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Prioritizing climate-smart agricultural land use options at a regional scale

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ABSTRACT

The promotion of climate-smart agriculture in different parts of the world requires a clear understanding of its relative suitability, costs and benefits, and the environmental implications of various technological interventions in a local context under current and future climates. Such data are generally difficult to obtain from the literature, field surveys and focused group discussions, or from biophysical experiments. This article describes a spreadsheet-based methodology that generates this information based on a region specific production function and 'target yield' approach in current and future climate scenarios. Target yields are identified for homogeneous agroecological spatial units using published crop yield datasets, crop models, expert judgement, biophysical land characterisations, assessment of yield gaps and future development strategies. Validated production/transfer functions are used to establish relationships between inputs (water, seed, fertilizer, machinery, energy, labour, costs) and outputs (crop yields, residues, water and fertiliser use efficiencies, greenhouse gas emissions, financial returns). The process is repeated for all spatial units of the region, identified through detailed mapping of critical biophysical factors, and for all suitable current and potential agronomic production technologies and practices. The application of this approach is illustrated for prioritizing agronomic interventions that can enhance productivity and incomes, help farmers adapt to current risk, and decrease greenhouse gas emissions in current and future climates for the flood- and drought-prone state of Bihar in north-eastern India. In general, climate smartness increases with advanced technologies. Yield is the least limiting while emission is the most limiting factor across the entire crop-technology portfolio for climate smartness. Finally, we present a robust climate smart land use plan at district level in Bihar under current and future climate scenarios.

1. Introduction

South Asia has witnessed robust economic growth over the past 20 years, yet it is home to more than one-fourth of the world's hungry and 40% of the world's malnourished children and women. Persistent climatic variability, which results in frequent droughts and floods, is among the major reasons for this. Climate change, manifested by depleting glaciers, increasing coastal erosion, frequent heat waves, rising sea level, frequent floods and droughts and varying rainfall patterns, is projected to exacerbate the existing pressures on land and water resources. Several global as well as regional studies have indicated that the productivity of food crops, livestock and fish may decline even in the short-term with significant effects later in the century, if corrective actions are not taken now to improve our adaptive capacity (Aggarwal, 2008; Naresh Kumar et al., 2013; Rosenzweig et al., 2014). Since these impacts on agricultural production influence poverty levels, especially in South Asia where >500 million people directly depend on agriculture for a living, it is evident that climate change can worsen poverty in the region. There is, therefore, an urgent need to develop strategies that can incentivise land use that would meet future food demand, increase farmers' income, build resilience, and wherever possible reduce emissions (FAO, 2010; Lipper et al., 2014).

Several technological interventions and policy measures may be able to bring about this transformation. Changes in agronomic practices, adoption of the new technologies and the use of relevant information (e.g. climate information based agro-advisories and weather index based insurance) at the farm level can be key components in improving the adaptation of agriculture to climate change (Byjesh et al., 2010; Naresh Kumar et al., 2014; Naresh Kumar and Aggarwal, 2013; Parihar et al., 2016). These options can significantly improve crop yields, increase input-use efficiencies and net farm incomes, and reduce greenhouse gas emissions (Smith et al., 2007). Many of these interventions

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have been successful in increasing production, income and building resilience among farming communities in many areas such as the Indo-Gangetic plains (Parihar et al., 2016). These interventions, however, come with varying costs and economic impacts, and their implementation requires critical investment decisions in relation to both on-farm capital and wider agricultural outreach programs. Their implementation also requires an understanding of trade-offs and synergies among them. Selecting appropriate interventions for maximizing the synergies and reducing the trade-offs requires decision support tools to facilitate identification of portfolios of appropriate technological interventions. Climate change associated uncertainties add to the complexity of prioritizing technologies. Further, this makes prioritization data hungry and complex. Since developing countries have invariably limited capital and resources to invest, there is a need to choose interventions that can meet multiple goals of development. At the same time, it is important to ensure that our actions today to promote adaptation do not lead to increased maladaptation or inequity in society over the long term.

There are relatively few studies in the literature showcasing work on prioritizing climate-smart agriculture interventions (Brandt et al., 2015; Tendall and Gaillard, 2015; Webber et al., 2014; Claessens et al., 2012). A key reason for limited studies on this subject is difficulty in obtaining data that can facilitate the analysis of changes in local biophysical characterization and production economics with the top-down policy changes and regional land-use. The typical minimum dataset required are economic yields of various commodities and the inputs used, such as irrigation and fertiliser, to produce them in different regions over several crop seasons. At the same time, the data should provide an assessment of costs and benefits, carbon sequestration and GHG emissions in order to understand the mitigation potential of various interventions. Traditional methods of research such as field and stakeholders' surveys, focused group discussions, regular national yield monitoring trials, and agronomic trials are generally inadequate to provide sufficient data to understand the synergies and trade-offs among production, resilience and mitigation in current and future climate conditions.

Several recent studies have shown the application of production functions, crop simulation models, and field experiments to generate such data for a region for food security planning (Shaffer et al., 2000; Aggarwal et al. 2001; Louhichi et al., 2010; Alary et al. 2016; Claessens et al., 2012; Webber et al., 2014; Tendall and Gaillard, 2015; Belhouchette et al., 2011; Rigolot et al., 2016). These bio-economic modelling studies used multiple approaches to generate input-output data for land use prioritisation for food security planning and other developmental goals. None of these studies, however, considered a climate-smart agriculture perspective, in particular GHG emissions. Several tools are now available that are able to provide quick estimates of GHG emissions of various agronomic interventions (Hillier et al., 2011). In this paper, our objective is to provide a spreadsheet based methodology to generate production, economic and environmental databases of agronomic interventions for different regions and for different climate change scenarios. The database developed here integrates from process based models (crop simulation models), weather generators and downscaler, tools and calculators (emission calculators, irrigation requirement calculators etc.). Since the dataset is a result of integration of different approaches, it is rich in information on biophysical and economic parameters. It characterizes current agricultural production processes and their dynamics for all districts at land unit scale in Bihar in relation to different climate change scenarios (RCPs). This dataset itself can lead to meaningful inferences for prioritizing interventions, regardless of any optimization framework, by exploring adaptation strategies for climate change though land unit or district-level analysis. Here, we present a simple agroecological analysis from the policy planning perspective for prioritizing a crop-technology portfolio across 38 districts in Bihar. The specific objective is to identify combinations of crop technology and district (agricultural land use) that lead to increases in productivity and income, and decreases in GHG emissions intensity.

2. Materials and methods

Bihar is located in the north-eastern part of India. It has geographic area of 94,163 km^2 divided into two parts by the river Ganges that flows from west to east. Over 66% of the geographic area is cultivated. Agriculture in Bihar is characterised with low productivity, substantial yields gaps, and high uncertainty and instability in production. There is a high proportion of small, marginal and landless farmers. Cropping intensity is also low (<1.4). About 60% of the gross cropped area is irrigated; tube wells are the main source of irrigation followed by canal irrigation. Bihar has a diverse climate and is prone to high climatic risks in terms of both deficit as well as excessive rainfall. Several climatic scenarios indicate the likelihood of increase in temperatures and huge shifts in rainfall patterns. The increasing temperature and changes in rainfall patterns can adversely affect the productivity and profitability of agricultural systems in the state.

2.1. Evaluation of regional resources, constraints and delineation of land units

Quantitative resource assessment remains a prerequisite for developing input-output relationships for identifying climate smart agricultural land use options. In this study, we demarcated 34 homogenous spatial units for quantitatively describing the input-output relations of the various crops and livestock activities by overlaying biophysical layers of soil texture class, drainage, flooding, rainfall and temperature (Fig. 1). Since most of the socio-economic baseline data is available at political boundary scale, we superimposed district boundaries on these 34 zones, which resulted in 194 land units; the smallest units of assessment in this study. Each land unit within an administrative block (here district boundary) differs from another by at least one biophysical attribute. This helps to characterise biophysical responses in the production process.

In the above process, soil datasets of National Bureau of Soil Survey and Land Use Planning (NBSS&LUP, 2002) at 1:1 million scale were used. This included attributes relating to information on soil depth, texture, soil pH, land drainage class and susceptibility to flooding. Soils in Bihar are dominantly sandy and loamy; however, in the southern part clay soils are dominant. Information on soil organic carbon, pH, electrical conductivity, Olsen P and available K were taken from Sharma et al. (2012). Flooding is one of the most important limiting factors in Bihar's agricultural production system during *Kharif* (rainy season) and to some extent in *Rabi* (winter season). About 41% of the total cropped area in the state is flood prone (Flood Management Information System, Government of Bihar, http://fmis.bih.nic.in/). We used long-term 10 min gridded average temperature and rainfall for Bihar based on the WorldClim dataset (Hijmans et al., 2005).

2.2. Production technology characterisation

Eight major crops, covering 90% of the gross sown area, dominate Bihar's agriculture land use. These crops are rice in rainy season (*Kharif*), Mung bean (Green gram) in summer, wheat, gram, mustard, lentil, and *khesari* (Lathyrus) in winter (*Rabi*) season, and maize in all three seasons. The suitability of these crops in different land units vary depending upon soil, water and climate. This was assessed based on expert judgement and land units unfit for a given crop were excluded from further analyses.

Crop yields in a land unit depend on its soil, climate, technology and related agronomic and monetary inputs. Farmers of Bihar follow several practices and technologies for various crops. In this study, we have considered 10 production technologies for all eight crops listed above. The baseline yields for irrigated and rainfed systems are denoted as T1 and

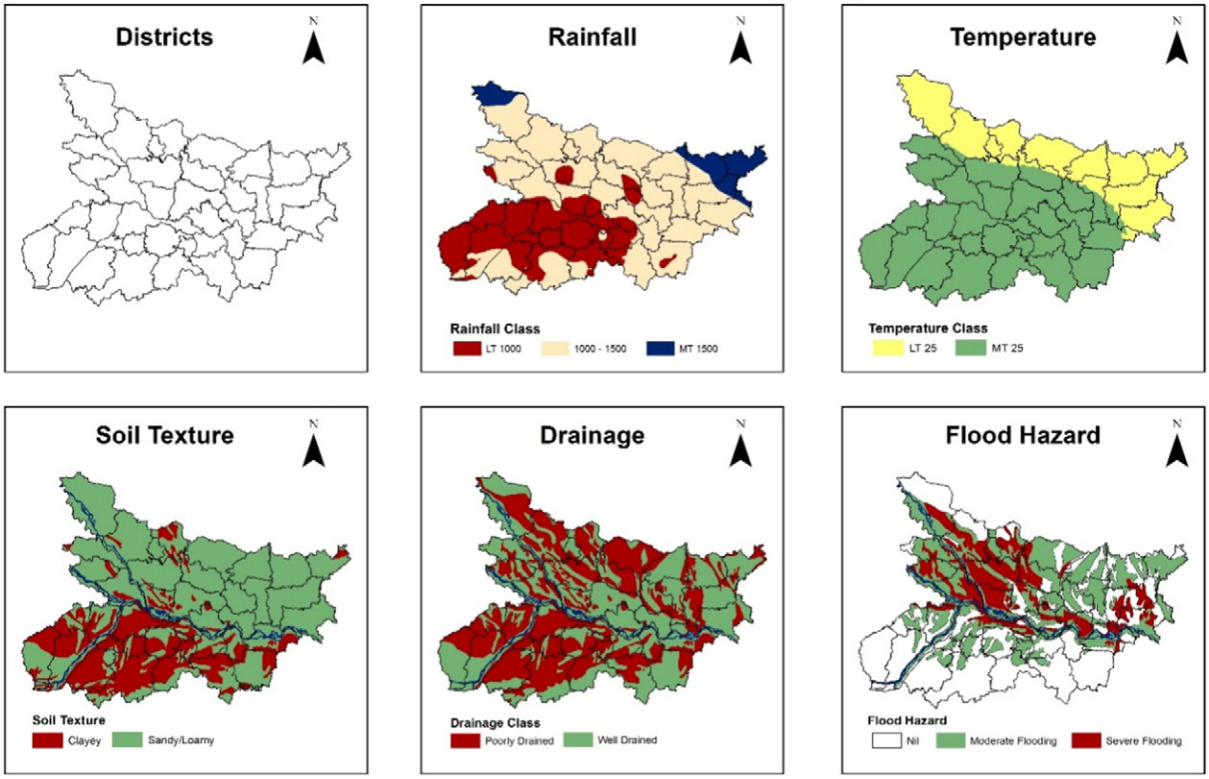

Fig. 1. Spatial datasets used in delineation of 194 land units in Bihar.

Table 1
Technology packages in 10 different treatments used in this study.

Technology characteristics	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Traditional cultivars	√	√								
Fertilizer application required to realize target yields	√	√	√	√	√	√	√	√	√	√
Water conservation practices			√							
Index based insurance			√						√	√
Improved cultivars			√							
Seed replacement			√	√	√√	√√√	√	√√	√√√	√√√
Biocide application		√		√	√	√	√	√	√	√
Additional secondary tillage					√	√√				
Leaf colour charts rice, wheat and maize)							√	√	√	√
Laser levelling and water management							√	√	√	√
Residue incorporation								√	√	√
Reduced tillage								√	√	√
Alternate wetting drying (rice)									√	√
Site specific nitrogen management										√
Improved irrigation pump efficiency										√
Farmer trainings										√
Average yield gap closure, %	–	–	*15*	*15*	*30*	*50*	*15*	*30*	*50*	*75*

T represents technology package, T1 and T2: current rainfed and irrigated technology; T3: improved rainfed technology; T4 to T6: different levels of intensification technology (low to high); and T7 to T10: different levels of climate smart technology (low to vey high). Multiple tics under seed replacement, tillage and biocide application indicates frequency of their operations.

T2. Since improvement in crop production is a major priority in the state, we have considered for this analysis seven additional packages of technologies for irrigated systems and one for the rainfed systems (Table 1). These technologies can be grouped into input intensification based in irrigated (T4, T5 and T6) and rainfed (T3) systems. Here the emphasis is on gradually increasing applications of irrigation, fertiliser and quality seeds. Technologies T7 to T10 represent different combinations/portfolios of climate-smart technologies for irrigated systems. In these, the emphasis is on yield growth through resource use efficiency and precision management of inputs.

For each land unit, a 'target yield level' was defined based on current measured yields (three-year averages for the period 2008–09 to 2010–11), simulated potential yields, and technology (Hengsdijk et al., 1996). Potential yields of rice, wheat, maize, gram and mustard crops were simulated using a well-validated crop growth model-InfoCrop (Aggarwal et al., 2006). As calibrated and validated crop models are not available for khesari (Lathyrus), mung bean and lentil, yield impacts on these crops were approximated using those of gram. These potential yield estimates were used for quantifying the scope of yield improvement with the current varieties that can be bridged in future with improved technology. The target yield approach helps in exploring options for future and thus in the planning process. Its major limitation is, however, its inability to consider impact of weather shocks.

2.3. Climate Change

Since climatic parameters directly or indirectly affect all edaphic and biological processes, these processes will have climate change impacts, though their magnitude may vary depending on sensitivity. We used an ensemble mean of 17 GCMs for each representative concentration pathways (RCP2.6, 4.5, 6.0 and 8.5) and time period (2020, 2050 and 2080) to calculate input: output relationships of crops. The MarkSim_Standalone was used to generate this data Jones and Thornton (2013) and Jones and Thornton (2015). Fig. 2 shows the average annual maximum and minimum temperature, and average annual

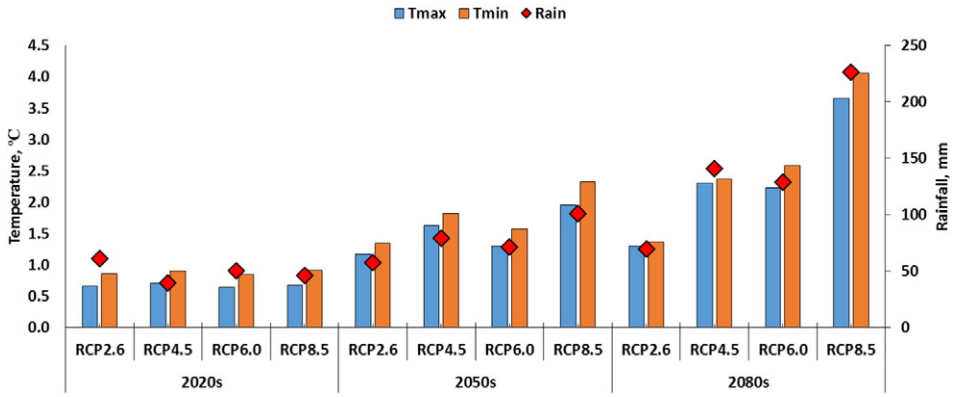

Fig. 2. Average annual maximum and minimum temperature and average annual rainfall anomalies under climate change scenarios.

rainfall anomalies under different climate change scenario during the 2020s, 2050s and 2080s. Climate models project increasing trends in both temperature as well as annual rainfall in Bihar. Maximum increase in temperature as well as rainfall occurs under the RCP8.5 scenario in the 2080s. These changes will have profound impacts on crop hydro-biophysical processes such as evapotranspiration and irrigation requirements in addition to yield attributes.

2.3.1. Yields under climate change

Yields changes under climate change (with CO_2 effect) are simulated using InfoCrop (Aggarwal et al., 2006). The simulations were done for four RCPs and three time periods (2020s, 2050s and 2080s) against the baseline (2010). The effect of climate change on crop yields, expressed as a percentage change relative to the baseline, is shown in Table 2 for irrigated conditions.

In general, irrigated wheat and maize show declines in yield. This decline becomes appreciable after the 2050s. Gram and mustard in winter show increases in yields. Yields of winter pulses, which are rainfed, are likely to increase owing to increases in winter rainfall.

2.4. Inputs-Outputs calculations

Inputs required to realize target crop yields and all other ancillary outputs are calculated under all climate change scenarios at different time slices for each land unit/technology combination. Key inputs assessed are irrigation requirements by source, labour requirement by type, and costs of inputs (fertilizer, labour, water). Key outputs are yields, by-products, and emissions. A technical coefficient generator (TCG) developed earlier by Aggarwal et al. (2001) based on current knowledge of production ecology was used to generate biophysical input/output data for each technology and land unit. The method integrates biophysical, agronomic, and socio-economic data to establish input-output relationships related to water, fertilizer, labour and GHG emissions. A simplified scheme of various calculations, the inputs used, driving variables and resultant outputs in the TCG is shown in Fig. 3 and the sources of various processes involved, and data sources is provided in Table 3. In this TCG, the technical coefficients were specifically developed to quantify differences in resource use of current (Technology levels 1 and 2) and future-oriented land-use options (Technology levels 3 to 10) aimed at increasing production and income. Key in calculating the technical coefficients was the target-yield oriented approach, which acted as the independent variable that dictated the inputs, i.e., nutrients, water, labour, pesticides and machinery, required to attain this yield (Fig. 3).

GHG emissions are calculated based on the amount of inputs used and related processes in the soil-plant-atmosphere continuum. The emissions were calculated using "The Cool Farm Tool", an open source spreadsheet based software (Hillier et al., 2011). It uses 'Tier2-type' methods, offering users simple menu choices for parameters that farmers can influence to reduce their carbon footprint. Apart from emissions from soil processes, we also considered the emissions resulting from on-farm activities such as irrigation pumping and tillage. The Global Warming Potential (GWP) values used (based on a 100-year time horizon) were 21 for CH_4, 310 for N_2O and 1 for CO_2. The GWP of different treatments was calculated using the following equation (Watson et al., 1996):

$$GWP = \text{Total\_}CO_2\text{\_Emissions}^{*44}/_{12} + CH_4\text{\_ac}^{*}21 * {}^{16}/_{12} + N_2O\text{\_ac}^{*}310 * {}^{44}/_{28}$$

Costs of fertilizers and farmyard manure (FYM), human and animal labour, hiring of tractors and procurement prices of produce as well as residues were derived from Government statistics. Total cost of production included costs of seeds, human labour, machine labour, irrigation, fertilizers, FYM, biocides and miscellaneous (10% of operational costs) costs. Gross income was the value of main produce (grain) and residue. Net income of the farmers was calculated as the difference between gross returns and total costs. All above inputs-outputs calculations were then repeated for four climate change scenario (RCP2.6, 4.5, 6.0 and 8.5) and three time-period (2020s, 2050s and 2080s). The key driving variables are climatic parameters and yields which then drives changes in all inputs and outputs like irrigation requirements, GHGs emissions etc.

2.4.1. Climate-smartness

The climate smartness of current land use was assessed using three benchmark indicators of CSA: productivity, incomes, and emissions. Any crop, technology or land unit is termed as climate smart whenever it has higher yield and income over the baseline and lower emission intensities. We used these indicators as binary at the district level to measure relative changes over the baseline. The binary framework and

Table 2
Simulated climate change impacts on productivity (% change over baseline) of irrigated crops in Bihar.

Period	Scenario	Wheat	Rice	Maize	Gram	Mustard
2020	RCP2.6	−2.83	−3.75	−8.98	−0.87	6.17
2050	RCP2.6	−1.86	−0.29	−14.35	1.00	8.90
2080	RCP2.6	−2.33	−13.24	−16.61	1.30	9.75
2020	RCP4.5	−2.99	−2.70	−13.00	−2.09	5.58
2050	RCP4.5	−2.41	−0.90	−15.71	7.41	12.33
2080	RCP4.5	−5.76	4.98	−15.79	10.47	10.74
2020	RCP6.0	−1.64	−2.31	−14.07	0.83	7.11
2050	RCP6.0	−1.11	0.49	−19.22	6.82	10.43
2080	RCP6.0	−7.56	4.62	−22.64	11.45	12.16
2020	RCP8.5	−1.81	−8.00	−10.86	0.59	6.06
2050	RCP8.5	−6.89	−3.16	−22.55	8.01	12.71
2080	RCP8.5	−24.14	−1.20	−34.88	13.48	4.53

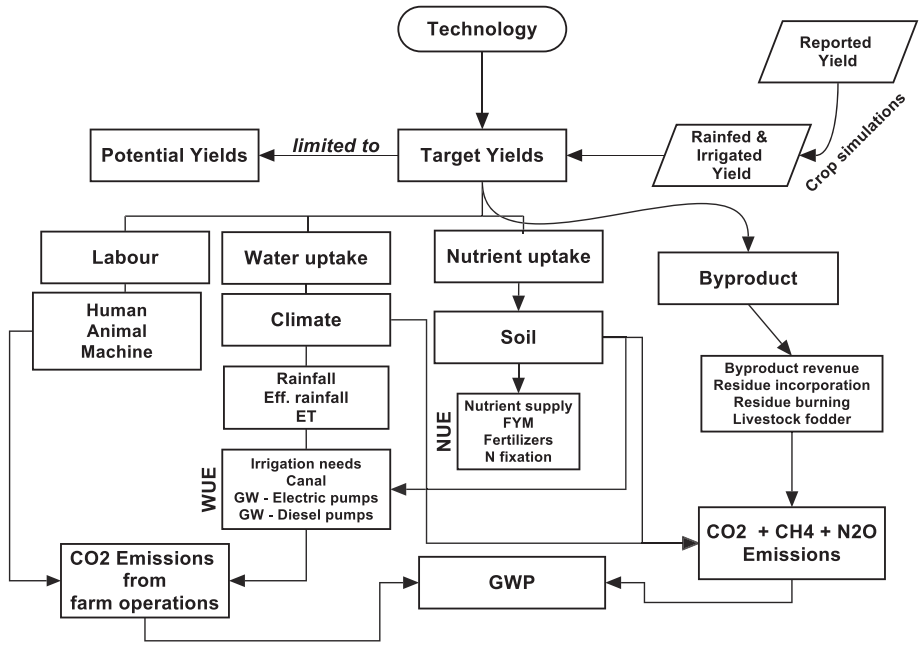

Fig. 3. Biophysical framework for generation of the data and parameters for the model toolkit (Where, Eff.rainfall: effective rainfall, ET: evapotranspiration, GW: groundwater, WUE: water use efficiency, FYM: farm yard manure, NUE: nutrient use efficiency, GWP: global warming potential).

district scale goes well with planning perspective although the results can be traced to land unit level. For policy planners this approach can help in prioritizing the resources to bring out the desired land use changes in region. Further, to overcome the limitations of binary formulation of the indicator framework, we also did analysis on the magnitude of smartness by adding differentials to benchmark indicators e.g. the sensitivity of having different levels (0 to 50%) of higher yields and income and lower emissions than the baseline.

2.4.2. Assumptions and uncertainties

Database development for this prioritization exercise relied mainly on secondary sources for data, dynamic crop simulation models, and simple input and output calculators. In this study, yield gap closure and technology stacking were done via expert judgement and crop growth simulations. Reported yields were broken down into rainfed and irrigated yields using site-specific simulations, and through area weights for reported irrigated and total sown areas. The production cost model does not include rental value of own land as a cost component. Key uncertainties arise through the use of GCM outputs; there are considerable uncertainties in downscaling as well as uncertainties in the GCMs themselves (Wilby, 2007). Confidence in projections depends on variable, season and the location. In this study, we used different scenarios and ensemble mean of 17 GCMs to assess likely climate changes and their impacts. The ensemble means and consideration of several scenarios can help to increase confidence in projection.

Table 3
Brief summary of approaches used for mapping input-output relationships of various crops and technologies in land units of Bihar.

Process	Approach
Future climatic conditions (CMIP5)	MarkSim GCM downscaler and weather generator
Impacts of climate change on crop yields	Dynamic crop growth simulation model (InfoCrop, Aggarwal et al., 2006)
Crop evapotranspiration	Reference evapotranspiration: Hargreaves' method (Hargreaves et al., 1985); Crop ET: FAO-56 single crop coefficient method (Allen et al., 1998); ET under yield reductions: FAO33-Crop yield response to water (Doorenbos and Kassam, 1979)
Effective rainfall	USDA formula (Dastane, 1974)
Irrigation	Water balances on demand and supply side
Fertilizer	Mass balances between demand and supply of nutrient from soil, it includes supply from soil, manure, residues, and biological fixation
Energy	For farm operations: based on secondary data; for irrigation: based on source of energy, ground water depth and irrigation requirements
GHG emissions	For crops using The Cool Farm Tool (IPCC tier-II methodology) and for irrigation and machine use by relating them to energy use

3. Results and discussion

3.1. Inputs-outputs under current and future climate

Table 4 shows selected inputs and outputs for rice crop under current and future climate scenarios averaged across all land units in Bihar. Results indicate that crop yields increase with input intensification (T6) as well as when climate-smart technologies (T10) in current as well as future climates. In the absence of such technologies crop yields and income are likely to go down with climate change. Climate-smart technologies need relatively less inputs, are more input efficient, but also cost more and cause more emissions, especially in future

Table 4
Illustration of key inputs-outputs calculated for rice at current and future climate for selected technological interventions. Data is mean of all land units for Bihar. T2 is baseline irrigated, T6 is input intensification T10 is climate-smart technology. For more details of T2, T6 and T10 please refer to Table 1.

	Current climate			Future climate, RCP8.5 – 2080s		
	T2	T6	T10	T2	T6	T10
Yield, kg/ha	1683	3154	3890	1663	3144	3885
Income, INR/ha	1093	14631	21103	937	14570	21496
Emission, kg CO_2EQ/ha	3095	3571	4109	3752	4298	4968
Irrigation requirement, mm	521	669	564	502	657	555
Effective rainfall, mm	503	503	503	529	529	529
WUE, kg yield/ha-mm	1.64	2.69	3.65	1.61	2.65	3.58
Nitrogen applied, kg/ha	23	50	40	19	45	39
Total cost, INR/ha	19244	24140	26802	19136	24060	26367

climates. The irrigation requirement in future climate does not increase significantly despite temperature increases because of increase in rainfall. Such results vary with crop and technology (data not shown).

A complete dataset of such inputs: outputs for all 194 land units, 8 crops and 10 technologies under current climate and future climate scenarios is available from the authors on request. These data provide valuable information related to the agricultural production process, the impact of technological interventions and climate change on yield, and incomes and greenhouse gas emissions at land unit scale.

3.2. Climate smartness of current land use in current and future climate:

The climate smartness of current land use was assessed using three benchmark indicators of CSA: productivity, incomes, and emissions (Table 5). Income here is calculated at current prices for all periods. Impact of technological interventions on productivity is modelled in database development through the target yield approach described above, and these interventions are likely to increase productivity. However, this effect may be offset by negative impacts of climate change on crop yields. The impacts are highest for wheat and maize in the winter season because of the rise in temperature. These impacts become appreciable after the 2050s. Net income remains a complex derivative of productivity, technology costs, climatic parameters such as rainfall (and its distribution) and temperature, and ground water depth, among other factors.

Table 5 indicates that the current land use will be less climate smart under the future climate. Rabi pulses and mustard are likely to show some yield gains, but these gains will be at the cost of higher GHG emissions. Income levels will go up slightly (~+7%) owing to marginal yield gains in rabi pulses and mustard; maize (kharif and summer) will start becoming a loss-making venture because of severe yield penalties under the future climate. Emissions will go up by + 17%, and the highest increase in emissions is projected for Mung bean. The increase in emissions is attributed to increased temperature leading to higher irrigation requirements, associated emissions from pumping, and increases in nitrous oxide emissions. Fig. 4 shows the change in emission intensity of current technology (T2) for RCP8.5 during the 2080s over the baseline averaged across all crops.

Fig. 4 also highlights the fact that current technologies will not remain climate smart in the future. The emissions for all crops for current irrigated technology will increase; however, this increase will depend on biophysical factors and future climate. The emission intensity of eastern Bihar will show the least increase, while southwestern Bihar (Aurangabad and Rohtas districts) will likely show the highest increase in emission intensity under future climate scenarios.

3.3. Alternate technologies and crops for enhancing climate smartness

Table 5 and Fig. 4 indicate that current land use will not remain climate smart in the future. However, new technological interventions can help offset this impact. We evaluated different technologies ranging from current farmer practices to very advanced farming practices (Table 1) at the district level for climate smartness. Climate smartness here is assessed across all crops, RCPs and future periods. The number of districts with an increase in yields and incomes over the baseline and a decrease in emissions are shown in Fig. 5. For all districts, the fulfilment of the criteria of climate smartness through gain in yields, increases in income and decreases in emissions intensity for a given technology is indicated by the "overall" series (Fig. 5). Out of 38 districts in Bihar, 36 districts are likely to maintain or gain productivity across all the crops and districts under T10 technology, although its climate smartness will be limited by income (31 districts) and emissions (18 districts).

For the T10 technology portfolio, the criteria of climate smartness is fulfilled in 15 districts. Climate smartness increases with advanced level of technologies, and yields are least limiting while emissions are the most limiting factors for climate smartness across all technologies.

A similar analysis for different crops across technology portfolios can guide in the selection of crops for climate smartness (Fig. 6). Climate smartness here is assessed across all technology portfolios, RCPs and future periods. The criteria of climate smartness are fulfilled in 20 districts for rice followed by 12 districts for gram. Maize in rabi (winter) season remains least climate smart because of the severe yield impacts under future climate scenarios. In general, rabi pulses will remain more climate smart than other crops. The analysis indicates that climate smartness is a complex characteristic that depends on crop, technology, and the biophysical conditions under which the crop is grown.

3.4. Robust climate smart land use plan

For each land unit, crop and technology portfolio, whenever the criteria of productivity increase, income increase and emission intensity decrease are met, it was termed a climate smart land use for that time period and climate scenario. To test robustness of this land use across the spectrum of climate scenarios and future periods, we calculated climate smartness across different RCPs (RCP2.6, 4.5, 6.0 and 8.5) and time scales (2020s, 2050s and 2080s). If land use was found to be climate smart across all climate scenarios and time-periods, then it is termed a robust climate smart land use plan. The likelihood of this land use remaining climate smart is more across a wide spectrum of variation under different climate scenarios and time-periods. Here we present the robust climate smart land use plans by district; this analysis is aggregated for the lowest level of assessment (land unit). Tables 6 and 7 indicate suitability of technological interventions at different districts under four climate scenarios and three time scales. The grey filled boxes in Tables 6 and 7 indicate the crop-technology combinations for districts which fulfil the criterion of climate smartness (increased yield and income and decreased emission intensity over the baseline) for given crop and technology portfolio across all the RCPs and future time periods.

From Tables 6 and 7, it is clear that the highest level of technology will not be sufficient to make all districts in Bihar climate smart. Baseline irrigated technology (T2) will no longer remain a climate smart option

Table 5
Yield, income and emission intensities of major crops (current irrigated technology) in Bihar under current and future climate (RCP8.5, 2080).

Crop	Yield, kg/ha		Income, INR/ha		Emission intensity, kg CO_2EQ/kg Yield	
	Current climate	Future climate (RCP8.5, 2080s)	Current climate	Future climate (RCP8.5, 2080s)	Current climate	Future climate (RCP8.5, 2080s)
Rice	1683	1663	1093	937	1.84	2.26
Maize (Kharif)	1865	1214	−2190	−6981	0.41	0.60
Gram	1846	2095	28555	34341	0.32	0.42
Khesari	1784	2024	10972	13742	0.29	0.38
Lentil	1589	1803	35330	41689	0.34	0.46
Mustard	1897	1983	30291	32267	0.35	0.44
Maize (Rabi)	3384	3113	10642	8530	0.26	0.32
Wheat	2335	1772	9466	3057	0.27	0.35
Mung bean	582	660	7222	9449	1.28	1.48
Maize (summer)	2865	2063	5830	−194	0.65	0.82

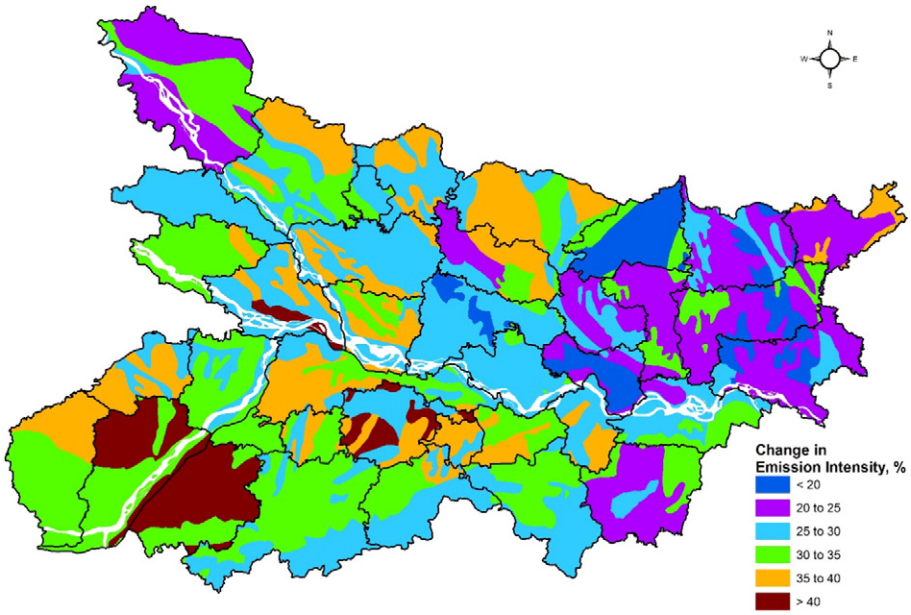

Fig. 4. Change in emission intensity of current technology (T2) for RCP8.5 at 2080 over baseline (2010).

in future. Under climate change scenarios, the improved rainfed technologies in *rabi* season will be benefited from increased rainfall and yields. From Tables 6 and 7 key climate smart districts under different technological interventions can be identified. The resources and constraint characterisation of each district or spatial unit differs by the technological intervention and crop, and so their suitability needs to be understood in the context of its resource use. From Table 7 it appears that wheat remains a viable option only with rainfed technologies because of increased winter rainfall. For irrigated wheat, negative yield impacts can be offset by technology adaptation, although emissions intensity in this case increases as a result of increased resource use. A close look at the districts, crop and technological interventions satisfying the criteria of climate smartness (Tables 6 and 7) across different climate scenarios and future periods suggests that when we move from baseline technologies towards advanced climate smart technologies, the number of districts satisfying the suitability criterion are increased.

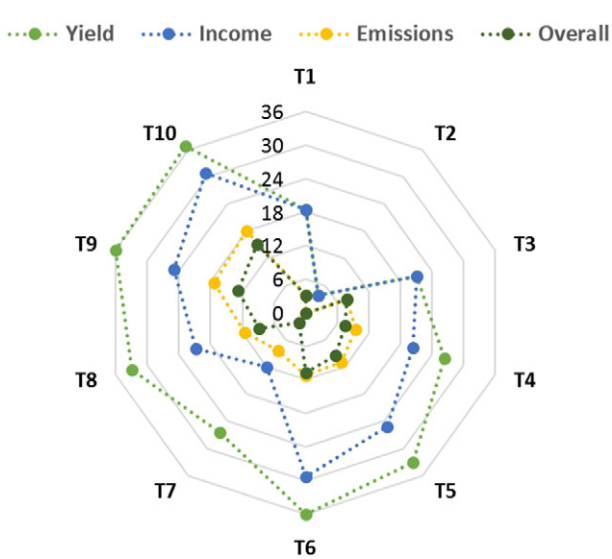

Fig. 5. Prioritized technology options: number of districts where CSA indicators (yield, income, emission and all three together) are improved over the baseline; T represents technology package, for more details please refer Table 1.

Rice remains suitable in the future under new technological interventions because of the low level of baseline yields (Fig. 5); this gives enormous scope for bridging the yield gap and raising incomes. Further, the emission intensity of rice at the baseline level is very high. Wheat, rabi and summer maize, mustard and *khesari* (Lathyrus) are worst affected by climate change, and this suggests that production of these crops may not remain profitable or environmentally friendly. Wheat and maize show negative yield impacts of 24.1 and 34.9%, respectively, under climate scenario RCP8.5 in the 2080s (Table 2). However, *Rabi* rain-fed technology remains a good adaptation option, as these crops are benefiting from a shift in rainfall pattern.

To check the magnitude of the climate smartness, we repeated the analysis (results not presented here) with different levels of thresholds applied to yield and income, in addition to baseline criteria of more yield and income and less emission intensity over the baseline. The thresholds used varied from 10% to 50%. The number of climate smart districts decreased with the increase in the level of the threshold.

For all crops and technological interventions and across all RCPs, yield limits climate smartness in about 16% of cases, income limits in 25% of cases, and emissions in 57% of cases (Fig. 7). The percentage of

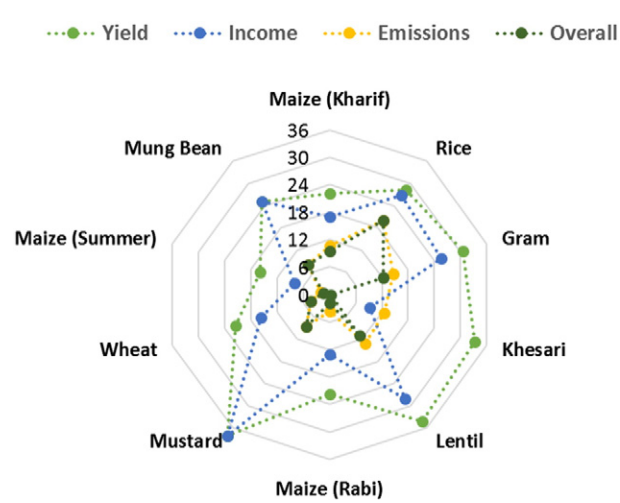

Fig. 6. Prioritized crop options: number of districts where CSA indicators (yield, income, emission and all three together) are improved over the baseline.

Table 6
Climate smartness of districts under different crop-technology portfolios for Kharif and summer crops (Grey filled boxes indicates suitability of crop-technology under four RCPs and three future time periods 2020s, 2050s and 2080s).

	Maize (Kharif)										Rice										Maize (Summer)								Mung Bean							
Districts	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T2	T4	T5	T6	T7	T8	T9	T10	T2	T4	T5	T6	T7	T8	T9	T10
Araria																			■	■																■
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Buxar					■	■		■	■	■					■				■	■										■	■	■	■	■	■	■
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Kishanganj														■	■	■	■	■	■	■												■			■	■
Lakhisarai					■	■		■	■	■			■	■	■	■		■	■	■																
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Nalanda					■	■		■	■	■				■	■	■	■	■	■	■												■			■	■
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districts that are climate smart decreases as we move from the 2020s to the 2080s (Fig. 7).

As not all districts will remain climate smart, even with the highest level of technological interventions, the best portfolio of crop-technology for each land unit must be used to its potential level for ensuring food security without damaging the environment.

4. Conclusions

The dataset generation methodology presented here combines biophysical datasets with a detailed technology coefficient generator. This generator integrates the knowledge base of several sciences and provides relatively easily the inputs required to realize target yields and ancillary outputs. With biophysical inputs, it becomes possible to characterize current agricultural production processes and their dynamics. Incomplete databases and issues around data quality remain major limiting factors in most developing countries; in these situations, database development will need to make use of several underlying assumptions. The methodology presented here gives a structure and theoretical foundation to deal with several of these challenges. Because this methodology also deals with vulnerability and impact analysis, it could be a valuable resource for researchers wishing to carry out for baseline assessments as well as climate change impact studies. An illustration of the use of the database developed for Bihar indicated highlighted key inputs and outputs in the agricultural production process under current and future climates. In general, climate change will affect yields of wheat and maize the most, of all the crops considered.

The database outlined here can be used to derive meaningful inferences for prioritizing climate smart interventions, by exploring adaptation strategies for climate change though bio-economic land unit level analysis. Simple agroecological-based analysis indicates that current technologies will not remain climate smart under future climate. We then identified alternate crops and technology for climate smartness – rice is noteworthy in this respect, because of its low level of baseline yields, which gives considerable scope for raising yields and incomes. In general, climate smartness increases with increasingly advanced levels of technologies. Yields (~16% cases) are least limiting while emissions (~57% cases) are the most limiting factor across the entire crop-technology portfolio. Finally, we presented a robust climate smart land

Table 7
Climate smartness of districts under different crop-technology portfolios for *Rabi* crops (Grey filled boxes indicates suitability of crop-technology under four RCPs and three future time periods 2020s, 2050s and 2080s).

	Gram										Khesari										Lentil										Maize (Rabi)										Mustard										Wheat									
Districts	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
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use plan at district level in Bihar under current and future climates. The number of climate smart districts decreased when moving from the 2020s to the 2080s. The highest level of technological interventions alone will not be sufficient for all districts to increase productivity and income, while reducing emissions intensity below baseline levels.

The methods used in the analysis are not without challenges. As noted above, the target yield methodology has much to contribute in the realm of agricultural planning, though what constitutes appropriate target yields in different situations remains a key question, particularly in studies that are attempting to incorporate the effects of changes in

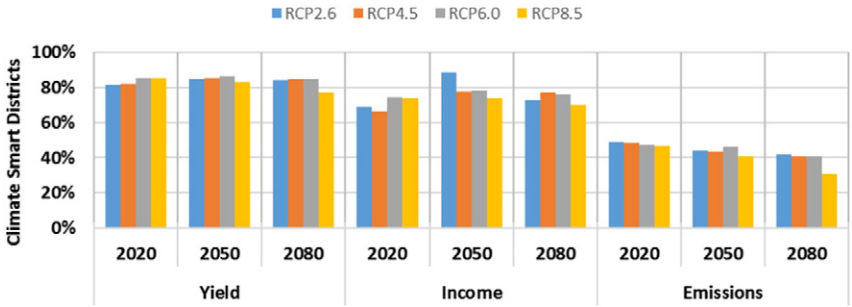

Fig. 7. Constraints for climate smartness.

climate and climate variability into the analysis. Such analysis is certainly data intensive. On the other hand, once an appropriate database has been set up for a region, it can facilitate a wide range of analyses, with the ultimate aim of providing actionable information to policy makers in the pursuit of their development objectives.

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