Agent-based social simulation: a method for assessing the impact of seasonal climate forecast applications among smallholder farmers

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Abstract

Seasonal climate forecasts provide probabilistic information on future climate on timescales of two to three months. Where this information is not presently used it is difficult to evaluate the impact it might have. In order to justify disseminating the information to marginal groups it is important that the potential impact of the forecast is explored so that the negative and positive effects are at least partially appreciated before use of the information is widely promoted. We use an agent-based social simulation model, based on empirical evidence from field work in Lesotho, to assess the impact of using seasonal forecasts among smallholder farmers. The impact of using the forecast depends on the agents’ initial household characteristics, what options they choose in responding to the forecast and the trust they place in the forecast (which in turn depends on their ability to learn and to follow their neighbours). Interaction of climate, crop productivity and social factors determines how much household-agents benefit or lose, evaluated in terms of crop yields and likelihood of exhausting food storage. Adoption of the forecast has the potential to decrease starvation among marginal household-agents but poor forecasts may do more harm than good. This work suggests that if forecasts are not correct more than 60–70% of the time, then they are unlikely to benefit
poor farmers. Poor forecasts, or forecasts that fail badly, when they do fail, lead to longer adoption timescales for forecast use. Further investigation into the impact of the forecast at the village level is encouraged before dissemination is actively pursued without appreciating potential impacts.

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Keywords: Seasonal climate forecast applications; Agent-based social simulation; Marginal farmers; Lesotho; Climate adaptation

1. Introduction

International efforts to improve societal responses to seasonal climate forecasts are a priority because of their potential for ameliorating the impacts of climate variability on marginal groups whose livelihoods are often highly impacted by climate (Agrawala et al., 2001; Hansen, 2002; Anderson, 2003). Despite this priority, there are few examples of how forecasts have been used by marginal groups (Eakin, 2000; Vogel, 2000). This dearth of information leads to uncertainty as to how forecast development should be approached. The understanding of the impacts that forecasts might have on marginal groups is paramount to evaluating adaptation to climate variability, a growing concern for the climate change community (Smit et al., 2000).

Research has shown that marginal farmers (those individuals that struggle to secure access to resources and services) are interested in receiving the seasonal forecast but the communication systems responsible for disseminating the forecast are poorly developed and resource and cultural constraints restrict response options (Archer, 2003; Eakin, 2000; Kirshen and Flitcroft, 2000; Mukhala et al., 2000; O’Brien et al., 2000; Vogel, 2000; Phillips et al., 2001; Walker et al., 2001; Ziervogel, 2004; Ingram et al., 2002; Patt and Gwata, 2002). Because forecasts are not widely used at present, the impacts of forecasts are difficult to assess (Ziervogel and Calder, 2003). Modelling approaches have been used successfully to assess the value of using seasonal forecasts for tactical decisions in other counties, such as Australia (Carberry et al., 2000; Hammer et al., 1996), but it is necessary to include the possible decision options when dealing with a group that has not previously used forecasts (Gadgil et al., 2002). Hansen (2002) suggests that a combination of modelling and descriptive approaches can help to provide holistic analyses and a co-learning approach where farmers and research both benefit. Other research has suggested that a modelling approach that incorporates climate and crop constraints and socio-economic factors be used as a tool for assessing the potential value and use of forecasts in southern Africa (Vogel, 2000). The model presented in this paper combines qualitative decision characteristics with quantitative environmental information and so integrates descriptive and modelling approaches.

The model represents household response to the integration of forecasts into rural communities at the village level. The objective is to develop a simulation that illus-
trates prospective pathways that might occur if households integrate the forecast into their decisions. Specifically we aim to investigate:

1. The pay-offs of using the forecast as a function of forecast accuracy.
2. How mean trust in the forecast of farmer-agents grows or declines as a function of forecast accuracy.
3. What the benefit of using the forecast might be in terms of yield, with and without interactions among farmer-agents and for different wealth profiles.

Forecast accuracy here refers specifically to rainfall, and is the percentage of time that the forecast and actual rainfall are in agreement. The modelled behaviour is supported by empirical data from Lesotho, giving a baseline data set with a realistic distribution of household characteristics and response options for using forecasts. The model is an abstraction of the Lesotho case study, but it does allow the analyst to explore the potential of seasonal forecasts among smallholder farmers. Since farmers have not received and used climate forecasts, the model is one way to explore scenarios of future development.

Section 2 describes the seasonal forecasts and highlights the difficulties associated with assessing their usefulness. The case study of smallholder farmers in Lesotho, on which the model is based, is then discussed. Agent-Based Social Simulation (ABSS) is then introduced as a technique that allows crop, climate and social factors to be coupled together for the exploration of the impact of seasonal forecast use. Section 3 outlines the model development and describes the results obtained; Section 4 discusses possible extensions of the model and the final section concludes with a model evaluation and the implication of the findings for future forecast application developments.

2. Background: seasonal forecasts, field work and agent-based social simulation models

2.1. Forecast dissemination and adoption

During the past few decades, climatologists have improved their ability to predict the seasonal climate (Cane et al., 1986; Palmer and Anderson, 1994; Martin et al., 2000; Murphy et al., 2001). These seasonal climate forecasts are based on ocean–atmosphere interaction such that sea surface temperatures (SSTs) determine future atmospheric perturbation states (Washington and Downing, 1999). This predictability is largely confined to the tropical atmospheric circulation and is principally dependent on El Niño-Southern Oscillation (ENSO)-related anomalies (Mason et al., 1996). Seasonal climate forecasts are available for temperature and rainfall.

Regional forecasts are produced in a number of regions including Australia, Latin America, the Caribbean, Pacific islands, Southeast Asia, West Africa, the Greater Horn of Africa and southern Africa (Basher et al., 2001; Stone and de Hoedt, 2000). In southern Africa, where the rainy season stretches from October to March, a regional consensus meeting, organised by the Drought Monitoring Centre (DMC)-Harare, is held in September (O’Brien et al., 2000; Basher et al., 2001). A six-month consensus forecast, that integrates the output of numerous seasonal forecast models,
is issued for October–March. A mid-season correction meeting is held in December to update the forecast for January–February–March. Each country adapts the regional forecast using local data to produce a national forecast.

The nature of the seasonal forecast means that it is not appropriate for all users, as there are numerous sector-specific constraints associated with using the forecast, which can limit uptake (Nicholls, 1999; Orlove and Tosteson, 1999; Patt, 2001). These can be separated broadly into problems of forecast dissemination and problems of forecast use. The national meteorological organizations are responsible for disseminating the forecast within their country. Most countries in southern Africa do not have well-developed dissemination strategies and so there is not great awareness of the forecast at the national level and even less at the local level (O’Brien et al., 2000). Furthermore, the coarse scale and temporal resolution of the forecast make it difficult to apply locally. Even with effective distribution of the forecast, the level of use is dependent on further factors; both the skill of the forecast and the credibility of the source play a role. The skill of the forecast is a measure of the degree of correspondence between forecasts and observation (Murphy, 1997). Skill scores such as this are an attempt to summarise the joint probability distribution of many climate variables, and as such may not bear directly on the probability of rainfall occurring, for example. The credibility of the forecast, which will determine the amount of trust users place in the forecast, is partly determined by past skill and partly by forecast communicators’ reputations (Patt, 2000, 2001; Patt and Gwata, 2002). Trust will also be affected by the way the forecast supports or contradicts local beliefs about the climate (Eakin, 1999). These beliefs might be based on cultural norms or environmental indicators. Improved credibility may therefore depend on improved forecasts and better data, it may depend on better communication that emphasises the probabilistic nature of the forecast and comes from a respected source or it may depend on adjustment of cultural and social perceptions that view the forecast in a favourable light.

Forecasts are innovations that have not been widely adopted, particularly among marginal groups. Traditional information dissemination literature would assess the success of adoption of forecasts, a type of innovation, as a function of the numbers of users that have already adopted the innovation in comparison to those who have not (Rogers, 1995). This may be inappropriate when there is not a high adoption rate and so few data. It does not enable the stochastic nature of adoption, associated with prospective technological innovations, to be anticipated (Mazzocco et al., 1992). Assessing the possible use and impact of forecasts, when they have not been available previously, requires a process-based model for the exploration of available future pathways of development. In this way, the potential range of impacts of forecast use can be captured (Stern and Easterling, 1999; Downing et al., 2000).

2.2. Lesotho: case study

Lesotho, a small mountainous country in southern Africa, provides a natural laboratory in which to assess how seasonal forecasts are being disseminated, perceived and used at a national and local scale. In Lesotho, the seasonal forecast is developed
using statistical methods that combine past climate data with seasonal ocean and atmospheric data. An analysis of the 2000 October–November–December rainfall forecast showed a skill of 56% of a hindcast compared to past data (Peshoane, 2000). The systems that disseminate forecasts in Lesotho are not particularly well developed (Ziervogel and Downing, in press). Lesotho Meteorological Services (LMS) has issued the forecast for six years but dissemination is not widespread. LMS hold an annual workshop to announce the forecast but the meeting is attended primarily by government officials, who tend not to disseminate the forecast beyond their immediate colleagues. The radio programmes that report on the workshop do not improve awareness of the forecast much, as they read out a press statement rather than expanding on the forecast characteristics and possible uses.

Field work, undertaken in one village in southern Lesotho, Ha Tlhaku, and supported by field work from other parts of Lesotho, has been used to develop the model. Modelled requirements for food, available resources and likely reactions to introduction of the forecast have been based on field work undertaken between September 2000 and November 2001.

A range of data elicitation techniques such as surveys, workshops and participatory tools were used to gather data. A role-play exercise was developed to elicit how farmers might use forecast information that they had not heard before. This participatory method enabled farmers to think through the situation with which they were faced at the beginning of the growing season, when presented with new information about the climate (the seasonal forecast). They were asked whether they would integrate the forecast into their decisions and if so, how. The scenario was first presented for the present year when they were asked about what decisions they faced that season. It was then repeated for the following year when a forecast of below normal rainfall was expected and lastly for a year with a forecast for above normal rainfall.

The role-play exercise elicited options that farmers thought they might pursue if they received the forecast, as seen in Table 1. The options suggest that abundant resources are not required for all responses. Some suggestions were more prevalent than others and some more appropriate for a wide range of users. Options such as changing cropping densities can be pursued by all households and many can change crop type by bartering with their neighbours, as is a common practise. Changing to drought resistant varieties might only be an option for households who can afford to buy new seed, unlike most households that keep their seed from the harvest to plant the following year.

The types of decisions that people mentioned they might undertake in response to the forecast were mostly short-term tactical decisions such as sowing less maize and wheat, planting earlier or protecting the livestock, rather than long-term strategic decisions. These decisions are a form of agricultural risk management. The focus on short-term decisions is expected when using new information. When these decisions seem an appropriate way of responding to the forecast, then more long-term decisions can be made in response to the forecast, depending on the risk preference of the decision maker (Carberry et al., 2000). The decisions chosen for use in the model, in response to the forecast, are the adjustment of cropping densities and the ratio of
maize to sorghum planted. These decisions are generally available to a wide range of farmers, including those with few resources.

The role-play results also suggest that farmers are in practice liable to ignore forecasts of dry conditions, but take heed of those for good rains. They do not want to accept that the season might be unfavourable, as that could result in food deficits and they do not have many alternative off-farm strategies. Additionally, farmers are more likely to use the forecast when they had been exposed to it for a number of years (Ziervogel, 2004).

Table 2 presents a selection of household characteristics, gathered from household interviews in Ha Tlhaku, that shows the diversity of field numbers and size (represented by amount of seed needed for one field as individuals did not always know

<table>
<thead>
<tr>
<th>Household (HH) identification</th>
<th>Number of fields</th>
<th>Amount of seed for all fields (kg/year)</th>
<th>Yield in best conditions (kg/year)</th>
<th>Yield in worst conditions (kg/year)</th>
<th>Number of HH members</th>
<th>Maize consumed by HH in 1 month (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>12.5</td>
<td>240</td>
<td>80</td>
<td>3</td>
<td>25</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>12</td>
<td>600</td>
<td>25</td>
<td>7</td>
<td>70</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>45</td>
<td>500</td>
<td>50</td>
<td>6</td>
<td>80</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>60</td>
<td>960</td>
<td>160</td>
<td>8</td>
<td>75</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>100</td>
<td>1920</td>
<td>480</td>
<td>7</td>
<td>80</td>
</tr>
</tbody>
</table>

Note. This is a selection of data that show a spread of household characteristics, as based on interviews in Ha Tlhaku. Although many households were interviewed in different villages, these data are extracted from the 11 household profiles that were compiled in Ha Tlhaku. More detailed data, on Ha Tlhaku and other villages, can be obtained from the authors.
the areal extent) and the yield in good and bad conditions. Most households in Lesotho have a vegetable garden and one field, with the average field size being 1.4 ha (Gay and Hall, 2000). Although the range in data is quite wide, household typologies have been distilled from it based on livelihood characteristics and have been used to characterise the farmer-agents in the ABSS model.

2.3. Agent-based social simulation

ABSS is a computational technique that attempts to model human behaviour. People, households or larger institutions are represented by a set of logical rules that determine uniquely for each agent how they will act in a given environment (Edmonds et al., 1996; Chattoe, 2000). Although these rules, and the priorities of agents, are stated, the inclusion of non-linear variables, and the processes of interaction between agents, and between agents and their environment, allows novel behaviour to emerge.

The agents can be said to hold opinions (beliefs about the environment or other agents based on limited knowledge), and these opinions may come to be held by an entire community through communication. Psychological, cultural and political constraints can be included as determinants of how agents behave. The contextual parameters can be specified and changed, which enables controlled experiments on the effect of changing social, economic and physical parameters to be measured (Moss, 1999). Non-economic motivations, such as preservation of environmental or cultural values, can enter into decisions, an important advantage over purely economically motivated models. This enables economic, social and biophysical elements to be considered in one model (Miller, 1998; Blench, 1999; Washington and Downing, 1999; Phillips et al., 2001). ABSS, therefore enables adaptation options to be evaluated; a growing concern for the climate change community (Smit et al., 2000). At the same time, the agents can have an internal metabolism and requirements for food, shelter and other necessities. Rules both for farming activity and for economic behaviour govern the ability of individual agents to acquire these necessities.

ABSS facilitates anticipatory evaluation of technology adoption. It is an exploratory method consistent with social science interests, as well as representing social behaviour in formal ways that link to models of natural systems. In exploratory models, dynamic behaviour is emphasised rather than equilibrium, which enables complex systems to be opened up so that rather than predicting outcomes, counter-intuitive behaviour can explored (Barreteau et al., 2001). ABSS has not been applied previously to seasonal forecasting, although other models have been used to address the anticipatory aspects of forecasts as emerging technology (Mazzocco et al., 1992).

3. The model

The set of simulated farmers used in the model is based on the information described in Section 2.2. The farmer characteristics include size of household, food
requirements, rate of change of trust in the forecast and the household characteristics from Table 2. A summary of the agents in the model and relationships between them is presented in Fig. 1.

Farmer-agents respond differently to the forecast depending on their initial resource base and decision-making preferences. Table 3 shows the progression of the model from the representation of crop, climate and forecast, through responses of individual farmers, leading finally to a set of 700 interacting household-agents, representative of a medium sized village.

### 3.1. Climate and crop parameterization

The climate data used in the model are based on the January–February–March (JFM) growing season rainfall data for Lesotho (Peshoane, 2000). The distribution of the JFM rainfall data for 39 years from the period 1960 to 2000 (no data were available for 1986/1987), presented in Fig. 3, shows that while dry and “normal” years occur with near equal frequency, wet years are rather less probable. As the forecast can only take one of the three values (above normal, normal or below normal),

<table>
<thead>
<tr>
<th><strong>World</strong></th>
<th>Four timesteps per year</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Household</strong></td>
<td>Number of fields, Number of occupants, Forecast Trust, Food stores, Rules for Adaptation</td>
</tr>
<tr>
<td><strong>Fields</strong></td>
<td>Maize or Sorghum, Plant Density</td>
</tr>
<tr>
<td><strong>Crop Parametrization</strong></td>
<td>Equations for yield</td>
</tr>
<tr>
<td><strong>Met. Office</strong></td>
<td>Forecast Skill</td>
</tr>
<tr>
<td><strong>Climate</strong></td>
<td>Rainfall Variability data</td>
</tr>
<tr>
<td><strong>Weather</strong></td>
<td>Seasonal Rainfall AN, N or BN</td>
</tr>
</tbody>
</table>

Fig. 1. A schematic representation of the agent-based social simulation model. Each agent type is represented by a box, in which the first field gives the agent type. The second field shows the data held by the agent and the third gives an indication of the agent behaviour. Arrows show the flow of information between the agents. All the agents are embedded in a world object, which controls the time steps.
mal), we represent the rainfall by assuming 40% of years are “below normal”, 40% “normal” and 20% “above normal”, with rainfall taking only one of the three discrete values 170, 300 and 460 mm respectively.

The two crop types considered are maize and sorghum, the primary crops planted in Lesotho. Yield is calculated as a function of rainfall and planting density. According to Rowland (1993), the response of sorghum is largely linear with rainfall, but with slope increasing as the density of planting increases. At a constant rainfall level, the yield varies approximately quadratically with density. The maximum of the quadratic moves to increased density and yield with increasing rainfall. The behaviour of maize is similar, but the slope of yield with rainfall is steeper, leading to better sorghum yields in dry conditions, but superior maize yield at higher rainfall. Annual household yields in Ha Thlaku varied significantly, so the national average yields have been used; near to 1 ton/ha for maize and 0.8 tonnes/ha for sorghum (Chakela, 1999; Bureau of Statistics, and Food and Agriculture Organisation, 2001). An approximation that captures the above features gives the following yield in tonnes/ha:

\[
\text{for maize: } (0.05 + 0.051r_{100})(d_{10} + 3) - (0.00875 + 0.000032r_{100})(d_{10} + 3)^2; \tag{1}
\]

\[
\text{for sorghum: } (0.05 + 0.027r_{100})(d_{10} + 3) - (0.007 + 0.000017r_{100})(d_{10} + 3)^2 + 0.3, \tag{2}
\]

for sorghum, where \(r_{100}\) is the seasonal rainfall in hundreds of millimetres and \(d_{10}\) is the density of plants in tens of thousands per hectare (i.e., \(d_{10} = 1\) implies 10,000 plants/ha). These relationships were derived for seasonal rainfall between 200 and
700 mm, and crop densities from 10,000 to 120,000 plants/ha. In Fig. 2, we show yield as a function of crop density for median above normal (AN), normal (N) and below normal (BN) JFM rainfall for both maize and sorghum. Also shown is the corresponding yield as a function of rainfall (see Whiteman, 1981 in Rowland, 1993). Although the intraseasonal rainfall variability is high, it is not included here, as a more detailed crop model would be required to capture the effects on crop yield.

3.2. Run 1: pay-offs of using the forecast as a function of forecast accuracy

We now consider how farmer-agents respond to the available forecast without regard to their neighbours’ behaviour. The best-case behaviour for “normal” condi-

![Diagram](image_url)
tions with our above parameterization has farmer-agents planting 80,000 plants/ha. If agents hedge their bets against dry conditions and satisfy their preference for maize by planting 60% maize and 40% sorghum, as suggested in the field work, then the average return, allowing for the variation in rainfall, is 960 kg (Table 5, middle row). If 100 kg of seed is saved for next year’s planting, then in a household of eight people with a field of 1 ha, each person can eat just over 100 kg of grain per year (cf. the mean of 128 kg of maize per person per year calculated from Table 2). This is not enough to ensure that households will not run out of food. Farmers in Ha Tlhaku suggested that grain can be stored for approximately 2 years, so the model farmers discard any grain that is older than this. Given a run of bad years, grain stocks may become exhausted. In Fig. 4(a), we show one realization of 50 years of simulated grain storage for a single eight-person household-agent where there is no variation in planting behaviour. The rainfall changes randomly with the distribution described in Section 3.1. Note that in 20 of the years the household is short of food.

In the role-play exercise in Ha Tlhaku, farmers provided a number of options for responding to the forecast (see Table 1). The two response options used in the model are a change in the ratio of maize to sorghum planted and the alteration of cropping density (Table 4).

The non-linearity of the crop response to planting density can lead to very severe penalties for farmer-agents whose planting is not well matched to the climate. This has implications for the effect of following a seasonal forecast that is not 100% accurate. Table 5 shows the effects on crop yield of maize and sorghum when planting at optimal densities for the given forecast. This pay-off matrix illustrates that the farmer-agent can reduce risk in years where above normal rain is forecast by planting a mixture of maize and sorghum, but this has less effect than simply planting at lower density. For example, in the case where above normal rain is forecast (460 mm), an agent who plants the optimal density of maize will be expecting a crop of
Table 4
Forecast response options

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Option 1</th>
<th>Option 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crop ratio (maize:sorghum)</td>
<td>Cropping density (seeds/ha)</td>
</tr>
<tr>
<td>Above normal</td>
<td>80:20</td>
<td>120,000</td>
</tr>
<tr>
<td>Normal</td>
<td>60:40</td>
<td>80,000</td>
</tr>
<tr>
<td>Below normal</td>
<td>40:60</td>
<td>40,000</td>
</tr>
</tbody>
</table>

Fig. 4. (a) Simulated times series of grain storage. Crop production for a single climate sequence of 50 years with 20% chance above normal rainfall, 40% normal and 40% below normal. Farmer-agents are assumed to plant 60% maize and 40% sorghum, at a density of 80,000 plants/ha. (b) Cumulative cost of poor years. Extra costs incurred as a result of crop failure in three cases. Solid line: no forecast, dotted line: forecasts always incorrect, plus (+): 65% correct forecast, and at most 10% two terciles out (i.e., wet forecast when it is actually dry or vice versa). Farmer-agents are assumed to adjust planting to give maximum yield when the forecast is correct.
nearly 2 tonnes/ha. If the actual rainfall is below normal, the return will be 0.1 tonnes/ha (although the rather wide bins in rainfall make this low a return somewhat unrealistic), whereas an agent that has planted expecting normal weather will still get 0.4 tonnes/ha of maize. So, following forecasts of high rainfall is a much higher risk strategy than following those for low rainfall, unless the forecast accuracy for wet years is considerably better than for dry. On the other hand, following the forecast in dry years confers only a small benefit over behaving as for normal weather.

In Fig. 4(b), we show three 50-year time sequences for a representative eight-member household-agent. In each of the three cases the climate sequence is the same, and the household-agent plants its crops as if it believes the forecast to be correct, when it is available. The middle line shows the case when there is no forecast – poor years lead to a deficit of grain, and the figure shows the cumulative cost of these years in terms of the number of tonnes of grain the household-agent would have to obtain through other means. The upper line shows the results of the worst case, where the forecast invariably fails, i.e., it predicts wet years (AN) when the actual rainfall is below normal and dry (BN) when there is above normal rain. In years when the rainfall is normal (N) it predicts either AN or BN at random. The lower line gives the result when the forecast is correct 65% of the time. Incorrect forecasts are assumed to be as bad as possible (AN when the rainfall is really BN and vice versa, which is to say incorrect by two terciles) at most 10% of the time.

Although Fig. 4(b) shows that poor forecasts can be damaging, it does not show how often the forecast needs to be right in order for farmer-agents to benefit overall. This is illustrated in Fig. 5. Five hundred random climate sequences each of 50 years were generated for the eight-member household-agent. The figure shows the accumulated cost at the 50 year mark as a function of the percentage of correct forecasts. Each point shows the mean and SD cost from the 500 sequences. The dotted line is the no-forecast case: Points must lie below this line for the forecast to be of benefit to the household-agent. The crosses show the case where, when a forecast fails, it is only really poor (i.e., forecast for a wet season when it is actually dry and a dry season when it is actually wet) at most 10% of the time. The upper points show the case when failed forecasts are always as bad as possible. From this we conclude: (1) The forecast must be correct more than about 60–70% of the time to benefit these

Table 5
Rainfall-yield pay-off matrix for sorghum and maize

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Actual rainfall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AN</td>
</tr>
<tr>
<td>Maize</td>
<td>2.3</td>
</tr>
<tr>
<td>Sorghum</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Notes. Expected yield amounts in tonnes per hectare. Rainfall amounts based on JFM total rainfall of AN = 460 mm, N = 300 mm and BN = 170 mm. Data are based on Eqs. (1) and (2), that were derived from Rowland (1993), and calibrated using the field work.
household-agents and (2) When the forecast fails, it must be very poor no more than about 10% of the time.

3.3. Run 2: mean trust as a function of forecast accuracy

So far we have examined the consequences for a farmer-agent who blindly follows a forecast when it is issued, irrespective of the impact on their productivity. The role-play exercise in Ha Tlhaku suggests that farmers become more likely to accept a forecast as familiarity increases, and that forecasts of poor conditions tend to be ignored (see Section 2.2). On the other hand, farmers are likely to lose confidence in the forecast if it fails often, or if they suffer from poor returns as a result of following a forecast of good conditions that turns out to be incorrect. As a model for this we allocate a floating point number to each farmer-agent that represents their level of trust in the forecast. The trust increases linearly by one unit per year whenever the forecast proves correct and decreases by the same amount when it is not. After 3 years, the farmer-agents have built up enough trust that they are prepared to begin using the forecast. In Table 6 we show the assumed probability of a farmer-agent using the forecast at given level of trust, depending on whether the forecast is AN or BN. These numbers reflect increasing confidence in the forecast, but a tendency to ignore those for below normal rainfall, as indicated in the role-play exercise. If trust is less than the threshold of three units, the forecast is not used at all.

To simulate the effect of failed forecasts on crop production, we adopt a ‘once bitten, twice shy’ formulation. The farmer-agents that are using the forecast drop their trust level back to the threshold value if a forecast for a wet year fails. If at the same time the resulting poor crop leads to exhausted food stocks, the subsequent rate of
increase in trust level is halved. If the forecast leads to exhaustion of food stocks a second time, then the farmer-agent adopts a ‘never again’ stance and does not use the forecast at all thereafter. Long-term trust in the forecast depends largely on the frequency with which wet conditions are forecast, but dry conditions are experienced in practice. In Fig. 6, we show the effects on the level of forecast trust for different levels of forecast accuracy. The figure shows the mean level of trust as a function of time, averaged over the same 500 climate sequences used previously, now run for 100 years, and the same household of eight, consuming 100 kg of grain/person/year.

If the forecast accuracy is sufficiently high then the mean trust can reach high levels, although it tends to saturate rather than increase without limit. There is a scatter about the saturated level that remains high, but it increases less rapidly than the $t^{1/2}$ behaviour that would be expected for a random walk (not shown). If the forecast fails badly more than at most 10% of the time (i.e., the forecast is for a wet year when it is dry and vice versa), then the mean trust level reaches a maximum, and thereafter declines. At the 10% level, the trust saturates after about 30 years, i.e., the quality of

<table>
<thead>
<tr>
<th>Trust</th>
<th>AN (%)</th>
<th>BN (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>75</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>85</td>
<td>60</td>
</tr>
<tr>
<td>5</td>
<td>95</td>
<td>70</td>
</tr>
<tr>
<td>&gt;6</td>
<td>100</td>
<td>80</td>
</tr>
</tbody>
</table>

Table 6
Level of trust for using the forecast

Fig. 6. Growth of mean trust when poor forecasts damage the trust level. As the number of failed wet year forecasts increases, the mean level of trust starts to decline. Note the long time scale over which this takes place. Scatter about the mean is of the same order as the mean itself. Forecasts are assumed correct 60% of the time. Solid line: at most 5% of failed forecasts incorrect by two terciles, dashed 10%, plus (+) 15%.
failed forecasts has a significant controlling effect on trust levels. Note that the timescale is much larger than the 3-year timescale on which the forecast begins to be used in the role-play exercise and is dependent on the accuracy of the forecast rather than the rate of increase of trust. If the accuracy with which the forecast is correct drops below 60%, then the trust level just saturates (although it begins to decline after about 90 years). In each case, at the 100 year mark, the scatter in the trust across climate sequences is of the same order as the mean, implying that in many cases the household-agents give up using the forecast even when on average the mean trust is positive.

3.4. Run 3: collective effects

We now ask how things might change when there is a range of behaviour and wealth in a population, and how this might be changed by social interactions within such a setting. We restrict ourselves, in this section, to the case where the forecast is correct 60% of the time and incorrect by two terciles (i.e., as bad as possible) at most 10% of the time.

We create a “village” of 700 household-agents, which are selected from one of the three household classes, each with a different initial store of grain, number of fields and household members. The household classes (better-off, average, poor) reflect the typical distribution of wealth in Lesotho and are based on field work and literature on Lesotho (Gay and Hall, 2000; Turner et al., 2001 – see Table 7). Separate to this, each household has an intrinsic sensitivity to the forecast, and a tendency to pay attention to the opinions of others.

For initial storage, we assume a Gaussian distribution, with variance of 0.2 tonnes, and mean as given in the table. We distribute the rate of increase of trust, again using a Gaussian distribution, with mean 0.5 and variance 0.2. Thus, only those on the more optimistic fringe of the distribution increase their trust at the rate of previous sections. We use the same distribution for the drop in trust that occurs when a forecast fails, although individual farmer-agents may have different values for their rates of increase and decrease of trust. The ‘once bitten, twice shy’ behaviour is also given a Gaussian spread – when the forecast for a wet year proves dry, farmer-agents drop their trust to a mean level of 2.5 and variance again of 0.2.

Opinion formation is an active area of current research. No definitive models exist that adequately describe how a social system will respond to environmental stimulus

<table>
<thead>
<tr>
<th>Class</th>
<th>Better-off</th>
<th>Average</th>
<th>Poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of fields</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Number of members</td>
<td>4</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>Mean initial store</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>% of population</td>
<td>20</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>
or how interactions between individuals within the system affect that response. We examine one possibility, where people adjust their own trust level by using a weighted average of theirs and those of others (see, e.g., Hegselmann and Krause, 2002). Denoting the trust of individual $i$ at time $t$ by $T_i$, we use the following recurrence relation between timesteps $t$ and $t + 1$:

$$T_i(t + 1) = T_i(t) + \sum_j a_{ij}(T, t)T_j(t) + B_i(t), \quad i \neq j$$

where indices $i$ and $j$ run from 1 to $N$, the number of individuals in the village, and bold face $T$ denotes the entire vector of trust for the whole village. $B$ denotes the background rate of change of trust as described in previous sections (a function of time, since it may be positive or negative in a given timestep, depending on the forecast outcome and whether the farmer-agent is adapting planting accordingly). The vector of weights, $a$, may be a function of time and of the trust vector itself. We imagine that four times a year, each villager is able to sample the trust level of every other village member. This might take place at village meetings, for example. In the simplest case, suppose that the weights are constant, equal and independent of $T$. If the weights are all positive and they sum to one (i.e., $a_{ij} = 1/(N - 1)$), then the trust vector rapidly collapses to a narrow range near the mean of the no-interaction trust distribution, despite the variation present in $B$. So, if individuals assign equal total weight to their own trust level and that of the rest of the village, a consensus of trust is reached over time.

To allow more freedom in choice of $a$, suppose that in any timestep an individual villager adjusts the weight they give to the trust of another by a fixed additive constant $k$ (e.g., 0.1). We remove the other restrictions on $a$, except that it must remain positive (negative values have unfortunate run-away consequences for this particular model, although a more realistic model could include the notion that some people may like to do the opposite of what others believe). We start from $a = 0$ and adjust the weights upward if another villager’s reaction to the forecast proves in the previous time step to have been right and downward if they were wrong. Now Eq. (3) is non-linear, but the effect is that the trust vector collapses almost to the linear case, with a timescale determined by $k$. Fig. 7 illustrates the history of trust variance (for all household classes) for a single model run in the cases with no social interaction and with the linear and non-linear interaction cases. In the no interaction case, the trust variance across the population tends to rise gradually (owing to the spread in sensitivity to forecasts) until forecast failure (near year 70 for example). Social interaction severely limits the variance in trust, despite the different rates at which trust in the forecast changes for each individual.

We can now discuss the effect of the forecast by reference to household class. A control run was performed in which no use of the forecast was made, and then runs with no social interaction, but including the forecast, as in previous sections, and finally a run with both forecast and non-linear social interaction. In the control case, where no attention is paid to the forecast, the results are rather uniform: because we have no variation within a class other than initial storage, the two-year storage limit
tends to lead to a single history for each class after only a few years. Once we intro-
duce forecasts, then the spread in belief also spreads the cost history. Five hundred
runs of the model were again made, each with 700 household-agents.

The following frequency plots show the effects of the forecast for the no-social-
interaction and the non-linear interaction cases. We show the case for eight-member
(poor) household-agents and ask whether the number of cases in which food short-
age occurs is changed by using the forecast. Fig. 8(a) shows the number of runs in
which use of the forecast led to an increase in the amount that must be spent to avoid
starvation. Only in a few of the runs was a large fraction of the population disadvan-
taged by forecast use. The maximum mean extra expenditure (over a single village)
over 50 years came to $0.9 \pm 0.5$ tonne of grain (i.e., nearly a full year of consump-
tion). The effect of non-linear interactions was to reduce slightly the number of runs
in which there was a deficit relative to the control, but the number of runs in which
nearly the whole population was affected was increased – when the forecast behaves
poorly, the whole population is involved, because of the convergence of opinion in
the model.

Fig. 8(b) shows the frequency plot for those benefited by the forecasts. In these
cases, spending as a result of running out of food was reduced, relative to the con-
trol, by using the forecast. The results are very similar to Fig. 8(a), reflecting the fact
that a 60% accurate forecast is only just worthwhile for these household-agents (cf.
Fig. 5).

Reductions in spending were modest, with a maximum mean gain of $1.4 \pm 0.2$ ton-
ces relative to the control. The effect of non-linear interaction was again to slightly
reduce numbers gaining overall, although in this case we did not see increases in the
number of runs where nearly all the population was affected. The results for six-
member household-agents (not shown) were similar to those for eight members,
but the six-member household-agents meet starvation levels less often. Gains and
losses were smaller than for the eight-member household-agents, being in the region of \(0.5\pm0.4\) tonnes.

In this model, four-member (better-off) household-agents do not starve. So, for these household-agents, we looked at the yield rather than the cost. For any household class, only a small fraction of each population gets lower yields in a significant number of runs. However, in up to one-third of runs, over 90\% of the population experience a net surplus. In this case the surplus can be significant, with a total mean excess yield over the 50 years of up to 5\(\pm\)0.5 tonnes. The effect of the forecast is in this case felt more by the wealthier household classes, except that the four-member household-agents have a peak in the yield improvement at 70\%. For this group the effect of non-linear interaction is to further improve yields (see Fig. 9(a) and (b)).

Fig. 8. (a) Number of runs in which a given fraction of the population spends more than control for eight-member household-agents. Solid lines: no interaction and dashed: non-linear interaction. (b) Number of runs in which a given fraction of the population spends less than control for eight-member household-agents. Lines are as for Fig. 7(a).
4. Discussion and suggestions for further work

4.1. Build up of trust

A somewhat surprising result in the above is the long time scale over which trust builds up, despite the three-year rate at which farmer-agents learn to believe in the forecast. The forecast accuracy is important, as can be seen from the following simple argument:

Suppose that trust $T$ increases linearly at rate $i$ if the forecast is correct, and decreases linearly at rate $d$ if the forecast is incorrect, and that the forecast is correct a fraction $p$ of the time. Then we can write for the mean trust $\langle T \rangle$ (over many sequences) after $N$ years:

![Diagram](image-url)
\( \langle T \rangle = N * (p * i - (1 - p) * d). \)

Clearly if \( p = 1 \), then \( \langle T \rangle = N * i \). This is the maximum possible, and we will reach a mean \( \langle T \rangle \) of 3 after three years if \( i = 1 \). However, we believe that \( p \) is nearer 0.5 than 1, which gives

\[ \langle T \rangle = 0.5 * N * (i - d). \]

Now if \( i = d \), \( \langle T \rangle = 0 \) – nobody will (on average) trust a forecast that is only right 50% of the time. If \( p = 0.6 \) and \( i = d \), then \( \langle T \rangle = 0.2 * N * i \) and now when \( i = 1 \), we only reach \( \langle T \rangle \) of 3 after \( N = 3/0.2 = 15 \) years. This is still an optimistic estimate of the mean if we assume that the trust level drops back to some small value when those adopting the forecast get a bad result – the individual sequences will briefly exceed \( T = 3 \) and then fall below. This slows the rate of increase of \( \langle T \rangle \) averaged over many sequences still further.

Can we make the mean rate of adoption increase more rapidly? If \( i = d \) and \( p = 0.5 \), the answer is clearly no – although the spread about the mean will be increased. If \( p = 0.6 \) and \( i = d \), then increasing \( i \) to 5 will get us to \( \langle T \rangle = 3 \) in 3 years (ignoring drops for failed forecasts). However, this implies that individual people are intrinsically ready to start using the forecast after only about 6 months rather than the 3 years suggested by field studies. Alternatively, we might put \( d = 0 \) (i.e., the limit of \( i \gg d \)), so that people never reduce their trust when the forecast fails. Then with \( p = 0.6 \) and \( i = 1 \), we get \( \langle T \rangle = 3 \) after 5 years.

### 4.2. Suggestions for further work

There are a number of areas where the model described here could be extended. First, there is a simplified representation of climate – rainfall is divided into three categories sampled with a crude frequency distribution, although such information is typical of the level of detail available from consensus forecasts. Further, we take no account of the effect of extremes that might lead to across the board crop failure for all household classes over an entire country.

Second, the crop parametrization is highly simplified. To begin with, we have allowed only for variation in rainfall, when temperature may have serious effects (unexpected frosts may destroy an entire crop). A more complete representation of crop response to climate is clearly called for (see, e.g., Challinor et al., 2003, for an example in the case of ground nut in India).

Third, although the response of people to the forecast itself and to each other has been addressed in the model, it could be explored further. In the role-play a number of response options were given and two of the most common ones were chosen for use in the model. Given a crop model, we can say what the best response in a given climate would be, but is this in fact what would be adopted on the ground? Farmers may be reluctant to risk changes in farming practice in the face of untried new information. Or, they may experiment with only part of their fields, reducing the costs of poor forecasts. Moreover, the perception of the forecast must be set in the context of local culture. Traditional beliefs about the climate and its representation in the local
environment may conflict with those suggested by the forecast. Although this was only a problem for a small proportion of the role-play participants, cultural objection may be stronger in other regions. The presentation of the forecast by extension officers, and the role of the village chief may either accelerate or hinder forecast adoption. Further field work is needed to try to find ways in which these kinds of effects can be faithfully rendered by the modelling process. In the context of interaction, more is needed in the exploration of opinion formation. It may be that although only a few people are made worse off by a good forecast, they are vocal or important community members. Such people may have a disproportionate effect on forecast impact.

Fourth, the economy, either local or global, is hardly represented in the current case. If people run out of food, are they able to buy it in? Is there sufficient local supply to allow this to happen? Many families own animals and gain income in other ways than through farming, either by share-cropping, selling whatever they can make from local materials, or else by seeking work outside the village. All of these factors not only determine how vulnerable a household may be to crop failure, but will affect their attitude towards ability to take on risk, and thus their ability to deal with the possible benefits of the forecast.

Last, finer time steps of farmer-agent responses could be included. For example, monthly timesteps could be incorporated to enable the initial strategy to be updated depending on how the predicted and actual climate compare through the season. This could enable disseminators to assess what impacts an improvement on the timing of dissemination would have, something users are concerned with.

5. Conclusions

The paper set out to achieve three aims. The first aim was to evaluate the pay-offs of using the forecast as a function of forecast accuracy. The model shows that unless the forecast accuracy is 60–70% or above, positive impacts from using forecasts are unlikely. Forecast accuracy is therefore paramount in determining the direct benefit of forecast use to marginal farmers. Additional to this, the model suggests that non-linearities in crop response (in this case to rainfall) are crucial to the usability of forecasts.

The second aim was to establish how the mean trust of individual farmer-agents changes as a function of forecast accuracy. The results show that the level of forecast accuracy determines the level of trust and that there is a threshold of below which trust will be lost significantly. If the forecast is accurate 60% of the time and very poor not more than 10% of the time, then trust saturates at 30 years. For some household-agents, the mean trust level saturates at the point where using the forecast begins to become economically advantageous. Many household-agents, if acting in isolation, may give up using forecasts earlier because of short-term losses, even though in the longer term using forecasts may be to their benefit.

The third aim was to measure the benefit of using the forecast in terms of yield, with and without farmer-farmer interaction and for different wealth profiles. Results
indicate that social processes have an impact on the effect of the forecast, both from the point of view of individual response and that of interaction between individuals. Poor farmer-agents benefit the most in the sense of reducing the likelihood of food shortage conditions (cf. Figs. 5 and 8(a) and (b)), but yield enhancement is better for the wealthier household classes.

The ABSS model highlights some of the potential impacts that seasonal forecasts might have on rural households in Lesotho. Since the model explores possible outcomes of individuals using information that they do not presently use, the results are hard to validate. However, field work and theoretical evidence supports many of the results. It suggests that seasonal climate forecasts are not a panacea to improving poor households’ rural livelihoods.

Although the model is a pilot and based on data from one area in Lesotho, it provides a holistic approach to assessing the impact of anticipatory information. The model is not being used for policy at this stage, so its merit is more in the exploratory realm of investigating possible ramifications of using a forecast of varying skill in different ways. Policies for sustainability cannot wait until all facts are known. Rather, we need to use information that is as robust as possible to plan and implement changes in technology and activities. By explicitly documenting the steps and associated assumptions used to produce the model, as well as listing the simplifications, we hope that it can be re-evaluated for another case, or if different factors are a priority that these can be changed at the appropriate level.

The evolution of trust highlights the importance of understanding the human agency of users and how it varies. Opinion formation and the establishment of trust is complex and forecast disseminators cannot expect to have credibility if they do not explain the probabilistic nature of the forecast and past forecast skill. The results also imply that a certain level of forecast skill is required in order for trust not to decline steadily. Forecast centres and disseminators might consider improving forecast skill before disseminating seasonal forecasts. They may also need to recognise that large forecast errors have differential impacts on trust. If the climate prediction is bi-modal with low confidence, forecast centres may wish to make sure users are aware of the uncertainties. If trust is lost, it may take some time be regained.

The model draws attention to the fact that villages cannot be treated as homogenous. The impact of the forecast on better-off and poor households differs significantly. If national level forecast dissemination strategies are prioritised, the model suggests that blanket targeting of rural groups will not necessarily address user needs. Further investigation into the impact of the forecast at the village level is encouraged before dissemination is actively pursued without appreciating potential impacts.

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