.1| 0.2  | 0.4 | 0.4 | −14.7|
| SCWF | −0.1 | 0.1 | 0.4 | 0.3 | −20.1| 0.3  | 0.4 | 0.4 | −11.5|
| SMPI | 0.0  | 0.4 | 0.3 | 0.6 | −0.9 | 0.3  | 0.4 | 0.4 | −11.5|
| UKMO | 0.1  | 0.2 | 0.4 | 0.4 | −11.2| 0.4  | 0.4 | 0.5 | −7.2 |
| MMEM | −0.2 | 0.2 | 0.4 | 0.4 | −16.0| 0.2  | 0.5 | 0.4 | −16.9|
with a correlation coefficient of 0.33 for the MMEM simulations, confirming our basic hypothesis of the better predictability of the large-scale features. However, the spatial structures of the second or the third PC (not shown) show a large heterogeneity within models, revealing internal variability of the models, and very few positive and significant correlations are found with the observed second and third PC. Therefore, only the first PC will be used in the rest of this paper and we then reconstruct the JAS Senegal observed and simulated rainfall by using solely this PC.

The correlation between this reconstructed index and the raw index in the observations is 0.79, which means that 72% of the rainfall variance is explained by this first mode of variability. The correlation between the simulated reconstructed index (also called the corrected simulations) and the observed Senegal rainfall has been largely improved compared to the ones using raw model rainfall outputs (Table 10) with three models—those of the Centre National de Recherches Météorologiques (CNRM), SMPI, and the Met Office (UKMO)—with a significant correlation coefficient value at 10% and the
corrected MMEM giving the highest correlation up to 0.42. The same three models and the MMEM simulation show an HKS greater than 0.5 while considering the prediction of the dry years. Another interesting point is that—once corrected with a simple PCA—the dynamical forecasts perform as well as the statistical ones for a comparable lag: the skill scores of the corrected MMEM simulation are close to the one of the April model. Four of the seven models showed positive economic value for dry year forecasts (the maximum is reached by the SMPI model with an EV = +8.5%), but the expected increase of income does not exceed 10% of the income of the control strategy. The corrected MMEM simulation shows a higher economic value (EV = +9.6%) for dry year forecasts than the individual model ensemble means.

4. Conclusions

The methodology developed in this paper assesses the value of seasonal forecasts for traditional farmers in West Africa. It helps to fill the lack of quantitative studies of seasonal climate forecasts in high-risk dryland smallholder farming systems and in regions with relatively good predictability of rainfall at a seasonal lead time. It takes into account both climate and economic valuations. The economic valuation relies on a simple bioeconomic model calibrated on a typical farm in center Senegal, which is used to simulate the farmers’ response and resulting farm income to the dissemination and the adoption of a forecast of rainfall categories. The application of the model to forecasts of categories of total seasonal rainfall (i.e., dryer than average, average, and wetter than average) in a deterministic context (i.e., either 100% forecast accuracy or farmers’ decisions dictated by the highest probability) has shown that predicting dryer seasons is the most promising for these farmers. In the case of an imperfect forecast, the adoption of a wetter season forecast exposes the farmers to a high risk of failure by favoring cash crops that are highly vulnerable to drought. In addition, the response to a dryer season forecast minimizes the climate risk by favoring robust crops such as millet and sorghum. The economic value of a dry forecast is thus very high, with an increase of income of 80% with respect to the control strategy in case of a perfect forecast. By investigating a large number of hypothetic random forecasts, we were able to estimate the forecast skill scores thresholds that need to be achieved in order to generate benefits for farmers. We have found that these skill scores were not as high as we expected. For instance, a forecast system that is able to predict 6 dry years over 10 years would be beneficial for farmers. However, when considering probabilistic forecasts, a very strong probability shift up to 0.6—possibly more than available calibrated forecast models for West Africa would ever produce—is required to shift the conditional expected value of seasonal rainfall outside of the bounds of the middle tercile.

We applied our methodology to two state-of-the-art approaches to climate predictions: statistical forecast methods that are close to the ones included in the operational PRESAO system but are transposed in a deterministic context and coupled atmosphere–ocean models included in the DEMETER project. We found similar skill and economic value of the statistical and dynamical forecast methods by considering the same lead time (April) and the same 31-yr hindcast period 1970–2000 and keeping only the large-scale variability of DEMETER model outputs. Both forecast methods would have been beneficial for Nioro du Rip farmers over this 31-yr period: by using only the forecasts of dryer years they would have increased their farm income by 13.8% for the statistical model and 9.6% for the bias-corrected multimodel ensemble mean. These two methods perform better than the adoption of persistence forecasts, which is part of the farmers’ common strategy.

The methodology and results presented in this paper are very first steps in assessing the economic value of seasonal forecasts in West Africa. It also brought forward some clues about what needs to be done to improve this evaluation:

- Our study does not take into account critical scale issues raised by the use of the coarse spatial resolution of climate models outputs. Because of high spatial variability of rainfall, the weather experienced by the farmers at the plot level in semiarid areas (Baron et al. 2005) might be quite different than the average value in one 0.5° square grid. Downscaling climate predictions (from the Senegal rainfall index grid cell to the Nioro du Rip region in our case) would probably affect the forecast skill and the economic value of the forecasts.
• Another limitation of our study is that we focus on the forecasts of categories of seasonal rainfall amount (July to September), which is less critical to farmers than predicting the onset and/or the end of the rainy season and the distribution of rainfall within the season (Ingram et al. 2002). However, despite substantial progress toward documenting the predictability of the onset of the rainy seasons (Fontaine and Louvet 2006) and the intraseasonal variability (Sultan et al. 2009), there is up to now no routinely reliable forecast of such variables in West Africa.

• Since forecasts and insurance are complementary risk management tools (Meza et al. 2008), their interactions should be investigated. The utility of forecasts can be increased when combined with insurance that allow a risk-averse producer to make management decisions based on probabilistic forecast information that would have too much uncertainty to act on without insurance (Carriquiry and Osgood 2007). Insurance systems that can be driven by climate information have already shown promising results in West Africa by reducing the year-to-year variability of farmers’ income, especially for cash crops such as maize and peanuts (Berg et al. 2009).

• Since the majority of farmers in the typical farm we modeled are involved in cash crops, the model is biased toward cash crops—that is, enhancing the economic value of forecasts. It would thus be important to do the same kind of economic value assessment but for subsistence farmers, which represent the majority of farmers in the Sahel–Sudan. However, in these regions they tend to produce only millet and have few alternative choices. Such study would thus require a much more detailed representation of local practices (different varieties of millet, different sowing dates, use of fertilizers, etc.) by using a crop model sensitive to these options (D’Orgeval et al. 2009; Moeller et al. 2008) and to evaluate the most suitable ones based on coupled simulations between crop models and seasonal climate forecasts (Hansen et al. 2006).

• Since seasonal climate forecasts are inherently probabilistic, a better integration of the probabilistic information in the decision process is required to improve the evaluation of forecasts (see, e.g., Mjelde et al. 1997).

However, while it is true that such exhaustive modeling exercises allow quantitative estimates of the potential benefits and risks of forecasts, they cannot fully capture the complexity of real life decisions. Multidisciplinary insights are required to analyze the dissemination, acceptance, and adoption of seasonal forecasts within local knowledge frameworks (Magistro and Roncoli 2001; Roncoli et al. 2000, 2002) in order to contribute in helping African farmers to get the best from climate science in a changing climatic environment.

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