Can smallholder farmers benefit from seasonal climate forecasts?

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Abstract

Constraints to use and shortage of credible demonstration raise questions about the potential for poor smallholder farmers to benefit from seasonal climate forecasts. I briefly discuss questions related to the degree of fine-scale predictability, farmers' ability to adjust decisions in response to forecasts, farmers' ability to bear risk, understanding of probabilistic forecasts, and distribution of benefits of forecast use. While not sufficient to fully answer the question posed in the title, the answers support guarded optimism.

Media summary

Examination of questions about the potential for poor farmers to benefit from seasonal climate forecasts supports guarded optimism and sustained effort to achieve that potential.

Key Words

Climate prediction, risk, adoption, poverty

Introduction

Seasonal forecasts appear to offer under-exploited potential to reduce rural poverty and food insecurity by empowering farmers to better manage climate risk, and by reducing the effect of climate risk as a barrier to intensification and adoption of innovation in favourable years. As climate forecast application moves from exploration to operationalisation, credible demonstration of use and benefit becomes increasingly important. Yet I see signs of growing pessimism based in part on the paucity of credible, well-documented demonstrations of use and benefit, and on studies that have shown lack of use or highlighted constraints to use. Those who question whether poor farmers can benefit also raise important questions related to limited fine-scale predictability, ability to adjust decisions in response, limited ability to bear risk, understanding of forecasts, and distribution of benefit. I briefly discuss the evidence related to each of these questions.

Is there enough predictability at the farm scale to be useful?

How much prediction skill exists at a farm scale?

Published studies summarize the distribution of predictability associated with the El Ni?o-Southern Oscillation (ENSO) or GCMs across the globe, but at the coarse scale of climatic zones or GCM grid cells. Gong et al. (2003) demonstrated how the skill of GCM-based seasonal climate forecasts tends to increase with increasing spatial aggregation relative to a single GCM grid cell. For NE Brazil, they also showed the degree to which downscaling to the scale of single stations reduces skill (Figure 1). Experience seems to support the generalization that forecasts that are skilful at an aggregate scale show only moderate decline at individual points. Whether downscaled skill is useful is an economic and not a meteorological question.

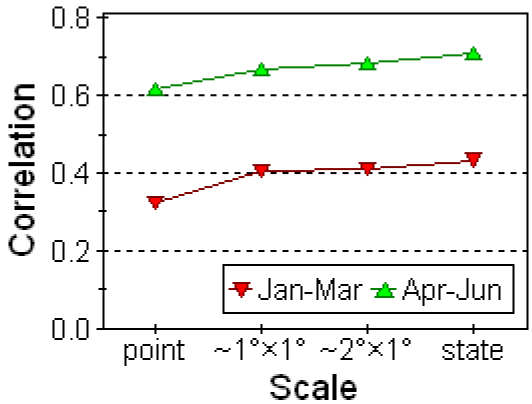

Figure 1. Correlation between observed and predicted rainfall in Cear?, Brazil, as a function of spatial aggregation. Data from Gong et al. 2003.

How does predictability of climate translate to predictability of agricultural impacts?

Decision makers are concerned with some response within the system they manage, not with seasonal climatic means. Barrett (1998) argued that predictions of relevant impacts will be less accurate than of climatic means due to accumulation of errors going from sea surface temperatures (SSTs), to local climatic means, to relevant impacts. He called for greater attention to methodology for predicting relevant impacts.

The argument that agricultural impacts are necessarily less predictable than climatic means overlooks two considerations. First, information beyond seasonal climate (e.g. antecedent rainfall, stored soil moisture) can contribute to predictability of crop response. Second, predicting impacts directly from climatic predictors instead of from predicted climatic means reduces accumulation of errors, and potentially incorporates information about rainfall distribution and other relevant meteorological variables that are embedded in climatic predictors, but lost when converting them into seasonal rainfall totals (Rosenzweig 1994). In a paper that arguably stimulated much of the interest in using seasonal forecasts to benefit farmers in Africa, Cane et al. (1994) showed that ENSO-related SSTs in the Pacific were correlated more strongly with maize yields (1970-1993) than with rainfall averaged across Zimbabwe. Methodology for long-lead crop forecasting based on seasonal climate prediction is advancing (e.g. Hansen and Indeje 2004). In a study of district-scale wheat forecasts from GCM-based climate predictions in NE Australia, Hansen et al. (submitted) showed higher predictability, prior to planting, for yields than for seasonal rainfall (Figure 2).

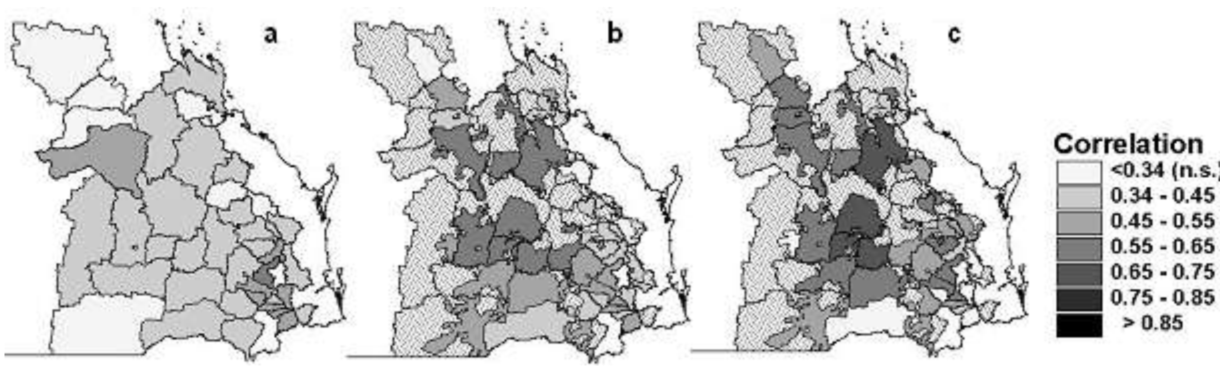

Figure 2. Correlations of (a) Jun-Sep rainfall, and (b) simulated (1968-2001) and (c) observed detrended wheat yields (1975-1993) with GCM-based hindcasts, Queensland, Australia. From Hansen et al. submitted.

If forecasts are more skilful at broader spatial scales, should we only target institutional users who influence farmers but work at a broader scale?

Relevant institutions must be involved when they can address constraints to responding to seasonal forecasts at the farm level, and when forecast responses involve interventions that institutions develop and promote. Some forecast responses with potential to improve the welfare of poor farmers (e.g. managing grain stocks for price stabilization, mobilizing resources for drought relief) do operate at aggregate scales. While policy makers and input suppliers operate at an aggregate scale, working through policy incentives or input supply to influence farmers' decision making does not fundamentally change the scale of the decision. The influence of local-scale forecast uncertainty on the livelihood impacts of a given farm decision will be the same regardless of who motivates the decision unless, for example, the policy incentive is coupled with some form of insurance to spread the risk of responding to probabilistic forecasts. The *Hora de Plantar* ("Time of Planting") program in NE Brazil illustrates the dangers of using policy to influence response to forecasts without adequate farmer participation (Orlove and Tosteson 1999; Lemos et al. 2002). *Hora de Plantar* sought to influence cultivar and planting date decisions by releasing seed based on seasonal forecasts. Highly-publicized instances where the program constrained farmers from planting what and when they had intended led to widespread resentment, and hurt the credibility of the forecast provider.

Do smallholder farmers have the capacity to respond to climate forecasts?

Several studies highlight constraints to farm-level decision responses to forecasts, including access to land, labour, appropriate seed, fertilizer, draught animals and credit; efficiency and accessibility of markets; and policy. This question is more complex and its answer more context-specific than the other questions I address in this paper. It should be answered with caution. First, expanding beyond the farm scale to include other actors, such as suppliers of production inputs and credit, might alleviate some constraints. Discussions with farmers and lenders in India suggested that seasonal forecasts might provide opportunity to relax credit restrictions for high-risk farmers in low-risk years, when payoff from intensified production coincide with reduced risk of defaults. Second, we need to allow sufficient time for learning, adaptation and adjustment before we evaluate whether response options are viable or constraints are intractable. Farmers often demonstrate remarkable resourcefulness once they are convinced of the benefit of an innovation. Finally, for the risk-averse farmer, there is good reason to expect that most of the benefit will come from predicting favourable climatic years. The frequent exclusive or disproportionate focus on adverse extremes misses the opportunity to intensify production, invest in soils, experiment with improved technologies and try relatively high-risk high-value enterprises under favourable climatic conditions, with potential carry-over benefits in terms of soil quality and future livelihood potential. Apparent constraints may not be insurmountable if climate applications are fully integrated with other agricultural development efforts.

Will climate forecasts that could be wrong expose farmers to unacceptable risk?

Climate risk is a persistent and characteristic feature of smallholder rainfed agriculture. Farmers employ a range of strategies to manage risk, often at the expense of average resource use efficiency, productivity and income. A skilful climate forecast, by definition, reduces risk in the sense of reducing the range of uncertainty of climatic outcomes relative to historic variability. The argument that poor farmers cannot afford to risk responding to skilful forecasts requires assuming that either: (a) they apply different decision criteria with and without the forecast, (b) they interpret the uncertainty of the forecast differently from climatic uncertainty without forecasts, or (c) forecasts impose some additional, non-climatic risks. Assuming forecast probabilities are understood, I find the suggestion incredible that a risk-averse farmer, who employs conservative risk management in the face of climate variability, would abandon caution in the face of a predicted incremental shift of probability. One interesting exception comes to mind. Policy instruments that seek to add value to forecasts by influencing decision making could lead farmers to respond to forecasts differently than they respond to climate variability, as the *Hora de Plantar* experience cited earlier illustrates.

The concept of a “wrong forecast” reveals a deterministic interpretation that is inconsistent with the inherent probabilistic nature of seasonal forecasts. There is, however, a very real danger that the uncertainty of a forecast will be lost or distorted somewhere in the communication process. Distortion can lead either to overconfidence and over-response that increases farmers’ exposure to risk and damages the credibility of the forecast provider, or under-response resulting in missed opportunity. Communicating the uncertainty of forecasts in transparent, probabilistic terms remains a crucial challenge.

Regarding the possibility that forecasts impose non-climatic risks, it is useful to distinguish between *substantive* (related to stochastic states of nature) and *procedural* (related to knowing how to apply a technology) uncertainty (Omamo and Lynam 2003). Application of skilful climate forecasts necessarily decreases substantive uncertainty, but adds procedural uncertainty during the process of learning and adaptation. This holds for any new technological innovation. Because seasonal forecast application is a new technology and potentially interacts with a range of production and livelihood decisions, it imposes substantial demands on management capacity. The process component of risk will decrease with time and experience. Education and training, and appropriate technical advice underpinned by sound research should accelerate learning and overcome process risk.

Can smallholder farmers with limited education understand probabilistic climate forecasts?

Yes. Recent studies and personal experience show that, with appropriate presentation and interaction, farmers across cultures and socio-economic classes can understand forecasts in probabilistic terms. In 2000, researchers met with farmer groups with no prior exposure to seasonal forecasts in three locations in Burkina Faso (Ingram et al. 2002). The farmers demonstrated accurate understanding of forecast probabilities after the researchers explained the forecasts, then asked them to randomly draw squares coloured according to tercile category and numbered in proportion to the forecast probabilities. To assess Zimbabwe farmers’ understanding of probabilistic forecasts, Patt (2001) conducted a series of games that involved betting on categorical outcomes of spinners. Participants’ choices responded to changing probabilities and payoffs, and improved with experience. By the final game, many learned to bet consistently on the outcome with the highest expected value. Luseno et al. (2003) asked pastoralists in Kenya and Ethiopia to allocate stones into piles representing rainfall categories used in operational seasonal forecasts, in proportion to their probabilistic expectations of upcoming seasonal rainfall. Although the majority had not received them, elicited forecast distributions agreed qualitatively with the official forecasts. Those pastoralists who received and expressed confidence in modern forecasts significantly updated their subjective distributions, despite the prevalence of indigenous forecasts and their relative unfamiliarity with modern forecasts.

Is the application of seasonal climate forecasts inherently biased against the poor?

This concern is based in part on the generally positive relationship between resource endowment, decision capacity and access to information. Furthermore, a study of forecast use within Peru’s fishing industry (Pfaff et al. 1999) drew attention to the potential for social stratification and power relationships to allow some groups to use forecast information to the detriment of less advantaged groups. On the other hand, Barrett (1998) argued that the potential benefits are greatest in poor, rainfed farming communities because (a) climate risk affects them disproportionately, and, (b) since risk tolerance tends to increase with wealth, the insurance value of forecast information should tend to decrease with wealth. Despite having less education and access to resources, a group of “marginal farmers” I met with in southern India showed greater understanding of climate risk and motivation to use forecast information to manage that risk, than a neighbouring group of “progressive farmers” whose entitlements largely buffered them from the livelihood impacts of climate variability. An econometric study of household data from ICRISAT village studies (Rosenzweig and Binswanger 1993) supports Barrett’s second argument. Results show that climatic risk reduces profitability per unit of productive asset, and does so more for poor than for wealthier farmers.

A survey of communal farmers in each of three natural resource zones in Zimbabwe allowed Phillips (2003) to stratify households by resource endowment. Access to forecasts was positively correlated with wealth in 1998-99, but not in 1997-98 when the media put more focus on the El Ni?o. In 1998-99, wealth had no effect on management responses among those farmers who received the forecast, although agroecological zone did influence use. Any inequities were associated with access to forecasts, and not with decision capacity associated with wealth. Phillips argued that aggressive dissemination could overcome any wealth bias.

Conclusions

On-farm use of forecasts raises important questions about fine-scale predictability, decision capacity, risk, understanding and equitability. Although the answers are sometimes context-specific, the evidence that I considered supports guarded optimism and sustained effort. Unfortunately, the state of climate forecast impact assessment lags behind other agricultural innovations. Advancing farm-level application of climate forecasts to the point where it can have widespread impact requires both greater integration with mainstream agricultural research and development, and greater attention to credible evaluation.

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