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Smallholder farmers managing climate risk in India: 2. Is it climate-smart?

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ABSTRACT

Research about adaptation of crops to climate change at a regional scale is based on simplifying assumptions about current and future weather and about farmer management practices. Additionally, the impacts of adaptations are usually measured only in production terms and the feasibility of implementing proposed adaptations is rarely tested. In this study into adaptations of rice based cropping systems to future climate scenarios in Telangana, India, all adaptations were generated through participatory engagement, and were field-tested with local smallholder households in three villages as well as by cropping system simulation analysis. Adaptation options were first evaluated for historical climate variability, with outcomes assessed in terms of production, profitability and environmental consequences before they were evaluated as climate-smart adaptations to medium term climate change. In an earlier study, participatory intervention at household level was used to identify and evaluate new practices. These adaptations to climate variability were then tested with the cropping systems simulator APSIM on local historical weather data. Here we test the applicability of these adaptations to likely climate scenarios in 2021–2040 by using and statistically downscaling two contrasting global circulation models to generate contrasting climate change scenarios for each location. Adaptations were simulated with these future climate data sets and evaluated in terms of their gross margin, yield, yield stability, gross margin stability, global warming potential, greenhouse gas emissions intensity and, where irrigation treatments were varied, net water use, irrigation water productivity, contribution to the recharge of aquifers and nitrogen leached from the root zone. Compared with variability in historic yields the simulated yield changes in 2021–2040 climate scenarios were modest and their direction was dependent on the global circulation model used. Sustainability polygons were used to compare historic and future climate scenarios. These polygons clearly showed that adaptation options mostly resulted in trade-offs between productivity and environmental outcomes and between competing environmental outcomes. Results that were simulated for historic weather were strongly reflected in the two future weather scenarios, leading to the conclusion that participatory action research with smallholder farmers, coupled with field testing and simulation analysis can produce practical, sustainable and productive adaptations to climate variability that are also climate smart in that they are robust for future climate scenarios to 2021–2040. We propose that sustainability polygons may be a useful quantitative tool for analysis of the degree to which adaptations may be regarded as climate smart.

1. Introduction

Climate change has already impacted agriculture and food production (Trenberth, 2011, Lobell et al., 2011, Coumou and Rahmstorf, 2012, Liu and Allan, 2013). Further increases in mean temperature and evapotranspiration; changes in rain patterns; increased variability both in temperature and rain patterns; changes in water availability; the frequency and intensity of 'extreme events' and sea level rise are projected by climate models (Rummukainen, 2012, Taylor et al., 2012). Such changes will continue to have profound impacts on agriculture (Easterling et al., 2007, Gornall et al., 2010, Beddington et al., 2012). However, climatic impacts on agriculture will be heterogeneous and ambiguous (Knox et al., 2012) and vulnerability will vary between

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crops and regions and with people's socio-economic conditions including inequality and oppression (Kates et al., 2012, Dow et al., 2013, Jayaraman and Murari, 2014). In addition to adapting to gradual climatic changes driven by greenhouse gas emissions farmers must also cope with year-to-year climate variability (Jayaraman and Murari, 2014).

Effective adaptation of agriculture to climate change will mostly result in gains to those who take the adaptive action and while governments can encourage adaptation through investment in research and development (R&D) and appropriate policy settings, it requires individuals to act. Consequently, adaptation to climate change will at most be motivated by a medium term outlook such as 5 to 25 years ahead. Farmers and other stakeholders might adapt to near term climate change but are unlikely to consider adaptation to longer term timelines (Kokic et al., 2011 and references cited within). Further, the rate of change in rural development in smallholder agriculture in South and Southeast Asia is such that farming beyond 2020 is likely to be comprehensively transformed. Additionally, with agricultural livelihoods often being precarious and climate dependent, adaptations will only be implemented if farmers are convinced that they will provide at least some immediate gains. In other words, climate change adaptations can only be contemplated if they are also successful adaptations to current climate variability (Robertson and Murray-Prior, 2014). Hence an important question is: will adaptation to historical climate variability serve farmers well in a future climate as suggested by Howden et al. (2007)?

1.1. Climate change projections for India

Climate change projections for India using the Coupled Model Intercomparison Project 5 (CMIP5) ensemble found that, by the 2030s, under a business-as usual representative concentration pathway (between RCP6.0 and RCP8.5) scenario, mean warming in India relative to preindustrial times is likely to be in the range 1.7–2.0 °C while precipitation is projected to increase by 4% to 5% compared to the 1961–1990 (historic) baseline. A trend for increased frequency of extreme precipitation days (e.g. >40 mm/day) is projected for the 2060s and beyond (Chaturvedi et al., 2012).

Barnwal and Kotani (2013) observed that while a number of simulation studies using global circulation model (GCM) scenarios predicted increased rice production in India (Mohandass et al., 1995, Lal et al., 1998, Rathore et al., 2002, Aggarwal and Mall, 2002), other more recent studies showed negative impacts (Auffhammer et al., 2006, Cline, 2007, Aggarwal, 2008). An overview of the IPCC Fifth Assessment report (IPCC, 2013) for India suggests that there is still significant uncertainty about yield impacts due to the difficulties in understanding and predicting monsoon behaviour (Jayaraman and Murari, 2014).

1.2. Case study villages

The three case study villages are located in three districts in the Telangana state (formally part of Andhra Pradesh) in south India: Warangal, in the Central Telangana agro climatic zone and Nalgonda and Mahabubnagar in the Southern Telangana Zone. Paddy rice, cotton, and to a lesser degree maize are the key kharif (monsoon) crops in these villages. Paddy rice is grown under irrigated conditions mostly using groundwater pumped from bore-wells. Cotton and maize are mostly grown as rainfed crops. The average holding size in the area is around 2 ha with predominantly smallholder farmers. The villages were selected to reflect the considerable variation in natural endowments for agriculture. Bairanpalli (Warangal district) is a village with better soil and water resources, while Gorita (Mahabubnagar district), and Nemmani (Nalgonda district) are villages with more limited resources. More details about the study villages and about the participatory approach taken to developing adaptations to climate variability are provided in Hochman et al. (2017). Briefly, participatory intervention commenced with discussions between researchers, farmers and NGOs about climate related issues in the rice based farming systems in the study villages. These discussions were used to identify new practices that could provide more adaptive and robust responses to climate variability. The suggested adaptations were then implemented in participatory on-farm experiments. Fields demonstrating these adaptations were monitored and results were discussed with participating farmers at regular 'Climate Club' village meetings. Crop and soil data from these fields were used to locally parameterise the cropping systems simulator APSIM. Local adaptation options that were trialled in the villages were then simulated using local soil and long term historical weather data. In each of the case studies, a number of adaptations that were developed and implemented in the villages were shown through simulation to be successful alternatives to current practice in terms of agricultural production, stability of yields and resource use efficiency. These adaptations are further examined in this study for their suitability to future climate projections.

1.3. Using simulation models

Dynamic, process-based crop and cropping system simulation models are commonly used in studies of climate change impact and risk (Tubiello and Ewert, 2002, Challinor et al., 2009, White et al., 2011, Angulo et al., 2013). The APSIM model (Keating et al., 2003, Holzworth et al., 2014) was chosen for this study for a number of reasons. Recent work has demonstrated that APSIM-Oryza is a reliable tool for simulating rice based cropping systems in South and South East Asia (Gaydon et al., 2017) and more specifically in the study area in India (Hochman et al., 2017). Importantly, APSIM was also chosen due to its Manager module's capability to closely mimic farmer management decision logic and subsequent actions.

APSIM captures the CO_2 enrichment effects on photosynthesis via modifiers of radiation use efficiency (RUE). Transpiration is a function of daily DM increment multiplied by transpiration efficiency (TE) which depends on vapour pressure deficit (vpd) and CO_2-level. Actual transpiration and photosynthesis are limited if available soil water is insufficient to meet transpiration demand. In APSIM-Maize RUE's sensitivity to CO_2 is described by a user-defined input ratio while in APSIM-Oryza, CO_2 response is simulated at the leaf-level and both the initial light-use efficiency of a single leaf and the CO_2 assimilation rate at light saturation are sensitive to CO_2 with a mimic of rubisco kinetics simulated hourly and scaled up over sunlit and shaded leaves to canopy assimilation (Jansen, 1990).

The APSIM model has been applied for over a decade to assess the impacts of climate change as well as adaptation and mitigation strategies. It has been used to determine climate change impacts for various region and crop combinations with analysis extended beyond crop production to consider environmental indicators of cropping systems as well to explore the abatement of greenhouse gas (GHG) emissions through reduced N_2O emissions and/or increased soil organic sequestration (Holzworth et al., 2014). Although APSIM's simulation of soil C balance (and hence emissions) has been validated in a number of studies in both flooded (Gaydon et al., 2012b) and non-flooded soil environments (Huth et al., 2010), the model makes no attempt to segregate gaseous C losses from soil organic matter cycling between carbon dioxide (CO_2) and methane (CH_4). This necessitates additional consideration of the global warming impact of simulated C-emissions when the cropping system is alternately flooded and non-flooded (such as a rice-wheat system), due to the different global warming potential of CO_2 and CH_4 (25 times the global warming potential of CO_2 for same mass).

1.4. Climate smart agriculture (CSA)

An emerging concept for dealing with multiple aspects of climate change is Climate Smart Agriculture (FAO, 2013; Campbell et al., 2014). Climate-smart agricultural practices are those which aspire to contribute towards three outcomes: i. Sustainable and equitable increases in agricultural productivity and incomes; ii. Greater resilience of food systems and farming livelihoods (i.e. greater adaptive capacity); and iii. Reduction of greenhouse gas emissions associated with agriculture. However, at the practice level there is still a need to underpin the CSA concept with robust criteria to determine whether practices are indeed climate smart or not, as otherwise the concept risks becoming a catch-all for any new agricultural technologies (Neufeldt et al., 2013; Rosenstock et al., 2016). We adopt the need for adaptations to meet the three above outcomes, using criteria derived as outputs from simulation modeling to more systematically evaluate how well these adaptations meet all three dimensions of CSA. We apply these criteria to a number of adaptations derived from the related study (Hochman et al., 2017) that combined simulation with a participatory framework for developing and testing locally relevant adaptations to climate variability in three villages in semi-arid tropical India.

2. Methods

The research described in this paper was conducted in the context of a broader integrated research program investigating adaptation to climate change in South and Southeast Asian smallholder rice based cropping systems (The Adaptation to Climate Change in Asia program – ACCA; Roth and Grünbühel, 2012).

2.1. Cropping systems simulation

The cropping system model APSIM was used with APSIM-Oryza (Bouman and van Laar, 2006, Gaydon et al., 2012a, 2012b) to simulate rice, with APSIM-Maize (Carberry and Abrecht, 1991) to simulate maize crops and with APSIM-Ozcot (Hearn, 1994) to simulate cotton. All simulations in this study were based on local parameterization that was established for the study villages as described in the earlier paper (Hochman et al., 2017). The study locations Bairanpalli in Warangal district Nemmani in Nalgonda district and Gorita in Mahbubnagar district are also described in greater detail in Hochman et al. (2017).

2.2. Global warming potential (GWP) and greenhouse gas intensity (GHGI) calculations

GWP outputs from APSIM (7.5) were calculated in units of CO_2 equivalents (CO_2 eq) calculated over a 100-year time horizon. Over this period the radiative forcing potentials assumed relative to CO_2 were 298 for N_2O and 25 for CH_4 (IPCC, 2007). The contribution of change in soil CO_2 to GWP was calculated from the difference in soil total carbon in the top 30 cm soil (as per the Kyoto protocol) from start of crop to end of crop. The APSIM variable used is carbon_tot() which is output as kg C/ha. This value is multiplied by the molecular weight ratio 3.664 (CO_2:C) to convert to CO_2.

The contribution of CH_4 to GWP was calculated for ponded rice crops. The APSIM variable C_atm (output as kg C/ha) emissions is calculated as the sum of emissions from fom, biom, hum and residue pools from soil layers to 30 cm depth. This value is calculated each day a pond is present. At end of crop, the final c_atm value is multiplied by the molecular weight ratio 1.336 to convert to CH_4 and further multiplied by 25 to convert to CO_2 equivalents.

The contribution of N_2O to GWP was calculated using the N2O_atm() variable from the top 30 cm soil layers (output as kg N/ha) summed from start to end of crop. This value is multiplied by the molecular weight ratio 1.57 to convert to N_2O and further multiplied by 298 to convert to CO_2 equivalents.

For cotton and maize crops GWP is the mean of the sum of CO_2 emissions plus N_2O emissions (CH_4 emissions are assumed to be negligible) per ha per season. For paddy rice crops GWP is the mean of the sum of CO_2 emissions plus CH_4 emissions plus N_2O emissions. For all

Table 1
Summary of modelling scenarios tested with APSIM for three farm sizes and options allocating a varying proportion of land to irrigated rice and to strategically irrigated cotton (or maize).

Size of farm	Current practice		Option 1		Option 2		Option 3		Option 4		Option 5	
	Irrigated rice and rainfed cotton		Use water saved to strategically irrigate cotton		Use water saved to strategically irrigate cotton		Use water saved to strategically irrigate cotton (with unlimited no. of irrigations)[1]		Use water saved to strategically irrigate cotton		Use water saved to strategically irrigate cotton	
	Irrig. rice (ha)	Cotton (ha)	Irrig. rice (ha)	Cotton (ha)	Irrig. rice (ha)	Cotton (ha)	Irrig. rice (ha)	Cotton (ha)	Irrig. rice (ha)	Cotton (ha)	Irrig. rice (ha)	Cotton (ha)
Small (2 ha)	0.8	1.2	0.6	1.4	0.4	1.6	0.4	1.6	0.2	1.8	na[2]	na[2]
Medium (3.2 ha)	0.8	2.4	0.6	2.6	0.4	2.8	0.2	3.0	na[2]	na[2]	na[2]	na[2]
Large (6 ha)	1.2	4.8	1.0	5.0	0.8	5.2	0.6	5.4	0.4	5.6	0.2	5.8

[1] Unlimited number of irrigation option applies only to the small farm.
[2] na = not applicable. These treatments do not comply with the strategic rules.

crops GWP is expressed as (kg CO_2 eq/ha/season). GHGI is the mean of the sum of CO_2 emissions plus CH_4 (for paddy rice crops) plus N_2O emissions per ha per kg of yield. It is expressed as (kg CO_2 eq/ha/kg yield).

Changes were also made to the default soil.xml file.

- Denitrification rate coefficient (kg soil/mg C per day) dnit_rate_coeff was changed from default 0.0006 to 0.001379 (Huth et al., 2010, Thorburn et al., 2010).
- N_2O losses from nitrification was "switched on" dnit_nitrf_loss was changed from default 0.0 to 0.002
- dnit_k1 was adjusted according to soil texture in the top 30 cm of the soil. For clay (all Bairanpalli and Gorita and Nemmani rice soils) dnit_k1 was set to 25.1. For Alfisols and Ultisols used to grow cotton and maize crops in Gorita and Nemmani dnit_k1 was set to 8.5. This value was arrived at after comparing simulated maize N_2O values produced with different dnit_k1 values to observed ranges of values found by Linquist et al. (2015). The derived dnit_k1 value is consistent with values suggested by Del Grosso et al. (2000) for comparable soil types.

2.3. Climate data and future climate scenarios

The baseline data set used daily historic weather data (1978–2009) recorded in Indian Meteorology Department (IMD) weather stations in close proximity to the case study villages. For future climate projections we used the linear, mixed-effect state-space (LMESS) method to generate location specific projections to 2021–2040 (Kokic et al., 2011), drawing on historical data for the case study locations and using outputs from two contrasting Global Circulation models (ECHAM5 for a relatively cooler and GFDL CM2.1 for a relatively hotter future climate) under the A2 SRES emissions scenario (approximately

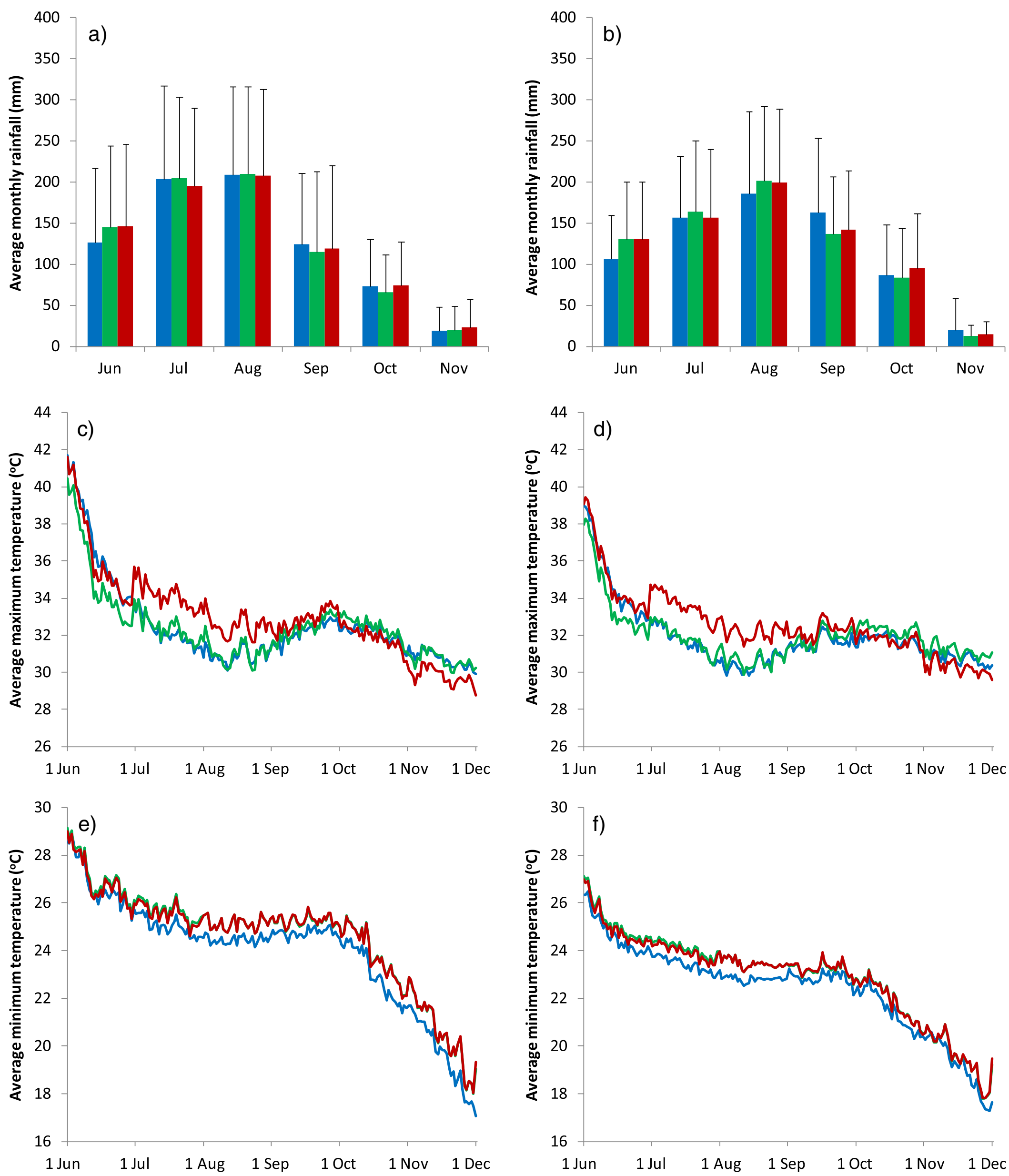

Fig. 1. Comparison of historical and future climate scenarios for average monthly rainfall (mm; whiskers show standard deviation above the mean) at a) Warangal and b) Mahabubnagar, average maximum daily temperature (°C) at c) Warangal and d) Mahabubnagar and average minimum daily temperatures (°C) at e) Warangal and f) Mahabubnagar in Telangana, India. Blue lines and columns represent the observational record (1978–2009); green represents ECHAM5 projection (2021–2040) while red represents the GFDL CM2.1 projection (2021–2040).

equivalent to representative concentration pathway RCP6) to 2021–2040.

The LMESS methodology was applied as described in Kokic and Crimp (2011). A multivariate state-space modeling approach was used to establish empirical relationships between GCM variables and location-specific climate. In so doing, we maintained important information regarding local observed trends and variability but also introduced important drivers of change from the GCMs. The state-space approach was used to jointly model quantiles of rainfall and temperature at monthly level, then a bootstrap simulation procedure (Efron, 1982) based on quantile matching was used to simulate future daily climate (Kokic et al., 2011). APSIM climate files also require solar radiation, vapour pressure and evapotranspiration. These variables where predicted from rainfall and temperature using empirical relationships based on NCEP reanalysis climate data for locations close to each climate station. This approach ensures that the future simulated climate is coherent across variables temporally, and displays distributional characteristics highly consistent with point level climate data.

2.4. Adaptation strategies

Three of the four adaptations that were tested in Hochman et al. (2017) were found suitable for managing climate variability. These three adaptations were further tested in this study as adaptations to two contrasting medium term climate change scenarios in the same locations.

2.4.1. Adaptation 1. Sowing rules

The sowing window for rainfed crops such as cotton and maize is between June 1 and July 17. While there is no generally accepted farmer practice with regards to when farmers sow rainfed crops, some farmers will sow these crops as soon as the monsoon season breaks locally (defined as two consecutive days where rainfall exceeds 2.5 mm). Given this sowing window, four main variations to the sowing rule were explored:

1. The 2 day rule: sow at 'onset of monsoon' following the IMD's definition (i.e. 2 consecutive days in which daily rainfall ≥2.5 mm)
2. The 50 mm rule: sow when cumulative rainfall ≥50 mm (accumulated over up to 4, 7, 10 or 14 days)
3. The 75 mm rule: sow when cumulative rainfall ≥75 mm (accumulated over up to 4, 7, 10 or 14 days)
4. The soil moisture rule: sow when soil moisture in top 15 cm is at 50% of the soil's plant available water capacity (PAWC) in Vertisols (hereafter referred to as black soils) or at 66% of PAWC in Alfisols and Ultisols (hereafter referred to as red soils).

These four sowing rules were evaluated, using baseline and future climate scenarios, in terms of their grain yields (t/ha), yield stability (CV of yield), gross margins (INR/ha; 1 USD ~ 65 Indian Rupees) based on data from a survey of household costs and prices received), gross margin stability (CV of GM), their Global Warming Potential (GWP; kg CO_2 equivalence/ha/season) and their Greenhouse Gas Intensity (GHGI; intensity of carbon (kg CO_2 equivalence/kg yield).

2.4.2. Adaptation 2. Strategic irrigation of rainfed crops

The common farmer practice is to grow cotton and maize as rainfed crops. Strategic irrigation of cotton and maize crops was deployed according to the rule: apply 50 mm when soil moisture falls below 50% of PAWC subject to -

1. at least 14 days between irrigations
2. maximum of 3 irrigations per season
3. for cotton start irrigations after 30 days after sowing (DAS) and stop at 120 DAS
4. for maize start irrigations after 14 DAS and stop at 21 days after anthesis

The soil moisture sowing rule was used for both rainfed and strategically irrigated options and for all three climate scenarios. The strategic irrigation adaptation was evaluated relative to purely rainfed crops, using baseline and future climate scenarios, in terms of their grain yields (t/ha), yield stability (CV of yield), gross margins (INR/ha) based on data from a survey of household costs and prices received), gross margin stability (CV of GM), and their GWP (kg CO_2 equivalence/ha/season) and GHGI (kg CO_2 equivalence/kg yield).

2.4.3. Adaptation 3. Reduced rice area for strategic irrigation of rainfed crops

This adaptation combines the two adaptations discussed above into an integrated, whole farm management package. Options investigated for sourcing water for strategic irrigation of rainfed crops from reduced paddy area varied by household type and particularly by farm size. We considered 3 representative households: 1. A small farm with 5 acres (2 ha) of which 2 acres were paddy and 3 acres were cotton; 2. A medium farm with 8 acres (3.2 ha) of which 2 acres were paddy and 6 acres were cotton; 3. A large farm with 15 acres (6.5 ha) of which 3 acres were paddy and 12 acres were cotton. For all farm types we assumed rice was ponded to 5 cm depth with daily irrigation as required to maintian the pondand rainfed cotton or rainfed maize using the starting soil water sowing rules as the current farmer practice. A minimum of half an

Table 2
The percent of years in which crops are not sown or in which sown crops fail when various sowing rules are applied to cotton and maize crops grown on black soils at Bairanpalli contrasting historic climate (1978–2009) with future climate projections using the GFDL CM2.1 (2021–2040) and ECHAM5 (2021–2040) models.

Sowing rule	Observed Weather			GFDL CM2.1			ECHAM5		
	Not sown (%)	Cotton fails (%)	Maize fails (%)	Not sown (%)	Cotton fails (%)	Maize fails (%)	Not sown (%)	Cotton fails (%)	Maize fails (%)
2 day	**0.0**[1]	**16.1**	**18.8**	**0.0**	**35.0**	**40.0**	**0.0**	**20.0**	**20.0**
75 mm in 4 days	43.8	0.0	0.0	45.0	0.0	0.0	45.0	0.0	0.0
75 mm in 7 days	37.5	0.0	0.0	20.0	0.0	0.0	20.0	0.0	0.0
75 mm in 10 days	28.1	0.0	0.0	15.0	0.0	0.0	15.0	0.0	0.0
75 mm in 14 days	25.0	0.0	0.0	10.0	0.0	0.0	10.0	0.0	0.0
75 mm	**9.7**	0.0	**0.0**	10.0	0.0	5.6	10.0	0.0	5.6
50 mm in 4 days	15.6	0.0	3.7	**5.0**	**0.0**	**5.3**	**5.0**	**0.0**	**0.0**
50 mm in 7 days	**9.4**	**0.0**	6.9	**5.0**	**0.0**	**5.3**	**5.0**	**0.0**	**0.0**
50 mm in 10 days	9.4	3.4	3.4	**5.0**	**0.0**	**5.3**	**5.0**	**0.0**	**0.0**
50 mm in 14 days	9.4	6.9	6.9	5.0	10.5	10.5	5.0	5.3	5.3
50 mm	3.1	16.1	16.1	5.0	10.5	10.5	5.0	5.3	5.3
Soil moisture	**9.4**	**0.0**	**3.4**	**5.0**	**0.0**	**5.3**	**5.0**	**0.0**	**0.0**

[1] For each climate scenario by crop combination bold numbers indicates rules with pareto-optimal outcomes.

acre of rice was retained in adaptation scenarios to allow self-sufficiency for a family of up to 5 people. A summary of the treatments for each farm type is provided in Table 1.

All the options in Table 1 were simulated for red and black soil types at the three villages using historical weather data (1978–2009) and outputs representing 2021–2040 scenarios from the two contrasting Global Circulation models ECHAM5 and GFDL CM2.1. Simulation outputs included yields; net water used; soil carbon status; soil nitrate leached beyond the root zone; and nitrous oxide emissions. Gross margins were calculated using cost and income data collected from the representative case study households. Post simulation analysis enabled the calculation of gross margins and this enabled the calculation of average gross margins and stability, represented by the coefficient of variation (CV) of gross margins.

2.5. Are adaptations climate smart?

In considering how climate-smart competing adaptations are, the outputs listed in the paragraph above are represented as sustainability polygons (Ten Brink et al., 1991, Moeller et al., 2014). These polygons allow for an integrated graphic representation of multiple sustainability indicators. They are designed to provide a holistic visual summary of how sustainable (or climate-smart) competing adaptation practices are. Each sustainability indicator is represented by a relative value from 1 to 0 where 1 is the most desirable outcome (highest or lowest depending on context, e.g. highest GM or lowest GWP. For a desirable attribute (e.g. GM) the relative sustainability value for any adaptation is calculated as the value of the adaptation divided by the value calculated for the highest among the competing adaptation options. For an undesirable attribute (e.g. GWP) the sustainability value of an adaptation is calculated by dividing the lowest value among competing adaptations by the value of that adaptation.

Using sustainability polygons, in which sustainability indicators are presented in a polygon, assuming equal weighting for all indicators, two criteria are applied to assess whether an adaptation is climate smart. First, the adaptation for which all the indicators are higher than the baseline can be considered climate smart and as a win-win in all respects. Ideally the most climate smart practice will have all values close to 1.0. However, in many cases, only some indicators are higher than the baseline, requiring a trade-off between the indicators. In this case a second criterion is the area of the polygon, where the polygon for the most climate-smart practice would encompass the largest area. In the second case, choice of which adaptation is the most climate-smart may require subjective weighting of the various sustainability indicators by various stakeholders. Relative weighting of indicators is essentially subjective but might be informed by the importance assigned to each indicator as well as by the range of values that each indicator displays. We therefore also display on the sustainability polygons the range of absolute values for each of the sustainability indicators.

3. Results

The observational weather data for the three Indian villages (Bairanpalli, Nemmani and Gorita) were sourced from nearby weather stations (Warangal, Nalgonda and Mahbubnagar respectively). The data spanned the period from 1978 to 2009. Missing data (16% of observations in Warangal and 10% in Mahbubnagar) were in-filled with IMD gridded data. A comparison between the two villages' minimum and maximum temperatures and rainfall during the monsoon season is provided in Fig. 1. Warangal (Fig. 1a) tends to be wetter than Mahbubnagar (Fig. 1b) in the first half of the kharif season (June to August) but drier in September and October. It is warmer throughout the season with the difference being greater in the minimum temperatures (Fig. 1c,d,e,f). Data for the third village (Nemmani) were intermediate between the other two and are not shown here for the sake of brevity (for a comprehensive set of results see the *Accessory Publication*). Both GCMs project future climate scenarios for 2021–2040 with warmer minimum temperatures than the historical record. Only the GDFL CM2.1 model projects warmer maximum temperatures, especially in July and August. Only small changes are projected for rainfall with both models projecting a wetter June for both locations with less consistent monthly changes projected for the remainder of the season. Overall, for Warangal and Mahbubnagar in 2021–2040, the climate projections of the GFDL CM2.1 model are warmer, especially in their maximum temperatures, than the climate projected by ECHAM5 (Fig. 1).

3.1. Adaptation 1. Sowing rules

3.1.1. Avoiding seedling losses

With both ECHAM5 and GFDL CM2.1 predicting higher future rainfall in June, the likelihood of a sowing opportunity was higher for almost all sowing rules in both villages. For historical weather data (1978–2009) on a black soil at Bairanpalli the 2 day sowing rule ensured a sowing opportunity in all years, however, it also resulted in seedling failures

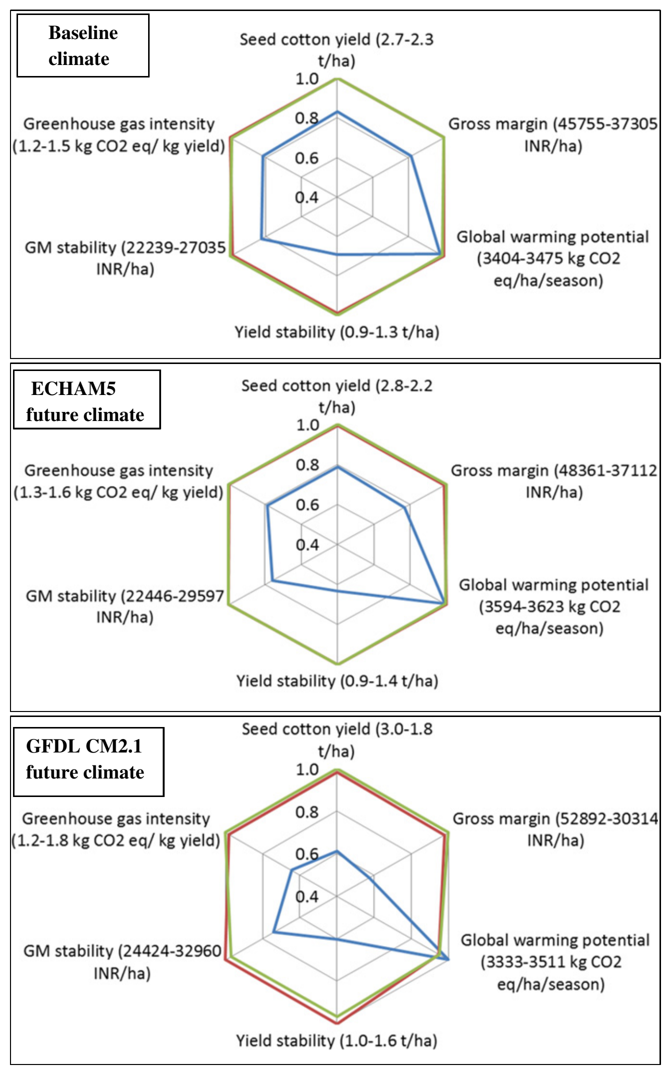

Fig. 2. Comparison of yield, gross margin, yield stability, gross margin stability, global warming potential and greenhouse gas intensity of cotton crops grown using the IMD 2 day sowing rule and the remaining two sowing rules with optimal trade-offs between sowing opportunity and seedling failure at Bairanpalli for a) baseline climate (1978–2009), b) ECHAM5 future climate (2021–2040) and c) GFDL CM2.1 future climate (2021–2040). Blue lines represent IMD 2 day sowing rule, red lines represent 50 mm in 7 days sowing rule and green lines represent soil moisture sowing rule. Ranges for each variable are shown in parentheses.

in 16.1% of years for cotton and 18.8% of years for maize. Of the remaining sowing rules the two with optimal trade-offs between sowing opportunity and seedling failure for cotton are the 50 mm in 7 days and the soil moisture sowing rules. For maize, the two sowing rules with optimal trade-offs between sowing opportunity and seedling failure are the 75 mm and the soil moisture sowing rules. For a future (2012–2040) Bairanpalli climate generated with the GFDL CM2.1 model, the 2 day sowing rule ensured a sowing opportunity in all years. However, it also resulted in seedling failures in 35% of years for cotton and 40% of years for maize. Of the remaining sowing rules there were four with optimal trade-offs between sowing opportunity and seedling failure for cotton and maize: 50 mm in 4 days, 50 mm in 7 days, 50 mm in 10 days and the soil moisture rule. For a future (2012–2040) Bairanpalli climate generated with the ECHAM5 model, the 2 day sowing rule ensured a sowing opportunity in all years. However, it also resulted in seedling failures in 20% of years for both cotton and maize. Of the remaining sowing rules there were four with optimal trade-offs between sowing opportunity and seedling failure for cotton and maize: 50 mm in 4 days, 50 mm in 7 days, 50 mm in 10 days and the soil moisture rule (Table 2). Similar results were observed for the red soil in Gorita (Accessory Publication Table 1).

For both Gorita and Bairanpalli, those sowing rule adaptations that were most successful in reducing the risk of seedling failure at the smallest cost in terms of missed sowing opportunities under the historical climate scenario were also among the most successful adaptations under both the ECHAM5 and GFDL CM2.1 scenarios for 2021–2040. For both villages, the value of these adaptations was increased when compared with the increased risk of failure associated with the alternative '2 day start' rule.

3.1.2. Sustainability polygons

The simulated effects of implementing different sowing rules (2 day rule against the two rules with the most optimal sowing opportunity versus crop failure trade-offs) on the long-term mean values of six sustainability indicators: yield, gross margin (GM), yield stability, GM stability, GWP and GHGI of cotton and maize crops grown in Bairanpalli are represented as sustainability polygons in Fig. 2.

For cotton crops in Bairanpalli using observed weather data, the 2 day rule had lower sustainability indicator values than the soil moisture and the 50 mm in 7 days rules which were approximately equal to each other for all indicators. In particular the yield stability indicator, the yield indicator, the GM and the GM stability indicators had values in the range of 0.70 to 0.83. While the GWP indicators were very close and the GHGI indicator was lower for the 2 day rule due to lower yields (Fig. 2, baseline climate). For cotton crops in Bairanpalli using future ECHAM5 generated weather data, the 2 day rule had lower sustainability indicator values than the soil moisture and the 50 mm in 7 days rules which were approximately equal to each other for all indicators. The same indicators that were lower for the 2 day rule in the observed weather data simulations were even lower for the ECHAM5 scenario (Fig. 2, ECHAM5). Similarly, for cotton crops in Bairanpalli using future GFDL CM2.1 scenario, the 2 day rule becomes even less sustainable for each of the indicators except GWP (Fig. 2, GFDL CM2.1).

For maize crops in Bairanpalli using observed weather data, the 2 day rule had lower sustainability indicator values than the soil moisture and the 75 mm rules. The 75 mm rule had higher indicators than the soil moisture rule, particularly for the yield stability and GM stability indicators. While the GWP indicator was about the same for the three rules, the GHGI indicator for the 2 day rule was around 0.6 due to

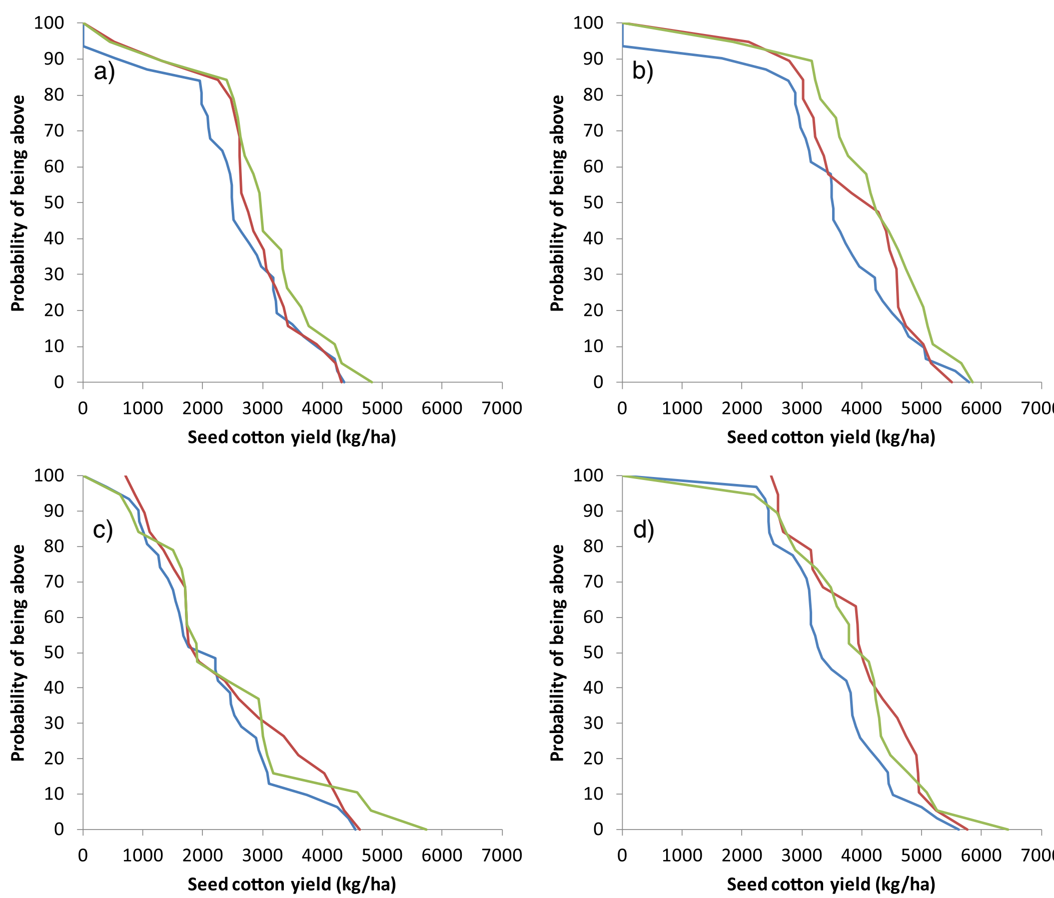

Fig. 3. Seed cotton yield response (probability of exceedance) of crops sown using the soil moisture sowing rule for a) rainfed crops at Bairanpalli, b) crops grown using strategic irrigation at Bairanpalli, c) rainfed crops at Gorita, d) crops grown using strategic irrigation at Gorita. Blue lines represent historical record (1978–2009); green represents ECHAM5 projection (2021–2040) while red represents the GFDL CM2.1 projection (2021–2040).

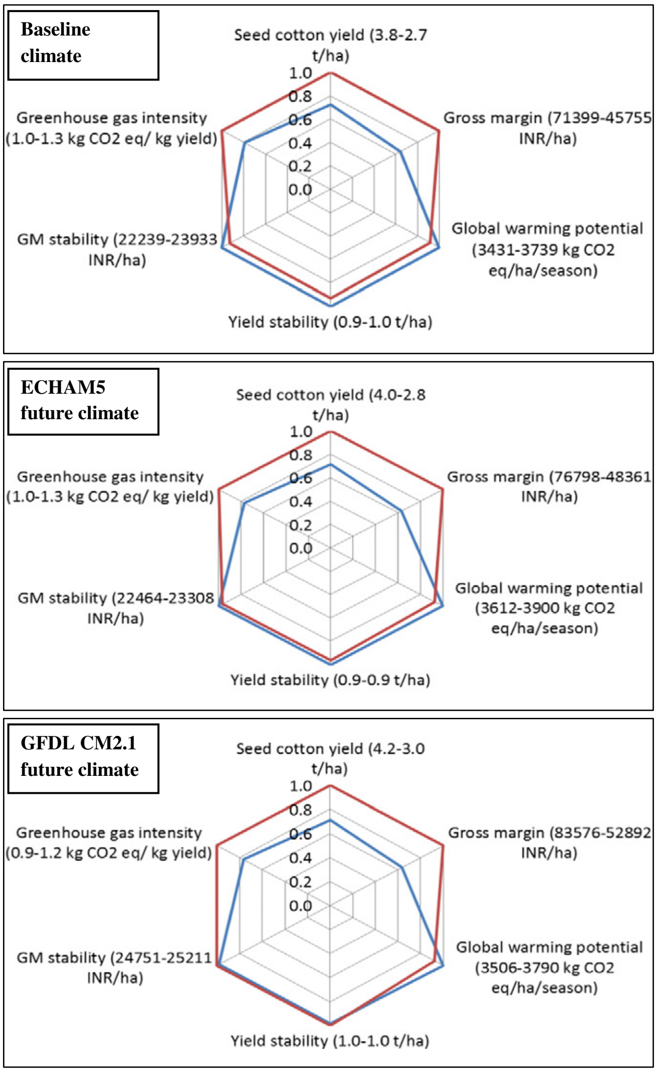

Fig. 4. Comparison of yield, gross margin, yield stability, gross margin stability, global warming potential and greenhouse gas intensity of rainfed and strategically irrigated cotton crops grown using the soil moisture sowing rule at Bairanpalli for 1) baseline climate (1978–2009), 2) ECHAM5 future climate (2021–2040) and 3) GFDL CM2.1 future climate (2021–2040). Blue lines represent rainfed crops, red lines represent strategically irrigated crops. Ranges for each variable are shown in parentheses.

lower yields. Similar results were observed when using future ECHAM5 generated weather data. When using future GFDL CM2.1 weather data, the 2 day rule becomes less sustainable for each of the indicators except GWP which is marginally lower for the 2 day rule. Indicator for the soil moisture and the 75 mm rules become close to equal (Accessory Publication Fig. 2).

Similar results were observed for cotton and maize crops in Gorita (Accessory Publication Figs. 3 and 4) and Nemmani (Accessory Publication Fig. 5).

3.2. Adaptation 2. Strategic irrigation of rainfed crops

3.2.1. Yield Probabilities

Strategic irrigation of cotton crops in the case study villages increased the yield probability distribution throughout the entire range of yield outcomes. In particular, the probability of yields exceeding 2 t/ha in Gorita and 3 t/ha in Bairanpalli was dramatically increased. This trend was true for the historical record as well as the ECHAM5 and GFDL CM2.1 scenarios for 2021–2040.

For both rainfed and strategically irrigated cotton in Bairanpalli the yields under the ECHAM5 scenario were stochastically dominant over the baseline projections over the whole yield range. The GFDL CM2.1 scenario in Bairanpalli was intermediate between the baseline and ECHAM5 scenarios. For both rainfed and strategically irrigated cotton crops in Gorita, yields projected for ECHAM5 and GFDL CM2.1 scenarios for 2021–2040 were stochastically dominant over the baseline scenario (Fig. 3).

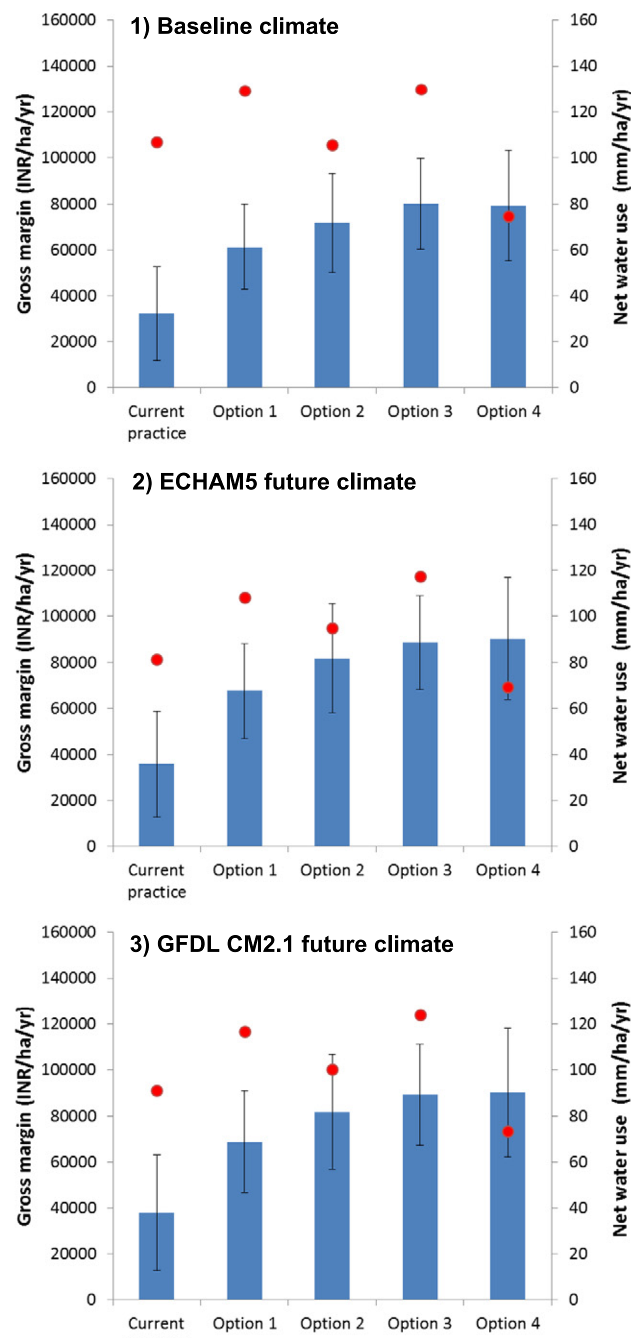

Fig. 5. Gross margin (blue bars) and net water use (irrigation-recharge, red dots) for adaptation options used on small farms at Gorita growing rice and cotton for 1) baseline climate (1978–2009), 2) future climate ECHAM5 (2021–2040) and 3) future climate GFDL CM2.1 (2021–2040).

3.2.2. Sustainability polygons

When comparing sustainability polygons across the three climate scenarios (baseline climate, ECHAM5 future climate and GFDL CM2.1 future climate) for cotton crops at Bairanpalli (Fig. 4) similar results were obtained regardless of the climate scenario: seed cotton yields, gross margin, and GHGI all improved by strategic irrigation while yield stability, GM stability and GWP were marginally worse with strategic irrigation. However, it should be noted that this slightly increased instability is around a much higher mean. For maize in Bairanpalli (Accessory Publication Fig. 8) sustainability indicators for grain yield, GM, yield stability and GM stability were improved under the three climate scenarios with the most dramatic improvements being in yield stability and GM stability. However, GWP and GHGI were increased in all climate scenarios.

A comparison of sustainability polygons for the three climate scenarios for both cotton and maize crops in Gorita (Accessory Publication Figs. 9 and 10) shows that all sustainability indicators for the strategic irrigation adaptation, with the exception of a relatively small increase in GWP that was more than compensated for in GHGI, were superior for each of the three climate scenarios.

3.3. Adaptation 3. Reduced rice area for strategic irrigation of rainfed crops

3.3.1. For the small farm in Gorita

Growing rice and cotton under the baseline climate scenario, current practice produced a mean annual gross margin of 32,266 INR/ha, a net water use of 106.9 mm/ha/yr and a water productivity (expressed as GM per mm of net water used) of 302 INR/mm. Adaptation option 3 resulted in the highest average annual GM of 79,998 INR/ha at the expense of a less sustainable net water usage of 130.1 mm/ha/yr but a higher water productivity of 615 INR/mm. Adaptation option 4 resulted in a slightly reduced average annual GM of 79,200 INR/ha but a much lower net water use of 74.6 mm/ha/yr resulting in a higher water productivity of 1061 INR/mm. Similar results were observed for the two future (2021–2040) climate scenarios ECHAM5 and GFDL CM2.1 (Fig. 5).

Comparisons of the sustainability polygons for the different adaptation options for small farms growing rice and cotton crops at Gorita using the baseline climate (1978–2009) and the future climate scenarios for 2021–2040 generated with the ECHAM5 and GFDL CM2.1 models are presented in Fig. 6. For the baseline climate, the current practice is least sustainable in terms of its gross margin, gross margin stability, GWP, GHGI, irrigation water used and irrigation water productivity. It is however the most sustainable in terms of aquifer recharge and leached nitrogen. Adaptation option 4 is most sustainable in terms of the amount of irrigation water used, irrigation water productivity GWP and GHGI and is intermediate for gross margin stability and for nitrogen leached. It is however least sustainable for groundwater recharge. Adaptation option 3 is superior to option 4 in its gross margin stability and recharge. However, it is less sustainable in terms of the irrigation amount, irrigation water productivity, GWP and GHGI. Adaptation options 1 and 2 tend to be intermediate between the current practice and adaptation option 3. While the absolute values of the sustainability indicators vary with climate scenarios, the relative positions of the sustainability indicators remained the same (Fig. 6).

3.3.2. For the large farm in Gorita

Under the baseline climate scenario, current practice produced a mean annual gross margin of 48,484 INR and a net water use of 24.3 mm/ha/yr resulting in a water productivity of 1996 INR/mm. Each adaptation option increased both average annual GM and net water usage (each 7 mm increasing GM by 10,000 INR). Adaptation option 5 resulted in the highest annual GM of 95,279 INR/ha and the highest net water use of 54.0 mm/ha/yr resulting in a lower water productivity of 1769 INR/mm. Similar results were observed for the two future (2021–2040) climate scenarios ECHAM5 and GFDL CM2.1 (Fig. 7).

Comparison of the sustainability polygons for the different adaptation options for large farms growing rice and cotton crops in Gorita using the baseline climate (1978–2009) and the future climate scenarios for 2021–2040 generated with the ECHAM5 and GFDL CM2.1 models are presented in Fig. 8. For the baseline climate scenario, as with the medium farm, the current practice for the large farm is least sustainable in terms of its gross margin, gross margin stability, GWP, GHGI, irrigation water used and irrigation water productivity. It is however the most sustainable in terms of aquifer recharge and leached nitrogen. Adaptation option 5 is most sustainable in terms of gross margin achieved, gross margin stability, the amount of irrigation water used, irrigation water productivity, GWP, GHGI, and nitrogen leached. It is however the least sustainable in terms of groundwater recharge and the amount of nitrogen leached. Adaptation options 1 to 4 are intermediate relative to current practice and adaptation option 5. While the absolute values of

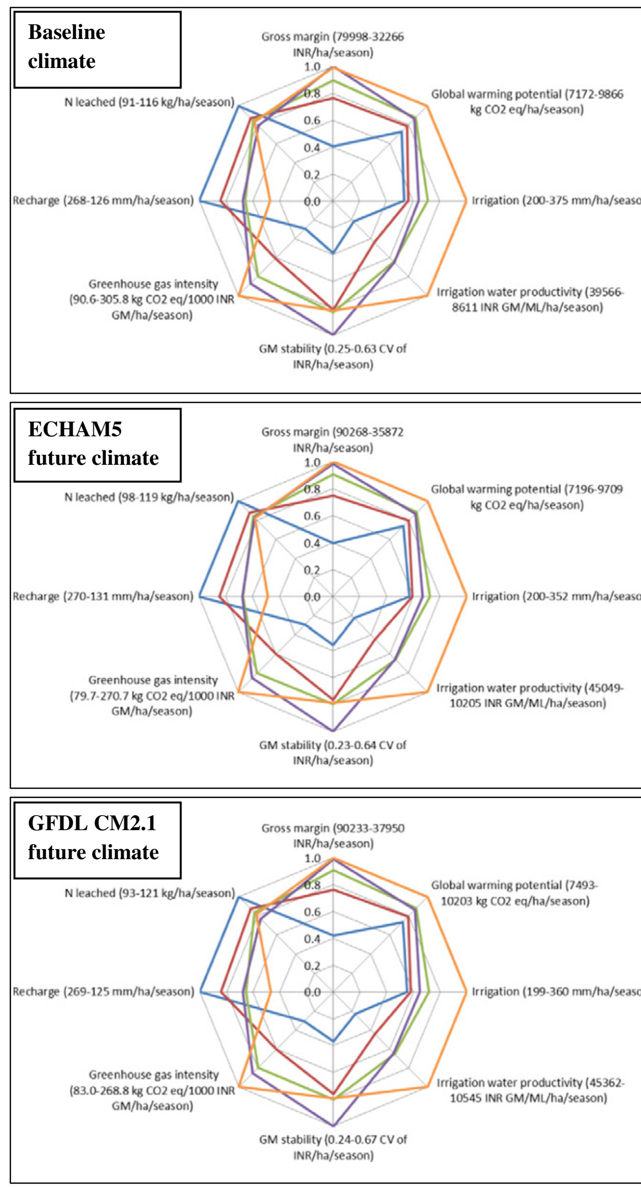

Fig. 6. Comparison of gross margin, global warming potential, irrigation, irrigation water productivity, GM stability, greenhouse gas intensity, aquifer recharge and N leached for each of the adaptation options used on small farms at Gorita growing rice and cotton for 1) baseline climate (1978–2009), 2) future climate ECHAM5 (2021–2040) and 3) future climate GFDL CM2.1 (2021–2040). Blue lines represent current practice, red lines option 1, green lines option 2, purple lines option 3 and orange lines option 4. Ranges for each variable are shown in parentheses.

the sustainability indicators vary with climate scenarios, the relative positions of the sustainability indicators remained the same (Fig. 8).

Similar observations were made for the medium rice-cotton farm in Gorita (Accessory Publication Figs. 23 and 29) as well as when maize substituted cotton in the cropping system (Accessory Publication Figs. 26, 32, 37 and 42) and when the same treatments were applied at Bairanpalli (Accessory Publication Figs. 12, 14, 17, 19, 22, 25, 28, 31, 34, 36, 39 and 41) and Nemmani (Accessory Publication Figs. 13, 16,18,21,24, 27, 30, 33, 35, 38, 40 and 43).

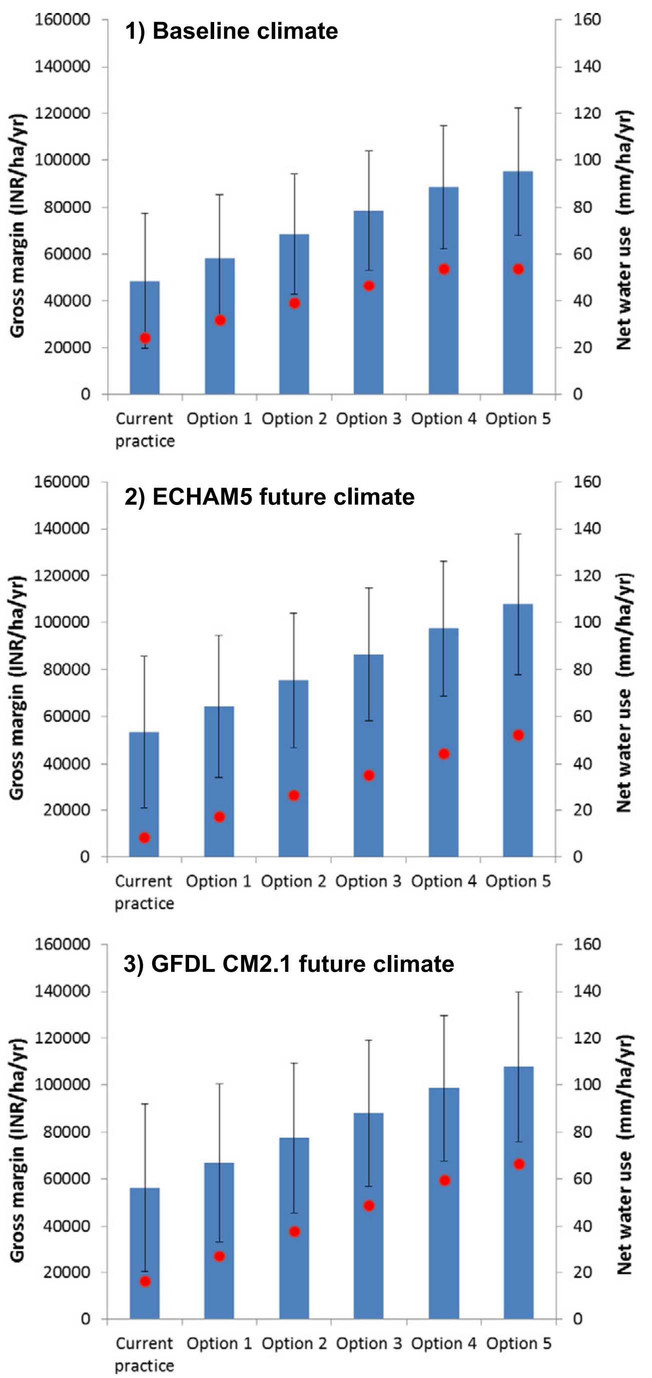

Fig. 7. Gross margin (blue bars) and net water use (irrigation-recharge, red dots) for adaptation options used on large farms at Gorita growing rice and cotton for 1) baseline climate (1978–2009), 2) future climate ECHAM5 (2021–2040) and 3) future climate GFDL CM2.1 (2021–2040).

4. Discussion

It is noteworthy, though not surprising given the expected rate of climate change to 2021–2040 (Chaturvedi et al., 2012), that the projected changes from either GCM models are relatively modest (Fig. 1). This is reflected in seed cotton yield potential for both the rainfed and strategically irrigated crops where the differences in the distributions of simulated yields between the historical record, the ECHAM5 and the GFDL CM2.1 scenarios was small relative to the range of yield outcomes due to year to year variability (Fig. 3). The presence of both positive and negative yield consequences depending on future climate scenario and village reflects and reinforces earlier ambiguities about medium term

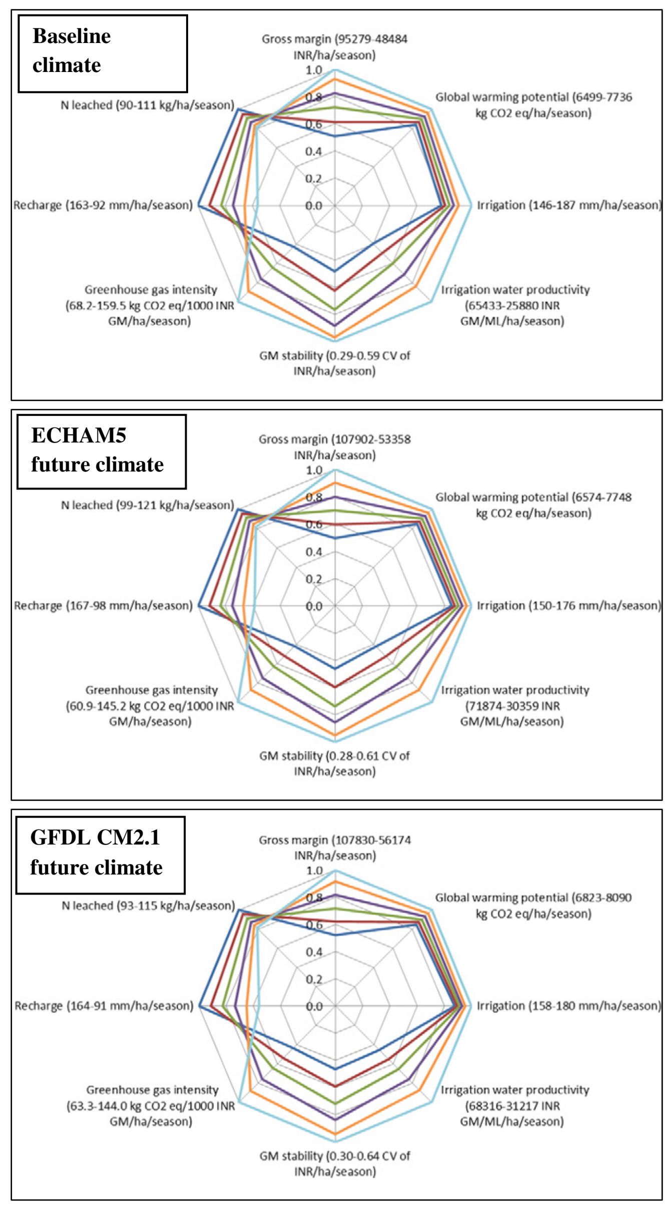

Fig. 8. Comparison of gross margin, global warming potential, irrigation, irrigation water productivity, GM stability, greenhouse gas intensity, aquifer recharge and N leached for each of the adaptation options used on large farms at Gorita growing rice and cotton for 1) baseline climate (1978–2009), 2) future climate ECHAM5 (2021–2040) and 3) future climate GFDL CM2.1 (2021–2040). Dark blue lines represent current practice, red lines option 1, green lines option 2, purple lines option 3, orange lines option 4 and light blue lines option 5. Ranges for each variable are shown in parentheses.

consequences of climate change as reported by Barnwal and Kotani (2013).

We found the sustainability polygons to be a useful means of assessing how climate smart the adaptations are. The sustainability polygons for sowing rules for cotton and maize in Bairanpalli and Gorita tend to show for each of the three climate scenarios that the adaptations to climate variability which improved yield outcomes tended to also improve the whole set of sustainability outcomes. Applying criterion one (i.e. all indicators greater than baseline), this is a climate smart win-win (×6) situation for yield and yield stability, gross margin and gross margin stability, reduced GWP and GHGI (Fig. 2).

The strategic irrigation of rainfed crops was a somewhat ambiguous adaptation with some trade-offs between sustainability indicators in the baseline climate scenario (Fig. 4). However, taking the area under the polygons (i.e. the second criterion) it is still possible to establish that strategic irrigation is a climate smart practice. However, to the extent that these adaptations were climate smart for the baseline climate, they maintained their relative positions for the future climate scenarios (Fig. 4).

The sustainability polygons for adaptations involving reduced rice area for strategic irrigation of rainfed crops demonstrated clear trade-offs between sustainability indicators. With this adaptation, the current practice was most sustainable in terms of the amount of nitrogen leached from the root zone and the amount of recharge beyond the root zone for each farm type. However, based on the area of the polygon, this option was invariably least sustainable in terms of overall gross margin, gross margin stability, the amount of water used for irrigation, irrigation water productivity, as well as GWP and GHGI. The same trade-off applied to each of the three climate scenarios. Here too, while there is no option that can consistently fulfil the three aspirations of climate-smart agriculture, the choice of trade-offs remains the same for the three climate scenarios.

The greater recharge consistently observed for the current practice is a consequence of more irrigation being applied across the whole farm and this effect is offset by the overall lower net water used in this option. Another consequence of reduced rice area adaptations is that more N is leached as a consequence of increased N leaching from the root zone of supplementally irrigated cotton and maize crops. However, the difference in N leached between the various treatments is relatively small (2–10 kg/ha/yr). Unless N leaching becomes a major sustainability issue it is likely that most stakeholders would agree that one of the lower rice area options is overall most sustainable. The observation that adaptation to historical climate variability also held for future climate scenarios, when viewed through the wider sustainability perspective, applied to the three adaptations considered in this study. In other words, for the three villages and three adaptations in this study, adapting to climate variability proved to be climate smart. This is encouraging given that the adaptations ranged from the simple sowing rule adaptation to the more transformative adaptation involving reduced rice irrigation area to enable strategic irrigation of rainfed crops.

5. Conclusions

This paper examines the performance of farmer tested adaptations to climate variability (baseline climate) against two contrasting scenarios of medium term climate change by deploying up to eight sustainability indicators that are consistent with the aspirations of 'climate-smart agriculture'. The indicators chosen have implications for food security, for economic viability, for maintaining the water resource and for reducing greenhouse gas emission intensity. We found the sustainability polygons to be a useful tool to systematically and quantitatively assess whether adaptations are climate smart. On balance, we conclude that the adaptations studied meet the criteria for climate smart practices in that they sustainably increased agricultural productivity and incomes; improved the resilience of food systems; improved farming livelihoods and reduced greenhouse gas emissions in current and future climate scenarios. Our results also show that irrespective of the climate scenario, we can sometimes expect adaptations to result in trade-offs between different desirable outcomes. The implication of this finding is that farmers and policy makers will need to prioritise or weight the various sustainability indicators.

The finding that the impacts of climate change scenarios for 2021–2040 are variable and small in comparison with existing climate variability does not imply that longer term climate change is unimportant. However, given that farmers are more likely to adapt to current climate variability, the assumption that such adaptations will hold for medium term climate change was found to hold true for adaptations tested in this study.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2016.11.007.

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