Agricultural Systems 149 (2016) 175–184

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

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

U.B. Nidumolu [a,*], M. Lubbers [b], A. Kanellopoulos [c], M.K. van Ittersum [b], D.M. Kadiyala [d], G. Sreenivas [e]

[a] CSIRO Agriculture & Food, Adelaide Laboratories, Australia
[b] Plant Production Systems Group, Wageningen University, The Netherlands
[c] Operations Research and Logistics Group, Wageningen University, The Netherlands
[d] International Centre for Research in Semiarid Tropics (ICRISAT), Patancheru, Hyderabad, India
[e] PJSTS Agricultural University, Rajendranagar, Hyderabad, India

ARTICLE INFO

Article history:
Received 15 March 2016
Received in revised form 16 September 2016
Accepted 18 September 2016
Available online 29 September 2016

Keywords:
Mathematical programming
Probabilistic seasonal forecasts
Crop choice
Climate risk
Small holder farmers
Profit maximisation

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

* Corresponding author.
E-mail address: uday.nidumolu@csiro.au (U.B. Nidumolu).

http://dx.doi.org/10.1016/j.agsy.2016.09.011

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)

case study village and included in the model i.e. black, sandy and red soils. Black soils (40 ha) (vertisols) are deep, fertile soils with high water holding capacity, while sandy soils (80 ha) and red soils (16 ha) are upland soils which are mainly poorer red granitic Alfisols and Ultisols. The main crops cultivated in the study village are paddy rice (irrigated), cotton, redgram, castor, maize and sorghum. Paddy rice nursery is raised during early June and cultivated with irrigation from groundwater. Paddy rice transplanting area is influenced by how the season develops i.e., in a 'normal' or 'above normal'/'excess' season the full extent of the planned transplanted area is covered and the transplanting area is reduced if the season turns out to be 'below-average' or 'deficient'.

2.2. Modelling framework

The modelling framework consists of (i) model Inputs (SCF probabilities/scenarios, labour and crop input costs, selling prices of crop products); (ii) linear programming with the main components consisting of objective function, constraints and activities (iii) model outputs (scenarios) generated in consultation with the stakeholders. The seasonal climate forecasts (rainfall for the upcoming season) from a number of sources including the India Meteorological Department's 'Long Range Forecast (LRF)' can be integrated with the model. The linear programming (LP) model uses the forecasts as weights when optimising for crop choice. The modelling components are represented in Fig. 3. The model is centred on the seasonal climate forecasts (5 classes of season type) which influence the crop type (6 crop types) linked to soil types (3). This combination of season types x crop types x soil types drives the crop choice model. Various inputs such as labour, fertiliser, fungicides, pesticides, machinery use contribute to costs while sale of crops (yield × prices) result in revenue. The model optimises for profit based on a set of resource constraints. The model in its current form is at a village scale i.e. the profit of the whole village is optimised subject to available resources at village scale. This implies that the individual objectives of different farmers and farm specific constraints are not taken into account explicitly. The model was developed at a village scale with an aim to engage with a larger farming community which is the focus of this work. Since we do not allow for exchange of resources i.e., there is no land and labour exchange between farmers, optimising at the village level approximates optimisation of an average farm. In case of large variation of available resources between farms, optimisation at farm level (or a group of farms based on a typology) would be more appropriate to model explicitly farm specific constraints.

2.3. Seasonal climate forecasts

Seasonal climate forecasts used here refer to forecasts of the upcoming season's total rainfall from the start of the growing season to the end of the growing season. The forecasts are based on either statistical or ocean atmosphere coupled physical models (Anderson, 2005). While the LP model used here can integrate any seasonal climate forecast available, in this case we use the India Meteorological Long Range Forecast (LRF) framework which uses five categories of growing season rainfall viz., 'deficient' (<90% Long Period Average (LPA), 'below normal' (90–96% LPA), 'normal' (96–104% LPA), 'above normal' 104–110% LPA) and 'excess' (>110% LPA) with respect to long period average (LPA) rainfall data for the kharif (monsoon season) (IMD, 2014). Seasonal climate forecast (LRF) by India Meteorological Department (IMD) is released in April and revised approximately six weeks later in early June. The forecast for the five growing season types ('deficient', 'below normal', 'normal', 'above normal', 'excess') is given with probabilities (or weights) attached to them. For example, the June 9, 2014 long range forecast using the 'Monsoon Mission Experimental Coupled Dynamical Model' update by IMD suggested the probabilities for the coming monsoon season in Telangana as 29% 'deficient', 13% 'below normal', 35% 'normal', 19% 'above normal' and 4% 'excess' (IMD, 2014). We acknowledge that the term 'normal' could be challenging as it infers that the relatively infrequent case of the seasonal rainfall being in the narrow range of 96% to 104% is normal. In the semi-arid regions variability is 'normal' and seasons wetter or drier than this narrow range are also 'normal'. However, we aimed to use language that was consistent with the Indian Meteorological Department and currently used widely by agronomists and farmers.

2.4. The bio-economic farm model

2.4.1. Overall design

The linear programing model (Fig. 2) was used to maximise expected gross margins and optimally allocate available farm resources to current and alternative agricultural activities accounting for resource availability and constraints. A number of scenarios were developed through this process to examine changes in resource constraints or cropping activities. The model helps to assess 'what if?' scenarios, which are based on quantified input–output relations for current crop production activities with the formulation of constraints as mathematical functions (Nidumolu et al., 2011; ten Berge et al., 2000). The general mathematical formulation of the linear programming model is:

$$max\left\{Z = \sum_{i,k} w_k \cdot gm_{ik} \cdot x_i\right\} \tag{1}$$

Subject to:

$$\sum_{i,k} w_k \cdot a_{i,j,k} \cdot x_i \leq \sum_k w_k \cdot b_{jk} \qquad \forall j \tag{2}$$

$$x_i \geq 0 \qquad \forall i \tag{3}$$

where Z is the total expected gross margin, x_i is the optimal level (ha) of activity i (defined as the area of a crop grown on specific soil type), w_k is the weight (probability of state of climate based on SCF classes) of k (i.e. 'deficient', 'below normal', 'normal'…), $a_{i,j,k}$ is the input-output coefficient of constraint j corresponding to activity i in state of climate k, b_{jk} is the right hand side of constraint j in state of climate k and gm_{ik} is the gross margin per ha of activity i in state of climate k. The gross margin is defined as expected revenues from sales of agricultural crop products minus variable costs including hired labour, seeds, machinery, fertilisers, pesticides and fungicides.

To include the probabilities of a forecast for the five different seasons in the model, a weighting method was used. In this method, all objective functions for each season type are combined into a single objective function. A weighing factor, representing the probability of a specific season type, is given to each objective before all objectives are added. Subsequently, an efficient set is generated through parametric variation of weights, as first introduced by Zadeh (1963).

The model was set up to run in two steps. In the first step ('Initial Forecast Run') the initial climate forecast is used to calculate the optimal

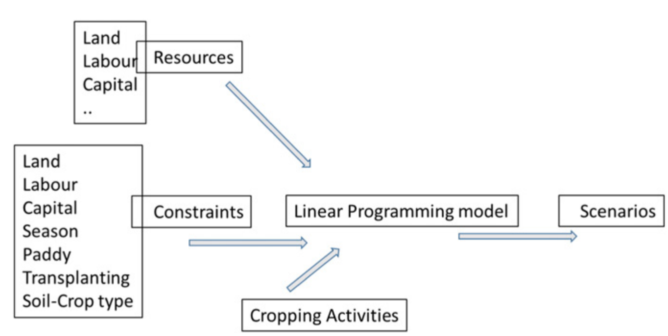

Fig. 2. LP model framework.
(Adapted from Nidumolu et al. (2011))

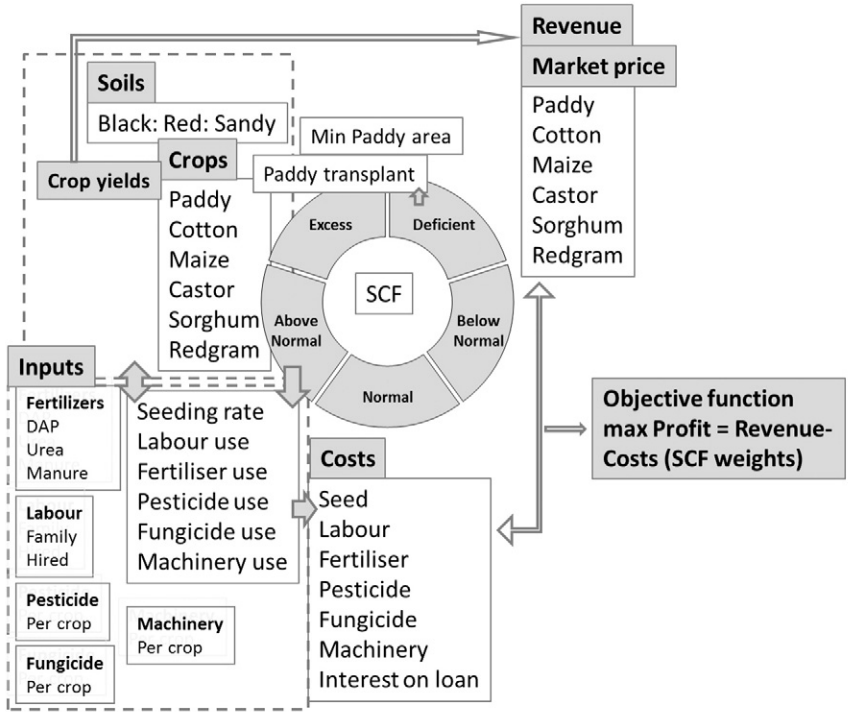

Fig. 3. Model components. Seasonal climate forecasts (SCFs) ('deficient', 'below normal', 'normal', 'above normal' and 'excess') and all objective functions for each climate type are combined into a single objective function. A weighting factor, representing the probability of a specific climate type, is given to each objective before all objectives are added. Subsequently, the efficient set is generated through parametric variation of weights, as first introduced by Zadeh (1963).

farm plan (at a village scale) and corresponding agricultural management decisions. Making decisions based on this initial forecast involves *'committed costs'* such as land preparation, selection of crop variety and seeding rate, fertiliser application and labour costs associated with these operations.

The second step uses a 'revised forecast' that is given six weeks later during the growing season. In the 'Revised Forecast Run', the initial forecast is replaced with the 'revised forecast'. In discussions with researchers at the local agricultural university, the timing of 'Initial Forecast Run' of the model was fixed for June 1 and the 'Revised Forecast Run' was fixed at July 15 (ca. 6 weeks after the first forecast). However, these periods can be modified as per the forecasts available with appropriate re-parametrisation of the model.

In the 'Revised Forecast Run', the output data file generated in the initial forecast run is used as the input file (with technical coefficients of crop choice, area planted in different soil types and all the inputs, i.e. labour, machinery, fertiliser, pesticides and fungicides) for the 'Revised Forecast Run'. The activity levels in this run remain the same as those in 'Initial Forecast Run' except the forecast (revised), the yields of crop (due to a short season if the start of the season is delayed) and labour use (labour requirements for a short season are assumed to be lower). In the 'Revised Forecast Run' there is some flexibility to adjust the decisions in 'mid-course' that were based on the initial forecast. These are in the category of 'uncommitted costs' which include top-up fertiliser, pesticide and fungicide use and labour use. These can be adjusted as per the revised forecasts while the 'committed costs' are part of the risk that farmers have taken.

An illustration of the possible effect of the revised forecast is the following. If the initial rainfall forecast is 'below normal' and the revised forecast suggests a 'normal' or 'above normal' season then the model chooses additional cropping area (as all the available land may not be used if the initial forecast is for a 'below normal' season) and crop choice. This is achieved by increasing inputs to cater to wetter than the initial forecast. Input and output coefficients for all combinations of crop × soil for initial and revised forecast and different states of climate have been specified in the model. If the revised forecast results in additional cropping area being recommended, inputs such as labour and fertiliser would be reduced to account for the necessary shorter duration of the revised crop as it is sown six weeks after the potential start of the growing season. Yields of crops will also be adjusted to a shorter cropping duration as a result of changed decisions later into the season. In the revised forecast, the yields are reduced by 15% due to a shortened season. These values can be adjusted specific to other geographies as required.

2.4.2. Objective function, resources and constraints

The key objective of the case study farming community is maximising gross margin using the resources available and with a set of cropping activities. Subsistence for food is considered by allocating a percentage of total land area available to paddy rice (30%), however the extent of transplant of this area is constrained by the seasonal forecast and soil type.

The area for cultivation available in the case study village is 136 ha. Constraints imposed in the model are based on the resources available. These include land and paddy rice transplant: (a) Land allocated to various crops cannot exceed total land available (b) paddy rice area has been constrained to 30% of total land available (black and red soils excluding sandy soils). Although rice is a staple food for the local population, it is a water-demanding crop and farmers have been advised by extension service to limit the area of paddy rice to conserve water particularly in the water constrained environment such as during 'below normal' or 'deficient' season. Water saved from reduced paddy rice area has been recommended to be diverted to other less water demanding crops as well as a way of conserving ground water that has been depleting significantly. Another constraint imposed on paddy rice is the percent area that can be transplanted based on the season i.e., if the season is projected to be 'deficient' then only 10% of the maximum area that can be transplanted will be used, if the season is forecasted to be 'below normal' only 40% of the maximum area that can be transplanted will be used. If the forecast is 'normal', 'above normal' or 'excess' then the maximum area to be transplanted (30% of Black and Red soil) will be used by the model. The model uses a 'transplanting function' for paddy rice and the percentage of transplanted area as defined by the farmers. Not all land needs to be sown in the model; a partial fallow is acceptable if food security constraints are met. These constraints have been included based on the practices of farmers. Labour requirements per crop per season are included as labour person days for the growing season per hectare. Labour is differentiated between family labour and hired labour, while cost of family labour is not included in the model calculations, hired labour is costed per person per day.

2.4.3. Data, and input and output coefficients

Data on the technical coefficients (Table 1) used in the model were gathered from the local farming community and expert knowledge from extension service and researchers from PJSTS Agricultural University (PJSTSAU) and International Crops Research Institute for Semi-Arid Tropics (ICRISAT). These include crop types, soil types, yields, input prices, costs and use of inputs such as fertiliser, pesticide, fungicide and labour. The crop market prices have been obtained from the website of the marketing department of the state.

The inputs used in the model include the following: forecast data includes the probabilities for five season classes viz. 'deficient', 'below normal', 'normal', 'above normal' and 'excess'. Available land at village level was determined per soil type i.e. black soils (40 ha), red soils (16 ha) and sandy soils (80 ha). The total agricultural area of the village (136 ha) is considered as this model is at a village scale. In terms of labour availability, kharif season is assumed to be of 150 working days. To calculate available agricultural land at village level we assumed that each household has access to 2.4 ha on average. Similarly, to calculate available family labour at village level we assumed 1.5 full time family members per family. Labour requirements per crop per ha and per season type have been gathered from a survey conducted in the case study village. The labour requirements in case of shortened season in the 'revised forecast' is reduced by 20% in comparison to the labour requirements for the full season. Price of hired labour was set at INR 150/person/day (US$ 2.30/person/day). Market prices for different crops were gathered from the online market prices published by the state government marketing department (i.e. average market prices - Table 1). Costs of pesticide, fungicide, implements and seed per crop type were gathered from the survey and various published reports. Fertilisers included urea, diammonium phosphate (DAP), and cattle manure. Urea and DAP application is calculated in kilograms per hectare while cattle manure application is calculated in cartloads per ha. Pesticides and fungicides are costed in per application per ha. The usages of different fertilisers, pesticides and fungicides are determined for each crop type, soil type and season type. Seeding rate is calculated as kg/ha and costed in INR/kg. Crop yield has been gathered from farmer survey, expert knowledge and published reports. Yield (kg/ha) is specified per crop by soil type and season type. The model results include:

- Crop areas by soil type
- Variable costs, revenue and profit at village scale
- Input (labour, machinery, fertilisers, pesticides and fungicides use)
- Expected gross margin for the village (the objective function value).

2.4.4. Scenarios and setup of the model runs

In this research, a scenario-based approach was used to analyse the impact of integrating seasonal forecast in crop choice decision. The scenario analysis aims to characterise the response of model endogenous variables (i.e. the outcomes of the process of optimising an objective function such as gross margin) to changes in exogenous conditions, such as prices, policy instruments and technologies. The modelling system allows the user to formulate the scenarios interactively, characterised by different indicator values and reformulates these scenarios by 'playing' with the model (Pitel, 1989; Romero and Rehman, 1989). Indicator values in this model refer to the technical coefficients or parameters such as yields and costs of inputs. A set of five scenarios were developed to demonstrate the model as a discussion support tool within the case study village. Scenario 1 (S1) is a crop choice decision made using equal chance (20%) of any of the five seasons being realised (no forecast is applied in this case). Scenario 2 (S2) is skewed towards a dry season with a 30% chance each of 'below normal' and 'deficient' seasons occurring, a 20% chance of 'normal' and 10% chance each of 'above normal' and 'excess' seasons occurring. S3 is skewed towards a 'normal' season with 40% chance of 'normal' and 20% and 10% each for 'above normal' and 'excess'. S4 is also skewed towards 'normal' with a 60% chance of 'normal' and 20% and 10% each for 'above normal' and 'excess' seasons occurring. S5 is skewed towards a wet season with a 50% chance of 'above normal' and 20% 'excess' seasons occurring. Scenarios 2–5 cover a range of forecasts from predominantly 'deficient' and 'below normal' to predominantly 'above normal' and 'excess' during the past 10 years and represent a wide range of seasons. While these scenarios cover representative seasons, the 2014 IMD Long Range Forecast is included in one of the model scenarios (Scenario 6) as a concrete example of a forecast.

Since the modelling uses a probabilistic forecast for crop choice, we used an ex-post analysis to compare how the results of the forecast compare with a season that was experienced by the farmers in the recent time. In the model used 100% chance of a season occurring, i.e., in a hindcast mode the season would have a 100% chance given that it is already occurred. This provided a way to demonstrate the validity of the model. As the key objective of the farmers is maximising profit, we analysed the sensitivity of the model to cost and price variations. We present the example of cotton to investigate the impact of price changes on profits as it is a key commercial crop in the region.

2.5. Participatory engagement workshops

As part of this project, we engaged with a number of stakeholders including farmers, extension service, agricultural input providers and decision makers at district and state levels to better understand the process of translating probabilistic seasonal forecasts into agricultural decision making. Four participatory engagement workshops were conducted with farmers over the period 2011–2014. Methods to engage with these stakeholders included focused group discussions, workshops, real-time exposure to the bio-economic modelling (operated real-time by researchers responding to queries from participating

Table 1
Crop prices; average yields by rainfall category and soil type (kg/ha).

Crop	Price INR/kg	Average yields: black soil					Average yields: red soil					Average yields: sandy soil				
		D	BN	N	AN	E	D	BN	N	AN	E	D	BN	N	AN	E
Maize	15.00	1250	3500	5500	5000	3750	1000	2500	3750	3000	2500	875	1500	2500	3125	2500
Castor	36.50						500	750	1125	1250	1500	375	500	1125	1250	1500
Cotton	48.00	1000	1500	2500	2375	1625	500	1000	1500	2000	2000	500	750	2000	1750	1000
Redgram	41.25						375	500	1125	1250	1000	375	375	875	1000	1000
Paddy rice	18.75	1875	3750	4375	4375	5000	3750	4375	4375	5000	5015					
Sorghum	17.85	500	500	750	750	500	375	625	750	750	500	250	500	1000	1000	1000

D - deficient; BN – below normal; N - normal; AN - above normal; E - excess.
Prices of crops used in the model (source: http://market.ap.nic.in/indexnew.jsp. April 2014). Average price has been used here to illustrate the model); Crop- soil constraints: Castor and redgram are not grown on the black soil; paddy rice is not grown on the sandy soil.

farmers) and semi-structured individual interviews with participating farmers. The PJ Telangana State Agricultural University (PJTSAU), a project partner, set up a rainfall recording meteorological station in the village and trained some farmers in recording the observations with the participation of a local non-governmental organisation. PJSTSAU has also been providing the farmers in the villages in the region with short-term (3–5 days) weather forecast advisories to help with farm operations. Participating farmers were aware, through project activities, about short-term deterministic weather forecasts, 1–3 monthly probabilistic seasonal climate forecasts and the challenge of using the seasonal forecasts in their cropping decisions. For this study fifteen participating farmers provided technical coefficients for the model such as input quantities and costs, market prices for different crops and labour requirements for different season types ('deficient', 'below normal', 'normal', 'above normal' and 'excess'). Once the model was developed using technical coefficients from the survey data, we operated the model with the farmers and researchers to check if the crop selection per season and revenue were consistent with their knowledge from the region. This validation process resulted in a few technical coefficients being fine-tuned, particularly the yields in different seasons. Fertiliser and pesticide inputs were also adjusted based on expert opinion from the agricultural university and agricultural department.

The final engagement workshop with ten experienced farmers was in November 2015 at the case study village to demonstrate the fully developed model and to seek feedback. In this workshop, participating farmers clarified on the paddy rice area constraint (total paddy rice area to be cultivated and the percentage of transplanting area based on the season) that was imposed on the model and agreed that it was generally the practice in their region. Also, keeping the season constant we varied the costs of inputs and prices of crops in the market one at a time to explore the impact on profits. At the final workshop, we also gathered formal feedback from the participating farmers on the crop choice bio-economic model as a tool for engaging on SCFs. The questions in the pre-workshop survey were (i) how do you rate your knowledge of SCF, on a scale 1–10 (where 1 is low and 10 is high), (ii) my understanding on how to use SCF in making crop choice decisions (no understanding to very high on a five step scale), (iii) What value will you place on SCF in your crop choice decision making, on a scale 1–10 (where 1 is low and 10 is high).

Post-workshop questions were (iv) how do you rate your knowledge of SCF, on a scale 1–10 (where 1 is low and 10 is high) (v) after this workshop my understanding of SCF is now (no understanding to very high on a five step scale), (vi) exposure to the crop choice model has improved my understanding of the role of SCF in crop choice decisions (strongly agree to strongly disagree on five step scale), (vii) the crop choice model is a useful way to discuss or engage on climate risk in agriculture (strongly agree to strongly disagree on a five step scale).

3. Results

3.1. Model outcomes

The crops and crop areas selected by the model, costs, revenue and profit under each of the five scenarios are presented in Table 2. In the crop choice decision made using only climatology, (Scenario S1 with equal chance (20%) of each of the five seasons being realised (no forecast is applied in this case), the model utilises the total agricultural land available and a significant area of land is allocated to redgram and the rest to maize and paddy rice. Scenario 2 (S2) is skewed towards a dry season where cotton is the predominant crop selected while the minimum area of paddy rice and small area of redgram are chosen. Scenario S3 is skewed towards a 'normal' season and the model chooses predominantly cotton and maize in addition to paddy rice and redgram as being the most profitable options. Scenario S4 is also skewed towards a 'normal' season where the crop choice remains the same as in S3, however, area with cotton is significantly increased while area of redgram is reduced to 0.5 ha. Scenario 5 (S5) is skewed towards a wet season 'above normal' (50%) and 'excess' (20%). Here, the model chooses redgram and maize as the key crops with paddy rice and cotton in smaller areas.

Table 2
Crop choice in Scenarios S1–S5 based on forecast for deficient (D), below normal (BN), normal (N), above normal (AN) and excess (E) seasons for each soil type.

Scenario	Crop	Soil type	Area planted (ha)	Revenue (INR '000)	Costs (INR '000)	Profit (INR '000)
S1: equal weight to each rainfall category	Maize	Black	40	2280	1476	803
(D – 20; BN - 20; N - 20;	Paddy rice	Red	12	992	799	193
AN - 20; E - 20)	Redgram	Red	4	2377	2229	148
	Redgram	Sandy	80	2541	2383	157
Total			136	8190	6887	1144
S2: dry season scenario	Cotton	Black	40	3168	2134	1033
(D – 30; BN - 30; N - 20; AN - 10; E - 10)	Paddy rice	Red	9	747	578	168
	Redgram	Red	7	198	191	7
Total			56	4113	2903	1208
S3: rainfall centred around normal season	Cotton	Black	62	4133	3549	584
	Maize	Sandy	40	2640	1541	1099
(D – 10; BN - 20; N - 40; AN - 20; E - 10)	Paddy rice	Red	13	1120	917	202
	Redgram	Sandy	3	105	77	27
Total			118	7998	6084	1912
S4: rainfall skewed towards normal and	Cotton	Sandy	80	6624	4880	1744
	Maize	Black	40	3015	1650	1364
above (D – 0; BN - 10; N - 60; AN	Paddy rice	Red	15.5	1351	1145	206
- 20; E - 10)	Redgram	Red	0.5	9	6	3
Total			136	10,999	7681	3317
S5: rainfall skewed towards a wet season	Cotton	Sandy	5	331	283	47
	Maize	Black	40	2820	1727	1092
(D – 0; BN - 10; N - 20; AN - 50; E - 20)	Paddy rice	Red	15.5	1425	1207	218
	Redgram	Red	0.5	2845	2136	709
	Redgram	Sandy	75			
Total			136	7421	5353	2066

As an illustration of using an actual forecast, we applied the IMD June 2014 experimental forecast discussed earlier. In this case, the model chooses cotton (94 ha), paddy rice (11 ha), maize (40 ha) and redgram (5 ha) as an optimal choice to maximise profit (Table 3).

As part of the ex-post analysis, if there is a perfect forecast (100%) of a 'deficient' season, cotton is allocated to about a third of total agricultural area with a minimum paddy rice area while the 2/3rd of the area is left fallow (Table 4). For a perfect forecast of a 'below normal' season cotton area chosen is the same as in the 'deficient' season with a small increase in paddy rice area and an additional choice of maize. In a perfect 'normal' season forecast the model chooses a significant cotton area of 80 ha followed by maize and paddy rice. In the case of an above 'normal' season redgram replaces cotton (with the same area as in 'normal' season) while maize and paddy rice areas remain the same as in a 'normal' season. In an 'excess' rainy season redgram is the dominant crop selected followed by maize, cotton and paddy rice (Table 4).

Table 3
Crop choice with IMD's June 2014 experimental forecast for each soil type.

Scenario	Crop	Soil type	Area planted (ha)	Revenue (INR '000)	Costs (INR '000)	Profit (INR '000)
S6	Cotton	Black	40	6718	5390	1327
(D – 29; BN - 13; N - 35;	Cotton	Sandy	54			
AN - 19; E - 4)	Paddy rice	Red	11	903	726	176
	Redgram	Red	5	170	139	31
Total			110	7791	6255	1534

Table 4
Crop choice with five possible season realisations.

Realised season	Crop	Soil type	Area planted (ha)	Revenue (INR '000)	Costs (INR '000)	Profit (INR '000)
Deficient	Cotton	Black	40	1840	1411	428
	Paddy rice	Red	2	118	84	33
Total			42	1958	1495	461
Below normal	Cotton	Black	40	2880	1426	1435
	Maize	Red	9	348	292	55
	Paddy rice	Red	7	551	387	163
Total			56	3779	2105	1653
Normal	Cotton	Sandy	80	7360	5008	2352
	Maize	Black	39	3234	1602	1631
	Paddy rice	Black	1	1378	1190	188
	Paddy rice	Red	16			
Total			136	11,972	7800	4171
Above normal	Maize	Black	39	2940	1827	1112
	Paddy rice	Black	1	1565	1358	207
	Paddy rice	Red	16			
	Redgram	Red	78	3234	2180	1053
Total			134	7739	5365	2372
Excess	Cotton	Red	15	1404	1120	284
	Maize	Black	23	1305	991	313
	Paddy rice	Black	17	1575	1320	254
	Redgram	Red	1	3330	2277	1053
	Redgram	Red	80			
Total			136	7614	5708	1904

Comparison of the scenarios presented in Tables 2 and 4 reveals the difference between model results calculated using the seasonal forecast and the actual realisation of the season i.e. if the season had a probability of 100% or in other words analysing the season ex-post. For example, if the forecast was skewed to 'below normal' season as in S2, the optimal choice as per the model is cotton (40 ha), paddy rice (9 ha) and redgram (7 ha) with a total profit of INR 1.2 M. When this is compared with the actual realisation of the 'below normal' season (100%), the model chooses cotton (40 ha), maize (9 ha) and paddy rice (7 ha) with an overall profit of 1.65 M INR. Thus, because of using an imperfect forecast 0.45 M INR is lost. Fig. 4 presents the results of the opportunity costs and losses for different cropping decisions based on the seasonal forecast. These occur when a crop choice decision is made based on a particular forecast and the experienced season is different to the forecast. For example, if the cropping decision is made on a forecast of a 'deficient' season and the season turns out to be 'normal' then there is an opportunity cost of not taking advantage of a 'normal' season. On the other hand if the seasonal forecast is for a 'normal' season and it turns out to be a 'below normal' season then there is a loss as result of the cropping decision.

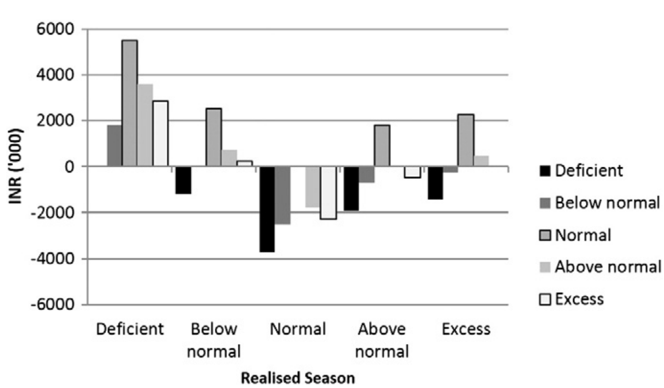

Fig. 4. Opportunity costs and losses for crop choice decisions based on seasonal forecasts. Y-axis represents the opportunity costs (positive values) or loss (negative values); X-axis categories represent the forecast season and the bars represent the realised season.

The model is very sensitive to a shift in cotton price and critical changes in crop choice can be observed as a result. An increase in the price of cotton from INR 46/kg to INR 48/kg shifts the crop choice from no cotton area being chosen to choosing 40 ha cotton, substituting maize. Paddy rice remains the same at 12 ha and redgram is reduced by 5 ha (Table 5). While cotton pricing is provided for illustrative purpose the model in general is sensitive to costs and prices.

In the case of initial and revised forecast analysis, results of using an initial forecast of a 'deficient' season are presented as an example (Table 6). The model chooses cotton (40 ha) and paddy rice (2 ha) while keeping the remaining 94 ha (out of a total 136 ha) available as fallow. The profit maximisation results in a total profit of INR 461,000. When the forecast is revised to 'below normal', the model maintains the cotton area as in previous forecast and adds 13 ha of maize and an additional 3 ha of paddy rice. In this case the crop choice results in a profit of INR 1.57 M. In the case of the revised forecast of a 'normal' season, the crops chosen are cotton (120 ha), paddy rice (5 ha) and redgram (3 ha) with a resulting profit of INR 3.8 M. When compared to the profits made in a 'normal' season of INR 4.17 M (Table 4), the lower profits in the revised forecast crop choice is due to the lower yields (hence lower profits) due to the shorter duration of the season.

3.2. Model outcome evaluation

In the case of 2014 cropping season, the farmers' crop choice and modelled crop choices are presented in Fig. 5. Farmers' crop choice data is from the survey at the workshop. Farmers have chosen the entire crop area available in the village while the model chose 24 ha less than the total land available. The modelled crop choice is consistent to the type and area of cropping. The seasonal rainfall for 2014 recorded in the village was 510 mm (district normal is 530 mm). We consider this value as a 'normal' year and used the 'normal' forecast to run the model in an ex-post mode. This result provides suitable confidence in the model that it is able to represent the recent farmer experience.

During the workshop in November 2015 in the study village, in response to the survey question on their crop choice without a forecast, farmers' consensus was that they would plant cotton (68 ha), maize (48 ha) and paddy rice (20 ha). To mimic and compare with farmers' crop choice, this model scenario was run with only three crops that were being grown for the season, i.e. cotton, maize and paddy rice. The model output for an equal chance of occurrence of each of the seasons (climatology) was maize (40 ha) and paddy rice (16 ha) and no cotton. The crop choice for maize and paddy rice is consistent to actual farmers' decisions. However, the model does not select cotton (while the farmers seem to take a chance given that cotton is a high risk high return crop), since the model does not deem cotton profitable with an equal chance of each of the season occurring.

Table 5
Crop choice in Scenario 1 (S1) using climatology and equal chances (20%) of deficient, below normal, normal, above normal and excess seasons – cotton price increase by INR 2/kg (compared to S1 in Table 2).

Crop	Soil type	Area planted (ha)	Revenue (INR '000)	Costs (INR '000)	Profit (INR '000)
Cotton	Black	40	3456	2513	943
Paddy rice	Red	12	992	799	193
Redgram	Red	4	2377	2293	148
Redgram	Sandy	75			
Total		131	6825	5605	1284

Table 6
Crop choice with revised forecasts.

Initial and revised forecasts	Crop	Soil type	Area planted (ha)	Revenue (INR '000)	Costs (INR '000)	Profit (INR '000)
Initial forecast - deficient	Cotton	Black	40	1840	1411	428
	Paddy rice	Red	2	118	84	33
Total			42	1958	1495	461
Revised to below normal	Cotton	Black	40	2880	1420	1459
	Maize	Red	13	424	419	49
	Paddy rice	Red	3	208	149	58
Total			56	3512	1988	1566
Revised to normal	Cotton	Black	40	11,328	7595	3733
	Cotton	Sandy	80			
	Paddy rice	Red	5	348	319	29
	Redgram	Red	3	104	74	29
Total			128	11,780	7988	3791
Revised to above normal	Cotton	Black	40	8942	6583	2358
	Cotton	Sandy	61			
	Paddy rice	Red	5	398	361	36
	Redgram	Red	11	495	336	159
Total			117	9835	7280	2553
Revised to excess	Cotton	Black	40	4041	3502	539
	Cotton	Red	11			
	Paddy rice	Red	5	399	358	41
	Redgram	Sandy	80	2805	2255	550
Total			136	7245	6115	1130
Initial and revised forecasts	Crop	Soil type	Area planted (ha)	Revenue (INR '000)	Costs (INR '000)	Profit (INR '000)
Initial forecast - deficient	Cotton	Black	40	1840	1411	428
	Paddy rice	Red	2	118	84	33
Revised to below normal	Cotton	Black	40	2880	1420	1459
	Maize	Red	13	424	419	49
	Paddy rice	Red	3	208	149	58
Revised to normal	Cotton	Black	40	11,328	7595	3733
	Cotton	Sandy	80			
	Paddy rice	Red	5	348	319	29
	Redgram	Red	3	104	74	29
Revised to above normal	Cotton	Black	40	8942	6583	2358
	Cotton	Sandy	61			
	Paddy rice	Red	5	398	361	36
	Redgram	Red	11	495	336	159
Revised to excess	Cotton	Black	40	4041	3502	539
	Cotton	Red	11			
	Paddy rice	Red	5	399	358	41
	Redgram	Sandy	80	2805	2255	550

3.2.1. Stakeholder engagement process

During the engagement with farmers we used the model in an iterative way. Participating farmers agreed with the model output of leaving a large portion of the agricultural land fallow in the rainfall 'deficient' season with only 40 ha of cotton and a small area of paddy rice planted. This was consistent with their experience as they optimise on the irrigation water available. Researchers at the agricultural university also agreed that this would be consistent with their recommendations to the farmers. Farmers also agreed with the model component that chose paddy rice transplanted area based on the season, which is consistent with their practice. Although for some of the farmers who have access to groundwater irrigation, seasonal forecast did not have the same value compared to farmers who relied only on rain. In the case of crop choice for a 'normal' season, cotton is the most profitable crop and as such a significant area was allocated to cotton by the model which was also consistent with farmers' practice. A wetter than 'normal' year would have an adverse impact on the yields as well as the quality of cotton, particularly if the season is wet during the harvest time. In the case of 'above normal' and 'excess' seasons, while the model crop choice was redgram as a predominant crop, only a few farmers in the village favoured redgram as opposed to the model allocations. Farmers reported that while they agree that redgram is a profitable crop, high labour requirements (and limited labour availability) and their perception that the crop is pest prone prevented them from choosing this crop. This discrepancy between model crop choice and farmer crop choice in the case study village provided a good discussion opportunity of ('rational') modelling results versus farmers' decisions based on local conditions and experience. Farmers suggested they would need researchers and extension to support them with agronomic and pest management advice to cultivate redgram. Participating farmers and researchers also engaged with the revised forecast component of the model and were in agreement with the assumptions made in the model on yields and inputs use about the shorter duration varieties. The major challenge they face, if the start of season is delayed and a wetter than forecasted season evolves, is access to seeds for the short duration varieties of crops and fertilisers. Increasing labour costs and non-availability of farm labour at critical times of farm operations were also highlighted as major constraints. The PJTSAU researchers acknowledge the potential of using this tool to discuss seasonal climate forecasts with a large network of extension service staff who are part of their university. This was reinforced from the interactions during the workshop.

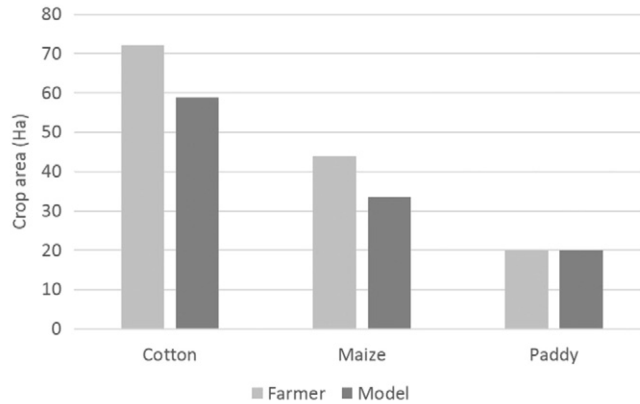

Fig. 5. Model validation for the season 2014. Farmers' crop choice and the modelled crop choice.

3.3. Response to feedback questionnaire

The responses to the survey questionnaire are summarised in Table 7. To the pre-workshop question (i) how do you rate your knowledge of SCF, on a scale 1–10 (where 1 is low and 10 is high): five out of ten farmers rated themselves 1 to 2, the rest ranked themselves between 6—8. For the same question post workshop (iv) how do you rate your knowledge of SCF (on a scale where 1 is low and 10 is high), the same set of farmers who rated themselves 1–2 in question (i) rated themselves 4–5 out a score of 10. The remaining five farmers said their understanding of the utility and limitations of SCF application had improved.

To the pre-workshop question (iii) what value will you place on SCF in your crop choice decision making, on a scale 1–10 (where 1 is low and 10 is high)?, five out of ten farmers selected a value greater or equal to 6. To the question (v) on improved knowledge on SCF after the workshop 7 out of 10 farmers agreed that their knowledge on the utility and challenges of SCF had highly improved. To the question (vi) if exposure to the crop choice model had improved their understanding of the role of SCF in crop choice decisions, 6 out of 10 farmers strongly

Table 7
Summary of responses from survey of farmers.

Questions	Pre-workshop	Post-workshop
How do you rate your knowledge of SCF, on a scale where 1 is low and 10 is high	5 farmers: 1 to 2 5 farmers: 6 to 8	4 to 5 Improved previous understanding
What value will you place on SCF in your crop choice decision making, on a scale (where 1 is low and 10 is high)		5 farmers: 6 and above
Exposure to the crop choice model has improved my understanding of the role of SCF in crop choice decisions (strongly agree to strongly disagree in five step scale)		6 out of 10 farmers 'agreed'
Crop choice model is a useful way to discuss/engage on climate risk in agriculture (strongly agree to strongly disagree on a five step scale).		7 out of 10 farmers 'agreed'

agreed with the statement. To the question (vii) if the crop choice was a useful approach to discuss/engage on climate risk in agriculture, 7 out of 10 farmers agreed with the statement. In a discussion on the current mode of delivery of SCF information, all farmers suggested that if the forecast is delivered with advice on crop choice that would increase the utility of the forecast.

4. Discussion

4.1. Methodology to improve the use of SCF

The work presented here is part of a larger project that explored if use of seasonal climate forecasts in agricultural decision making can enhance food security in the Indian Ocean rim region. The present study is an attempt to 'demystify' the probabilistic nature of seasonal climate forecasts for both researchers and farming community. The modelling exercise eventuated from the challenge of how to engage researchers, extension and farmers on SCF as a part of portfolio of climate risk management tools in rainfed agriculture. While a number of approaches have been developed to communicate SCF as climate risk management information, there is limited literature on integrating the SCF information into a scenario analysis such as a bio-economic tool.

Significant financial and intellectual resources across the globe are being invested in developing and improving the skill of seasonal climate forecasts. However, their uptake among farm advisors and farmers is low due to limitations in understanding forecasts and timeliness of their availability and difficulties in translating the climate results into operational decisions such as when and what crop to sow. If the results from using SCF are improved over those assuming climatology, there is potential value for forecasts in the context of climate risk management. Modelling approaches such as the one presented in this study could provide ways in which researchers and extension advisors can discuss seasonal climate forecasts with the farming community. It should however be noted that this modelling tool is meant to be a discussion support tool used to describe consequences of different pathways and not prescriptive on what options (crop choice) to take. The development of the model provided an opportunity to build 'social capital' on managing climate risk among farming community in the village. This was possible due to participation of the farmers from the inception of the project, providing technical coefficients, participating in feedback sessions, interacting with the model (operated by researchers) and the final validation workshop.

4.2. Results for the case study village

In a scenario where there is an equal chance of any of the seasons occurring, redgram and maize seem the most profitable crops while some paddy rice area is included. When the forecast is skewed towards a slightly dry season compared to equal chance scenario, the model optimises by reducing the paddy area and choosing cotton over maize and significant area is left fallow. In a scenario where the forecast is centred around a 'normal' and 'above normal' season the model choses cotton and maize as major crops with an increase in paddy area compared to the 'dry' season. In a scenario skewed towards an 'excess' season the cotton area is significantly reduced while redgram and maize dominate the crop choice. Feedback from farmers on crop choice based on season by the model was consistent with their current operations. This provides confidence on the validity of the model as well credibility that the tool can be used to engage farming communities on climate risk. However, there were also discrepancies between the modelled crop choice and farmers' practice, particularly regarding redgram. While the redgram is selected as profitable by the model, farmers have constraints in growing this crop and suggested that they need agronomic advice to pursue this crop. This also applies to sorghum. These crops were included in the model as they are more prevalent in the region than in the selected study village. This discrepancy also points at the risk averse farming in the semi-arid regions where farmers are reluctant to take up 'new' crops and prefer to continue with crops that they have expertise or traditional knowledge about.

The model is sensitive to small price changes and caution is needed in selecting the prices and should involve consultation with the farmers and extension services so the model results are relevant to the region of interest. While the model responds to small changes to prices, farmers are more likely to consider the solutions cautiously and in line with their responsive, 'lean not jump' and adaptive risk management. The modelling tool also helps in exploring different price options in a scenario-building exercise and links season and prices to arrive at an optimal solution that would provide additional complexity to the discussion on risk. Although the aspect of inter-relationships between seasonality and prices is not explored in this model, it is acknowledged that this relationship is important and needs further investigation in subsequent model development. From the model results on opportunity costs and losses (Fig. 4), it is evident that if the crop choice is based on an expectation of a 'normal' season then there is a loss if any of the other seasons manifest. This result cautions on planning cropping choice based on the assumption of a 'normal' season alone and therefore the importance of a risk management approach to minimise losses from an unfavourable season or taking advantage of a favourable season. In terms of the 'Revised Forecast Run', farmers often tend to be responsive to the unfolding of the season and the revised forecast model mimics their decision making behaviour. Although in the revised model forecast only one window of opportunity to carry out a mid-course correction is included in the present model, theoretically several time steps could be included where alteration of decisions and adjusting of inputs can take place.

4.3. The usefulness and use of the farm model by farmers

From the several interactions during the development of the model and subsequent feedback the bio-economic model presented here it appears to be of value to a majority of farmers. The value they placed on the modelling tool was that it facilitated the exploration of consequences ('what if?' scenarios) of implementing SCF in farming systems through identifying different cropping allocation decisions under different season types. The opportunity costs and losses as a result of crop choice based on a seasonal forecast provide useful insights into discussions on climate risk and challenge in applying SCF in crop choice decision making. It is however, important to recognise that smallholder farmers are responsive in their decision making and hence they may not make irreversible choices but are likely to take mid-course corrections if the season they planned for does not manifest. For example, if they planned their cropping choice based on a 'normal' season and it turns out to be a 'deficient' or 'below normal' season they are more likely to reduce their inputs such as top-up fertiliser and thus reduce losses from a poor season. On the other hand, if the initial forecast is for a 'below normal' season and turns out to be a 'normal' or 'above normal' season, then larger areas would be brought under cultivation with increased inputs to take advantage of the 'good' season. By combining the results of the 'Initial Forecast Run' with those of the 'Revised Forecast Run' model, farmers can reconsider decisions that were made initially, in order to minimise part of the risk they have taken or to maximise returns in the event of a better than forecasted season. The questionnaire among participating farmers revealed an improved understanding of the utility and challenges of seasonal climate forecasts. They pointed out that mere delivery of seasonal climate forecasts does not help them with their decision making but advice on translating this information into cropping decisions would be helpful. It was clear in the interactions with the farmers that tools that allow discussion on the crop choice and the implications of various decisions helped them with improved understanding of SCFs.

Acknowledgements

The work presented in the paper is part of the Australian Aid Agency for International Development (AusAID)/Australian Department of Foreign Affairs and Trade (DFAT) and CSIRO funded project "Can seasonal climate forecasts improve food security in Indian Ocean Rim countries in a variable and changing climate?". We acknowledge AusAID/DFAT and CSIRO. Farming communities and in-country partner institutions participated in this activity with enthusiasm and contributed to discussions and provided valuable feedback on the model. Peter Hayman (South Australian Research and Development Institute, Adelaide) provided insights into challenges of applying SCF in agricultural decision making and discussion around using the term normal in SCF. D.R. Reddy (PJTS Agricultural University, Hyderabad), V. Nageswara Rao (ICRISAT, Hyderabad), T. Chiranjeevi (Livelihoods and Natural Resources Management Institute) provided useful inputs and feedback on the model. David Gobbett and Alison Laing from CSIRO provided useful comments to improve the manuscript.

References

Anderson, D., 2005. Overview of Seasonal Forecasting. In: Troccoli, A., M., H., Anderson, D., Mason, S. (Eds.), Seaonal Climate: Forecasting and Managing Risk. Springer Academic Publishers, Dordrecht/Boston/London, p. 499.

Ash, A., McIntosh, P., Cullen, B., Carberry, P., Stafford Smith, M., 2007. Constraints and opportunities in applying seasonal climate forecasts in agriculture. Aust. J. Agric. Res. 58, 952–965.

Clewett, J.F., McKeon, G.M., 1990. The use of seasonal climate forecasting in agricultural management in Queensland: case studies in pasture and shallow storage evalutation. First International Symposium on Integrated Land Use Management in Tropical Agricluture Brisbane.

Coleman, J.S., 1988. Social capital in the creation of human capital. Am. J. Sociol. 94, S95–S120.

Hammer, G.L., Holzworth, D.P., Stone, R., 1996. The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. Aust. J. Agric. Res. 47, 717–737.

Hansen, J.W., 2002. Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. Agric. Syst. 74, 309–330.

Hansen, J.W., Mishra, A., Rao, K.P.C., Indeje, M., Kinuthia Ngugi, R., 2009. Potential value of GCM-based seasonal rainfall forecasts for maize management in semi-arid Kenya. Agric. Syst. 101 (1-2), 80–90.

Hardaker, J., Pandey, S., Patten, L., 1991. Farm planning under uncertainty: a review of alternative programming models. Rev. Mark. Agric. Econ. Aust. Agric. Resour. Econ. Soc. 59, 9–22.

Hayman, P.T., Crean, J., Mullen, J., Parton, K., 2007. How do probabilistic seasonal climate forecasts compare with other innovations that Australian farmers are encouraged to adopt? Aust. J. Agric. Res. 58, 975–984.

Hayman, P., Whitbread, A., Gobbett, D., 2008. Practicing agronomy in an uncertain climate – using simulation modelling to study seasonal drought and the impact of ENSO in the Southern Australian grains belt. In: Unkovich, M. (Ed.), Global Issues Paddock Action. Proceedings of the 14th Australian Agronomy Conference. Australian Society of Agronomy, Adelaide regional.org.au/au/asa/2008/plenary/farming-uncertain-climate/5939_hayman.htm.

Hayman, P.T., Nidumolu, U., Howden, M., 2013. Managing production risk from agricultural intensification with seasonal climate forecasts: experience with decision analysis in southern India and Sri Lanka. In: Van Ittersum, M.K., Giller, K. (Eds.), Global Food Security Conference. Elsiever, Noordwijkerhout, The Netherlands.

IMD, 2014. Long range forecast update for 2014 southwest monsoon rainfall. India Meteorological Department 2014. Web page http://www.indiaenvironmentportal.org.in/files/file/Long%20range%20forecast%20update%20for%202014.pdf.

Janssen, S., van Ittersum, M.K., 2007. Assessing farm innovations and responses to policies: a review of bio-economic farm models. Agric. Syst. 94, 622–636.

Kokic, P., Nelson, R., Meinke, H., Potgieter, A., Carter, J., 2007. From rainfall to farm incomes—transforming advice for Australian drought policy. I. Development and testing of a bioeconomic modelling system. Aust. J. Agric. Res. 58, 993.

Kolb, D., 2004. Learning styles inventory. In: Lowey, A., Hood, P. (Eds.), The Pwer of the 2 × 2 Matrix. Jossey-Bass; A Wiley Imprint, San Fransisco, CA.

Marshall, N.A., Gordon, I.J., Ash, A.J., 2010. The reluctance of resource-users to adopt seasonal climate forecasts to enhance resilience to climate variability on the rangelands. Clim. Chang. 107, 511–529.

Meinke, H., Sivakumar, M.V.K., Motha, R.P., Nelson, R., 2007. Preface: climate predictions for better agricultural risk management. Aust. J. Agric. Res. 58, 935–938.

Meza, F.J., Hansen, J.W., Osgood, D., 2008. Economic value of seasonal climate forecasts for agriculture: review of ex-ante assessments and recommendations for future research. J. Appl. Meteorol. Climatol. 47, 1269–1286.

Millner, A., Washington, R., 2011. What determines perceived value of seasonal climate forecasts? A theoretical analysis. Glob. Environ. Chang. 21, 209–218.

Nelson, R.A., Holzworth, D.P., Hammer, G.L., Hayman, P.T., 2002. Infusing the use of seasonal climate forecasting into crop management practice in North East Australia using discussion support software. Agric. Syst. 74, 393–414.

Nidumolu, U.B., Lubbers, M., Alary, V., Lecomte, P., Van Keulen, H., 2011. A discussion support model for a regional dairy–pasture system with an example from Réunion island. J. Agric. Sci. 149, 663–674.

Nidumolu, U.B., Hayman, P.T., Hochman, Z., Horan, H., Reddy, D.R., Sreenivas, G., Kadiyala, D.M., 2015. Assessing climate risks in rainfed farming using farmer experience, crop calendars and climate analysis. J. Agric. Sci. 1–14.

Pitel, J., 1989. Multiple Criteria Analysis for Agricultural Decisions. Elsevier, Amsterdam.

Power, S.B., Plummer, N., Alford, P., 2007. Making climate model forecasts more useful. Aust. J. Agric. Res. 58, 945.

Romero, C., Rehman, T., 1989. Multiple Criteria Analysis for Agricultural Decisions. Elsevier, Amsterdam.

Shankar, K.R., Nagasreea, K., Venkateswarlua, B., Maraty, P., 2011. Constraints and suggestions in adopting seasonal climate forecasts by farmers in South India. J. Agric. Educ. Ext. 17, 153–163.

Stephens, E.M., Edwards, T.L., Demeritt, D., 2012. Communicating probabilistic information from climate model ensembles-lessons from numerical weather prediction. Wiley Interdiscip. Rev. Clim. Chang. 3, 409–426.

Stone, R.C., Meinke, H., 2007. Weather, climate, and farmers: an overview. Meteorol. Appl. 13, 7.

ten Berge, H.F.M., van Ittersum, M.K., Rossing, W.A.H., van de Ven, G.W.J., Schans, J., van de Sanden, P.A.C.M., 2000. Farming options for The Netherlands explored by multi-objective modelling. Eur. J. Agron. 13, 263–277.

van der Wal, M., De Kraker, J., Offermans, A., Kroeze, C., Kirschner, P.A., van Ittersum, M., 2014. Measuring social learning in participatory approaches to natural resource management. Environ. Policy Gov. 24, 1–15.

WMO, 2014. The WMO Strategy for Service Delivery and its Implementation Plan. World Meteorological Organisation, Geneva.

Zadeh, L., 1963. Optimality and non-scalar-valued performance criteria. IEEE Trans. Autom. Control 8, 59–60.

Ziervogel, G., Calder, R., 2003. Climate variability and rural livelihoods: assessing the impact of seasonal climate forecasts in Lesotho. Area 35, 403–417.

Ziervogel, G., Bithell, M., Washington, R., Downing, T., 2005. Agent-based social simulation: a method for assessing the impact of seasonal climate forecast applications among smallholder farmers. Agric. Syst. 83, 1–26.