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Investment Planning to Minimize Climate Risk in Agricultural Production

An Optimization Model for a Semi-Arid Region in India

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ABSTRACT

The primary aim of this study is to prioritize investment required for scaling up climate-smart agriculture (CSA) technologies across different districts of Telangana state, which is in the semi-arid region of India. First, we analysed the trade-offs between expected agricultural income and its deviation across districts under drought and normal weather scenarios. The conventional MOTAD model was extended with various climate-smart technologies to assess their role in minimizing the trade-offs under various weather scenarios. A district-level panel dataset on cost of cultivation and crop production for 11 major crops under six different climate-smart technologies and farmers' traditional practices (FTPs) for five years (2010-11 to 2014-15) has been used. The dataset comprised a collation of official statistics on cost of cultivation, focus group interviews with farmers over the years, and data from experimental plots of Regional Agricultural Research Stations. The analysis reveals that the adoption of CSA technologies is likely to reduce production risk by 16% compared to FTPs while achieving optimum levels of crop income. Under a scenario of higher probability of drought, production risk is likely to increase by 12% in the state under FTPs; the adoption of CSA technologies could reduce the risk by 25%. The study suggests increasing investments in farm ponds and un-puddled machine transplanting in rice to minimize the risk-return trade-offs under a higher drought frequency scenario. Finally, the study generates evidence for policymakers to make informed investment decisions on CSA in order to enhance farming systems resilience across districts in the semi-arid state of Telangana, India.

Keywords: Climate Smart Agriculture, Agricultural Technology, Investment Planning, Risk Minimization

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ACRONYMS

ADL	Adilabad
BBF	Broad Bed and Furrow
CRI	Crop Residue Incorporation
CSA	Climate Smart Agriculture
DRP	Drip Irrigation
FAO	Food and Agriculture Organisation
FGD	Focus Group Discussion
FPN	Farm Pond
FTP	Farmers' Traditional Practice
GCA	Gross Cropped Area
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IMD	India Meteorological Department
KAR	Karimnagar
KHA	Khammam
KVK	Krishi Vigyan Kendra
MED	Medak
MHB	Mahabubnagar
MOTAD	Minimization of Total Absolute Deviations
NAL	Nalgonda
NZM	Nizamabad
QP	Quadratic Programming
RF	Ridge and Furrow
RNG	Rangareddy
UPM	Un-puddled Machine Transplanting of Rice
WAR	Warangal

INTRODUCTION

The arid and semi-arid tropical countries of the developing world account for approximately 30% of the world's total land area and are inhabited by 38% of the developing countries' poor, 75% of whom live in rural areas. Over 45% of the world's hungry and more than 70% of its malnourished children live in these regions (Selvaraju, Gommes and Bernardi, 2011). Weather and climate are the main drivers of agricultural production and heavily influence overall variability of food production in this region. Growing frequency of extreme heat and cold, droughts and floods, and various forms of climatic variability have drastic impacts on agricultural productivity, farm incomes, and food security in this region (Battisti and Naylor, 2009). Therefore, adaptation to climate variability is key to reducing vulnerability to longer term climate change. A long-term adaptation strategy in agriculture depends on addressing similar issues in the short term, recognizing the fundamental truth that adaptation is a location-specific and continuous learning process (FAO, 2008). Adaptation strategies must therefore contribute to current development priorities, reduce vulnerability, and be in sync with the shorter planning horizons of the farmers. Climate-smart agriculture (CSA) (Aggarwal et al., 2018; Lipper et al., 2014) has proven to be an effective strategy to achieve "win-win" outcomes by integrating climate change adaptation into the planning and implementation of sustainable agricultural strategies. CSA calls for a set of actions by decision-makers, from the farm to global levels, to enhance the resilience of agricultural systems and livelihoods and reduce the risk of food insecurity in the present as well as the future. In the absence of such efforts, agriculture and food systems are likely to be less resilient and there is higher risk of food insecurity. Mainstreaming CSA into development policy and action requires the support of appropriate investment strategies for scaling up CSA technologies that are feasible, accessible and affordable for farmers in the arid and semi-arid tropics. However, the feasibility of climate-smart technologies varies across crops, soil types, weather conditions, and the availability of natural resources across different sub-regions within a region. How to allocate land to feasible, accessible and affordable climate-smart technologies presents the farmer with a typical problem of portfolio selection. The optimal allocation of land and other resources across crops and technologies are expected to be guided by the risk-return trade-off faced by smallholder farmers in arid and semi-arid regions. Thus, the effective implementation of policies and investment strategies to scale up CSA would to a large extent depend on the risk attitude of farmers.

Risk attitude, as described in the expected utility theory developed by von Neumann and Morgenstren (1944), determines a farmer's preferences among alternative farm plans based on expected income (E) and associated income variance (V). The set of farm plans can be derived with the aid of a quadratic programming (QP) model that minimizes V for each possible level of E. The QP model was originally proposed by Freund in the mid-1950s and has been widely adopted since then. Overcoming the application problem of the QP model, Hazell (1971) developed a linear alternative to it called the MOTAD (Minimization of Total Absolute Deviation) model, which has computational advantages and provides an efficient set of farm plans quite like that obtained by the QP model. Moreover, MOTAD is theoretically as valid as quadratic programming in solving expected utility problems under the previously outlined assumptions (Johnson & Boehlje, 1981), and has been extensively used in international studies in recent decades (Hanf, 1970; Boisvert & McCarl, 1990; Hardaker, 1997; McCarl, 1998; Bechtel & Young, 1999; Ridier, 1999; Harwood, 1999; Stott, 2003). On the other hand, prospect theory, derived from expected utility approaches, proposes that decision-makers are risk averse in the domain of gains and risk seeking in the domain of losses (van Winsen et. al. 2016).

Compared to the abundant international research, studies on farmers' risk attitude in India are very few. Most economic literature largely focusses on cost-benefit analysis of various agricultural technologies, cost of adaptation to climate change, and economic impact of various agricultural policies on farmers' income, crop production, and input use (Goswami et al. 2011; Bhatt et al 2003; Khatri-Chhetri et.al. 2017; Mittal, 2018; Pal et al. 2019). A few studies describe the problem of resource allocation at the farm level to maximize production or income of the farmers (Singh et. al 2012; Jain et al. 2017; Dunnett et.al. 2018). However, few studies focus on resource allocation across climate-smart technologies taking into account weather-related risk. Hence a literature gap exists on the analysis of climate-induced risk in decision-making processes for allocating existing resources across various climate-smart technologies. As the impact of climate change is heterogeneous across various regions, adaptation must be site specific, and this requires site-specific knowledge. It is therefore important to identify context-specific and efficient sets of climate-smart technologies that reduce climate-induced risk of farmers. Further, an investment plan is required to scale up those climate-smart technologies within the planning region.

It is against this backdrop that this study aims to estimate investment on CSA and its distribution across districts of the state of Telangana in the semi-arid region of India. The additional investment required for scaling up CSA technologies across districts of this state is the key concern of this study. To accomplish that, the trade-off between the expected income of the state and deviation of income across districts has been analysed under drought and normal weather scenarios. The conventional MOTAD model has been extended with various climate-smart technologies to assess their role in minimizing that trade-off under various weather scenarios. A district-level panel dataset on cost of cultivation and crop production was prepared for 11 crops, 6 climate-smart technologies, and farmers' traditional practice for five years, from 2010-11 to 2014-15. Official statistics on cost of cultivation, focus group interviews with farmers over the years, and data on experimental plots of Regional Agricultural Research Stations were collated for the panel dataset. Although farmers face various risks that affect their income, this study has limited itself to the production risk they face due to climate variability. Given the price level, deviations in net returns from crop production across years have been modelled as production risk and solved for minimizing risk and maximizing expected income. In this study, agricultural land, investment and CSA technologies' potential area were considered as constraints and the annual average production of the selected crops in Telangana state was considered as the minimum crop production target for investment planning.

MATERIAL AND METHOD

The analytical framework for this study originates from the MOTAD model developed by Hazell and Norton (1986). The model is described below.

Sets

'd' districts of Telangana state /

ADL	Adilabad,
NZM	Nizamabad,
KAR	Karimnagar,
MED	Medak,
RNG	Rangareddy,
MHB	Mahabubnagar,
NAL	Nalgonda,
WAR	Warangal,
KHA	Khammam/
'yr'	years of analysis /2011, 2012, 2013, 2014, 2015/
'c'	crop selected for the study / cotton, soybean, groundnut, maize, red gram, green gram, tomato, turmeric, paddy, batavia, mango/
'scrp (c)'	selected crop for the model /cotton, soybean, groundnut, maize, red gram, green gram, tomato, turmeric, paddy/
'an (c)'	annual crop /batavia, mango/
't'	technology selected for crops /
BBF	broad bed and furrow,
FTP	farmers' traditional practice,
RF	ridge and furrow method,
CRI	crop residue incorporation,

FPN	farm pond,
DRP	drip irrigation,
UPM	un-puddled machine transplanting of rice

Variables

OMGVR	sum of square of negative deviation from average net return of the crop in the state as a whole
OMG	expected net return from crop cultivation used in the income maximization model
XT(d,c,t)	district-wise, crop-wise, technology-wise land use
Z(d,yr)	year-wise negative deviation in net return of each district

Parameters

lambdast	expected income of farmers used in the risk minimization model
pr(d,yr)	probability that a year will be a drought year for a district
netrn(d,c,t,yr)	district-wise and year-wise net return from crop technology
avmrgc(c)	state average net return of the crop
potnarea(d,c,t)	district-wise, crop-wise potential area of technology
crtechsuit(d,c,t)	district-wise suitability of crop
area(d,an)	district-wise area under annual crop
gcrop(d)	district-wise total area under field crop
prodn(c)	five years' average production of crops considered as minimum production target
totinv	total investment by farmers that includes operational cost, technology cost, and fixed costs associated with crop cultivation

Equations

$\frac{1}{2}\sqrt{OMGVR} = \sum_{d} \sum_{yr} Z_{d,yr}$ eq. 1

$OMG = \sum_{d} \sum_{c} \sum_{t} \sum_{yr} netrn_{d,c,t,yr}\, pr_{d,yr} XT_{d,c,t}$ eq. 2

$lambdast = \sum_{d} \sum_{c} \sum_{t} \sum_{yr} netrn_{d,c,t,yr}\, pr_{d,yr} XT_{d,c,t}$ eq. 3

$\sum_{c} \sum_{t} \left(netrn_{d,c,t,yr} - avmrgc_{c}\right) pr_{d,r} XT_{d,c,t} + Z_{d,yr} \geq 0$ eq. 4

$XT_{d,c,t} \leq potnarea_{d,c,t}$ eq. 5

$\sum_{t} XT_{d,an,t} crtechsuit_{d,an,t} = area_{d,an}$ eq. 6

$\sum_{scrp} \sum_{t} XT_{d,scrp,t}\, crtechsuit_{d,scrp,} \leq gcrop_{d}$ eq. 7

$\sum_{d} \sum_{t} \sum_{yr} yield_{d,c,t,yr}\, pr_{d,yr} XT_{d,c,t} crtechsuit_{d,c,t} \geq prodn_{c}$ eq. 8

$\sum_{d} \sum_{c} \sum_{t} ccult_{d,c,t} XT_{d,c,t} \leq totinv$ eq. 9

Eq. 1 and Eq. 2 are two objective functions used in this model. Eq. 1 refers to risk that we minimize in this case and eq.2 refers to expected income that we maximize. In the first stage, we minimize risk and estimate expected income endogenously with the help of eq. 2. Secondly, we maximize income and estimate risk associated with that maximum level of income. Eq. 3 refers to fixed expected income that can be used for sensitivity analysis to analyse the trade-off between expected income and risk. Eq. 4 estimates the negative deviation of net return from the state's average net return from the crop. In this case, the negative deviation of net return of a crop is observed due to technology, district, and weather conditions in the year of cultivation. Therefore, if the negative deviation is higher for a technology, investment for its upscaling will be risky for farmers. Therefore, risk-averse farmers will allocate land in such a way that this risk can be minimized. In other words, risk minimization would result in inclusive growth in the state as it tries to achieve parity in income across districts.

IMPLEMENTATION OF THE MODEL

This model was implemented for the state of Telangana in India. The state has 10 districts, however, this model has excluded Hyderabad district as it is a metropolitan city. Telangana state has almost 4.4 million ha of agricultural land, of which 1.7 million ha are irrigated. Its gross cropped area (GCA) is around 5.3 million ha with a cropping intensity of 120%. Of the total GCA, 60% is devoted to cotton, rice, maize, red gram, soybean, and green gram. In addition, mango, sweet lime (batavia), tomato, and turmeric are major horticultural crops grown, which together occupy around 230,000 ha of the 800,000 ha grown to horticultural crops (GoI, 2019). For this study, care was taken to select crops in a way that would include most of the GCA of the state. The selected crops are listed in the previous section and details about their distribution across districts are reported in Table 1.

The crops selected in this study cover around 88% of the GCA of the state (Table 1). The proposed investment planning model for this study, therefore, would capture almost the entire agricultural area of the state.

After selecting the major crops, we identified the CSA technologies that are suitable for them and estimated their maximum potential area across the districts. To identify and undertake initial prioritization of CSA technologies, we undertook a literature review and conducted a stakeholders' consultation workshop on 6 and 7 December 2017 at ICRISAT, Hyderabad, India. A participatory multi-criteria analysis was followed to prioritize CSA technologies for Telangana (Kumar et. al., 2018). Consequently, a list of highly prioritized technologies was chosen. In addition, we reviewed several research articles and reports and conducted focus group discussions (FGDs) with farmers to estimate the maximum potential area for the selected technologies considering rainfall, access to irrigation, soil type, market access, size of land holding, etc. (Venkateswarlu et. al, 2012; ICRISAT, 2016; Rupan et. al, 2018). For example, broad bed and furrow technology is suitable only in black soils used to grow cotton and soybean. The farm pond (FPN) technology was acceptable to those farmers who owned at least 2 ha of farmland, with the exception of a small proportion (5%) having less than 2 ha of land. Tables 2 and 3 provide a detailed description of the maximum potential area for the CSA technologies across crops and districts. Please see Table A in Appendix to get detail about focus group meetings conducted in different districts of Telangana and types of participants. As reported in Table 2, cotton and soybean were chosen for the climate-smart practice of broad bed and furrow (BBF), whereas cotton, maize, groundnut, red gram and green gram were considered for ridge and furrow (RF) practice for in-situ moisture conservation. Crop residue incorporation (CRI) was considered only for cotton. Based on FGDs, cotton, maize, groundnut, mango, batavia (sweet lime), tomato, and red gram were considered to promote rainwater harvesting for supplemental irrigation through farm pond (FPN) with sprinklers, and cotton, maize, groundnut, mango, batavia, tomato, red gram and turmeric were considered for drip irrigation systems (DRP). Un-puddled machine transplanting (UPM) was considered for paddy cultivation. A maximum of 94% of the area under soybean has potential for BBF technology adoption, whereas the maximum potential for its adoption in cotton is 12% of the area. Since Adilabad and Nizamabad districts together account for almost 88% of the area under soybean and Adilabad district accounts for 20% of the cotton area in the state, the potential area for BBF technology is largely located in these two districts (Tables 1 and 3). Around 37% of the potential area for BBF technology lies in Adilabad district, followed by 21% in Nizamabad district (Table 3). However, at the state level, the maximum potential area for BBF technology is only 8% of the total cropped area (estimate based on selected crops) of Telangana state.

The maximum potential area for RF technology is 45% of the total cropped area, and it is the technology with the highest potential in this study because of its suitability across multiple crops and soils. Table 2 reveals that 100% of the area under red gram, 96% under green gram and 78% under cotton has potential for RF technology. The maximum potential area for CRI technology is 13% of the total cropped area of the state, but only for cotton. A maximum of 36% of the cotton area in the state would be suitable for the technology. In terms of districts, the technology's highest potential area is in Adilabad (28%) followed by Karimnagar (14%), Khammam (13%), Warangal (12%), and Nalgonda (11%). Each of the remaining districts occupies less than 10% of total potential area for CRI. The maximum potential area that could get supplemental irrigation through FPN was estimated as 14% of the total cropped area of the state. At the current level of crop yields and market prices, FPN intervention will be suitable only if the harvested rainwater is utilized for a combination of batavia, tomato, mango, groundnut, maize and cotton. A maximum 61% of the area under tomato has the potential for FPN technology followed by 47% under mango, 36% under batavia, 25% under cotton, 24% under maize, and only 12% under groundnut. The highest potential area (63%) for FPN technology was largely distributed between Mahabubnagar, Adilabad, Medak, and Nalgonda districts. In the case of DRP technology, the maximum potential area of 12% of total cropped area in the state was distributed across batavia, tomato, groundnut, turmeric, groundnut, mango, and cotton. Among these crops, the potential area is highest for batavia (80%), and more than 50% for groundnut, tomato, mango, and turmeric. Karimnagar and Warangal districts together occupy almost 50% of the potential area for DRP. The UPM transplanting technology is meant only for paddy cultivation. Paddy occupies 30% of total cropped area in the state while 49% of its area was estimated to be the maximum potential area for this technology. Karimnagar and Nalgonda together occupy around 43% of the potential area for UPM.

As a next step, we estimated yields of different crops under farmers' traditional practice and with CSA technology, and the benefit-cost ratio for each CSA technology corresponding to every crop. To undertake this analysis, first we analysed the monthly district-wise annual rainfall data spanning 5 years from 2010-11 to 2014-15 as obtained from the India Meteorological Department (IMD). Based on the IMD definition, we classified different districts during 2010-2015 under two situations: drought (up to 75% of normal rainfall) and normal (> 75% of normal rainfall) as reported in Table 4.

As evident from Table 4, most of the districts in Telangana are drought-prone and experienced at least two drought years between 2010 and 2015. Therefore, we analysed crop yields and benefit-cost ratio for both drought and normal weather situations. District-wise average yield of crops was calculated based on the actual district level data available from various rounds of Agricultural Statistics at a Glance published by the Government of Telangana and Government of India between 2010-11 and 2014-15 (GoT, 2018).

Similarly, district-wise modal prices of crop outputs in different markets of Telangana collected from *Agmarknet* were used to calculate district-wise returns (GoI, 2018). State-wise cost of cultivation data for most the selected crops was obtained from the Commission for Agricultural Costs and Prices data published by the Government of India. To estimate the cost of cultivation at the district level for all the major crops like paddy, maize, cotton, red gram and green gram, we used plot-level data for Telangana state published by the Government of India. Since plot-level data were not available for soybean, we used plot-level data from the adjoining state of Madhya Pradesh in India. It may be noted that these datasets do not provide yield and cost of cultivation data for all the selected technologies. Since the selected technologies are still at their infancy in terms of stage of adoption in Telangana, the data obtained for yield and costs were taken into account based on farmers' current crop cultivation practices. To estimate the technology-wise change in crop yield and cost of cultivation, we used multiple sources of information: (i) evidence from published literature (Venkateswarlu et al, 2011; Kumar et al., 2011; Kumar et al., 2016; Srinivasarao et al., 2014; Sivanappan, 1994; Rao et al., 2017; Narayanamoorthy, 2006; Kumar et al., 2008;); (ii) focus group discussions conducted with farmers in different districts of Telangana, and (iii) data collected from on-farm trials of various Regional Research Stations and Farm Science Centres or Krishi Vigyan Kendras (KVKs) across districts for different years. Farmers who had adopted any of the selected CSA technologies were chosen for the FGDs. Scientists based in KVKs across districts and Regional Research Stations of the State Agricultural University supported us in identifying farmers who have been using CSA technologies. The estimated crop yields and benefit-cost (BC) ratios for adoption of different CSA technologies are presented in Tables 5 and 6, respectively. Crop yields and benefit-cost ratios for adoption of CSA technology were different under drought and normal weather situations. We considered the drought and the normal situations as described in Table 4.

Technologies that are suited to the crops were taken into account to report yield and BC ratio. Yield data were obtained from experimental plots of research stations and farmers' fields across districts. In addition, we collected data on crop-wise cost of cultivation for each technology to estimate the BC ratio for each crop and each technology.

As observed (Table 5), cotton is the only crop for which five CSA technologies (BBF, CRI, DRP, FPN and RF) are suitable. Among these, the average yield of cotton was the highest for DRP under both normal and drought weather situations. Under normal weather conditions cotton yield does not vary significantly among FPN, BBF, CRI and RF technologies, but under drought situations, cotton yield with CRI technology is almost 10% (0.95 with CRI and 1.04 with BBF and 1.03 with FPN) lower than with BBF and FPN technologies. The yield difference between CRI and RF is about 5% under drought. However, compared to farmers' traditional practice, climate-smart technologies resulted in improvement in cotton yields by 7% to 25%. The highest improvement was observed for DRP and the lowest for CRI technology. The improvement in crop yields across technologies has resulted in higher BC ratios for CSA technologies under both drought and normal situations. But the BC ratio for CRI under drought situation stands at less than one (0.97) which implies an economic loss to farmers. On the other hand, the BC ratio for farmers' traditional practice stands at 0.93 under drought situation and 1.22 under normal situation for cotton (Table 6). However, in the case of other CSA technologies, BC ratios were more than 1 under both normal and drought situations.

Apart from cotton, groundnut and maize are the two crops for which there are three suitable CSA technologies, namely, DRP, FPN, and RF (Table 5). Of these technologies, yields of both crops are higher with DRP compared to their respective farmers' traditional practice under both drought and normal weather situations. Their yields are similar for FPN and RF under both normal and drought situations (Table 5). The BC ratios for both groundnut and maize are highest in the case of DRP technology under both the weather scenarios, followed by RF technology and FPN. This is because of the higher fixed cost involved in adopting FPN than RF technology.

In the case of batavia, mango, and tomato, DRP and FPN are two climate-smart technologies suitable in the state of Telangana. The yield of batavia under DRP technology is 22.3 tons per ha followed by 18.92 tons per ha for FPN technology and 17.78 tons per ha for farmers' traditional practice under normal weather situation. However, irrespective of technology, the yield of batavia falls under drought conditions. In the case of DRP technology, the state average yield stands at 16.34 tons per ha during a drought year, which is 26% lower than the yield obtained with the same technology under normal weather situation. In the case of FPN technology, the state average yield of batavia stands at 15.34 tons per ha, which is 19% less than the yield under normal weather situation. Nevertheless, with both DRP and FPN, the level of yield under drought situation is much higher compared with farmers' traditional practice, which is 13 tons per ha. This is because farmers can use harvested rainwater from the farm pond for life-saving irrigation and DRP technology helps in using the limited water most efficiently. The BC ratios of 4.26, 4.05, and 3.57 obtained under drought situation for batavia under DRP, FPN and farmers' traditional practice, respectively, demonstrate the utility of CSA technologies (Table 6).

In the case of tomato, the average yield with DRP technology under normal weather situation (17.27 tons per ha) is almost 3.5 tons per ha higher than with the farmers' traditional practice and around 2.5 tons higher than under FPN technology (Table 5). In a drought situation, the yield of tomato falls by around 3 tons per ha with DRP technology, 1.3 tons per ha with FPN technology, and 2.3 tons with farmers' traditional practice (Table 5). Yet its yield remains much higher for DRP technology compared to farmers' traditional practice. As a result, the BC ratio for DRP technology under drought situation was highest at 2.62, followed by 2.53 for FPN technology, and 2.15 for farmers' traditional practice. Under normal weather situation, the BC ratios for DRP, FPN and farmers' traditional practice technologies were 3.15, 2.77, and 2.59, respectively (Table 6).

Coming to mango, crop yield with farmers' traditional practice decreases by almost 1 ton per ha in a drought year compared to a normal year. With DRP and FPN technologies, at least 1 ton per ha higher yield was observed as compared to farmers' traditional practice even in a drought year. Crop yield with DRP technology was higher than with FPN under both drought and normal situations (Table 5). As a result, a high BC ratio is observed for DRP technology (3.06) followed by FPN (3.02) and farmers' traditional practice (2.56). The order of technologies was similar in terms of their respective BC ratios under normal weather situation but with higher values than in a drought year.

In the case of pulses (green gram and red gram), RF was the only CSA technology identified. Yield of pulses does not vary significantly between farmers' traditional practice and RF technology under normal weather conditions (Table 5). But under a drought situation, yields are significantly higher with RF technology than with farmers' traditional practice. In green gram, yield with RF technology is higher by 0.06 tons under drought and 0.03 tons under normal situation compared to farmers' traditional practice. In red gram, the differences in yield between farmers' traditional practice and RF technology for drought and normal weather situations is 0.06 tons per ha and 0.01 tons per ha, respectively (Table 5). Thus the BC ratios for RF technology are higher under drought situation than normal situation. The result suggests that RF in pulse crops is attractive only under a drought situation.

Finally, only one CSA technology each was suitable for three other crops: BBF for soybean, DRP for turmeric, and UPM for paddy (Table 5). Yield of soybean decreases from 1.24 tons per ha to 1.20 tons per ha between normal and drought conditions with farmers' traditional practice. With BBF technology, yield increases to 1.69 tons per ha in a normal year and to 1.39 tons per ha under drought conditions. Therefore, the BC ratio with BBF was much higher under both weather scenarios (Table 6).

Similarly, DRP results in increase in turmeric yield by 1.33 ton per ha in normal years and 1.18 tons per ha under drought situation compared to farmers' traditional practice (Table 5). The BC ratio with farmers' traditional practice is more than 3 under both the weather scenarios. Investment in DRP technology will be beneficial to farmers as the BC ratio for this technology is higher than in the farmers' traditional practice under both the weather scenarios.

Crop yield and BC ratios for UPM transplanting in paddy cultivation are not significantly different from farmers' traditional practice but the technology is climate-smart in the sense that it saves irrigation water and time on sowing.

In short, this study revealed that irrespective of the CSA technology, there will be a loss in yield due to drought. However, the adoption of CSA technologies will minimize yield loss and in most cases farmers will reap higher benefits than in traditional practices. Since the yield and BC ratios took into account state-wise average yields and BC ratios, the effectiveness of these technologies will differ across districts. The district-wise and technology-wise average yield data is available as supplementary material with this article. Table 7 describes the additional investment required to adopt the climate-smart technologies in different districts. The additional investment includes the cost of new capital goods, their operational cost, and the cost of training and extension. Capital goods include the equipment needed for BBF, RF, CRI, and DRP and the cost of constructing ponds and sprinkler irrigation equipment. These costs were converted into annualized average cost by considering their life span. Since the capital goods required vary in terms of their cost and life span, estimating the un-discounted annualized average investment for these technologies helps us to compare investment cost across technologies. For example, about INR 53 billion of additional investment was required to implement FPN technology over 667,000 ha of agricultural land for supplemental irrigation, thrice the additional investment required to implement DRP across 550,000 ha. However, the difference between the capital cost of DRP and FPN in terms of annualized investment requirement was only about INR 600 million (Table 7), much lower (INR 3783 for DRP and INR 3975 for FPN) if we consider the annualized investment requirement on a per hectare basis (Table 7). If we consider investment cost per ha of their potential area, the difference between FPN and DRP is only about INR 200. Both DRP and FPN are capital-intensive technologies while other CSA technologies need small investments.

The distribution of additional investment needed across districts indicates that Mahabubnagar district alone requires 19% of total investment to scale up climate-smart technologies. Karimnagar, Warangal, Nalgonda, and Adilabad districts need major shares of 16%, 14%, 11%, and 11%, respectively, of the total potential investment on CSA. The distribution of investment largely depends on the types of feasible technology and their potential area.

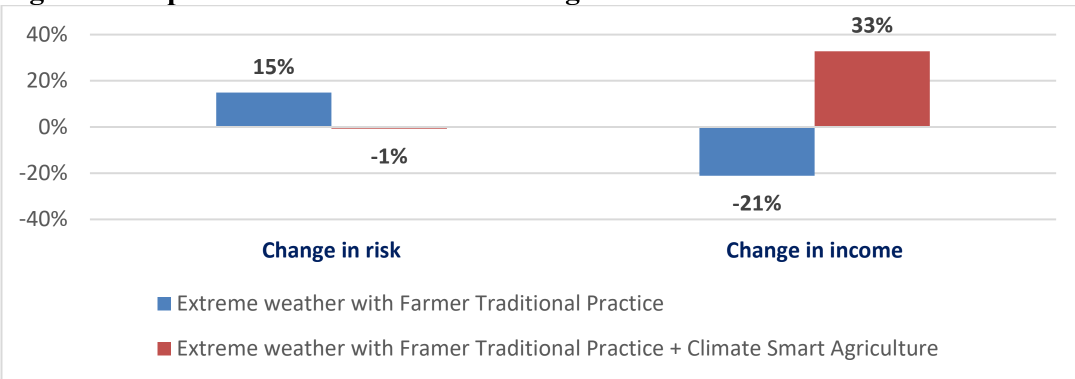
The potential investment across districts and technologies is not optimum since a single technology is feasible for multiple crops and multiple technologies are feasible for a crop. Therefore, the implementation of the optimization model described earlier was needed to estimate optimum level of investment and thereby its allocation across districts and crops. While implementing the model, we discarded the budget constraint so that optimum level of investment and its allocation across districts can be estimated. So the allocation of investment in the model would depend on the level of risk these technologies will minimize without compromising current levels of crop production. We have used GCA of the districts as land constraint to capture unobserved resource constraints in farming across the districts. The results from the model are described in the following section.

RESULTS AND DISCUSSION

An analysis of the annual rainfall pattern in Telangana state suggests that drought as an extreme weather event is a major challenge across districts. We applied the MOTAD model to two scenarios – the current weather pattern and extreme weather pattern. As observed from Table 4, most of the districts in Telangana experienced at least two drought years between 2010 and 2015, suggesting that even if the current weather pattern were to continue, there would still be a 40% chance of any district facing drought. Thus, we defined two scenarios for our analysis: the first is the prevailing weather situation where there is a 40% chance of a district facing a drought year and the second is an extreme weather situation that assumes there is a 60% chance of a district facing a drought year. The model uses the parameter 'pr (d,yr)' to capture these two scenarios. In the first scenario, the value of this parameter is assigned as 0.2 for all the years for all the districts (i.e. 0.2 * 5 =1). In the second scenario, the value of this parameter is assigned as 0.3 for drought years and around 0.13 for normal years (i.e., 0.3*2+0.13*3 = 1). As a result, these two scenarios help us to analyse the trade-off between income and risk when the frequency of extreme weather event increases and how technology interventions can minimize the income risk due to it. We have not considered market risk in this analysis. The net return measured in this model is based on constant price of 2014-15. The income risk considered here is synonymous with production risk that arises due to weather shock. Given these scenario assumptions, we solved this model for risk, income, and land use.

Figure 1 describes the impact of extreme weather scenario on risk and income of farmers. An increase in the frequency of drought increases risk by 15% and decreases income by 21% as compared to the current weather pattern in the study area. The adoption of CSA technology can reduce the risk by 1% and raise farmers' income by 33%. Therefore, it can be argued that the selected CSA technologies are effective in building resilience in the farming system of Telangana state. However, we also need to examine how technology adoption reduces risk-return trade-off; how much yield loss these technologies can minimize, and which technology needs to be given priority for investment. In the subsequent analysis, we have tried to answer these questions.

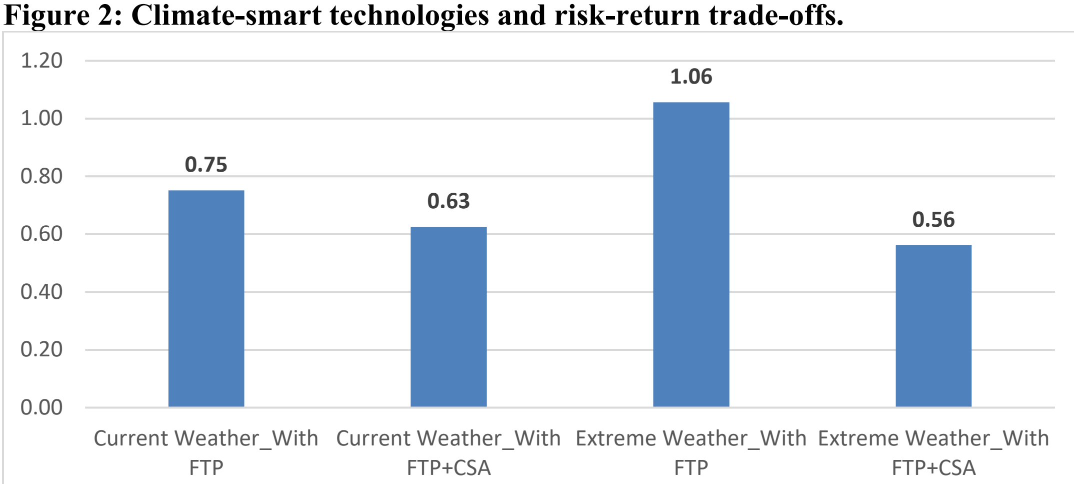
Figure 1: Impact of climate-smart technologies on income risk.



Source: Authors' estimate.

Figure 2 describes the risk-return trade-off. The literature on finance suggests that the coefficient of variation is the best estimate for risk-return trade-off and is the key to financial decision-making by an investor. This study used model simulated results to estimate the coefficient of variation. The risk-return trade-off would increase from 0.75 to 1.06 if there is an increase in the frequency of an extreme weather event under the business as usual scenario with no CSA technologies adopted. That the adoption of CSA technologies would reduce the trade-off from 0.75 to 0.63 under current weather scenario, and the adoption would in turn reduce trade-offs to 0.56 under extreme weather scenario holds promise. This implies that CSA technologies would prove to be more effective under extreme weather conditions.

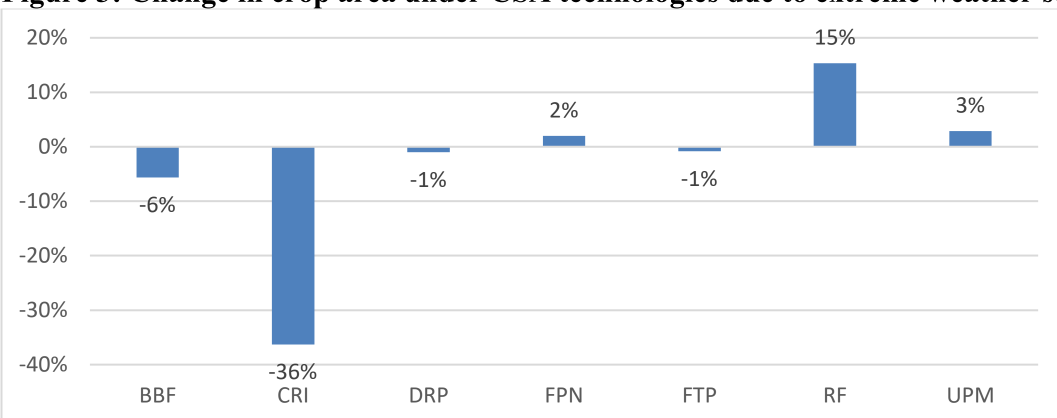
Figure 2: Climate-smart technologies and risk-return trade-offs.



Source: Authors' estimate.
[FTP – farmers' traditional practice, CSA – climate-smart agriculture]

Not all CSA technologies would be equally effective in reducing the risk-return trade-off. To understand the relevance of different CSA technologies, we analysed the change in area under different technologies under extreme weather scenario compared to the current weather scenario (Figure 3). The analysis suggests that the area under RF, FPN, and UPM technologies would increase by 15%, 2%, and 3%, respectively under extreme weather scenario while it could fall under CRI, BBF and DRP by 36%, 6%, and 1%, respectively. The area under farmers' traditional practice would also decrease marginally by 1% due to extreme weather situation.

Figure 3: Change in crop area under CSA technologies due to extreme weather scenarios



Source: Authors' estimate
[BBF – broad bed and furrow; CRI – crop residue incorporation; DRP – drip irrigation; FPN – farm pond; FTP – farmers' traditional practice; RF – ridge and furrow; UPM – un-puddled machine transplanting of rice]

A variation in the economic feasibility of technologies across crops may result in different technologies competing for a single crop, and so particular crops may compete to reduce trade-off between weather-induced risk and income given the GCA across districts. The area under a CSA technology for a crop is likely to increase if that reduces the risk-return trade-off given the available resources for adoption. Thus under extreme weather scenarios compared to the current weather scenario, an additional 162,000 ha will be allocated to cotton with RF technology. At the same time, the cotton area with CRI, FTP, and BBF will be reduced by 134,000 ha, 33,000 ha, and 19,000 ha respectively (Table 8). This would result in a reduction in 25,000 ha under cotton due to increase in frequency of drought events. The reduction in cotton area under CRI technology reflects the decrease of 162,000 ha under CRI in Adilabad district, while the area under CRI increases in Medak district only by 28,000 ha. In the case of BBF technology, a decrease of 27,000 ha in Rangareddy district outweighs the increase in Karimnagar district by 8,000 ha (Table 9). Thus, we observe a 19,000 ha fall in area under BBF, which was mainly for cotton crop, while at the same time the area under maize increases by 29,000 ha under extreme weather scenario with farmers' traditional practice (FTP) (Table 8). The area under FTP would also increase by 1,000 ha for red gram under extreme weather scenario. The additional area under FTP for maize and red gram would replace the area under cotton and paddy (Table 8). However, the total area under FTP would decrease by 15,000 ha in the state under extreme weather scenario. In short, CSA technologies would replace an additional 15,000 ha under farmers' traditional practice as we have assumed that the total cropped area of the state remains unchanged. As revealed in Figure 3, the area under DRP would decrease by 1% in extreme weather scenario compared to the current weather scenario due to the replacement of its area by FPN for mango cultivation. Since mango is an annual orchard crop, and our model considers cropped area as fixed, the adoption of FPN by replacing DRP is not a major change; rather it involves water management to adapt to the weather-related impacts on mango. In case of paddy, we observed an increase in 2,000 ha due to higher allocation of area under UPM technology replacing the area under FTP. A higher allocation of area under UPM was observed in Rangareddy district (17,000 ha) whereas there was a fall in area by 3,000 ha in Nizamabad district (Table 9). It is also interesting to note that although the overall area under RF technology is likely to increase under extreme weather scenario, its area under red gram is likely to decrease by 8,000 ha (Table 8). The decrease in area under RF technology in Medak district would be replaced by CRI technology (Table 9). The technology-wise area under batavia, green gram, groundnut, soybean, tomato, and turmeric is not likely to change under extreme weather scenario as compared with the current weather scenario.

Our analysis has three major outcomes. First, even if the current weather pattern continues and farmers become risk averse, their incomes are likely to decrease unless they adopt new CSA technologies to adapt to climatic shocks. Second, though the area under some CSA technologies under extreme weather scenario is likely to decrease, their significance in reducing the risk-return trade-offs at the district level should not be ignored. Finally, the allocation of area under a CSA technology across various crops and districts would depend on the maximum potential area for that technology and its effectiveness in reducing risk-return trade-offs. Our analysis has proved that these CSA technologies together can reduce risk by 33% even in extreme weather scenario.

However, it is important to understand how much of the maximum potential area would be utilized for each CSA technology across districts in order to prioritize technologies for out-scaling. Therefore, we estimated the utilization of the maximum potential area for every technology across districts (Table 10). The estimates show the utilization of potential area under extreme weather scenario. The optimization model results suggest that 88% of the total potential area of BBF technology in Telangana would be utilized and most of the districts would utilize its full potential area except Rangareddy and Karimnagar districts. In Rangareddy district, only 1% of BBF's potential area is likely to be utilized and 55% in Karimnagar. For CRI, the potential area is likely to be utilized fully in Khammam, Mahbubnagar, and Warangal district, however, at the state level it is likely to be only 40%. Medak was also identified as a potential district for CRI, utilizing its 76% of the potential area. The overall utilization of potential area for DRP was estimated at 73%, with the highest utilization in Khammam (100%), Mahabubnagar (96%), Nalgonda (99%), Rangareddy (93%), and Warangal districts (77%). The utilization of DRP potential area in other districts is likely to be less than 30%. The overall utilization of FPN technology in the optimization model stands at 30% and full potential utilization was observed in Khammam and Warangal districts followed by 64% in Nizamabad. Despite a significant increase in area under RF technology under extreme weather scenario (Figure 3), only 52% of its potential area is likely to be utilized at the state level. No district is likely to utilize the full potential area of RF technology, with a maximum likely utilization of 89% in Khammam district. The UPM technology was useful only for paddy and most of the paddy-growing districts are likely to utilize its full potential except Nizamabad. Thus overall utilization of potential area for UPM stands at 74%.

It is evident from our analysis that despite the availability of funds to adopt new technologies, optimum allocation does not suggest full utilization of the potential area for each technology across districts. Rather, the utilization of the potential area of different technologies was largely dependent on how effective they are in reducing risk-return trade-offs without compromising current levels of production of the crops, keeping overall gross cropped area constant. Our results suggest that promoting the right technology for the right place and crop could lead to better yields from agriculture than would investments to increase cropping intensity. The CSA technology interventions were found to be very effective for adapting to climate shocks to agriculture in the state of Telangana. To promote CSA technologies as identified in our analysis, supporting investments are needed. Hence we estimated an optimum level of investment required to promote CSA technologies across the districts (Table 11). The analysis suggests that about INR 2.8 billion additional investment would be required (annualized value of investment) to scale up and out the selected CSA technologies across districts and crops in Telangana. Mahabubnagar and Warangal districts need 22% and 23%, respectively, of the total additional investment, followed by 16% for Karimnagar, 13% for Khammam, 8% for Nalgonda, and 7% for Nizamabad. Adilabad, Medak and Rangareddy districts each would need less than 5% of the total additional investment required. A comparison of this result with the estimates presented in Table 7 shows that the optimum level of additional investment is about half the investment we have estimated under the assumption that all the districts utilize the full potential area of the technologies. However, the distribution of investment across districts as presented in both the tables remain almost the same.

CONCLUSIONS

Climate variability and change pose a serious challenge to the agriculture sector across the world. The semi-arid and arid regions in particular are more vulnerable due to their agro-climatic conditions and frequent extreme weather events. Growing urbanization and population and the consequent rise in competition between agricultural and non-agricultural use of lands and increasing food demand are further exacerbating these challenges. If the agriculture sector remains at its subsistence level in these dry regions, climate variability is likely to seriously threaten the livelihoods of billions of people who depend on agriculture. Inclusive growth and poverty alleviation in the face of climate change will remain an unfinished agenda of governments unless context-specific climate-smart practices supported by appropriate investments are promoted. Although researchers and practitioners across the globe have been exploring new technologies to mitigate and adapt to climate variability and change, policies that promote context- and region-specific investments will be the key for upscaling climate-smart agricultural technologies. Policymakers need to pay heed to strategizing investments to scale up feasible climate-smart agricultural technologies at the regional level.

In this context, this study contributes significantly to filling the knowledge gap on how to optimally allocate investments to minimize risk-return trade-offs through scaling up of CSA technologies in Telangana state. Our analysis has shown that select CSA technologies will be effective in reducing the income risk of farmers even if the frequency of drought events increases. Our model does not prioritize CSA technologies based on their profitability and level of potential alone; rather, it identifies the most effective ones for crops by region that will reduce variability in farm income. For example, drip irrigation and farm pond technologies are highly profitable and weather resilient, but the model which prioritizes risk reduction considers a 73% and 30% utilization of their potential area, respectively, even if the investment is not a constraint. In the absence of such a modelling exercise, the entire focus would have been on scaling up both these technologies without considering the risk reduction of about INR 4.7 billion investment that would get allocated to promoting the technologies to their full potential. However, the potential of these technologies varies across districts and such allocation of investment may not solve the problem of weather-induced risk minimization in different districts. Given the nature of high resource requirement for implementation, large farmers would benefit more than marginal and small farmers.

Our analyses identified CSA technologies that are feasible for multiple crops and affordable by marginal and small farmers for scaling up. The optimization exercise suggests that only INR 2.8 billion annualized value of investment would be required to reduce risk-return trade-offs in the agriculture sector in semi-arid Telangana even under increased frequency of extreme events. This enables the preparing of an investment portfolio at the district level to minimize risk-return trade-offs, focusing mainly on improving economic efficiency and building climate resilience, with no focus on increasing cropping intensity. Since this analysis does not consider market risk, an important factor, the recommended investment portfolio would depend on effective market institutions and improved market efficiency. An integrated investment strategy to scale up climate smart agriculture in semi-arid regions would also require greater research on the market risk component along with climate risk.

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Table 1: District-wise* distribution of cropped area.

	ADL	KAR	KHA	MED	MHB	NAL	NZM	RNG	WAR	All	% share in total cropped area
Cotton	20%	14%	10%	7%	13%	16%	1%	3%	15%	100%	35%
Groundnut	1%	5%	3%	1%	60%	11%	1%	5%	15%	100%	4%
Maize	3%	16%	5%	20%	22%	1%	13%	6%	14%	100%	14%
Mango	7%	20%	29%	7%	11%	10%	1%	6%	10%	100%	2%
Batavia	0%	5%	0%	1%	19%	72%	0%	2%	1%	100%	1%
Tomato	15%	8%	4%	13%	15%	6%	8%	24%	8%	100%	1%
Soybean	44%	5%	0%	6%	0%	0%	44%	0%	0%	100%	4%
Red gram	15%	2%	2%	10%	41%	11%	1%	13%	4%	100%	6%
Green gram	6%	7%	9%	21%	10%	18%	8%	5%	17%	100%	3%
Paddy	4%	20%	10%	8%	11%	23%	12%	2%	10%	100%	30%
Turmeric	16%	24%	0%	4%	0%	0%	29%	8%	20%	100%	1%
Total area of selected crops (‘000 ha)	554	685	402	431	780	705	384	199	560	4700	100%
GCA- All crops (‘000 ha)	601	700	453	553	978	730	450	255	596	5315	
Area under selected crops (as % of GCA)	92%	98%	89%	78%	80%	97%	85%	78%	94%	88%	

* ADL = Adilabad, KAR = Karimnagar, KHA = Khammam, MED = Medak, MHB = Mahabubnagar, NAL = Nalgonda, NZM = Nizamabad, RNG = Rangareddy and WAR = Warangal.
Source: Authors' compilation using data from Directorate of Economic and Statistics, Ministry of Agriculture Cooperation and Farmers Welfare, Govt. of India. https://eands.dacnet.nic.in/

Table 2: Crop-wise maximum potential area for CSA technologies* (% of the total area under each crop)

Crop Name	Irrigated area	Rainfed area	Total area	BBF	RF	CRI	FPN	DRP	UPM
Cotton	13%	87%	100%	12%	78%	36%	25%	9%	-
Groundnut	89%	11%	100%	-	11%	-	12%	63%	-
Maize	36%	64%	100%	-	64%	-	24%	25%	-
Mango	65%	35%	100%	-	-	-	47%	52%	-
Batavia	100%	0%	100%	-	-	-	36%	80%	-
Tomato	76%	24%	100%	-	-	-	61%	61%	-
Soybean	10%	90%	100%	94%	-	-	-	-	-
Red gram	0%	100%	100%	-	100%	-	-	-	-
Green gram	4%	96%	100%	-	96%	-	-	-	-
Paddy	98%	2%	100%	-	-	-	-	-	49%
Turmeric	100%	0%	100%	-	-	-	-	50%	-
All Crops	**47%**	**53%**	**100%**	**8%**	**45%**	**13%**	**14%**	**12%**	**15%**
Total area under selected crops (‘000 ha)	**2199**	**2501**	**4700**	**368**	**2128**	**589**	**667**	**554**	**694**

*BBF= broad bed and furrow, RF= ridge and furrow method, CRI= crop residue incorporation, FPN=farm pond, DRP=drip irrigation, and UPM=un-puddled machine transplanting of rice.
Source: Authors' estimate

Table 3: District-wise* share (%) of maximum potential area for CSA technologies**

Districts	Gross Cropped area share	BBF	RF	CRI	FPN	DRP	UPM
ADL	12%	37%	16%	28%	17%	4%	3%
KAR	15%	8%	9%	14%	9%	25%	20%
KHA	9%	0%	9%	13%	9%	6%	9%
MHB	17%	8%	21%	9%	21%	18%	11%
MED	9%	13%	12%	9%	13%	4%	8%
NAL	15%	2%	15%	11%	12%	8%	23%
NZM	8%	21%	3%	2%	5%	7%	12%
RNG	4%	8%	5%	3%	7%	3%	3%
WAR	12%	3%	10%	12%	7%	25%	10%
All District	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

*ADL = Adilabad, KAR = Karimnagar, KHA = Khammam, MED = Medak, MHB = Mahabubnagar, NAL = Nalgonda, NZM = Nizamabad, RNG = Rangareddy and WAR = Warangal.

** BBF= broad bed and furrow, RF= ridge and furrow method, CRI= crop residue incorporation, FPN=farm pond, DRP=drip irrigation, and UPM=un-puddled machine transplanting of rice.

Source: Authors Estimate

Table 4: Weather situation across the districts between 2010-11 and 2014-15

District	Rainfall sufficiency/deficiency across districts				
	2010-11	**2011-12**	**2012-13**	**2013-14**	**2014-15**
Adilabad	Normal	Drought	Normal	Normal	Drought
Nizamabad	Normal	Normal	Normal	Normal	Drought
Karimnagar	Normal	Drought	Normal	Normal	Drought
Medak	Normal	Drought	Normal	Normal	Drought
Rangareddy	Normal	Drought	Normal	Normal	Normal
Mahabubnagar	Normal	Drought	Normal	Normal	Normal
Nalgonda	Normal	Drought	Normal	Normal	Drought
Warangal	Normal	Drought	Normal	Normal	Normal
Khammam	Normal	Normal	Normal	Normal	Drought

Source: Authors' compilation using India Meteorological Data

Table 5: Technology-wise* crop yields (tons/ha) under different weather conditions

Crops	FTP		BBF		CRI		DRP		FPN		RF		UPM	RT
	D	N	D	N	D	N	D	N	D	N	D	N	D	N
Batavia	13.1	17.8					16.3	22.2	15.3	18.9				
Cotton	0.89	1.17	1.04	1.24	0.95	1.250	1.12	1.46	1.03	1.24	0.99	1.22		
Green gram	0.51	0.59									0.57	0.62		
Groundnut	1.48	1.63					1.93	2.12	1.68	1.73	1.67	1.72		
Maize	3.16	4.00					3.47	4.40	3.57	4.24	3.61	4.25		
Mango	5.11	6.25					6.38	7.82	6.10	6.63				
Paddy	2.68	3.16											2.87	3.37
Red gram	0.47	0.53									0.53	0.54		
Soybean	1.20	1.24	1.3	1.69										
Tomato	11.4	13.8					14.3	17.2	13.4	14.6				
Turmeric	4.73	5.28					5.91	6.61						

*FTP= farmers' traditional practice, BBF= broad bed and furrow, RF= ridge and furrow method, CRI= crop residue incorporation, FPN=farm pond, DRP=drip irrigation, UPM=un-puddled machine transplanting of rice, D = Drought, and N = Normal

Source: Authors' compilation using data from Directorate of Economic and Statistics, Ministry of Agriculture Cooperation and Farmers Welfare, Govt. of India. https://eands.dacnet.nic.in/, stakeholder consultation, farmers focus group discussions across districts over the years.

Table 6: Technology-wise* benefit-cost ratio for different crops under different weather conditions.

Crops	FTP		BBF		CRI		DRP		FPN		RF		UPM	
	D	N	D	N	D	N	D	N	D	N	D	N	D	N
Batavia	3.57	4.86					4.26	5.79	4.05	4.99				
Cotton	0.93	1.22	1.08	1.30	0.97	1.27	1.12	1.47	1.05	1.26	1.03	1.27		
Green gram	2.66	3.07									2.74	2.95		
Groundnut	1.65	1.82					2.07	2.28	1.82	1.87	1.88	1.93		
Maize	1.30	1.65					1.37	1.73	1.39	1.65	1.48	1.74		
Mango	2.56	3.14					3.06	3.75	3.02	3.28				
Paddy	0.95	1.12											0.99	1.17
Red gram	1.02	1.14									1.12	1.16		
Soybean	3.15	3.25	3.24	3.94										
Tomato	2.15	2.59					2.62	3.15	2.53	2.77				
Turmeric	2.18	2.44					2.70	3.02						

*FTP= farmers' traditional practice, BBF= broad bed and furrow, RF= ridge and furrow method, CRI= crop residue incorporation, FPN=farm pond, DRP=drip irrigation, UPM=un-puddled machine transplanting of rice, D = Drought, and N = Normal
Source: Authors' compilation using data from Commission for agricultural costs and prices, Ministry of Agriculture Cooperation and Farmers Welfare, Govt. of India. https://eands.dacnet.nic.in/, stakeholder consultation, farmers focus group discussions across districts over the years.

Table 7: District-wise* additional investment on CSA technologies and its distribution across districts**

CSA technologies	District-wise share of total annualized investment (% of total additional investment for whole state)										Annualised investment in whole state (Million INR)	Annualised investment (INR/ha)	Investment (once in life cycle of technology) (Million INR)	Life of technology (years)
	ADL	KAR	KHA	MED	MHB	NAL	NZM	RNG	WAR	All				
BBF	37	8	0	13	8	2	21	8	3	100	34	91	168	5
CRI	28	14	13	9	9	11	2	3	12	100	157	267	1574	10
DRP	4	25	6	4	18	8	7	3	25	100	2096	3783	16765	8
FPN	17	9	9	13	21	12	5	7	7	100	2652	3975	53041	20
RF	16	8	8	12	22	14	3	6	9	100	137	61	649	5
UPM	3	20	9	8	11	23	12	3	10	100	524	755	5244	10
Total for all technologies	11	16	8	9	19	11	7	5	14	100	5600	8064	77441	
Annualized investment (Million INR)	643	896	438	489	1043	642	368	282	800					

*ADL = Adilabad, KAR = Karimnagar, KHA = Khammam, MED = Medak, MHB = Mahabubnagar, NAL = Nalgonda, NZM = Nizamabad, RNG = Rangareddy and WAR = Warangal.
** BBF= broad bed and furrow, CRI= crop residue incorporation, DRP=drip irrigation, FPN=farm pond,, RF= ridge and furrow method, and UPM=un-puddled machine transplanting of rice.
Source: Authors' estimate

Table 8: A comparison of absolute changes in technology-wise area ('000 ha) under different crops under extreme weather and current weather scenarios.

CSA technology	Batavia	Cotton	Green gram	Groundnut	Maize	Mango	Paddy	Red gram	Soybean	Tomato	Turmeric	Total
BBF	0	-19	0	0	0	0	0	0	0	0	0	-19
CRI	0	-134	0	0	0	0	0	0	0	0	0	-134
DRP	0	0	0	0	0	-4	0	0	0	0	0	-4
FPN	0	0	0	0	0	4	0	0	0	0	0	4
FTP	0	-33	0	0	29	0	-12	1	0	0	0	-15
RF	0	162	0	0	0	0	0	-8	0	0	0	155
UPM	0	0	0	0	0	0	14	0	0	0	0	14
Total area	0	-25	0	0	29	0	2	-7	0	0	0	0

* BBF= broad bed and furrow, CRI= crop residue incorporation, DRP=drip irrigation, FPN=farm pond, FTP= farmers' traditional practice, RF= ridge and furrow method, and UPM=un-puddled machine transplanting of rice.
Source: Authors' estimate

Table 9: A comparison of the absolute changes in technology-wise* area ('000 ha) across districts under extreme weather and current weather scenarios.**

CSA technology	ADL	KAR	KHA	MED	MHB	NAL	NZM	RNG	WAR	All
BBF	0	8	0	0	0	0	0	-27	0	-19
CRI	-162	0	0	28	0	0	0	0	0	-134
DRP	0	0	0	-4	0	0	0	0	0	-4
FPN	0	0	0	4	0	0	0	0	0	4
FTP	0	-12	0	0	-16	0	3	10	0	-15
RF	162	4	0	-28	16	0	0	0	0	155
UPM	0	0	0	0	0	0	-3	17	0	14
Gross Cropped Area	0	0	0	0	0	0	0	0	0	0

* BBF= broad bed and furrow, CRI= crop residue incorporation, DRP=drip irrigation, FPN=farm pond, FTP= farmers' traditional practice, RF= ridge and furrow method, and UPM=un-puddled machine transplanting of rice.
** ADL = Adilabad, KAR = Karimnagar, KHA =Khammam, MED = Medak, MHB = Mahbubnagar, NAL = Nalgonda, NZM = Nizamabad, RNG = Rangareddy, and WAR = Warangal
Source: Authors' estimate

Table 10: Utilization (%) of potential area of different CSA technologies* across districts under extreme weather scenario**

CSA technology	ADL	KAR	KHA	MED	MHB	NAL	NZM	RNG	WAR	All
BBF	100%	55%	100%	100%	100%	100%	92%	1%	99%	88%
CRI	0%	0%	100%	76%	100%	0%	0%	0%	100%	40%
DRP	28%	64%	100%	25%	96%	99%	25%	93%	77%	73%
FPN	8%	36%	100%	11%	11%	17%	64%	14%	100%	30%
FTP	25%	58%	17%	35%	35%	57%	46%	34%	27%	39%
RF	71%	14%	89%	41%	45%	24%	52%	66%	83%	52%
UPM	0%	100%	0%	100%	100%	100%	74%	100%	0%	74%

* BBF= broad bed and furrow, CRI= crop residue incorporation, DRP=drip irrigation, FPN=farm pond, FTP= farmers' traditional practice, RF= ridge and furrow method, and UPM=un-puddled machine transplanting of rice.
** ADL = Adilabad, KAR = Karimnagar, KHA =Khammam, MED = Medak, MHB = Mahbubnagar, NAL = Nalgonda, NZM = Nizamabad, RNG = Rangareddy, and WAR = Warangal
Source: Authors' estimate

Table 11: Optimal allocation of investment across CSA technologies* and districts.

Districts	BBF	RF	CRI	FPN	DRP	UPM	Total for the district (Million INR)	Allocation by district
Adilabad	26%	26%	10%	2%	0%	0%	78	3%
Nizamabad	30%	3%	25%	6%	4%	0%	204	7%
Karimnagar	5%	3%	25%	27%	8%	0%	466	16%
Medak	16%	8%	3%	4%	1%	46%	121	4%
Rangareddy	0%	5%	7%	4%	1%	0%	84	3%
Mahabubnagar	12%	11%	4%	6%	37%	54%	630	22%
Nalgonda	4%	8%	15%	7%	8%	0%	236	8%
Warangal	5%	18%	5%	19%	33%	0%	649	23%
Khammam	1%	18%	6%	24%	8%	0%	373	13%
Total	**21**	**71**	**352**	**976**	**1325**	**95**	**2840**	100%
Allocation by technology (%)	0.7	2.5	12.4	34.3	46.5	3.3	100	

* BBF= broad bed and furrow, RF= ridge and furrow method, CRI= crop residue incorporation, FPN=farm pond, DRP=drip irrigation, and UPM=un-puddled machine transplanting of rice.

Source: Authors' estimate

Appendix A: Detail about focus group meetings conducted in Telangana

S. No.	FGD details	Participants	Size	When	Where
1	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	20	05-07-2017	Chinna Adirala village, Jadcherla mandal, Mahabubnagar district
2	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	10	01-11-2017	Kapparla village, Tamsi mandal, Adilabad district
3	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	12	03-11-2017	Katnepalli village, Choppadandi mandal, Karimnagar district
4	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	9	24-11-2017	Kambalpalle village, Sadasivapet mandal, Medak district
5	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	8	28-11-2017	Kothagudem rural, Khammam district
6	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	10	29-11-2017	Marriguda village and mandal, Nalgonda district
7	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	12	24-07-2018	Bhoompalle village, Sadasivanagar mandal, Nizamabad district
8	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	15	21-08-2018	Shadnagar, Rangareddy district

S. No.	FGD details	Participants	Size	When	Where
9	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	25	17-01-2019	Rukmapur, Chakunta and Kolimikunta villages, Choppadandi mandal, Karimnagar district
10	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	20	18-01-2019	Boraj, Gimma, Arli villages, Jainath mandal, Adilabad district
11	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	18	11-06-2019	Arjalabavi and Challapalli villages, Nalgonda mandal and district
12	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	17	12-06-2019	Shettypalem village, Vemulapalli mandal, Nalgonda district
13	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	15	13-06-2019	Kusumanchi village and mandal, Khammam district
14	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	9	13-06-2019	Rajeswarapuram village, Nelakondapalli mandal, Khammam district
15	FGD on Climate Smart Agriculture (CSA) practices	Farmers, Agriculture department officials and ICRISAT staff	16	16-09-2019	Katakshapur village, Atmakur mandal, Warangal district

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