Delivering climate risk information to farmers at scale: the Intelligent agricultural Systems Advisory Tool (ISAT)

Working Paper No. 243

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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RESEARCH PROGRAM ON
Climate Change, Agriculture and Food Security

CGIAR

CCAFS

Working Paper

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Correct citation:
Rao KPC, Dakshina Murthy K, Dhulipala R, Bhagyashree SD, Gupta MD, Sreepada S, Whitbread AM. 2019. Delivering climate risk information to farmers at scale: the Intelligent agricultural Systems Advisory Tool (ISAT). CCAFS Working Paper no. 243. Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Available online at: www.ccafs.cgiar.org

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The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) is a strategic partnership of CGIAR and Future Earth, led by the International Center for Tropical Agriculture (CIAT). The Program is carried out with funding by CGIAR Fund Donors, Australia (ACIAR), Ireland (Irish Aid), Netherlands (Ministry of Foreign Affairs), New Zealand Ministry of Foreign Affairs & Trade; Switzerland (SDC); Thailand; The UK Government (UK Aid); USA (USAID); The European Union (EU); and with technical support from The International Fund for Agricultural Development (IFAD). For more information, please visit https://ccafs.cgiar.org/donors.

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CCAFS Working Paper no. 243

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Abstract

One of the strategies for helping smallholder farmers cope with climate variability and change is the provision of climate services that better decision making around the planning and management of agricultural systems. However, providing such services with location specific timely and actionable information to millions of farmers operating across diverse conditions requires innovative solutions. ICRISAT and its partners have developed and piloted one such system called "Intelligent agricultural Systems Advisory Tool – ISAT" capable of generating and disseminating data driven location specific advisories that assist farmers in anticipating and responding to the emerging conditions through the season. Using a decision tree approach, a structured and systematic approach to decision making was devised that considers the insights obtained from the analysis of historical climatic conditions, climate and weather forecasts and prevailing environmental conditions. Microsoft India developed a platform to access real time data from various 'public' sources, perform the data analytics, implement the decision tree and generate and disseminate messages to farmers and associated actors. The ISAT generated advisories are designed to support both pre-season planning and in-season management.

During the 2017 monsoon, ISAT was piloted with 417 farmers across four different locations. The messaging system worked extremely well in picking appropriate location specific message from the database and delivering the same to the mobiles of the registered farmers. Mid and end season surveys revealed that more than 80% of the farmers from all villages were satisfied with the frequency, relevance and understandability of the messages delivered. About 58% of the farmers rated the messages are reliable by being correct more than 75% of the times and helped them in managing their farms better by conducting farm operations timely with reduced risk. Compared to farmers in the control villages, groundnut yields of farmers in treatment villages are higher by ~ 16% but this results varied between -7.7 to 56.2%. This study has demonstrated the opportunities available to harness the untapped power of digital technologies to provide actionable advisories timely to smallholder farmers using appropriate data analytics and information dissemination systems.

Keywords

Climate information services; smallholder farmer; Decision tree; Decision making; Seasonal climate forecasts; Data analytics; Climate variability; Groundnut farming; Risk management; Mobile messages.

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Acknowledgements

This work was implemented as part of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), which is carried out with support from CGIAR Fund Donors and through bilateral funding agreements. For details please visit https://ccafs.cgiar.org/donors. The views expressed in this document cannot be taken to reflect the official opinions of these organizations. The Sehgal Foundation is also gratefully acknowledged for additional financial support.

Contents

Acronyms

ANGRAU	Acharya NG Ranga Agricultural University
APSIM	Agricultural Production Systems sIMulator
APSDPS	Andhra Pradesh State Development and Planning Society
BoM	Bureau of Meteorology
CFS	Climate Forecasting System
CPC NOAA	Climate Prediction Centre National Oceanic and Atmospheric Administration
CV	Coefficient of Variation
ENSO	El Nino Southern Oscillation
ERFS	Extended Range Forecasts System
FGDs	Focus Group Discussions
GDDP	Gross District Domestic Product
ICRISAT	International Crops Research Institute for the Semi-arid Tropics
ICT	Information and communication Technologies
IITM	Indian Institute of Tropical Meteorology
IMD	Indian Meteorological Department
IOT	Internet of Things
ISAT	Intelligent agricultural Systems Advisory Tool
ISMR	Indian Summer Monsoon Rainfall
NCEP	National Centre for Environmental Protection
OC	Organic Carbon

ONI	Oceanic Nino Index
PAWC	Plant Available Water Capacity
SCF	Seasonal Climate Forecasts
SMS	Short Message Service
SST	Sea Surface Temperature
SOI	Southern Oscillation Index
UAVs	Unmanned Aerial Vehicles

Introduction

Traditionally, smallholder agriculture in developing countries is intended at meeting the primary objective of producing sufficient food to meet the family needs and doing it without taking risks or compromising on the household financial security. However, the growing demand for cash income and the need to make production more economical and efficient is transforming smallholder agriculture into a more commercial activity that seeks profit. Such transformation calls for well-planned and carefully managed systems that make best use of available resources and technologies (FAO, 2014). Since performance of crops depends on a number of location specific soil and climatic conditions which are highly variable both in space and time, planning and management of agricultural systems should consider both risks and opportunities to maintain productivity and achieve higher levels of profitability.

Coping with the impacts of variable climatic conditions is one of the most complex and difficult challenges that the smallholder farming community in dry tropics is facing. Climate variability which occurs at many temporal scales, from seasons to years to decades and beyond, has both direct and indirect impacts. While variability in the amount and distribution of rainfall during the season has a direct impact on the productivity of agriculture, the uncertainty and risk associated with this variability over the seasons and years makes decision making difficult and subjective affecting the profitability and overall viability of the systems (van de Steeg et al., 2009, Rao et al., 2011). Overlaid on this are the projected changes in climate which are likely to exacerbate existing variability in rainfall and frequency of occurrence of extreme events. Despite uncertainty over the precise nature and extent of these changes, most climate change projections for the region indicate an increase in temperatures by about 2.5^0C to 3.0^0C accompanied by modest and seasonally variable increases in precipitation (5–10 %) by mid-century (IPCC, 2007). These small changes in climate can have huge impact on agriculture especially in the semi-arid tropics where conditions are marginal for crop production. Under such variable and changing climatic conditions, effective and efficient management of agricultural systems should aim at both reducing the risks and capitalizing on the opportunities through adoption of proactive risk management practices which unfortunately have not received much attention. In the absence of science based information, farmers tend to rely on their own perceptions and experiences which may not match reality.

Over the years, agricultural research has generated enormous amount of data, information and knowledge which when properly analysed and interpreted has the potential to generate useful insights into how crop growth and performance responds to the effects of various stresses and their interactions. Research has also developed a number of tools and models, which make it possible to translate these insights and knowledge into relatively simple decision rules that can guide decision making by farmers operating under uncertain and risky conditions (van Ittersum and Donatelli, 2003). However, the full potential of this knowledge and tools remained untapped due to a number of constraints. Important among them are non-availability of data analytics enabled decision support systems and lack of information dissemination systems for timely delivery of regularly updated advisories to millions of end users (Jones et al., 2017).

Recent advances in Information and Communication Technology (ICT) coupled with the exponential growth in access to and use of internet have opened the doors for huge never seen before opportunities for developing integrated services with unlimited capacity to capture and process data from multiple sources and generate and deliver useful information to end users (Wolfert et al., 2017). A large number of Internet of Things (IOT) networks and services are already in operation and these networks also include drones and other unmanned aerial vehicles (UAVs) which can provide real time information on growth and performance of crops. Such information will greatly enhance the capacity to identify emerging problems and provide timely advice on interventions (PWC, 2016). These networks, which experts estimate to link about 30 billion objects by 2020 (Nordrum, 2016), are expected to be the primary sources of data collection and its flow to multiple users. In order to monetize on these emerging opportunities, there is a need to develop intelligent platforms that bring together seamless field data from millions of connected devices and advanced data analytics that link data with process models to generate information that help farmers in making more informed decisions. Such systems that convert big data into actionable information have the potential to bring revolutionary changes in the way farmers understand, think and act in managing the systems profitably and sustainably.

ICRISAT in collaboration with Indian Meteorological Department (IMD), Acharya NG Ranga Agricultural University (ANGRAU) and MICROSOFT has developed and piloted an automated messaging system, "Intelligent agricultural Systems Advisory Tool – ISAT", capable of generating and disseminating data driven location specific advisories that assist in farm level decision making. This integrated system compiles the required data including real time data from various sources, analyses the data, identifies relevant management interventions and disseminates the same to registered users. This report summarises the steps followed in the development and implementation of the tool and key learnings from the pilot studies conducted on groundnut based farming systems in Anantapur district in Andhra Pradesh, India. The focus of this study is more on developing data analytics as required to support informed decision making in planning and managing agricultural systems productively and profitably using climate information. Attention was also paid to scalability and flexibility to customize to meet additional requirements.

Key decisions that ISAT is designed to support are those which are influenced by climatic conditions. This includes pre-season planning activities such as selection of right crops and allocation of land to selected crops and in-season management operations such as land preparation, planting, inter-cultural operations and harvesting. Since pre-season planning depends on a realistic assessment of conditions during the coming season, the analysis made a critical analysis of historical trends in rainfall, realistic assessment of the skill in predicting climate and weather conditions and the value of this information to serve as a basis to anticipate and manage climate risks by making more informed decisions. This information was then used to develop a decision tree in which a specific decision rule was developed for each of the decisions that the end user is expected to make while managing the systems.

This report provides a detailed account of the process followed in developing ISAT. It includes a brief description of the target district and the major challenges that the farmers in the district are struggling to cope with, followed by a stepwise description of ISAT tool development and testing.

Development of ISAT

For the development and testing of ISAT, the chronically drought prone Anantapur district in the state of Andhra Pradesh, India was selected. Predominance of rainfed agriculture, low and erratic rainfall conditions which make the district highly drought prone with seven drought years out of every ten years and past work by ICRISAT is the basis for selecting the district.

About Anantapur district

Anantapur is the largest district in the state of Andhra Pradesh, India with a geographical area of 1.913 m ha divided into 63 mandals, administrative units above village (Figure 1). According to 2011 census of India, it is the 7th most populous district in the state with a population of 4.1 million of which 72% is rural (APEDB, 2018). Agriculture remains the predominant activity in the villages, with 80 percent of total workers engaged, either as cultivators or agricultural labourers. The Gross District Domestic Product (GDDP) of the district is ₹35,838 crore (US$5.6 billion) of which agriculture contribution is ₹9,944 crore (US $ 1.6 billion) or 27.7%. For the FY 2013-14, the per capita income at current prices was estimated to be ₹69,562 (US$1,100) which is 35% lower than the state and national per capita income of about ₹ 1.07 lakh (US $ 1602.6) (APEDB,2018).

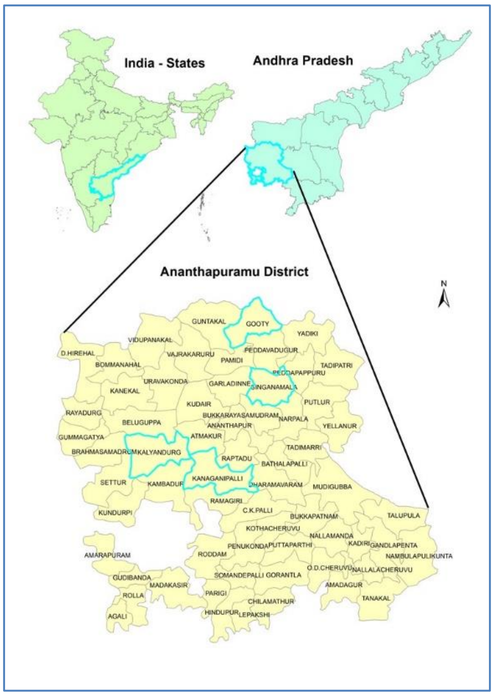


Figure 1. Location of Anantapur district and the four mandals where ISAT was piloted

The district is predominantly agrarian with lands that are marginal for crop production. Of the total area, about 60% is under agricultural use and 10% is under forest cover. The landscape is characterised by hills, ridges and undulating to gently sloping lands. According to the land capability classification, nearly 70% of the land in the district falls in groups III and IV which are lands suitable for cultivation with intensive soil conservation practices. More than 80% of the 1.15 m ha area under agriculture is rainfed. Farmers in the district are largely dependent on a single crop of groundnut which is cultivated on more than 80% of the land under rain-fed agriculture. Sorghum, maize, cotton, foxtail millet and pigeonpea, mostly as intercrop, are the other crops grown during the kharif season under rainfed conditions.

Chickpea is cultivated as a rabi crop mostly in the black soils. As is the case with any rainfed agriculture, productivity and profitability of groundnut is greatly influenced by the amount and distribution of rainfall which varies widely both within and between the seasons.

Due to its position in the rain shadow area, the district fails to get the benefit of either of the monsoons which are the main sources of rainfall in the district. While Western Ghats cuts off the movement of south-west monsoon, the location of the district in the margins of the North-East monsoon zone limits the amount and duration of rainfall during this season. As a result, the district receives low and erratic rainfall during both south-west and north-east monsoon periods making it chronically drought prone. With an average annual rainfall of 550 mm, it is the second lowest rainfall receiving district in the country after Jaisalmer in Rajasthan. Annual and seasonal rainfall exhibits high variation both within and between the seasons. With a coefficient of variation (CV) of 45% in the south-west monsoon (kharif season) and 60% in the north-east monsoon (rabi season) rainfall, the climate is highly risky for crop production. Management of climate sensitive systems such as agriculture under these highly variable conditions requires informed decision making in planning and managing the systems to minimize risks and take advantage of favourable conditions.

Decision making by farmers

The first step in the process of developing ISAT is to identify key decisions that the farmers make and understand the factors influencing those decisions. Focus Group Discussions (FGDs) were held with farmers and extension officers of Ministry of Agriculture from the four selected mandals of Gooty, Kalyandurg, Kanaganapalli and Singanamala.

Farmers identified climate variability as the biggest challenge that they are struggling to cope with. Given the low and erratic nature of rainfall and its strong influence on the performance of crops, it is not surprising to note that more than 80% of the farmers have ranked climate variability as the number one constraint in managing their farms profitably (Figure 2). About

77% of the participants have indicated that in more than 50% of the years they fail to recover the investments made and more than 70% of the farmers claim that farming is getting worse due to worsening climatic conditions. While farmers claim that the amount of rainfall has declined over the years, no such trend was observed in the monthly or seasonal rainfall amounts recorded at ANGRAU research station at Rekulakunta in the district. Declining soil fertility and increased incidence of pests and diseases are the other two high ranking constraints. No major differences were observed in the perceptions across the villages or levels of education.

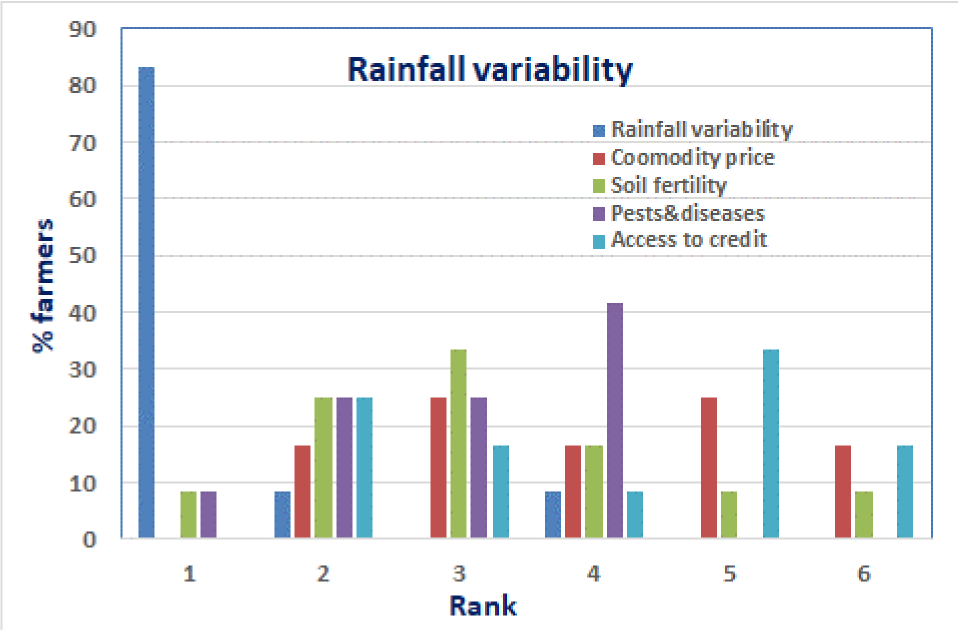


Figure 2. Ranking of major constraints by farmers from Gooty, Kalyanadurg, Kanganapalli and Sinaganamala mandals in Anantapur district

Almost all participating farmers felt that they have very limited crop choices for rainfed cultivation. Groundnut is the preferred crop and it is also the only cash crop that they can grow profitably under average conditions in this environment. According to them, 1 t/ha is the breakeven yield to recover costs of production at the current input and output prices. Important management practices whose timely operations can have a significant influence on the production and productivity of groundnut are land preparation, time of planting, plant population, application of gypsum and other soil amendments and time of harvesting.

During the FGDs, farmers have identified various decisions that they normally make as part of planning and managing groundnut based cropping systems along with the criteria used in making those decisions. Planning starts at least one month before the actual start of the season in the first fortnight of June and continues through the season until harvesting in the month of October (Table 1). Farmers prefer to complete the preparatory operations and keep the fields ready for planting by end of May or early June so that they can go for planting with the earliest possible opportunity that arises between first fortnight of June and first fortnight of August. Outside this planting window, farmers opt for alternate drought tolerant crops such as foxtail millet, fodder sorghum and short duration pulses like green or black gram. For delayed planting after August, horse gram is the only option. Rainfall before and during the short period in which these operations are to be carried out is the most important factor influencing the decisions.

Table 1. Key pre-season planning and in-season management decisions that farmers in the groundnut growing areas of Anantapur district make between May and October and the criteria used in making those decisions

Month	Key decisions made	Criteria or basis used in making decisions
May	• Land preparation including establishing bunds and other soil and water conservation structures, tillage and residue management	• Erosivity of the land • Level of land degradation • Capacity to invest • Availability of Gov. subsidy/support • Soil moisture and workability
	• Transport and application of soil amendments such as sand, tank silt and farmyard manure	• Status of physical and chemical properties if the soil • Availability of amendments • Availability of labour and transport
	• Shelling and seed preparation	• Time to start of the season • Availability of labour
	• Crop planning including crops to be planted and area to be planted	• Past experiences • Performance during the previous season

		• Expectation of the coming season • Availability and suitability of land for various crops • Household needs • Market demand and prices • Capacity to invest
June	• Planting GN+PP intercrop (early planting preferred)	• Rains during the second fortnight • Status of land preparation • Availability of seed
	• Planting long duration drought tolerant crops such as castor	• Rains during the second fortnight • Status of land preparation • Availability of seed
July	• Planting if not planted already	• Amount of rainfall during the week • Status of land preparation • Availability of labor
	• Inter-culture/weeding if planted	• Amount of rainfall during the week • Level of weed infestation
August	• Planting groundnut (first fortnight) in unplanted fields	• Amount of rain during the week
	• Planting late season crops (Horsegram, greengram, castor, pigeonpea sole, blackgram, fodder sorghum, foxtail or pearl millet, cowpea) in unplanted fields during the second fortnight	• Revised crop plans • Amount of rain • Availability of seed
	• Pest control in planted fields	• Level of pest/disease incidence • Rains/winds/cloudiness/temperature • Capacity to invest
	• Gypsum application (45 DAS) in planted fields	• Rainfall during the week • Status of the crop • Availability of gypsum
	• Plant cotton on black soils	• Amount of rainfall during the week • Availability of seed • Capacity to invest/Ability to take risk
	• Plant GN on light black soils	• Amount of rainfall during the week • Availability of seed
September/October	• Harvesting of early planted groundnut	• Amount of rainfall • Soil conditions • Cloudiness • Availability of labour
	• Planting horsegram and fodder sorghum in vacant fields	• Amount of rainfall during the week
	• Planting groundnut/chickpea on black soils	• Amount of rainfall during the week

Data analytics to understand and support decision making

Since amount of rainfall is the main driver for various decisions, 55 years continuous daily rainfall data from Regional Research Station of ANGRAU located at Rekulakunta (latitude 14.69°N and longitude 77.67°E) in Anantapur district was analysed to characterize variability and uncertainty, possible trends in that variability and relationship between the observed variability and large scale climatic phenomena such as El Nino and La Nina events.

Annual and seasonal rainfall and its variability

The mean annual rainfall at this location is 567 mm of which 62% occurs during the kharif (June to September) and 25% during rabi (October to December) seasons (Table 2). Annual rainfall varied from 175 to 990 mm with a coefficient of variation (CV) of 31%. The variability is much higher with seasonal rainfall. During the main kharif season rainfall varied between 117 and 857 mm with a CV of 45% while that during the rabi season varied between 10 and 378 mm with a CV of 60%. Rabi season rainfall is important for crops planted late during the kharif season, long duration crops such as pigeonpea which come to flowering and pod formation during rabi season and for crops such as chickpea sown in rabi season on black soils.

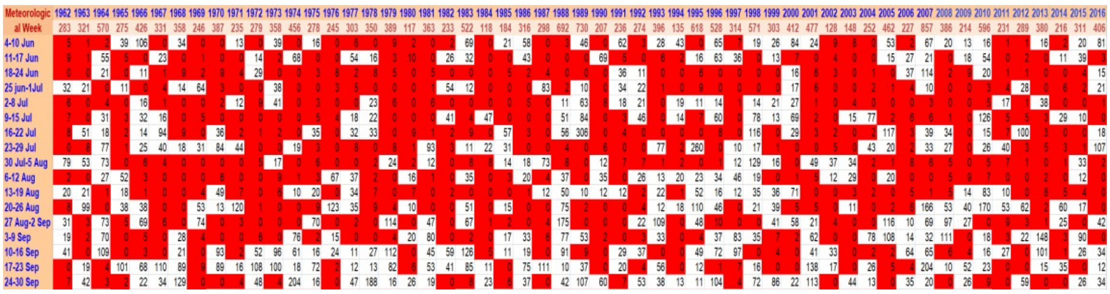
Table 2. Key characteristics of annual and seasonal rainfall amounts (N=55) recorded at Regional Agricultural Research Station, Rekulakunta, Anantapur, Andhra Pradesh

Variable	Annual	Kharif	Rabi
Rainfall amount (mm)			
Average	567	350	142
Minimum	176	117	10
Maximum	990	857	378
Coefficient of variation (%)	31	45	60
Rainy days with >2 mm (No)			
Average	38.2	22.1	10.4
Minimum	21	10	2
Maximum	59	39	20
Weekly rainfall (mm)			
Average	10.9	20.3	10.9

Minimum Maximum	0.0 306	0.0 306	0.0 219
Number of weeks >10 mm	12.36	6.98	3.29

The number of rainy days and weekly rainfall amounts were analysed to understand the distribution of rainfall during the crop season (Table 2). In this analysis, any day with 2 mm or more rain was considered as a rainy day. During the kharif season, number of rainy days varied between 10 and 39 with an average of 22.1 and that during rabi varied between 2 and 20 with an average of 10.4 days. This highlights the importance of distribution of rainfall during the 110-120 day crop growth period. Average weekly rainfall during kharif season is 20.3 mm but varied from nil to as high as 306 mm creating wet and dry periods of different length. Prolonged dry spells of 4 weeks or longer occur in many years (Figure 3) impacting adversely the growth and productivity of most crops.

Figure 3. Distribution of weekly rainfall during the Kharif season from meteorological week no 23 (4-10 June) to week no 39 (24-30 September) between 1962 and 2016



This within and between the season variability in rainfall, generates high levels of uncertainty and risk. When faced with uncertainty and in the absence of more specific and relevant information, decision makers tend to make decisions based on their perceptions which are founded on casual observations. Such perceptions tend to be biased towards higher risk and the decisions made under their influence may not incorporate the true risk involved (Rao et al., 2012). Integrating true risk into decision making requires quantified information on risk and its consequences as well as possible options to manage it. One of the most widely used measures to quantify risk is the one based on probability distribution functions.

Available evidence from experiments conducted at ANGRAU research station in Anantapur suggests that groundnut crop performs well in almost all seasons that receive at least 300 mm rain during the Kharif season. From the historical data the chance of getting the same is 58%, which is the true risk for groundnut production in this environment (Figure 4). Millets or short duration legume crops such as black gram or green gram require 200 mm rainfall and probability of getting the same during kharif season is 90%. Hence, depending on their risk taking ability farmers can make informed decision in selecting the crop(s) that best meets their requirement.

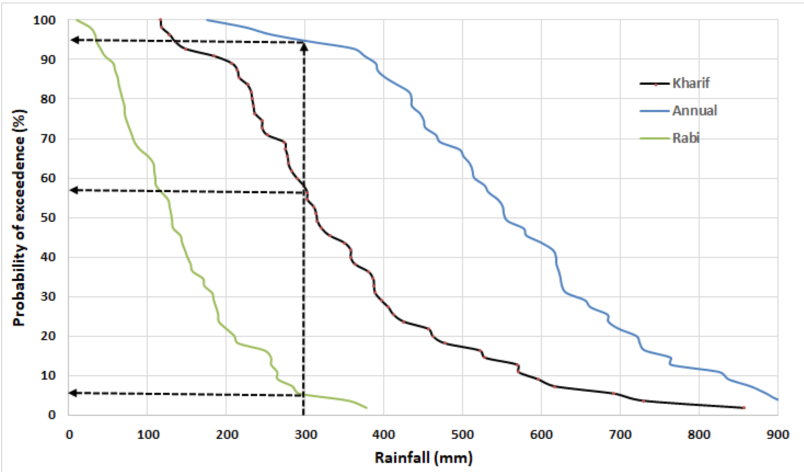


Figure 4. Probability of exceedence of annual, kharif and rabi season rainfall at Anantapur based on 55 year observed rainfall data from 1962 to 2016

Seasonal rainfall requirement for groundnut

Based on the FGDs, it is evident that farmers should harvest at least 1 t/ha to recover their investment and make profit from groundnut cultivation. Using system simulation model APSIM, simulation analysis was conducted to identify the minimum amount of rainfall required during the crop season to achieve one ton groundnut pod yield (Figure 5). Since the amount of rainfall required depends on plant available water holding capacity (PAWC) of the soil, simulations were carried out under a range of PAWC conditions. Results indicate that on a relatively deep soil with more than 100 mm PAWC, groundnut yields tend to be more than one ton in the seasons with 300 mm or more rain irrespective of its distribution. This requirement increased with decreasing PAWC of the soil and on a medium soil with 80 mm PAWC the amount of seasonal rainfall required to achieve the same yield increased to 350 mm.

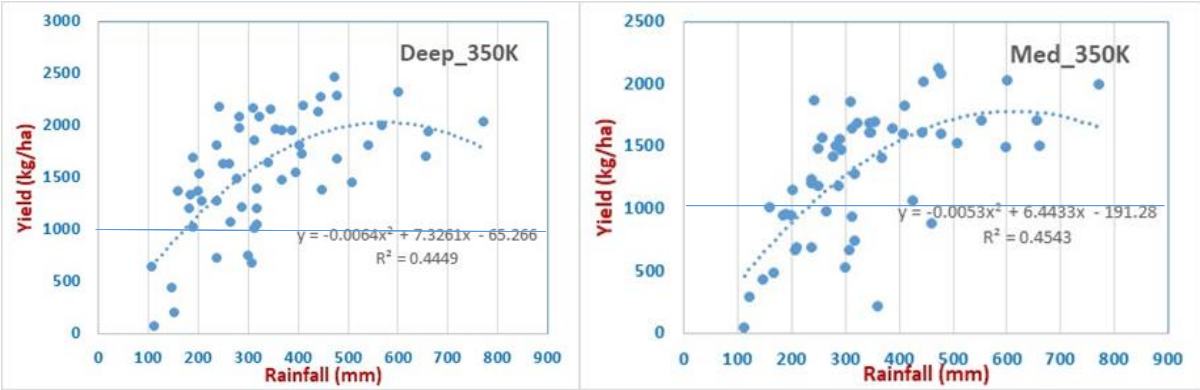


Figure 5. Relationship between the amount of rainfall during the crop season and yield of groundnut on deep soils with 100 mm (left) and medium deep soil with 80 mm (right) plant available water capacity

Distribution of seasonal rainfall

Distribution of rainfall, especially for the length and frequency of occurrence of dry spells, was assessed using weekly totals. A week with less than 10 mm rainfall and with no day during the week recording more than 5 mm is considered as dry week. The analysis is focused on the probability of occurrence of dry spells of four week or longer, which according to simulation analysis severely constrain the growth and performance of groundnut.

Dry spells of four week or longer have occurred in 29 of the total 55 years or in 53% of the years. It is significant to note that most of these dry spells have occurred during the years in which kharif season rainfall is less than 350 mm. Of the 29 seasons with long dry spells, 22 or 76% of the seasons have occurred during the 32 years in which the amount of rainfall received during the season is less than 350 mm and the remaining 7 or 24% of the seasons have occurred in the 23 years that received more than 350 mm rainfall (Figure 6). This clearly establishes that the chance of getting a long dry spell of more than four week is much higher during the seasons in which rainfall is less than 350 mm compared to those with more than 350 mm. Further analysis of annual and seasonal rainfall totals showed no increasing or decreasing trend as perceived by farmers but the ten year moving coefficient of variation (CV) of seasonal rainfall showed an increasing trend during kharif season and declining trend during rabi season (Figure 7). The CV of kharif season rainfall which tend to be around 30% during the period from 1960 to 1980, has increased to more than 40% since 1990 and varied between 40 and 60% during the past 26 years. This probably influenced the farmer’s perception about declining rainfall especially in the recent years.

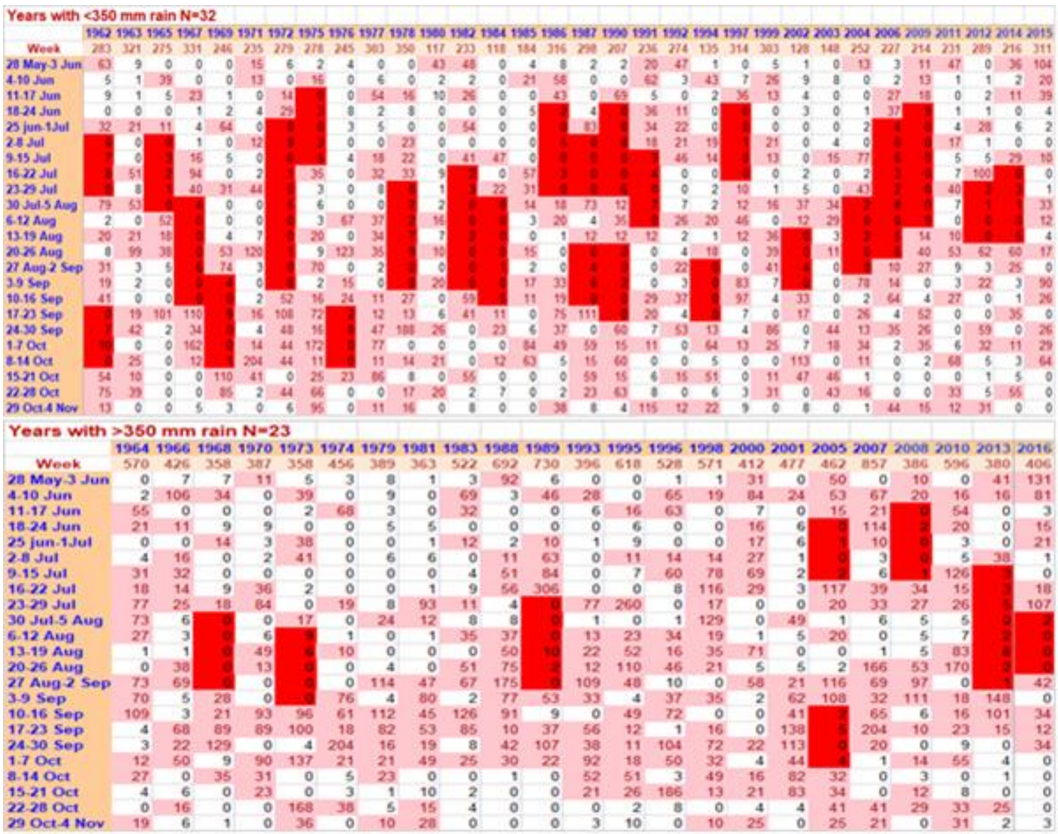


Figure 6. Distribution of dry weeks (weeks with less than 10 mm rain) during the crop growing period from June to October in Anantapur during the years in which seasonal rainfall is <350 mm (top) and >350 mm (bottom)

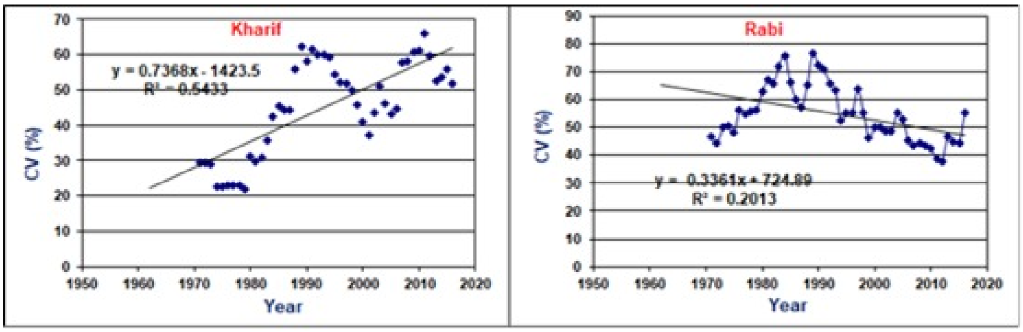


Figure 7. Ten year moving average of coefficient of variation (CV) in kharif and rabi season rainfall amounts

Rainfall variability and ENSO events

Several studies have indicated that statistically significant inverse relationship exists between El Nino Southern Oscillation (ENSO) phenomenon and inter-annual variability of the Indian monsoon (Walker and Bliss, 1932; Gadgil et al., 2007; Kumar et al. 2006; Rajeevan and Pai, 2007, Azad and Rajeevan, 2016). Hence, most seasonal forecasts including the Indian summer monsoon rainfall (ISMR) predictions use ENSO as one of the predictors (Rajeevan et al., 2006). An important feature of ENSO is its high predictability.

The occurrence and intensity of El Nino or La Nina events is computed based on the magnitude and direction of change in parameters such as Oceanic Nino Index (ONI), Southern Oscillation Index (SOI) and Sea Surface Temperature (SST). Though all indices predict the occurrence of ENSO events fairly well, they differ in predicting the intensity of the event. Based on the ONI, events are defined as warm (El Niño) events when five consecutive overlapping three month periods at or above the +0.5o anomaly and at or as cold (La Niña) events if ONI is below the -0.5 anomaly. The threshold is further broken down into Weak (with a 0.5 to 0.9 SST anomaly), Moderate (1.0 to 1.4), Strong (1.5 to 1.9) and Very Strong (≥ 2.0) events. In case of SOI, sustained negative values of lower than −7 indicate El Niño episodes and positive values of greater than +7 indicate La Niña episodes. When SST is used as criteria to define ENSO events, persistent NINO3 or

NINO3.4 values cooler than −0.8 °C are considered to be indicative of La Niña, while persistent values warmer than +0.8 °C are indicative of El Nino.

A complete list of El Nino and La Nina events that occurred between 1960 and 2016 and their intensity based on the changes in the three different indices are summarized in Table 3. The table includes only the events classified as moderate and strong and excludes events that are classified as weak. Further, we considered the events that started during or before June to August quarter since past studies reported a good correlation between the indices during this period and rainfall and performance of agriculture during the kharif season of that year (Kumar et al., 2006). A total of eleven years were classified as moderate or strong El Nino events based on the changes in ONI and SOI indices while SST based classification put ten years in this category. Similarly, moderate to strong La Nina events were predicted in eight years based on changes in ONI, 14 years based on SOI and in 13 years based on SST changes. The period 1970-75 was the wettest period with La Nina conditions persisting for most part of this period.

Table 3. Historical moderate and strong El Nino and La Nina events based on Oceanic Nino Index (ONI), Southern Oscillation Index (SOI) and Sea Surface Temperatures (SST) (The years highlighted are common to all indexes)

Based on Oceanic Nino Index (ONI) (http://ggweather.com/enso/oni.htm)		Based on Southern Oscillation Index (SOI) (http://www.bom.gov.au/climate/enso/enlist/)		Based on Sea Surface Temperature (SST) (http://www.bom.gov.au/climate/enso/enlist/)	
Moderate	Strong	Moderate or Weak to Moderate	Strong or moderate to strong	Moderate or Weak to Moderate	Strong or moderate to strong
El Nino					
1963-64	1965-66	1972-73	1965-66	1965-66	1972-73
1986-87	1972-73	1977-78	1982-83	1994-95	1982-83
1987-88	1982-83	1993-94	1987-88	2002-03	1987-88
1991-92	1997-98	2009-10	1991-92	2009-10	1991-92
2002-03	2015-16		1994-95		1997-98
2009-10			1997-98		2015-16

			2015-16		
La Nina					
1970-71	1973-74	1964-65	1973-74	1964-65	1973-74
1998-99	1975-76	1970-71	1974-75	1970-71	1974-75
1999-00	1988-89	1971-72	1975-76	1971-72	1975-76
2007-08		1988-89	2010-11	1998-99	1988-89
2010-11		1998-99	2011-12	1999-00	2010-11
		1999-00		2000-01	2011-12
		2000-01		2007-08	
		2007-08			
		2008-09			

In general, depressed rainfall was recorded in the district during El Nino years while enhanced rainfall was recorded during La Nina Years (Figure 8). The average rainfall during El Nino years is 26-35% lower compared to non El Nino years. Much of this decline is observed in the month of July. The July month rainfall during El Nino years is 70-81% lower compared to non-El Nino years. Kharif season rainfall during La Nina years is 44-56% higher compared to non La Nina years. During La Nina years, enhanced rainfall was recorded in all the months from June to October with highest being in the month of August which received 80-145% higher rainfall compared to non La Nina years followed by July (53-56%), October (37-53%) and September (27-29%). Rainfall during the months of September to October, which coincides with flowering and grain filling stages of groundnut is one of the key factors influencing the final yield.

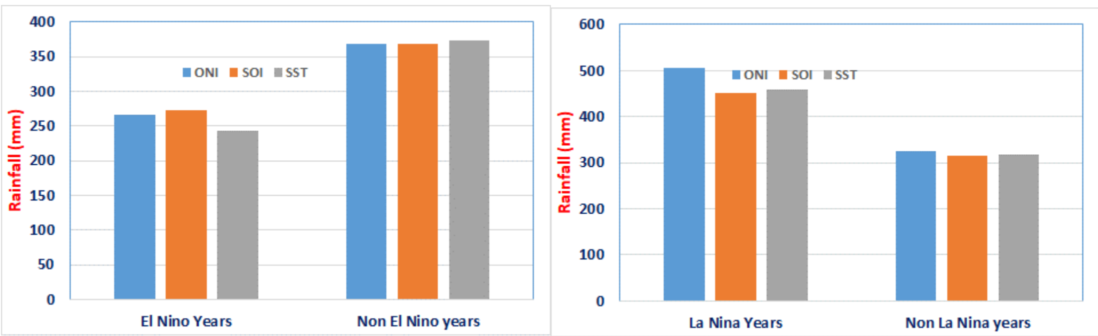


Figure 8. Rainfall during Kharif season (Jun-Sep) in El Nino and non El Nino years (Left) and La Nina and non La Nina years (Right) identified based on Oceanic Nino Index (ONI), Southern Oscillation Index (SOI) and Sea Surface Temperature (SST)

Another important feature of El Nino and La Nina years is the occurrence of long dry spells of four week or longer duration (Figure 9). Using the criteria described above, distribution of dry spells of four weeks or longer were assessed for all those years that were classified as medium to strong El Nino or La Nina events by all the three indices. In the 14 El Nino years between 1962 and 2016, the chance of occurring a long dry spell of four weeks or longer is nearly 80% while the same in case of La Nina years is less than 15%. These trends in the amount and distribution of seasonal rainfall and dry spells and probabilities associated with them are valuable insights which when used in decision making contribute to substantial risk reduction.

Figure 9. Distribution of dry spells of four weeks or longer at Anantapur during El Nino and La Nina Years

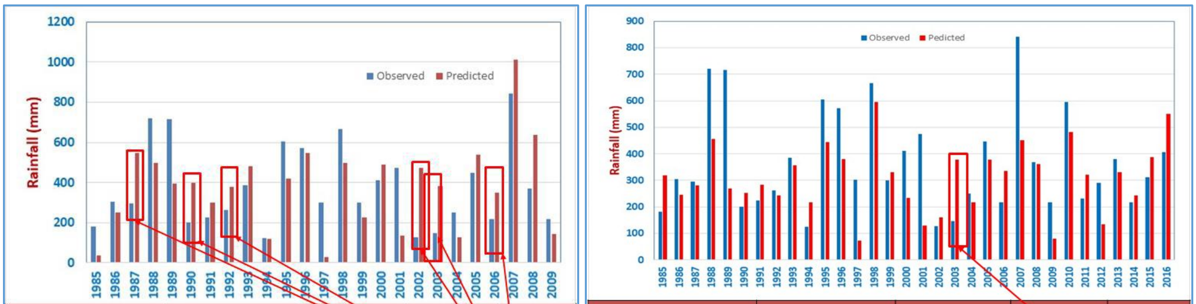
Seasonal climate forecasts to guide planning

Though seasonal climate forecasts have the potential to serve as a basis especially for pre-season planning operations, the probabilistic nature of the information and relatively lower skill compared to short-term weather forecasts suggests the need for caution in using them. Despite these limitations, several studies across the world have shown that the available skill in SCF has the potential to make significant contribution to the planning and conducting farm operations with reduced risk (Hansen et al., 2011). In India, seasonal climate forecasts are issued by IMD in two stages - first stage in April/May and the second stage in June. These forecasts are prepared using the dynamical global climate forecasting system (CFS) model, which is an adopted version of the National Centers for Environmental Prediction

(NCEP), USA. The first stage forecast predicts rainfall over the country as a whole while the second stage predicts seasonal rainfall over various geographical regions. Currently, efforts are on to provide forecasts at the block level.

We have analysed block level forecasts generated on an experimental basis by Indian Institute of Tropical Meteorology (IITM) and by the Extended Range Forecasts System (ERFS) for their usefulness in planning farm operations in Anantapur (Figure 10) district. The available forecasts from 1985 to 2016 were compared with actual rainfall during that season. The forecast skill was assessed based on the outcome of the decisions made using the forecast than on the amount of deviation between predicted and observed. For example, during 1988, 1989 and 2007, actual rainfall is much higher than the amount predicted by ERFS downscaled forecasts. Since higher rainfall in these environments will have no negative impact on the performance of cops and farmers are not expected to suffer any loss on their investment, such forecasts are considered as useful. The chance of suffering a loss on investments is high in case the predicted rainfall is less than the actual rainfall, as is the case in 2003.

Since the season must receive a minimum of 300 mm rainfall to achieve the breakeven yield of 1 t/ha groundnut yield, we used this as a threshold value to assess the skill in the SCFs. In general, the downscaled forecasts from IITM were found to overestimate the wet seasons compared to ERFS forecasts which tend to overestimate the dry seasons. Of the 16 years that were predicted to get more than 300 mm rainfall by the IITM methodology, the forecast was found to be true in 10 years (Figure 10). Similarly, ERFS system predicted below normal conditions in 20 years with six misses. The important feature of ERFS predictions is that, though it missed to predict correctly the above normal rainfall in 6 years, its prediction of below normal season has only one miss. With only one miss out of 32 forecasts, ERFS forecasts are considered to be well suited for decision making especially by the risk averse farmers since the possibility to lose on the investments is extremely low.



Prediction	Total (Climatology)	Total (Predicted)	Hits	Misses
Below normal <300	12	9	6	3
Above normal >300	13	16	10	6

Prediction	Total (Climatology)	Total (Predicted)	Hits	Misses
Below normal <300	15	20	14	6
Above normal >300	17	12	11	1

Figure 10. A comparison of seasonal rainfall predictions with actual rainfall using the downscaled forecasts from IITM (left) from 1985-2009 and ERFS (right) from 1985-2016 for Anantapur district

Decision tree for pre-season planning

Based on the results from the above analysis, a decision tree was developed to support important pre-season planning decisions that included which crop to grow, which cropping system to adopt, how much land to allocate to identified crops and systems and what inputs to be purchased or prepared for. Since the outcome of all these decisions depends on the expected seasonal conditions, informed decision making requires a realistic expectation of the seasonal conditions. The decision tree for pre-season planning is focused on this.

Analysis of 55 years climatic data has indicated that there is a 58% probability to get 300 mm or more rain during kharif season. This probability has changed substantially when the years were grouped using the seasonal climate forecast and occurrence and strength of ENSO events. Using the downscaled SCF from IITM and ERFS, the years were grouped into two based on whether the predicted rainfall is more or less than 300 mm. Of the 25 years for which IITM downscaled forecasts are available, 12 years were forecasted to get more and 13 years to get less than 300 mm. Similarly, of the 32 years for which ERFS forecasts are available, 12 years were predicted to get more and 20 years less than 300 mm (Table 4). The probability to get 300 mm rain in each of these groups is significantly different and varied from 0% in the years forecasted to get less than 300 mm rain with El Nino conditions to 100% in the years forecasted to get more than 300 mm with a La Nina event. Hence, the seasons forecasted to get above normal rainfall with La Nina type conditions are least risky and those forecasted to get below normal rainfall with El Nino conditions are highly risky for groundnut cultivation.

Table 4. Average rainfall (mm) and probability to get >300 mm rain in the years forecasted to get above and below normal seasons based on IITM and ERFS downscaled forecasts and occurrence of El Nino and La Nina events. Figures in the parenthesis are number of years

Season type	IITM downscaled forecast with 400 mm limit		ERFS downscaled forecast with 350 mm limit	
	Average rain (mm)	Probability to get >300 mm rain	Average rain (mm)	Probability to get >300 mm rain
All forecast years				
Above normal	512 (12)	83%	506 (12)	92%
Below normal	216 (13)	23%	286 (20)	30%
Above normal years				
With La Nina	602 (7)	100%	639 (5)	100%
Without La Nina	449 (5)	71%	410 (7)	86%
Below normal Years				
With El Nino	234 (5)	0%	228 (7)	14%
Without El Nino	254 (8)	14%	317 (13)	31%

To facilitate the decision making, a decision tree was developed with SCFs and ENSO conditions as internal nodes (Figure 11). The test conditions at these nodes are amount of rainfall expected based on the SCF and presence or absence of El Nino or La Nina phase. This guides the decision maker to pick the most optimal scenario from the four possible scenarios and make decisions based on the risk level associated with that scenario.

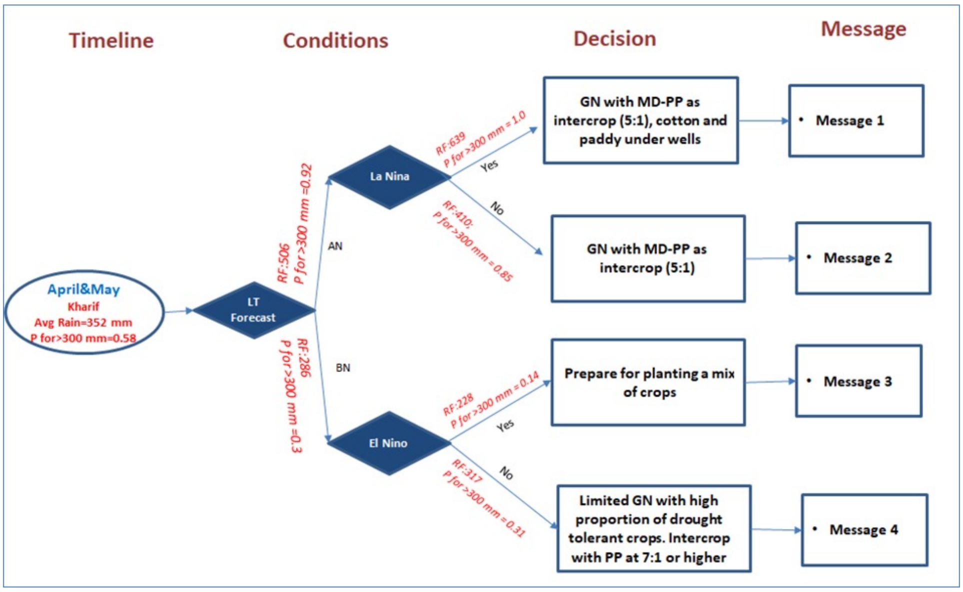


Figure 11. A decision tree to support pre-season planning decisions by smallholder farmers with due consideration to historical trends and seasonal climate, El Nino and La Nina forecasts. (RF is rainfall and P is probability)

Using the outcome of FGDs and expert opinions, which identified a number of different crop and management options that are best suited to each of the four types of seasons, a short advisory that is convenient to send through SMS or share in social sites like facebook, twitter and google+ was developed. Below are the messages relevant for the four scenarios that the decision tree analysis leads to.

Message 1. Above normal seasons with La Nina conditions: These type of years receive more than 600 mm rain during June-September and tend to be very good seasons for most crops, including groundnut. Long dry spells of four weeks or more are not common ($p<0.14$) and there is a good possibility of high rainfall during September and October. An intercrop of groundnut with pigeonpea in the ratio of 3 to 5:1 is a good option. There is also a good potential for rice under wells with limited irrigation and cotton as rainfed crop in high water holding soils.

Message 2. Above normal seasons without La Nina conditions: These type of years generally receive more than 400 mm during June-September and are well suited for most crops, including groundnut. Rainfall is generally well distributed with less than 17% probability of dry spells of four weeks or more. Good rainfall is also expected during September and October in some years. Intercrop of groundnut with pigeonpea in the ratio of 5:1 is a good option. It is also a potential season to allocate a part of the land to cotton and other commercial crops.

Message 3. Below normal seasons with El Nino conditions: These type of years receive depressed rainfall, and average rainfall during these years tend to be less than 250 mm which is inadequate for most crops. There is a very high chance (75%) of a dry spell of 4 weeks or longer. Consider planting a mix of crops to minimize risk. It is advisable to allocate up to 50% of the farm to drought tolerant crops. Use a row ratio of 7:1 or higher if planning a groundnut pigeonpea intercrop.

Message 4. Below normal seasons without El Nino conditions: During these type of years, average rainfall during kharif (June-September) tends to be less than 300 mm. There is 44% or higher chance of getting a dry spell of 4 weeks or longer, leading to severe reduction in the yield potential of various crops. It is advisable to allocate at least 25% of the farm to drought tolerant crops.

Crop management under variable conditions

In-season crop management is another important componet of rainfed agriculture since the poerformance of crops is significantly influenced by the timeliness and precision with which various operations from land prepareation to harvesting are carried out. Most of these operations are influenced by the start and progress of the rainy season. Initially, a scenario analysis was conducted to identify the best planting time, plant population and cropping systems using APSIM with historical climate data. Simulations were conducted with three representative soil types classified as deep (PAWC = 118 mm and OC in 0-15 cm layer = 0.31%), medium (PAWC= 80 mm and OC in 0-15 cm layer = 0.21%) and shallow (PAWC = 45 mm and OC = 0.31%). Locally popular groundnut variety TMV 2 was used in the simulations. We used the version calibrated by Nageswara Rao et al. (2004) for this location.

Optimum planting time

Optimum planting time was identified by setting up fortnightly sowing windows from the beginning of June to end of August. Planting was done on any day within the window after receiving 30 mm or more rain over a period not exceeding five days. Groundnut planted between the second fortnight of July and first fortnight of August gave best yields, especially on medium and shallow soils which constitute majority of the soil types in this region (Figure 12). On deep soils, planting up to the end of August is feasible. Planting earlier than 15 July is not a preferred option. In this area September is the wettest month and is best suited for pegging and pod formation. Groundnut planted during the first fortnight of July or earlier fails to make use of these favourable conditions.

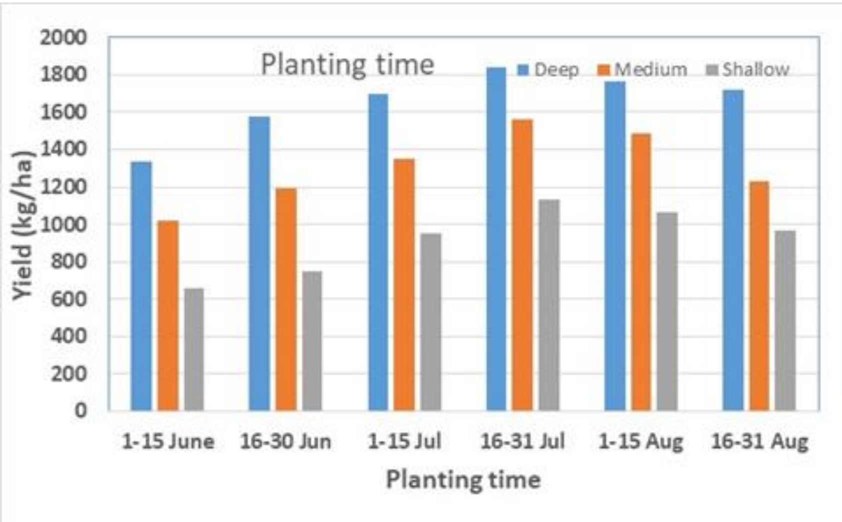


Figure 12. Effect of planting time on groundnut yields on three different soil types

Faced with uncertainty, farmers tend to go for planting with the earliest opportunity that occurs after the onset of monsoon in the month of June. This is not a good practice since groundnut planted during this period performs poorly (Figure 13). Two factors are responsible for this. First, the hot dry summer period from March to May, during which temperatures in excess of 40^{0}C are common, dries the soil close to air dry moisture limits. Planting with first rains in the month of June without giving time to build profile moisture will face severe moisture stress in case planting is followed by a dry spell of one or two weeks. Second, June planted crops come to flowering in August, during which time the probability of occurrence of a dry spell is very high and this adversely impacts the pegging and grain formation. Hence, it is advisable to skip planting in June though farmers in the region prefer it, perhaps influenced more by the fear of losing a crop season than by the actual performance of the crop.

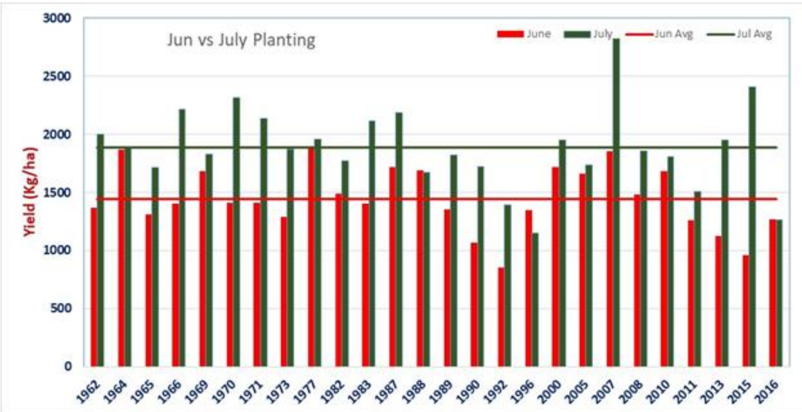


Figure 13. Comparison of groundnut yields of crops planted in June and July months

Optimum plant population

In the moisture stressed areas, crop yields are strongly influenced by planting density. In case of groundnut cultivation, seed cost constitutes nearly 30% of the total cost of production. Hence, optimizing plant density is one of the options to reduce cost of cultivation and utilize available soil moisture efficiently. The effect plant population on groundnut yields on deep, medium and shallow soils was assessed by simulating the performance of groundnut under a range of plant densities between 200 and 450 K plants/ha with a spacing of 30 cm between rows. The response of groundnut yield to increasing plant population was different on different soils and during different season types. In the seasons during which amount of rainfall is less than 300 mm, plant density above 300 K plants/ha showed no benefit on all types of soils (Figure 14). In the seasons with more than 300 mm rainfall, yields responded positively to increased plant density, up to a density of 400 k/ha on deep soil. On medium and shallow soils, the increase in yield with plant populations higher than 300K/ha is marginal.

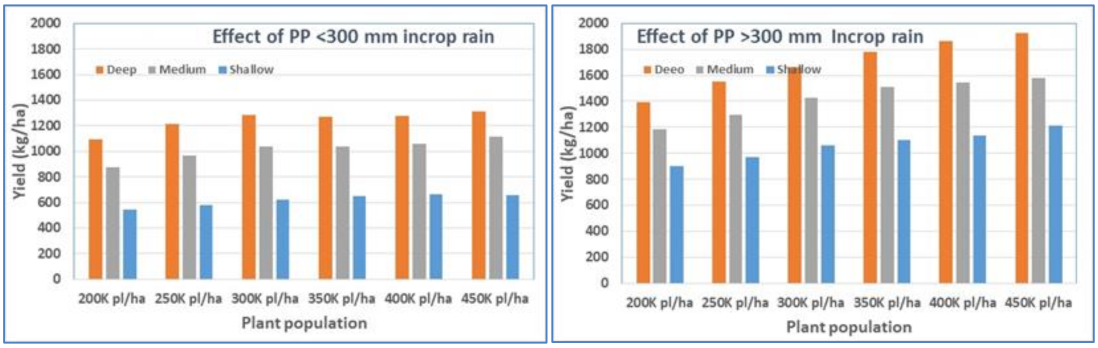


Figure 14. Effect of plant population on groundnut yields on deep, medium and shallow soils during seasons with less than 300 mm (left) and with more than 300 mm (right) rainfall

Cropping systems

Though groundnut based systems are the most popular and widely practiced cropping system in the district, the final selection of crops and cropping systems for a given season is influenced by the progress South-West monsoon makes after its onset in the month of June. Rainfall during the month of June is mainly used for land preparation. First fortnight of July is considered early for planting groundnut. Depending on the expectations about the season, long-duration crops like cotton and castor are planted with any planting opportunity. The second fortnight of July and first week of August is the best time to plant groundnut with pigeonpea as intercrop. Second and third week of August are also considered suitable for planting groundnut-pigeonpea intercrop but farmers diversify their farms by including other crops such as foxtail millet and sorghum on small areas. From last week of August, farmers opt for planting drought tolerant crops such as sorghum, finger millet and foxtail millet or short duration pulses like greengram and cowpea. Beyond September farmers prefer planting fodder sorghum or horsegram since no other crop can be grown with limited rainfall during October to December.

Though groundnut-pigeonpea intercropping is the most favoured system, farmers make adjustments to the row ratios of main and intercrop depending on time of planting. When planted during the optimal planting window, farmers plant one row of pigeonpea for every five rows of groundnut which will be increased to seven rows of groundnut with delayed planting. The performance of groundnut-pigeonpea intercrop system under different row ratios was assessed using APSIM. The simulation analysis has indicated that groundnut performed better in years with less than 300 mm rain during the season and pigeonpea did well in the years that received more than 300 mm rain (Figure 15). Most of these seasons which received less than 300 mm are shortened seasons either due to delayed onset or early cessation.

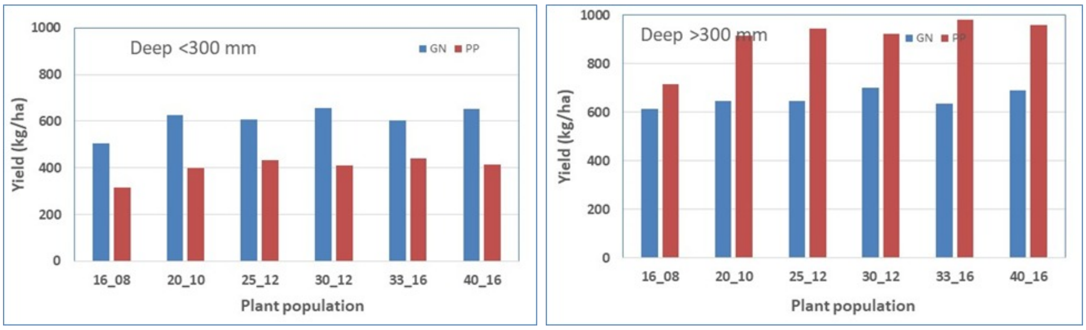


Figure 15. Effect of groundnut and pigeonpea plant populations on yields during the seasons with less than 300 mm rainfall (left) and with more than 300 mm (right) rainfall

Decision tree for in-season crop management

In-season crop management decisions by farmers are generally influenced by the real time information on the amount of rainfall received since onset of rainy season. Early or delayed onset, breaks within the season and early or delayed cessation are the challenges that farmers struggle to cope with. During the 17 week rainy season, from standard meteorological week no 23 (4-10 Jun) to 39 (24-30 Sep), the probability of receiving 10 mm or more rain during a week exceeds 50% in only four weeks and CV of weekly rainfall is always greater than 100 for all weeks during this period (Figure 16). Such high variability introduces lot of uncertainty and makes decision making extremely challenging.

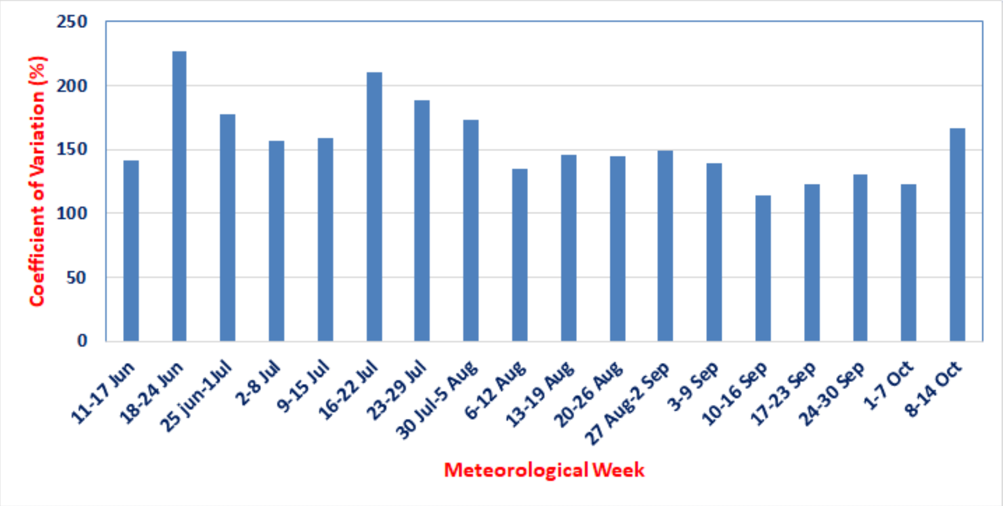


Figure 16.Coefficient of Variation (%) in weekly rainfall during the kharif season at Anantapur

Currently, it is possible to get reliable information about actual rainfall received since the onset of monsoon, forecast for the next week and outlook for the following week. Many state governments have established extensive rainfall gauging networks which provide regularly updated real time rainfall data. For example the Andhra Pradesh State Development Planning Society (APSDPS) disaster mitigation program manages a network of 1,876 rain gauges distributed all over the state with at least one gauge in every 100 km2. The data from these weather stations is accessible through internet (http://www.apsdps.ap.gov.in/pages/weather_observations/automatic_weather_station.html). Also available are the weekly weather forecasts at block level and bi-weekly outlooks at district level from IMD which are regularly updated and made available through their web site. Together, they make it possible to assess weather conditions over a three week period reliably which when integrated with decision making can assist in planning of various operations.

Time of planting is one of the key decisions that farmers have to make after the onset of monsoon to achieve good yields. Early planting without allowing time to accumulate sufficient moisture in the soil profile can lead to poor establishment or sometimes complete failure when planting is followed by a dry spell of two week or longer. Using the same decision tree approach, a week by week decision matrix that can guide decision makers towards making balanced and well-reasoned decisions from planting to harvesting was developed. The decision tree is based on rainfall during the past week, forecast for the next week and outlook for the next two weeks leading to eight possible scenarios every week. Each scenario will lead to a decision which is captured and sent as a short message. An example decision matrix for the meteorological weeks 23 (4-10 June) and 24 (11-17 June) is presented in Figure 17 and associated messages in Figure 18. The threshold values used to test the condition are based on results from simulation analysis. Generally, planting and other operations are conducted based on moisture content in the soil. However, considering the high variability and associated difficulties in making accurate estimates of real time soil moisture, rainfall is used as a surrogate measure of soil moisture. Under rainfed conditions, rainfall is the only source of soil moisture and there exists a good relationship between amount of rainfall and soil moisture content. Similar decision trees were constructed for all weeks during the main cropping period from June to October and the decision tree for a specific week focuses on activities that are expected to be carried out in that week. The content of the message linked to eight possible scenarios every week changes to cover the key decisions that are to be made during that week, location and crops of interest to the registered farmers.

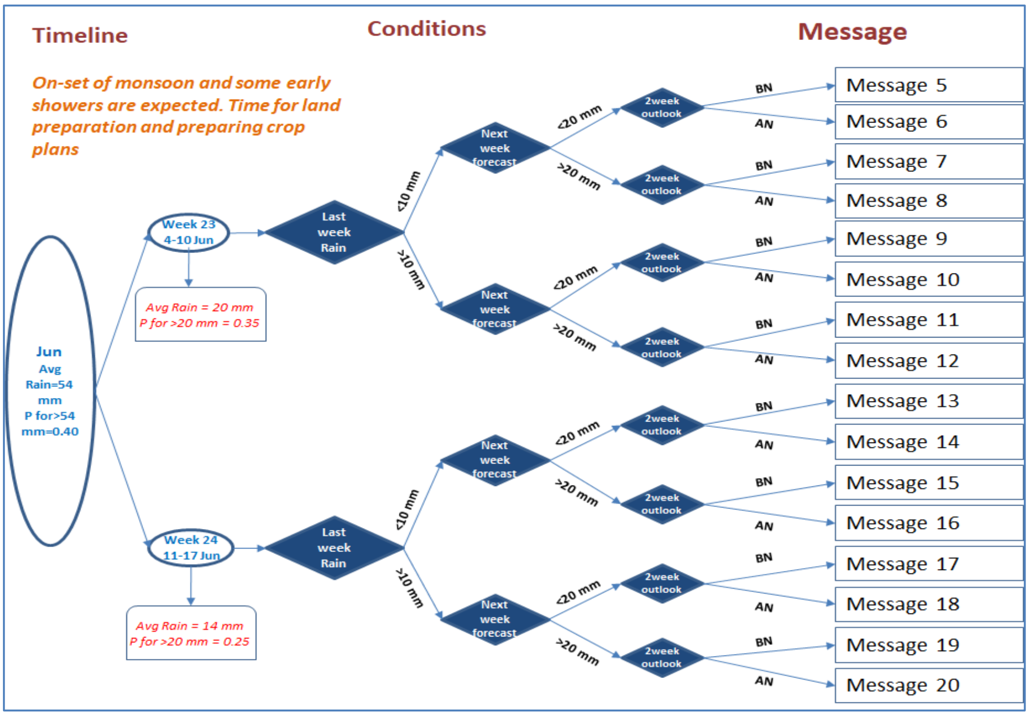


Figure 17. Decision matrix for the standard meteorological week 23 (4-10 June) and 24 (11-17 June) during which monsoon is expected to set

LW<10; NW<20; 2WO: BN
Message 5: *The monsoon is not yet active. Wait until a good rain is received.*

LW<10; NW<20; 2WO: AN
Message 6: *The monsoon is not active yet but the forecast for next two weeks is positive. Time to plan for operations such as land preparation and application of FYM.*

LW<10; NW>20; 2WO: BN
Message 7: Though *some rain is expected during the coming week, forecast for the next two weeks is indicating limited rain. Wait and continue with land preparation, preparing seed, transporting FYM and other preparations.*

LW<10; NW>20; 2WO: AN
Message 8: *Some rain is expected during the coming week with positive forecast for the next two weeks. Get ready with operations such as land preparation and application of FYM.*

LW>10; NW<20; 2WO: BN
Message 9: *Some areas received rain last week but forecast for the next two weeks indicates not much rain forthcoming. Wait and continue with land preparation, preparing seed, transporting FYM and other operations.*

LW>10; NW<20; 2WO: AN
Message 10: *Some areas received rain with a possibility to get more rains during the coming two weeks. Get ready to perform operations such as land preparation and application of FYM.*

LW>10; NW>20; 2WO: BN
Message 11: *Some areas received rain last week with a possibility for more rain this week. Since two week forecast is not positive, wait and continue with land preparation, preparing seed, transporting FYM and other operations.*

LW>10; NW>20; 2WO: AN
Message 12: *Some areas received rain last week with more rain forecasted for the next two weeks. Complete land preparation for early planting.*

Figure 18. An example set of messages for the week 23 linked to the eight possible scenarios in the decision tree

Convert decision trees into executable programs

Putting the decision tree into action involves getting or accessing real time data from various sources as required to test the criteria set at each node, evaluate the criteria and select most appropriate action depending on the location specific information on soil and cropping system. Microsoft, India has developed the required algorithms to implement these steps. The data requirement to implement the pre-season and in-season decision trees included SCF, El Nino-La Nina conditions, past week rainfall, next week forecast and two week outlook. The information is available at the web sites of the respective organizations (Table 5).

Table 5. Variables used in the decision tree and data sources to test the variable

Variable	Organization	Web site
Seasonal climate forecasts	IMD	http://www.imd.gov.in/pages/monsoon_main.php
	ERFS	http://www.tropmet.res.in/erpas/ http://nwp.imd.gov.in/cfs_rf.php
	CPC NOAA	http://www.cpc.ncep.noaa.gov/products/international/nmme/html_seasonal/precip_anom_sasia_body.html
El Nino La Nina outlooks	BoM	http://www.bom.gov.au/climate/enso/outlook/#tabs=Outlook
	CPC NOAA	http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/enso_advisory/ensodisc.shtml
Daily rainfall data	APSDPS	http://www.apsdps.ap.gov.in/pages/weather_observations/automatic_weather_station.html
Weekly forecast	IMD	http://www.imdagrimet.gov.in/dwf/Andhra%20Pradesh
	aWhere	http://www.awhere.com/
Bi-Weekly outcome	IMD	http://www.imd.gov.in/pages/extended.php

The online decision portal designed by Microsoft, accesses the data from these sources and tests the conditions at different nodes and picks the appropriate message (Figure 19).

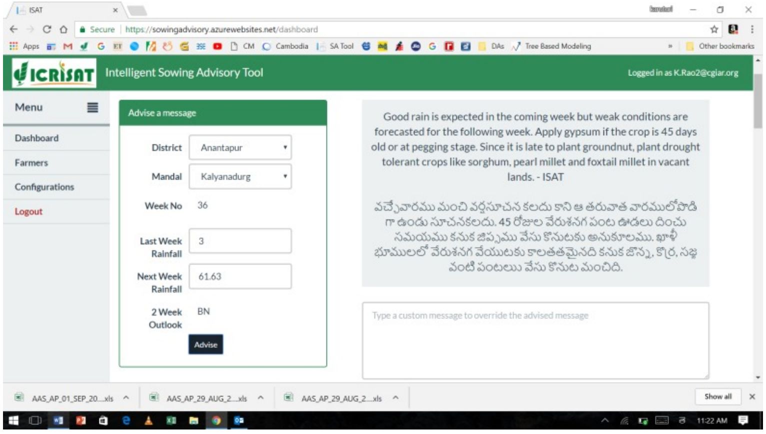


Figure 19. Screenshot of dashboard that picks appropriate messages from the database based on the outcome of decision tree

The portal was configured to compose messages in local languages and send automatically to the corresponding recipients based on their locations (Figure 20). The messages are customized at mandal levels and all farmers registered to that mandal receive the same set of advisories. The dashboard is flexible enough to handle even finer grained separation, for example village level. The configuration settings for the tool allows the user to perform the following operations and the same can be altered from the dash board.

- Threshold settings: to configure the weekly thresholds and override them if needed
- Message settings: to configure the exact message in any language which needs to be sent to a recipient, based on the decision tree
- Mappings: to bind the messages to the nodes of the decision tree
- Outlook Settings: to configure the short term outlooks to the decision tree.

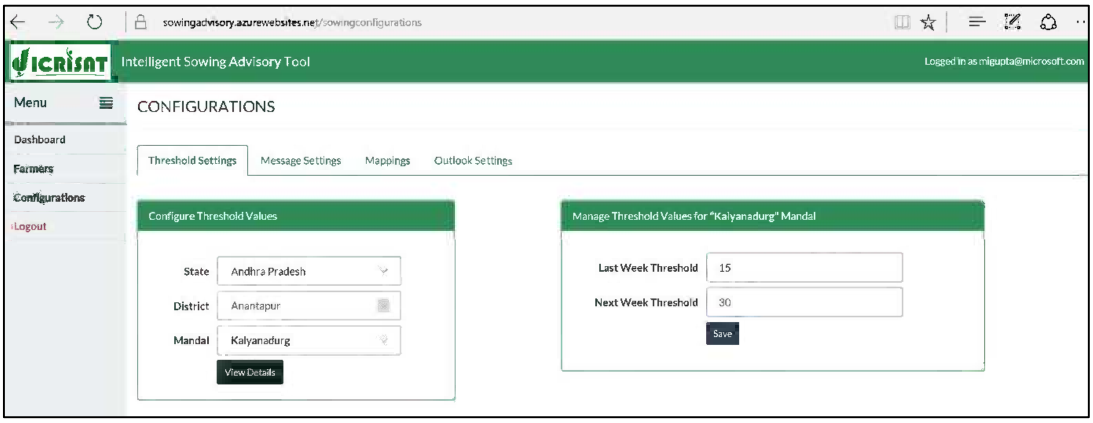


Figure 20. Screenshot of the configuration tab in the dashboard

The dashboard sends out automated message every Friday, based on the rhythm decided upon. The messages are picked from the message configuration setting as described above. The admin group has an option to edit the message before sending it out to the farmers. The dashboard is linked to an information dissemination system that includes a list of farmers registered to receive the messages with details about their mobile number, village, mandal and district. The list of farmers can be edited and modified from the 'Farmer' tab on the portal. This is maintained under more stringent administrative control to make sure that the correct message reaches to the correct farmer based on his/her location.

Testing and evaluation of ISAT tool

ISAT was field tested at four locations in Anantapur district to assess the functioning of the system and to evaluate the potential contribution of the information disseminated by the tool in improving pre-season planning and in-season crop management. Initially, the implementation team visited the villages and sensitized the farmers about the tool and the type of messages that they will receive after registering with the program. In two of the four villages, Turkapally in Gooty mandal and Gubanapalli in Kalyandurg mandal, the team made a detailed presentation about the high variability in the climate and how this variability affects the decision making by creating uncertainty and confusion. They have also presented with and discussed about the probabilistic nature of climate information and potential role this information can play in managing the risks and opportunities created by variable climatic conditions. In the remaining two villages, West Narasapuram in Singanamala mandal and Ramapuram in Kanaganapalli mandal, farmers were briefly explained about the program and registered the willing farmers into the program. Hence, while assessing the performance of ISAT, we considered these four villages under two categories. The first two villages which received advisory and went through the skill enhancement program are referred to as "AES" (Advisory + Enhanced Skill) villages and the other two villages that received only advisory are referred to as "ABS" (Advisory + Base level Skill) villages.

A total of 417 farmers have registered to receive the messages and village wise details of the registered farmers are summarised in Table 6. All registered farmers have a mobile but most of them are basic phones with only calling and SMS facility. Very few farmers, about 6.7% own a smart phone. In all four villages, most farmers have no access to SCF information but few farmers follow climate information provided by radio, TV and other mass media channels. These are mostly weather forecasts or updates. Agriculture is the main livelihood accounting for 64% of the total household income. Casual employment and livestock are the other two main livelihood activities, which together contribute 30% to the total income. Average size of household is 4.22 and average size of land holding is 9.0 acres (3.4 ha). In general, the literacy rate is very low. About 31% of the farmers interviewed have no formal education and another 26% have only some years of primary schooling.

Table 6. Demographic characteristics of the sample population

Variable	Gubanapally/ Kalyanadurg	Turkapally / Gooty	Ramapuram/ Kanaganapalli	West Narasapuram /Singanamala	All Villages
No of Households	115	104	112	86	417
Farmers growing groundnut as main crop	106	68	105	73	352

Red soil	114	3	112	83	312
Farmers with smart phone	8	19	0	1	28
Receiving SCF	5	0	6	1	12

Advisories were sent to the mobiles of registered farmers on every Friday through the season in the form of short messages. Though the messages were prepared both in English and Telugu, almost all farmers opted for Telugu version. The performance of the system was evaluated by conducting two surveys. First one, the mid-season survey was conducted halfway through the season in the month of August, 2018 and the second after the harvest of the crop in December, 2018. The mid-season survey is a brief exploratory one to find out whether farmers are receiving messages regularly and how planting and other operations have progressed. The end-season survey is a more detailed assessment covering a range of issues from delivery, appropriateness and usefulness of the information to contribution of the information to change decisions and benefits derived from the changed decisions.

The mid-season survey covered 348 of the 417 registered farmers while 363 farmers participated in the end-season survey. In both surveys, a nearby village was included as a control village. The farmers in these villages have not received any information and are not aware about the work going on in the other villages. A minimum of 25 farmers were interviewed in each village. Most farmers covered by the survey are men. Hence, no attempt was made to conduct gender disaggregated analysis. This low level of women participation is a true reflection of the conditions in the district. In these areas, participation of women in decision making is extremely low. However, most farmers indicated that within the household women make significant contribution while making various decisions including those related to farm management. Further, most women do not own or have access to mobile phone.

In general, the system worked very well by delivering messages regularly to 95% of the registered farmers (Table 7). In the case of remaining small percent of farmers, the failure is mainly due to the type of mobile phone and the way message inboxes were configured. Most mobiles owned by farmers are very old basic models with limited storage. Some of these mobiles were not set to automatically overwrite older messages when the inbox is full. This affected the delivery of new messages when old messages were not deleted from inbox. This problem was fixed by making required changes to settings with help from a local service provider. Among other problems, splitting the messages into two or more messages while delivering the original message was experienced by some farmers. This is partly due to the use of local language whose word or character count tend to be higher compared to that in English. Because of this, the original message was spilt into two or more messages as per the character limit set by the service provider. This splitting is arbitrary and the resultant messages are not clearly understood unless they are put together to read as one message.

Table 7. Farmer assessment of access, timeliness and appropriateness of the messages

Village*	Received messages		Timing and frequency		Clear and ease to understand		Relevance of issues covered		Info sharing with others	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gubanapalli *(Kalyanadurg)*	99.0	1.0	84.5	15.5	98.1	1.9	93.2	6.8	32.0	68.0
Turkapalli *(Gooty)*	100.0	0.0	82.2	17.8	94.5	5.5	95.9	4.1	34.2	65.8
Rampuram *(Kanaganapalli)*	89.8	10.2	71.3	28.7	85.2	14.8	61.1	38.9	25.9	74.1
West Narasapuram *(Singanamala)*	92.4	7.6	78.5	21.5	75.9	24.1	64.6	35.4	43.0	57.0
All villages	95.0	5.0	78.8	21.2	88.7	11.3	78.0	22.0	33.1	66.9

* Mandal names are in parenthesis

Nearly 79% of the farmers are satisfied with the weekly frequency of the messages and with updates coming on every Friday which is also the day on which IMD releases its weekly weather forecast. In terms of clarity and understandability of the messages, 89% of the farmers felt that the messages are clear and easy to understand. However, some differences were observed between the expectations of farmers and the issues covered by the messages. While most farmers, about 78%, felt that the messages are covering all major issues relevant at that time, some farmers felt that the messages have no information about the management of mango and other horticultural crops and about the occurrence and management of pests and diseases. Lack of information on horticultural crops is understandable since the focus is on annual field crops. However, the demand for information on pests and diseases is extremely high but there are serious challenges in meeting this demand. There is a possibility to send general alerts about possible pest and disease scenarios based on climatic conditions such as prolonged wet and dry periods but their reliability is very low. Sending frequent alerts with low probability of success, will impact adversely the reliability and acceptability of the entire system. Hence, no efforts were made to incorporate pest and disease alerts in ISAT generated messages.

Major differences were observed in the opinions expressed by farmers from AES and ABS villages. While more than 93% farmers from AES villages are satisfied with the coverage of issues, 61-65% farmers from ABS villages have expressed satisfaction. Similar differences were also observed in the rating of clarity and understandability of the messages. This highlights the need to create awareness and enhance capacity of end users to understand and use the information provided.

Reliability and usefulness of the messages in decision making

End user perception about reliability of the information provided is one of the essential performance parameters, since acceptance and utilization of the information largely depends on it. Across the villages, 72% of the farmers rated the information provided through short messages is highly reliable and useful while another 19% rated it as acceptable (Table 8). This rating of reliability is based on the observations farmers have made by comparing the advance information received through SMS at the beginning of the week with actual conditions during the week. About 58% of the farmers rated the information as “mostly correct” or “correct 75% of the times” and another 33% rated it as “correct more than 50% of the times”. This observation reflects the farmer’s practical experience rather than systematic assessment. Since the opinions are captured immediately after the season, they are considered to be more unbiased and credible.

Table 8. Farmer assessment of the reliability of the information provided

Village*	Reliability of the information (% farmers)				Reason for reliability (% farmers)			
	Highly Reliable	Acceptable	Unreliable	Do not know	Mostly correct	Correct >75% times	Correct >50% times	Mostly incorrect
Gubanapalli *(Kalyanadurg)*	74	23	1	2	10	52	35	1
Turkapalli *(Gooty)*	89	8	0	3	14	62	22	0
Rampuram *(Kanaganapalli)*	66	26	4	5	12	42	35	4
West Narasapuram *(Singanamala)*	63	15	1	20	8	33	37	1
Total	72	19	2	7	11	47	33	2

* Mandal names are in parenthesis

Since much of the information in the advisory is based on climate and weather forecasts, the reliability scoring given by farmers is a direct reflection of forecast skill. Though the forecasts are not accurate, the good rating given by farmers is a clear indication that the current skill is useful in decision making. For example, before start of the season and SCF was made available, 58% of the farmers were expecting a poor season (Table 9). Majority of these farmers (68%) have indicated that their expectation is based on the poor rainfall during the previous season which they expected to repeat. After climate forecast from IMD, which predicted a normal rainfall, was made available 86% of these farmers changed their opinion and expected a more favourable season than they were anticipating initially. One of the main reasons for changing their expectation is that the forecast is more scientific compared to local information which is based on beliefs and unscientific measures. In the end season survey, 74% of the farmers rated the season as good compared to 12% before the start of the season and only 6% of all farmers rated the season as poor which is a substantial drop from 58% at the start of the season.

Table 9. Farmer expectation about seasonal rainfall at the start and after the season

Village*	Expectation at the start (%)			Change after message (%)	Rating at the end (%)		
	Good	Average	Poor		Good	Average	Poor
Gubanapalli *(Kalyanadurg)*	11	11	79	78	48	38	15
Turkapalli *(Gooty)*	5	55	40	92	75	19	3
Rampuram *(Kanaganapalli)*	13	29	58	93	93	6	2
West Narasapuram *(Singanamala)*	16	37	47	84	82	16	1
Total	12	31	58	86	74	20	6

* Mandal names are in parenthesis

The mandal level weekly rainfall forecasts from two sources, IMD and “aWhere”, were also evaluated by comparing the predicted and observed rainfall amounts for sixteen weeks starting from 26th week (25 Jun-1 Jul), except for the weeks 37 (10-16 Sep) and 38 (17-23 Sep) for which forecast data is missing. Though there is no one to one match between the amount of rainfall forecasted and actual rainfall during that week, the forecasts were able to provide a reasonable indication about the type of wet or dry conditions that can be expected over the coming week (Figure 21). It is important to note that the comparison is between the site based observation and grid based forecast. Comparison of daily cumulative rainfall amounts also confirm the close relationship between the trends in observed and forecasted (one day advance) rainfall amounts. However, major deviations were observed in case of heavy rainfall forecasts.

Figure 21. Predicted and observed weekly rainfall amounts (above) and cumulative rainfall during kharif 2017 for Gooty (middle) and Singanamala (bottom) mandals in Anantapur district

The opinions expressed by farmers about reliability of the information provided through SMS highlights how imperfect information can be used as a basis for informed decision making and derive benefits. During the pre-season FGDs, only 3% of the farmers have indicated that the forecast information is reliable and useful in making decisions related to planning and management of their farm activities. However, more than 90% of the same group of farmers rated the forecast based advisory as reliable and useful. This is a highly significant change in the attitude of the farmers towards climate information brought by their exposure and awareness about the uncertainties and limitations associated with climate information and by the practical experience gained by using the information. Such attitude changes will have far-reaching consequences by changing the way in which farmers make decisions and conduct various operations.

Contribution to change decisions and value of changed decisions

Since the value of advisory depends on its contribution to make better decisions, attempts were made to capture the same in both mid and end season surveys. The mid-season survey collected information about the type of crops planted, time of planting and area planted to each crop. In this area time of planting is one of the most important operation and major differences were observed in the way planting was carried out by farmers in treatment and control villages. Most farmers in the treatment villages planted the crop within the optimal planting window while those from control villages planted either very early as in Kalyandurg and Kanaganapalli or late as in Gooty (Figure 22). Another contrasting feature is the difference in the period during which the planting was carried out. In control villages planting was done over a long period of time compared to treatment villages in which more than 80% of the farmers completed the sowings over a short period of 2-3 days. In case of Singanamala, most farmers planted castor which is a long duration drought tolerant crop and it is generally planted using the earliest planting opportunity. These results clearly establish that farmers planting decisions are influenced by the information provided through advisories.

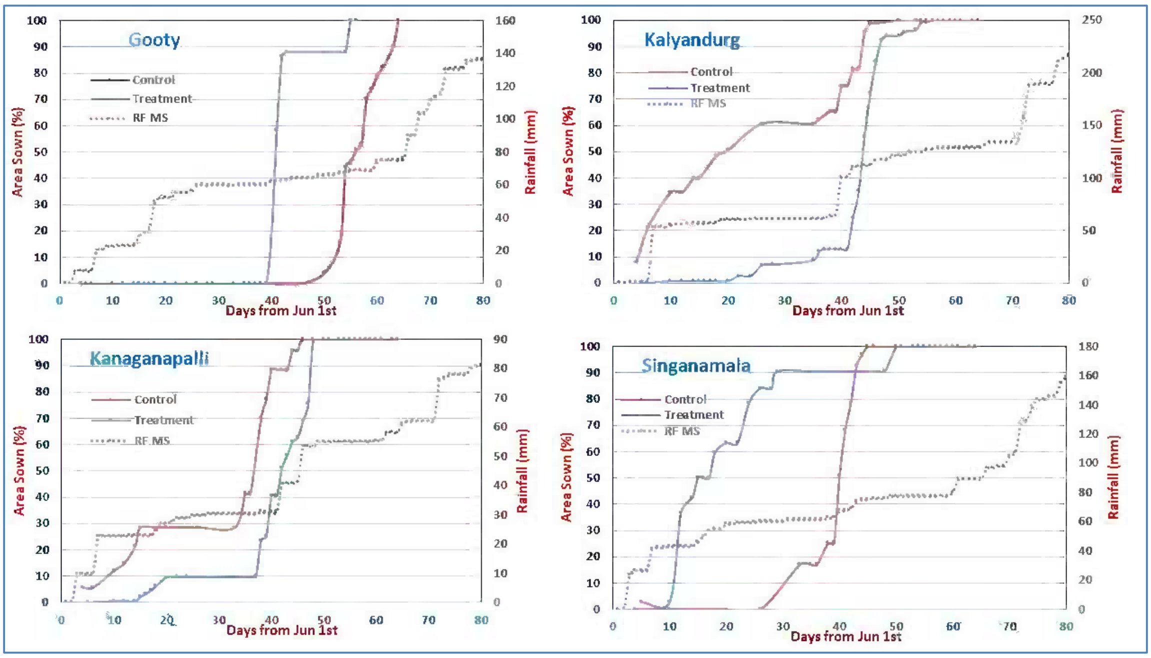


Figure 22. Trends in planting of groundnut in the treatment and control villages and rainfall from 1st June during 2017 kharif season for Gooty, Kalyandurg, Kanaganapalli and Singanamala mandals of Anantapur district

More detailed information about changed decisions was collected during the end season survey by asking farmers whether the information provided through advisories helped them in planning farm operations or not and if helped, what are those operations and how the information helped. Overall, 78% of the farmers have indicated that the advisories helped them in planning various farm operations through the season (Table 10). While almost all farmers in the AES villages of Gubanapalli and Turkapalli have used the information in planning various operations, the utilization is low in case of ABS villages. About 46% of the farmers from Ramapuram and 79% from West Narasapuram have used the information. Among the operations, more than 66% farmers used the information in planning harvesting and 57% used it in scheduling spraying and fertilizer applications. Though a significant difference was observed in the sowing pattern between treatment and control villages, only 46% farmers have indicated that their sowing decision was influenced by the advisory. The percentage is especially low in case of West Narasapuram where most farmers planted castor. Advisory has least influence in conducting land preparation, which is understandable since most farmers will prepare the land irrespective of the type of season and crop to plant.

Table 10. Utilization of ISAT advisory in planning various operations by farmers (% farmers) in the four villages

Village*	Planning	Harvesting	Spraying and fertilizer	Intercultural operations	Sowing	Land preparation
Gubanapalli *(Kalyanadurg)*	97	85	36	45	71	9
Turkapalli *(Gooty)*	97	97	32	38	80	8
Rampuram *(Kanaganapalli)*	46	61	83	58	30	2
West Narasapuram *(Singanamala)*	79	22	73	65	6	5
Total	78	66	57	52	46	6

* Mandal names are in parenthesis

To get an idea about the level of advisory influence on the final decision, farmers were asked to indicate the same on a scale of 0-100%, where 0% indicates no influence and 100% indicates that the decision is entirely based on the advisory. Farmers have a difficulty in responding to this mainly due to the difficulty in separating the contribution of advisory information from that of their own rationale or influence of information from other sources. With help from the enumerators, farmers were able to make some indication about potential contribution of advisory. Majority of the farmers have rated the contribution of advisory as 50% or more and much of this is on timing the operation (Table 11).

Table 11. Farmer assessment of the influence of ISAT advisory information (on a scale of 0-100%) to decision making

	Harvesting	Intercultural operations	Planting	Allocation of land
Gubanapalli *(Kalyanadurg)*	95	93	80	68
Turkapalli *(Gooty)*	97	96	90	66
Rampuram *(Kanaganapalli)*	68	63	26	0
West Narasapuram *(Singanamala)*	53	81	14	3
Total	78	82	51	33

Another approach we tried to assess the farmer perceived value of the advisory is by gauging their continued interest in receiving the messages and by getting an idea about the value they attach to the advisory based on the observed benefits. In case of farmers interested to continue with the program, the level of interest was assessed by asking them to select one of the three options provided. The first option is for farmers who are fully convinced about the value of the information and certainly want to continue to receive the advisories. The second option is for those farmers who are convinced with the value of the information and interested in receiving the advisories but at no cost. The third option includes those farmers who believe that the information is useful but do not mind missing the advisories. About 96% of the farmers have indicated their interest in continuing with the program and receive the messages (Table 12). While 91% of them selected the first two options, 5% opted for the third. These differences are also reflected in the perceived value of the information which is the portion of the income earned during the season that they attribute to the advisory based decisions. With the exception of Gubanapalli, the perceived value from the advisory based decisions by the first two groups is 4-6 times higher than the value perceived by the third group. In Gubanapalli only two farmers are under this group. It is interesting to note that the perceived benefit by the second group is higher than the first group.

Table 12. Farmer interest in continue to receive the messages and their perceived value of the information in managing the systems

Village*	Continue to receive messages (% farmers)			Value of the information (Rs)			
	Yes_certainly	Yes_if possible	Yes_do not mind	Yes_certainly	Yes_if possible	Yes_do not mind	All
Gubanapalli *(Kalyanadurg)*	47	50	2	528	1264	1750	924
Turkapalli *(Gooty)*	56	41	0	1670	1842	-	1742
Rampuram *(Kanaganapalli)*	26	61	7	2957	5709	213	4271
West Narasapuram *(Singanamala)*	61	25	10	4377	2135	600	3261
Grand Total	45	46	5	2344	3229	556	2607

* Mandal names are in parenthesis

Considering the positive feedback on the value and usefulness of the information, farmers were asked to indicate how the advisories have helped them. Farmers have indicated four major ways in which advisories have helped them in planning farm operations (Table 13). These include providing reliable information about climate, practical advises about various operations, enhanced confidence in decision making and make them think about various alternatives before making the final decision.

Table 13. Farmer assessment (% farmers) of contribution of ISAT information to decision making

Village*	Source of reliable information	Advise about various operations	More confident decision making	Make me think and act

Gubanapalli *(Kalyanadurg)*	41.8	26.2	24.3	5.8
Turkapalli *(Gooty)*	58.9	15.1	13.7	9.6
Rampuram *(Kanaganapalli)*	27.8	20.4	19.4	20.4
West Narasapuram *(Singanamala)*	13.9	43.0	24.1	12.7
Grand Total	34.7	25.9	20.7	12.4

* Mandal names are in parenthesis

Benefits from changed decisions

Making timely decisions, better management of crops, reduced cost of cultivation and better crop selection are the four ways by which farmers were benefitted with information form the advisory (Table 14). About 41% of the farmers felt that the advisories helped them in making better and timely decisions in conducting farm operations. About 7% of the farmers have indicated that they are benefitted either by reducing the cost of cultivation or by advisory based crop selection. Much of the reduction in cost of cultivation is from plant protection activities. Though the advisories have no specific information on the occurrence of pests and diseases, farmers scheduled their spraying operations based on the forecast. The low contribution of pre-season advisory to crop selection is a reflection of the limited crop choices available to the farmers in this region.

Table 14. Farmer assessment (% farmers) of benefits from improved decision making using ISAT advisories

Village*	Benefits from improved decision making (% farmers)			
	Timely decisions	Better management	Reduced cultivation cost	Selecting right crops
Gubanapalli *(Kalyanadurg)*	44.7	26.2	7.8	3.9
Turkapalli *(Gooty)*	53.4	24.7	6.8	4.1
Rampuram *(Kanaganapalli)*	32.4	26.9	3.7	17.6
West Narasapuram *(Singanamala)*	36.7	26.6	10.1	0.0
Grand Total	41.0	26.2	6.9	7.2

Note: Not included in the table is the “cannot say” group which accounts 26% farmers on “benefits from improved decision making” and 8% farmers on “suggested changes”

* Mandal names are in parenthesis

The overall benefit from access to climate information was computed by comparing the yields achieved by farmers in the treatment villages with those achieved by farmers in the control villages. Though more than 20 crops are under cultivation in these villages, groundnut is the only crop that is grown by all farmers in all the villages. Pigeonpea is the other crop that is grown more widely but this being a long duration crop, harvesting and threshing was not completed at the time the survey was conducted in December. Hence, we limited the assessment to performance of groundnut. In general, groundnut yields were found to be higher in the treatment villages compared to control villages except for Kanaganapalli where yields in control village are 7.7% higher compared to treatment village (Table 15).

Table 15. Groundnut yields achieved by farmers in treatment villages with access to climate information and by farmers in the control villages without access to climate information

Mandal	Treatment		Control		% change
	Village	Groundnut Yield (kg/ha)	Village	Groundnut Yield (kg/ha)	
Gooty	Turkapalli	1118	Mamuduru	716	56.2
Kalyandurg	Gubanapalli	939	Kurabarahalli	741	26.7
Kalaganapalli	Rampuram	695	Balepalem	753	-7.7
Singanamala	West Narasapuram	1305	Chinna Maltigondi	945	38.0
All		923		795	16.2

A critical examination of the yield trends in all villages indicate a strong influence of planting time on groundnut yields. For example, in Gooty mandal farmers in the treatment village planted 10 to 15 days earlier compared to farmers in the control village. This is within the optimal planting window and the crop was benefitted by the good rainfall the area received 15 days after planting by which time the crop was germinated and entered the active growing period. In case of control village, farmers missed this opportunity by planting 10-15 days late (Figure 23). In case of Kalyanadurg mandal, farmers from control village started planting very early in the season and the planting continued for more than a month. The plots which were planted very early in the season faced severe stress during the prolonged dry spell that followed sowing. In the treatment village, most farmers planted groundnut in the second week of July after receiving 40 mm rainfall and benefitted by the good rainfall that followed. The small negative difference in the yields achieved by farmers in the control and treatment villages of Kanganapalli mandal reflects the very similar planting pattern followed by farmers in these villages (Figure 23). Though a 38% higher increase in groundnut yield was recorded in the treatment village over control village in Singanamala mandal, the total area under groundnut in the treatment village is very low. In this village most farmers planted castor and the area planted to groundnut accounted less than 12% of the total 543 ac planted during the season. As indicated earlier, the decision to plant castor was influenced by the failure of groundnut crop during the past four seasons and recommendation by the local agencies. This highlights the importance of informed decision making. Most farmers who followed this advice failed to capitalize on the season since castor is not a profitable options during the seasons that receive normal or above normal rainfall. Hence, empowering farmers to make informed decisions by providing the required information will be more appropriate and effective over prescriptive extension which is directive and rigid.

Though planting time seems to be the major contributor to the observed differences in yields achieved by farmers in the control and treatment villages, the contribution of climate information in conducting operations such as scheduling fertilizer and pesticide applications cannot be ignored. The benefits from these and from timely harvesting may not reflect in the production or productivity figures, but contribute significantly to the grain and stalk quality whose value cannot be assessed precisely. Also difficult to measure are benefits accrued from risk reduction and change in the attitude towards managing climate induced uncertainties.

Overall assessment

Considering various tangible and intangible benefits, farmers were asked to rank the usefulness of climate information in planning and managing agricultural systems on a scale 1-5, where 5 represents highest level of benefits. More than 87% of the farmers rated the service by assigning 3 or higher score with an average score of 3.3. About 86% of the farmers gave a rating of 3 and 4 while 13% farmers rated it as 1 and 2 (Figure 23). Most of the farmers who gave a low score are the farmers who are concentrating on irrigated component of their farm or involved with cultivation of mango and other perennial tree crops which are not covered by the advisory. Though the average score of 3.3 is good, it does not reflect well the significant benefits that the farmers gained. This probably is an indication of the difference between their expectations and those realized. To meet their expectations fully, the advisories should be tailored to meet the full needs and requirements of individual farmers. Given the diversity of smallholder farmers, meeting individual farmer requirements is a formidable challenge. However, there are opportunities to improve the current system and provide farmer specific advises.

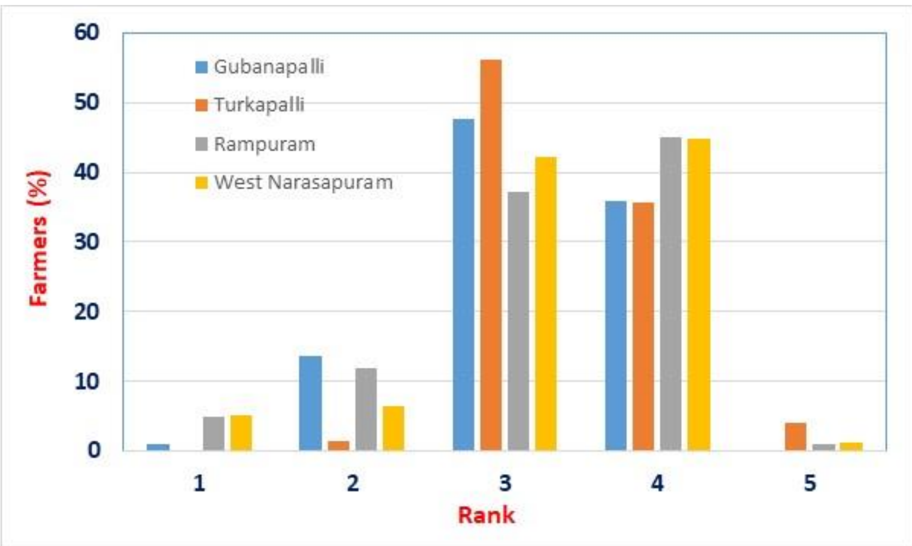


Figure 23. Ranking of usefulness of ISAT advisories by participating farmers on a scale of 1-5

Conclusion/recommendations

Though there is considerable interest in promoting climate services to increase the resilience of smallholder farmers to impacts of climate variability and change, providing effective climate services remains a challenge. This study has demonstrated the opportunities available to harness the untapped power of digital technologies to compile up to date and real time information from widely distributed sources and analyse and present the same in user friendly formats to millions of end users. It also highlighted the scope to enhance and strengthen the effectiveness and value of the climate services by integrating them with appropriate data analytics that provide actionable insights to address end user concerns.

One of the major hurdles in promoting use of climate information based services is the end user concern about the reliability or accuracy of the information. Most end users are pessimistic about climate forecasts and consider them as unreliable for use in decision making. Evidence form this study suggests that it is possible to change this perception by converting and presenting climate information in an actionable form. The same group of farmers who perceived forecasts as unreliable, have rated forecast based advisories as reliable and useful. The exposure they got made them realize that the forecasts, though not perfect have enough skill to use in planning farm operations and benefit from reduced risk and improved profitability. This change in the attitude of farmers towards the role of climate information will have far-reaching consequences on the way farmers make decisions and conduct operations.

Climate services also play an important role in reducing biases or influences of certain extreme events and make decision making more realistic. The case of Singanamala is an example of this. In this village farmers decided to opt for castor, a drought tolerant but less profitable crop, since they suffered losses by planting groundnut in the past 3-4 seasons. This is also a decision supported by some of the developmental agencies. As a result they missed the opportunity to benefit from a season that is good for groundnut. This type of decisions can be avoided if farmers and their support agents are supported to make informed decisions that make best use of the seasonal conditions.

Providing access to climate information or products based on climate information alone is insufficient to achieve the desired results because of the probabilistic nature of the information and difficulties associated with interpretation and utilization of such information. There is a need to enhance the capacity of the farmers and their support agents to understand the uncertainties associated with the information and its potential impact on the outcome. This is extremely important for continued and sustained use of climate information based services.

ISAT clearly demonstrated the opportunities available for improving the productivity and profitability of smallholder farms using smart technologies that combine digital connectivity with intelligent processing. It is possible to develop more advanced systems to develop and deliver even farmer specific information once the required input datasets are built and made accessible. Such systems reduce the farmer reliance on extension and other agencies for information and enables them make better and timely decisions which, under uncertain environmental conditions are vital for efficient and productive management of agricultural systems. This type of systems are also easy to take to scale and reach millions of end users cost effectively.

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