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Engaging farmers on climate risk through targeted integration of bio-economic modelling and seasonal climate forecasts

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ABSTRACT

Seasonal climate forecasts (SCFs) can be used to identify appropriate risk management strategies and to reduce the sensitivity of rural industries and communities to climate risk. However, these forecasts have low utility among farmers in agricultural decision making, unless translated into a more understood portfolio of farm management options. Towards achieving this translation, we developed a mathematical programming model that integrates seasonal climate forecasts to assess 'what-if?' crop choice scenarios for famers. We used the Rayapalli village in southern India as a case study. The model maximises expected profitability at village level subject to available resource constraints. The main outputs of the model are the optimal cropping patterns and corresponding agricultural management decisions such as fertiliser, biocide, labour and machinery use. The model is set up to run in two steps. In the first step the initial climate forecast is used to calculate the optimal farm plan and corresponding agricultural management decisions at a village scale. The second step uses a 'revised forecast' that is given six weeks later during the growing season. In scenarios where the forecast provides no clear expectation for a dry or wet season the model utilises the total agricultural land available. A significant area is allocated to redgram (pigeon pea) and the rest to maize and paddy rice. In a forecast where a dry season is more probable, cotton is the predominant crop selected. In scenarios where a 'normal' season is expected, the model chooses predominantly cotton and maize in addition to paddy rice and redgram. As part of the stakeholder engagement process, we operated the model in an iterative way with participating farmers. For 'deficient' rainfall season, farmers were in agreement with the model choice of leaving a large portion of the agriculture land as fallow with only 40 ha (total area 136 ha) of cotton and subsistence paddy rice area. While the model crop choice was redgram in 'above normal and wet seasons, only a few farmers in the village favoured redgram mainly because of high labour requirements, and the farmers perceptions about risks related to pests and diseases. This highlighted the discrepancy between the optimal cropping pattern, calculated with the model and the farmer's actual decisions which provided useful insights into factors affecting farmer decision making that are not always captured by models. We found that planning for a 'normal' season alone is likely to result in losses and opportunity costs and an adaptive climate risk management approach is prudent. In an interactive feedback workshop, majority of participating farmers agreed that their knowledge on the utility and challenges of SCF have highly improved through the participation in this research and most agreed that exposure to the model improved their understanding of the role of SCF in crop choice decisions and that the modelling tool was useful to discuss climate risk in agriculture.

1. Introduction

Managing agricultural production risk is important in the context of improving food security and sustaining rural economies. Climatic uncertainty requires decision makers to prepare for the full range of possibilities (Hansen, 2002). Seasonal climate forecasts (SCFs), which are forecasts for the upcoming season (1–3 months), are increasingly becoming part of the portfolio of risk management strategies because they reduce the sensitivity of rural industries and communities to climate risk (Hansen et al., 2009). Advances in modelling SCFs has been an important contribution of climate science for managing climate risk particularly in agriculture. However, adoption of SCFs in farm decision making has so far failed to live up to the expectations of the scientific community (Meinke et al., 2007). Reasons cited for low uptake of SCFs include the complexity and probabilistic nature of the information

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provided, i.e. they are relatively complex, difficult to trial and only partially compatible with existing practices (Hayman et al., 2007; Power et al., 2007). This poses a challenge for many farming communities in interpreting and using the probabilistic SCF to improve agricultural decision making (Marshall et al., 2010). Many critical agricultural decisions (including which crop to sow, fertiliser application and crop protection management options) that interact with climatic conditions must be made several months before the impacts of climate occur.

There is a large body of literature citing examples of where SCF have utility in both developed and developing countries and the challenges in using SCF (Millner and Washington, 2011; Shankar et al., 2011; Stephens et al., 2012; Ziervogel and Calder, 2003). Ash et al. (2007) point to the insufficient integration of forecast information with farmers' decision making as a key constraint in the widespread adoption of SCF by farmers. In particular, the probabilistic nature of the forecasts needs to be better communicated. Probabilistic here refers to the chance of occurrence of an event, in this context the amount of rainfall forecasted for the upcoming season. The World Meteorological Organisation (WMO) has increasingly emphasized the need for end-user engagement in delivering weather and climate information (WMO, 2014). A number of approaches have been developed to translate the complex SCF to support decision making for a range of stakeholders from policy makers to farmers (Stone and Meinke, 2007). SCF incorporation into decision support tools has been undertaken using simulation models (Clewett and McKeon, 1990; Hammer et al., 1996; Hayman et al., 2008; Nelson et al., 2002), empirical econometric models (Kokic et al., 2007), and agent-based models that were focused on simulation of household interactions (Ziervogel et al., 2005). However, these approaches have limitations of systems level, as the focus is largely on crop simulation and not at farm level. In case of econometric models, large datasets are needed for modelling and they are often focused on quantifying production technology instead of decision making processes. Agent based models are often developed based on assumptions and decision rules between agents which may not be entirely suitable to integrate seasonal climate forecasts in decision making. Risk and stochastic programming based farm planning models (Hardaker et al., 1991) have been used to account for risk in farm level managerial decisions. These models are more likely to be useful in policy level analysis but pose challenges when trying to communicate with farmers.

Bioeconomic farm models have been used to optimise farm production planning decisions and enable explorations of “what-if” questions at farm level (Janssen and van Ittersum, 2007). Very often these models are deterministic, assuming that all model parameters are known in advance. However, in practice, many critical agricultural decisions depend on climatic conditions which are highly uncertain and not known at the time of decision making. The probabilistic results of SCFs can be used in mathematical programming farm models to account for uncertainty of climate and its consequences on optimal agricultural management decisions. Such a framework could be used as discussion-support tool with key stakeholders and extension officers to design production plans and agricultural management decisions. The development of scenarios in this way allows stakeholders to establish risk-based responses to different climate events. Meza et al. (2008), in their review of economic value of seasonal climate forecasts recommend the use of bioeconomic optimisation modelling approaches to value SCF “ as these approaches are rich enough to incorporate the qualitative knowledge from social science approaches realistically”. Bio-economic modelling approaches also allow for ‘facilitated social interaction between researchers and farmers’ and enable stakeholder partnerships to generate relevance of research and analysis to decision makers (Nelson et al., 2002).

This paper describes the development of a generic bio-economic farm model that uses information on SCFs to account for uncertainty of expected climatic conditions so as to optimise crop choice decisions at farm level. Using a smallholder farming system, we demonstrate that this model can be used to engage farmers by simplifying the inclusion of seasonal climate forecasts into a discussion support process. The seasonal forecast in this work refers to the amount of rainfall during the growing season from June to October. It does not, however, indicate the distribution of the rain throughout the season. The model chooses the crop type and the area to be planted and produces data on various agricultural management variables such as fertiliser, pesticide, fungicide, labour, machinery use, costs and profit. In the model, objective functions for multiple climate forecasts are combined into a single objective function. The model has been used as a discussion support tool to communicate SCF with the case study farming community and the researchers on managing climate risk. An important contribution of the participatory model development process has been the building of ‘social capital’ (Coleman, 1988) and ‘social learning’ (van der Wal et al., 2014) around managing climate risk among the farming community in the case study village. We adopted a reflective learning process based on the Plan–Do–Observe–Reflect of the Kolb learning cycle (Hayman et al., 2013; Kolb, 2004) highlighting that the modelling is not an end in itself but supported a co-learning process among researchers and the farming community.

2. Materials and methods

2.1. Case study

Rayapalli village in Telengana State (Fig. 1) in south India has been chosen as a case study location for this work. The case study village was selected from the range of project locations on the basis that here farming is predominantly rainfed (Nidumolu et al., 2015) and thus the value of seasonal climate forecasts is likely to be higher compared to irrigated agriculture. The village is located about 100 km south-west of Hyderabad city. The south-west monsoon during June–October, with a growing season rainfall of 800 mm, is the main source of water for crops (using groundwater for irrigating paddy rice is an exception). Three dominant soils types have been identified by the farmers in the

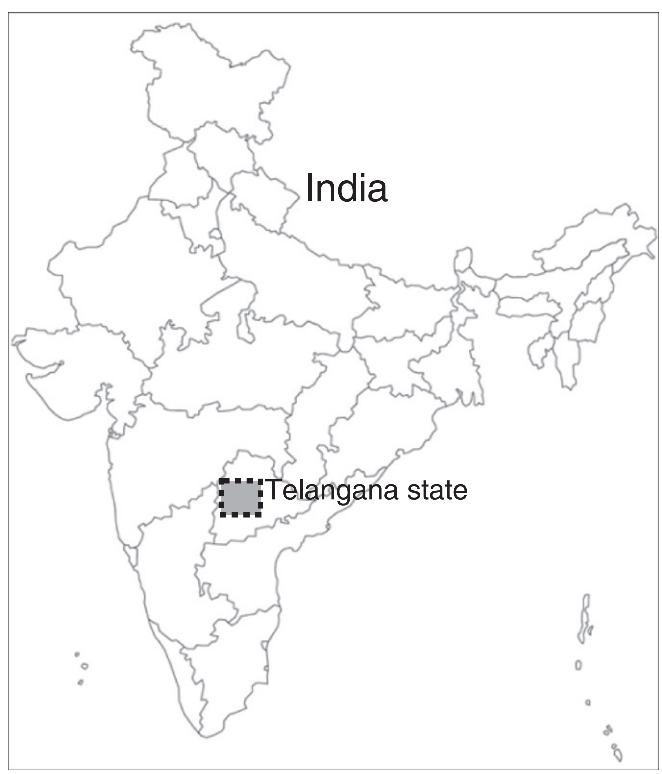

Fig. 1. Study region.
(Figure source: http://www.freeusandworldmaps.com/html/Countries/Asia%20Countries/IndiaPrint.html)