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Multi-objective land use allocation modelling for prioritizing climate-smart agricultural interventions

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ABSTRACT

Climate-smart interventions in agriculture have varying costs and environmental and economic impacts. Their implementation requires appropriate investment decisions by policy makers that are relevant for current as well as future scenarios of agro-ecology, climate and economic development. Decision support tools are therefore needed to assist different stakeholders to prioritize and hence implement appropriate strategic interventions. These interventions transform agriculture ecosystems to climate-resilient, adaptive and efficient. This paper outlines the mathematical modelling framework of one such, the Climate Smart Agricultural Prioritization (CSAP) toolkit. This toolkit employs a dynamic, spatially-explicit multi-objective optimization model to explore a range of agricultural growth pathways coupled with climate-adaptation strategies to meet agricultural development and environmental goals. The toolkit consists of three major components: (i) land evaluation including assessment of resource availability, land suitability, yield and input-output estimation for all promising crop production practices and technologies for key agro-ecological units; (ii) formulation of scenarios based on policy views and development plans; and (iii) land-use optimization in the form of linear programming models. Climate change and socio-economic drivers condition the land evaluation, technological input-output relations, and specification of optimization objectives that define modelled scenarios. By integrating detailed bottom-up biophysical, climate impact and agricultural-emissions models, CSAP is capable of supporting multi-objective analysis of agricultural production goals in relation to food self-sufficiency, incomes, employment and mitigation targets, thus supporting a wide range of analyses ranging from food security assessment to environmental impact assessment to preparation of climate smart development plans.

1. Introduction

The Climate Smart Agriculture (CSA) is an integrative approach to address the interlinked challenges of food security, climate change impact, and ecological sustainability (Lipper and Zilberman et al., 2018; Steenwerth et al., 2014). To achieve these, three objectives are defined: (i) sustainably increasing agricultural productivity to support equitable increase in farm incomes, food security and development; (ii) adapting and building resilience of agricultural and food security systems to climate change; (iii) and reducing greenhouse gas emissions from agriculture (FAO, 2013). A range of technological, institutional and policy options has been proposed to help agriculture become climate-smart, including weather insurance, spatial weather forecasts, agricultural diversification, stress-tolerant crop varieties, community management of soil and water resources, and policies related to water and carbon management (Thornton et al., 2017; Shirsath et al., 2017; Khatri-Chhetri et al., 2017; Long et al., 2016; Lipper et al., 2014; Vermeulen et al., 2012). These interventions have varying costs and economic impacts. Moreover, the effectiveness of these interventions depends on agro-ecological condition of a region and their adoption is highly influenced by the socio-economic characteristics of the agrarian society of that region (Khatri-Chhetri et al., 2017; Sapkota et al., 2017). Therefore, the implementation of CSA requires appropriate investment decisions in both on-farm capital and wider agricultural outreach

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programmes. Furthermore, climate-smart investment can have a wide range of scales ranging from the single field up to the national level. It is unlikely that investment in any single intervention will provide optimal benefits, but rather an integrated portfolio of interventions is required to best support adaptation to climate change in agriculture across a range of scales. This spatial complexity is compounded by the long timeframes associated with climate change, requiring further consideration of when as well as where to prioritize investment in any set of intervention options. If climate-smart technologies provide net benefits to farmers irrespective of climate change – so termed no-regrets options (Thornton and Lipper, 2014; Willows and Connell, 2003) – then the investment is preferred as soon as possible. However, given the costs of investment in the short-term under constrained budgets, and with the benefits of adaptation, increasing with the progressive impacts of climate change, it may be preferable to delay investment until full benefits can be realised. Decision support tools are therefore needed that can assist different stakeholders to prioritize appropriate and timely strategic interventions to transform agricultural practice to become climate-resilient, efficient and adaptive (Tanure et al., 2013). Given the competing social, economic and environmental dimensions of adaptation decisions, Multi-Criteria Analysis (MCA) is becoming increasingly popular in supporting the development of adaptation strategies. MCA differs from traditional risk management tools. It can retain competing objectives separately rather than aggregating them into a single, weighted decision metric (Willows and Connell, 2003). MCA (Prabhakar, 2014; Feltmate and Thistlethwaite, 2012; Lobell et al., 2008) and tools based on MCA such as Adaptation Decision Matrix (ADM) (Mizina et al., 1999) have been used widely in prioritizing technology options in agriculture. Several other tools such as fuzzy-analytical hierarchical process (Sanneh et al., 2014) and crop simulation model-based adaptation decision tools (Webber et al., 2014) have also been used. Several other tools and methodologies including participatory methods (Arshad et al., 2017; Khatri-Chhetri et al., 2017; Mwongera et al., 2017; Taneja et al., 2014) have been reported for adaptation prioritization (e.g., Willows and Connell, 2003; Lobell et al., 2008; Cross et al., 2012; Sanneh et al., 2014; Webber et al., 2014; Ilori and Prabhakar, 2015; Brandt et al., 2017). However, there is a lack of dynamic and spatially-explicit optimization tool to explore a range of agricultural growth pathways under different climate change scenarios.

This study presented here builds over work done by Shirsath et al. (2017), where prioritization of the climate-smart agricultural land use options at a regional scale were showcased using the databases generated through a spreadsheet-based methodology. In this methodology, however, the pillars of climate smart agriculture were treated separately and finally integrated through climate smartness index. The climate smart agriculture has a wide range of objectives including – food security, increase in farmers' net income, improvement in resource use efficiency, climate resilience, and GHG mitigation. The single objective models cannot take into account the trade-offs or synergies between economic efficiency and environmental efficiency which was not addressed in the earlier work using detailed bottom-up biophysical and socio-economic databases as described by Shirsath et al. (2017). Therefore, a multi-objective modelling framework with detail consideration of spatial heterogeneity in terms of bio-physical characteristics and resource endowments is necessary to make CSA adoption decisions for a range of stakeholders. Given this motivation, we have taken into consideration multiple objectives for optimization purpose. In addition, the trade-offs among the various competitive (optimal) solutions (corresponding to different objective function) has been considered to estimate the decision space which will minimize the trade-offs among the competitive objectives so that climate smart technologies can be prioritized in more sustainable manner. Hence, this paper outlines a multi-objective prioritization toolkit based on a spatially explicit bottom-up biophysical framework, and demonstrates a case study for prioritization of CSA technologies in Bihar state, India. The toolkit supports analysis of trade-offs between objectives and identification of efficient solutions. Results shows that the toolkit is capable in optimizing different adaptation options based on bio-physical conditions of a particular location.

2. Materials and methods

2.1. Model description

In its current formulation the Climate Smart Agricultural Prioritization (CSAP) toolkit is flexible in its capability to model agricultural production at a wide range of spatial and temporal scales. A typical analysis with the CSAP toolkit starts with the identification of land units, which define the spatial resolution of the study, and then proceeds with preparation of biophysical and socio-economic datasets for the multi-objective analysis. Although database development and multi-objective analysis can be developed separately, we recognise that they are highly interdependent, in view of the nature of the explicit assumptions made during development of both the database and the toolkit. Application of the CSAP toolkit therefore encompasses all stages of data processing, assumption setting (e.g. land-unit, season and crop suitability) and mathematical model formulation. A simple flow-chart outlining this process is shown in Fig. 1.

2.1.1. Spatial land units

The effectiveness of technological interventions is strongly determined by local bio-physical conditions, climate change impacts,

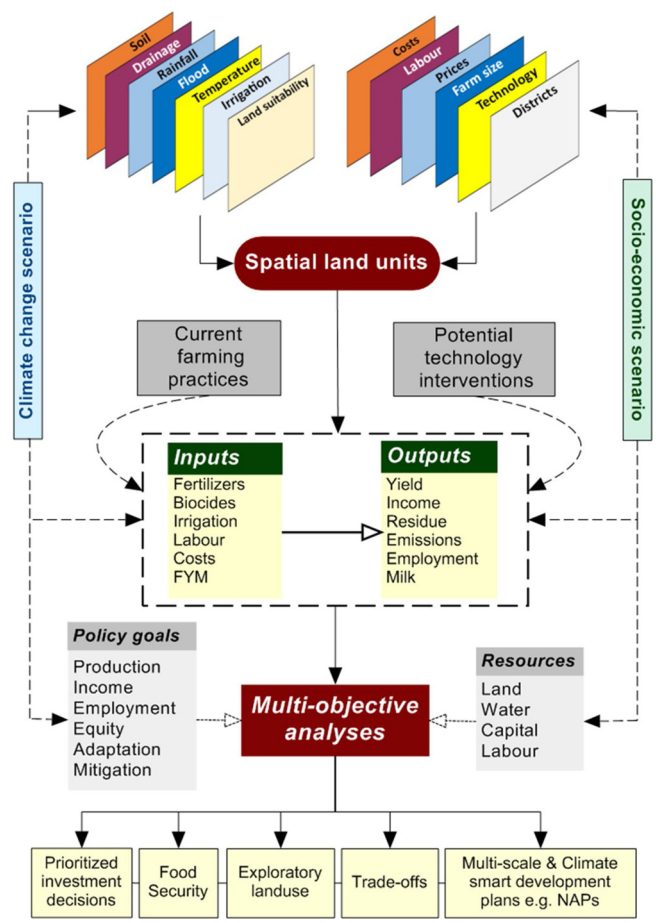

Fig. 1. Schematic diagram of the CSAP toolkit illustrating key component and their relationship. White arrows with solid outline indicates use of transfer functions for output calculations. White arrows with dashed outline indicates modular choice options for selection of the objectives and the resources constraints.

adaptive capacity and resource endowments both in space and size of production unit. As a result, no single intervention can be assumed to be generally applicable or a 'best-bet' at the landscape, regional and national scales. Each location here represents a homogeneous production area which, whilst still clearly much larger than any single farm, provides a reasonably accurate model of local production conditions and resulting crop-technology performance. CSAP toolkit uses homogeneous parcels of land designated as "land units". Within each location we can further differentiate representative farm-sizes, which may exhibit different levels of resource constraints and costs (e.g. labour, water access, working capital), and/or constrained access to particular technologies. This "land unit" approach has also been used by Agrell et al. (2004) and Aggarwal et al. (2001).

2.1.2. Dynamic agricultural development pathways

The CSAP toolkit is disaggregated over a number of discrete time-steps forming a sequence of future system states. At each future time a detailed crop-technology-specific land-use pattern is identified and a range of performance metrics derived, covering production levels, emissions, and employment, for example. The result is a pathway linking sequential system states that transitions from the current to some future system that optimises the specified objective over the total time horizon.

2.1.3. Uncertainties in future climate and socio-economic scenarios

The performance of any adaptation intervention will be conditional on future climatic conditions and the biophysical response of agricultural systems to those conditions, both of which are subject to high levels of uncertainty. In addition to this climate-centric set of uncertainties we must also recognise an entwined set of uncertainties associated with wider socio-economic development most-relevant to the agricultural sector in developing countries, such as constraints of institutions, infrastructure, and knowledge. Interventions should therefore be analysed and prioritised when they perform best across a potential spectrum of future climate and socio-economic scenarios i.e., are robust. In order to take into account this uncertainty we implement a scenario-specific disaggregation of the model. A demonstration of the segmentation of the dynamic and stochastic model horizon is provided in Fig. 2. The toolkit identifies decisions that are robust against future uncertainty (i.e. 'no-regret options') whilst identify the option to delay sensitive decisions until better information regarding climate outturn is available. In this context the information of value to the decision maker is the set of priorities defined by options taken in the short-term that are robust to future climate change.

We recommend the application of a model formulation representing multiple climate scenarios including such constraints if climate uncertainty is to be the focus of scenario analysis in a particular practical application. Given computational limitations, in examples presented in Sections 3 and 4 we focus our analysis on multi-objective optimization under various land-use constraints (e.g. uncertainty in policy objectives and socio-economic conditions), rather than an explicit analysis of climate uncertainty.

2.1.4. Multiple-objective analysis

For analysis of trade-offs between objectives and identification of efficient solutions, we first identify extreme values for the competing objectives by optimising each in isolation. Based on these extreme values a decision space can be identified within which all further trade-off solutions will be located, being bounded by observed upper and lower extremes in the respective objectives. Bio-physical, economic and environmental constraints on the maximum (or minimum) level of objectives within this decision space are then formulated and applied in a second round of model solutions (*trials*). In order to generate a set of trials that provide good coverage of the decision space we used Latin-Hypercube sampling (Mckay et al., 1979). We first identify a sample increment for each objective based on even segmentation of the observed objective range. A set of constraint levels is generated by sampling from the uniform distribution within each increment starting from the minimum objective level. Each trial identifies an optimal performance in each objective achievable under varying levels of constraint in other objectives. A random allocation variable is then assigned to each constraint level. These levels are then combined into a set of trials by matching based on the allocation variable. Finally, we screen the resulting set of model solutions to identify only *efficient* solutions. The resulting efficient frontier provides valuable information regarding the trade-offs between the two-objectives and highlights where the marginal cost of achieving one objective in favour of the other is minimised i.e. *efficient* frontier is characterised by a set of solutions from which no single objective can be improved without deteriorating another. In the context of agricultural adaptation, a set of efficient options could be identified through trade-off among the key objectives of employment, climate mitigation and food security. Options in this context are not defined at the outset by their constituent policy action but identified and characterised by their relative cost-benefit trade-offs across a range of competing objectives. The analysis constrains the adaptation options to a limited set of viable alternatives and provides the critical trade-off information required to support, if not explicitly make, the prioritization decision (Niang-Diop and Bosch, 2004). For this purpose, the information provided by the efficient frontier is invaluable.

2.2. Mathematical formulation

The dynamic land-use allocation in the toolkit is based on the minimum cost pathways to meet future demand targets under a range of agricultural growth scenarios. From these modelled growth pathways, we can determine priorities for investment in each period, both in delivering baseline growth and in adapting to the additional burden of climate-change. Modelled investment decisions constrain the optimised land-use patterns in each period. These land-use patterns comprise crop-technology combinations allocated to defined *land unit* conditional

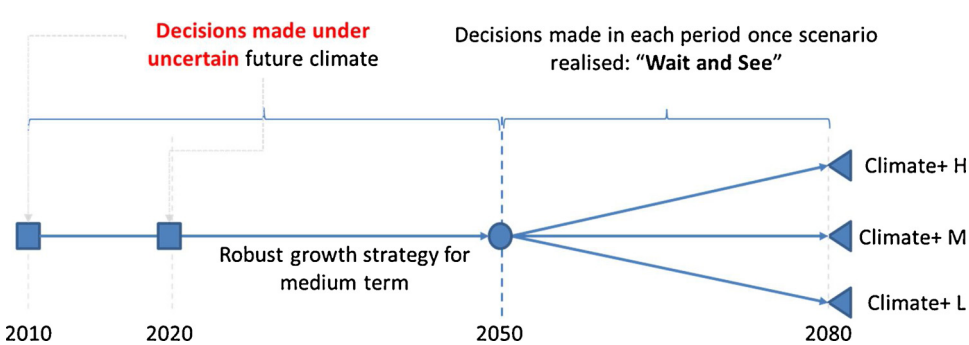

Fig. 2. Time consideration in CSAP toolkit illustrating segmentation of model horizon for robust recourse decisions and delayed options (Note: Robust decisions are made uniformly across underlying climate scenarios whilst flexible future decisions are made for each scenario once climate outturn is realised).

on area, labour and water constraints. This dynamic allocation is further constrained by scenario-specific constraints on (i) the rate of land-use change, (ii) the scale of reallocation of existing production, and (iii) the suitability of crops and technologies to particular land units – specifically the limited application of high-technology on small and marginal farms. Here we present a condensed formulation for mathematical clarity. On this basis the toolkit is developed around a primary activity variable $x_{i,j,t,s}$ that represents the area allocated to a particular crop-technology $'i'$ within a particular land-unit $'j'$ at a given time t for each climate scenario $'s'$. From the variable $'x'$ we can determine two further variables specifying the total *increase* in area under each crop and technology ($y_{i,j,t,s}$) and the associated *investment* in increasing the working capital within each land-unit ($z_{j,t,s}$). The relationship between these variables is defined as:

$$y_{i,j,t,s} \geq x_{i,j,t,s} - x_{i,j,t-1,s} \quad \forall\ i, j, t, s \tag{1}$$

$$z_{j,t,s} \geq \sum_i x_{i,j,t,s} \cdot c_{i,j,t,s} - \sum_i x_{i,j,t-1,s} \cdot c_{i,j,t-1,s} \quad \forall\ j, t, s \tag{2}$$

$$x_{i,j,t,s},\ y_{i,j,t,s},\ z_{j,t,s} \geq 0 \quad \forall\ i, j, t, s \tag{3}$$

Importantly, when measuring investment areas and associated costs we only measure the *increase* in cropping area under technological intervention or associated cost. In Eq. (2) we sum over crop and technology combinations, allowing existing working capital to mobilise freely among new production activities within each land unit. However, any additional costs of production at a given time-step *above that required in the previous time-step* are recorded as investment costs. Production costs for each activity ($c_{i,j,t,s}$) are variable over time in order to model the impact of climate-change on crop production. As a result, even if cropping activities are held constant the impact of climate-change can be observed where investment is required to maintain productive area. We recognise that our representation of investment costs is limited to only changes in the total production cost between time-steps. We do not account for costs of outreach and extension effort required in order to facilitate the adoption of new technologies or the cost and inefficiency of delivering the increase in working capital (e.g. via public or private credit).

The toolkit is constrained at a biophysical level by the availability of land, water and labour resources. Eq. (4) represents this block of resource constraints in the standard linear programming (LP) formulation. Activity coefficients (A, e.g. seasonal irrigation water requirement, monthly labour requirement etc.,) and resource limits (B, e.g. land area, labour availability etc.,) are exogenously varying with time and for specific climate scenarios. Within this set of constraints, a range of spatial and temporal disaggregations can be applied. For example, in our case study presented below activities are defined and parameterised at a biophysical land-unit level (N = 194) whilst water and labour constraints are applied at an aggregate district level (N = 38). Land-units are mapped to districts on a one-to-one basis within the constraints implied by Eq. (4). In the temporal domain labour constraints are applied on a monthly, or single 'peak' month, basis whilst land is constrained on a seasonal basis – a single unit of land being available for cropping in three seasons within any single year.

$$A_{t,s} \cdot \boldsymbol{x} \leq B_{t,s} \quad \forall\ t, s \tag{4}$$

In addition to the classical set of resource limits a number of additional constraints are formulated to model the dynamics of the system under a range of growth scenarios.

$$x_{i,j,t,s} = x^0_{i,j} \quad \forall\ i, j, s, t = 1 \tag{5}$$

$$\sum_i x_{i,j,t,s} \geq \sum_i x^0_{i,j} \quad \forall\ j, s, t > 1 \tag{6}$$

$$\sum_i \sum_j x_{i,j,t,s} \cdot Y_{i,j,t,s} \geq T_t \quad \forall\ t, s \tag{7}$$

$$\sum_i \sum_j y_{i,j,t,s} \leq R_{t,s} \quad \forall\ t, s \tag{8}$$

Following calibration the land-use pattern for the first position of the dynamic model is fixed via Eq. (5) to calibrated levels ($x^0_{i,j}$). Under particular growth strategies we can then apply Eq. (6) to constrain the total area under production for each land-unit at latter time period to be at least that observed at the base period. In the absence of this constraint the model can freely reallocate production in the spatial domain. In the analysis presented below we term these scenarios *local* and *global* respectively

Eq. (7) ensures that the growth pathway achieves the target level production at each future time period (T_t). Technically, the level of production is specified as the product of the cropped area and the scenario- and period-specific yield of the selected crop-technology at each location ($Y_{i,j,t,s}$). In practice, this target level may be adjusted downwards to a feasible maximum level of production if target production levels are not achievable. Further, the toolkit is actually expressed over indices representing crop and technology separately. Similarly, the location index 'j' is spliced into separate indices for biophysical land unit, land type (i.e. rain-fed, irrigated) and farm size (e.g. marginal, medium, large etc.).

In the absence of additional constraint the model will shift rapidly from the calibrated initial time period ($t = 1$) to optimal configurations driven by those objectives outlined below. We therefore implement Eq. (8) to constrain the increase in area under new crop and technology combinations to a specified upper bound ($R_{t,s}$) for each period to time t. The upper bound R is calculated assuming a specified maximum annual rate of land-use change in each year of the period prior to time t. This assumes a fixed rate of technology adoption across the aggregate of all crop-technology combinations, combining increased expansion in current technologies with intensification and climate-smart options. As in the case of production targets, a more refined analysis could specify adoption rates and associated constraints specific to each crop-technology combination.

Given the set of constraints outlined above, we consider two key objectives applied in the analysis algorithm outlined below; maximising production and minimising net-present cost:

$$\max_{x,y}\left[\sum_s P_s \cdot \sum_t \sum_i \sum_j x_{i,j,t,s} \cdot Y_{i,j,t,s}\right] \tag{9}$$

$$\min_{x,y,z}\left[\sum_s P_s \cdot \sum_t \left\{\left(\gamma_t \cdot n_t \cdot \sum_i \sum_j x_{i,j,t,s} \cdot [p_i \cdot Y_{i,j,t,s} - c_{i,j,t,s}]\right) - \left(\delta_t \cdot \sum_j z_{j,t,s}\right)\right\}\right] \tag{10}$$

In the case of multiple future climate-scenarios being specified, Eq. (9) maximises *expected* production as the product of total production over the model horizon for each scenario weighted by the likelihood of each scenario (P_s). This objective is applied in a model with Eqs. (1), (4) and (8) to identify whether specified target levels are achievable.

Eq. (10) is applied in a model containing Eqs. (1)–(8) in order to identify growth pathways that maximizes the expected net-present value of the farm margin over the model horizon given exogenously specified prices (p). We assume that investment occurs at a constant rate within each period so that discount factors applied to investment costs (δ) represent the average factor for the period prior to position $'t'$. The activity variable (x) relates to the operating point at each model position (e.g. snapshot year). We linearly interpolate between subsequent time periods to calculate representative discount rates (γ) and time-weights () to be applied to each operating point. The further technical detail about the mathematical formulation of this model can be obtained as a supplementary material with this article.

2.3. Data specification

A wide range of data is required to apply the CSAP toolkit in a practical decision making context. A summary of data requirements of the toolkit is provided below (Table 1) for a typical CSA prioritization exercise. Shirsath et al. (2017) also describes approaches for developing

Table 1
Minimum dataset required for a typical prioritization exercise using Climate Smart Agricultural Prioritization (CSAP) Toolkit.

Domain	Data Specification	Typical Source
Biophysical	Dynamic climate change impacts (on temperature, precipitation etc.,)	Global Circulation Models (GCMs) and downscaling tools (e.g. MarkSim-Jones and Thornton, 2013, 2015)
	Likelihood of different climate scenarios	Assumptions developed with decision makers
	Water availability	Reported Government Statistics or model based estimates
	Agricultural crop suitability and productivity as function of climate, soil, water etc.,	Dynamic crop model simulation, assumptions developed with subject matter specialist
	Model of greenhouse gas emissions from production	Emission calculators e.g. The Cool Farm Tool (Hillier et al., 2011), emission coefficients
	Historical and baseline production levels	Reported Agricultural statistics
Economic	Labour availability and cost	Reported Agricultural statistics
	Model of agricultural production costs (input-output) for range of technology options	Reported Agricultural statistics and technology characterisation
	Characterisation of market effects on prices of factor-inputs and outputs	Literature
	Import costs and export revenues	Reported Agricultural statistics
	Discount rates applied to costs and benefits	Reported Agricultural statistics
Social	Feasible rates of land-use change	Literature
	Adoption rates for new technologies	Literature
	Stratification of producers (e.g. farm-size, intrinsic technology)	Literature
	Competing and complementary targets for production, mitigation, employment etc.,	Development plans
	Budget allowance for intervention	Development plans

the database component of the CSAP toolkit in an applied context. The database includes biophysical (e.g. soil, water, temperature, precipitation and production), economic (e.g. input costs, market prices for output and discount rate) and social (e.g. adoption rate, farm typology and budget allowance for intervention) datasets.

2.4. Analysis algorithm

In carrying out our analyses we undertake a series of sequential optimization runs that can be considered to constitute a general model algorithm for the analysis of (i) agricultural growth pathways, (ii) the impact of forecast climate change on these pathways, and (iii) adaptation actions to mitigate climate impacts. A high-level overview of this algorithm is provided below.

1 **Base-year system calibration**
- Run the toolkit comprising only the base-year (i.e. $t = 1$) with the objective to maximise production up to but not exceeding the level observed in base-year data for each crop within each land-unit;
- Run the toolkit again with the objective to minimise the sum absolute errors in cropping area relative to base-year data for each crop within each land-unit;
- From the resulting base-year land-use pattern specify parameter $x^0_{i,j}$;

2 **Baseline growth scenario**
- Setup the toolkit with baseline-climate data (e.g., current climate fixed over model horizon) and specify a local or global growth scenario (i.e., include or exclude eqn. 6);
- Run the toolkit to maximise net present value of the farm margin; the resulting growth pathway is referred to as the *baseline* scenario.

3 **Climate-change impact and adaptation scenarios**
- Setup the toolkit with climate-change scenario data and specify the growth scenario to be consistent with that applied in the baseline scenario above;
- Run the toolkit with constraint fixing activity variables ($x_{i,j,t,s}$) at levels in *baseline* scenario calculated in step 2.2. The resulting growth pathway is referred to as the *impact* scenario.
- Remove constraint on activity levels. Run the toolkit to maximise net present value of the farm margin. The resulting growth pathway is referred to as the *adaptation* scenario.

The result of the above algorithm is a set of three growth scenarios termed: (i) *Baseline*; (ii) *Impact*; and (iii) *Adaptation*. Whilst these can be analysed as stand-alone scenarios, further information can be derived from analysing the variation between them. Principally the variation between optimised investment and activity variables in *Baseline* and *Adaptation* scenarios explicitly identifies priorities for climate adaptation as distinct from underlying agricultural sector development. In practice the development of growth pathways that explicitly account for forecast climate-change in their design constitutes a key role in *planned climate adaptation*. These pathways implicitly minimise the impact of climate change on the growth pathways in that they are optimised under conditions for the specified climate scenario(s). In practice therefore we choose to focus on developing climate-robust growth scenarios through step 3.3. However, by comparing growth scenarios developed with and without climate-change (i.e. steps 3.2, 2.2 and 3.3) we can measure the cost of planned adaptation as additional to growth in a benign climate. This analysis is presented below, providing a valuable bottom-up estimate of climate adaptation costs to compare against top-down estimates of investment and financial-flows required to climate-proof future agricultural development (Parry et al., 2009).

2.5. Application of CSAP toolkit

A case-study application of the CSAP toolkit has been developed for the Indian state of Bihar. Bihar is one of the most vulnerable states in India to climate change. Incidence of frequent floods and drought, extreme heat stresses, and other climate related risks are posing threats to agricultural production in Bihar. This study considered major crops-rice and maize in rainy season (kharif), pulses (lentil, gram, and lathyrus), wheat, maize and mustard in winter (rabi) season, and maize and mung bean in summer season. Currently, these crops together occupy more than 85% of gross cropped area in Bihar. Table 2 shows a list of interventions in different technology portfolios used in the study. The selected technologies represent current technologies, intensification technologies and climate-smart technologies. Current technologies have two levels, current rainfed (T1) and current irrigated (T2). An improved rainfed technology (T3) is also considered which is also an intensification technology categorised separately to mark its distinction from the irrigated technologies. Intensification technologies applied to irrigated areas and these have three levels (T4–T6). The climate smart technologies (for irrigated areas) with four levels (T7 to T10) are considered in this analysis. The crop technology index (i) represents 10

Table 2
Technology interventions in different technology portfolios 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, Improved cultivars			√							
Index based Insurance			√						√	√
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										√

T represents technology package, T1 and T2: Current rainfed and irrigated technology; T3: improved rainfed technology; T4–T6: Different levels of intensification technology (Low to High); and T7–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.

crop and 10 technologies. The crop yields, area and technology characteristics were also included in the CSAP toolkit.

In this study, we demarcated Bihar into 34 homogenous spatial units and superimposing it with the district boundaries resulted in 194 land units; the smallest units of assessment in this study. Each land unit within an administrative block differs from another by at least one biophysical attribute. The land-unit index (j) is further split into 3 constituent indices representing (i) biophysical land-units each mapped uniquely to the set of districts, (ii) land type, distinguishing rainfed from irrigated land areas and (iii) farm size categories. This analysis refers four model setups comprising alternative sets of constraints on growth pathways. These constraints were developed along two axes. First, the degree to which the level of baseline production at each land-unit, type and farm size (e.g. marginal, rainfed farms in a given land-unit) are preserved in future land-use patterns, preventing free re-allocation of production to more cost-efficient locations. The inclusion or exclusion of the constraint distinguishes these *Local* and *Global* allocation. Second, a binary constraint on the suitability of particular technologies for given farm sizes – specifically small and marginal farms – can be included. This distinguishes so-termed *Marginal* or *Consolidated* technology allocation. In the consolidated case technologies can be freely allocated to any land-unit (e.g., there is no limit on the application of climate smart technologies). We refer to the resulting set of constrained systems as *Local-Marginal* (*LM*), *Local-Consolidated* (*LC*), *Global-Marginal* (*GM*) and *Global-Consolidated* (*GC*).

Local-Marginal refers to the scenario when climate smart technologies are not feasible to the marginal farmers to a particular land unit because of its size of farm and other constraints associated with it such as capital/financial, mechanisation, scalability etc. besides maintaining baseline crop-mix. This is the most practical scenario where cropping patterns are relatively stable. Whereas, under Local Consolidated scenario, we assume that all size groups are free to choose efficient technology and baseline crop mix is maintained. This scenario can be seen as manifestation of land pulling type of policies over local marginal scenario. When we assume that technology is constraint for the marginal farmers but total production of the state will be obtained from the most cost effective land unit without any minimum production target to each land unit, this scenario is called Global-Marginal. The Global-Marginal scenario considers that advance technologies are not feasible to the marginal farmers, but they can change their cropping pattern to adapt with the climate change impacts and the choice of crop can be driven by the market opportunity for a particular crop. Thus motivation behind this scenario is that, crop specific market infrastructure will be created in the region where production of that crop is cost effective. Finally, the GC scenario is an optimistic scenario where farmers will be efficient enough to choose either crop or technology or both according to the agro-ecological condition of the region and the state planner will be able to institutionalize their policy interventions and effective institutional mechanism to achieve climate smart agriculture in the state. Current agriculture production systems in South Asia are operating near to Local Marginal scenario under stable cropping systems whereas the Global Consolidation probably is the least likely scenario. Here, we primarily focus on the contrasting LM and GC scenarios.

3. Results

3.1. Baseline validation

Prior to analysis of growth pathways, the toolkit was first evaluated in order to test whether it is able to reproduce the reported production of each crop at a district level for the base-year 2009–10 (please see Appendix –III, Fig. S1 in Supplementary files). The solution proceeds by first identifying a land-use pattern that matches reported production (kt) and area (kha) levels by crop and by district in the representative baseline year. A second calibration was then carried out to minimise the absolute deviation to reported production area whilst achieving the best-fit production schema. The baseline validation ensures that the input data and constraints were realistic and allow to develop a modelled land-use pattern that matches with the observed pattern to a good degree of accuracy. Residual errors observed during these calibrations were largely due the constraints on water availability and assumptions regarding crop suitability in the given land-units. The ratio between irrigated and rain-fed production was largely controlled in the area calibration given the target production level, relative yields of the two technologies (current irrigated and rain-fed technology) and availability of rain-fed and irrigated land in each district.

3.2. Scenarios

Baseline, impact and adaptation scenarios were determined in accordance with the algorithm outlined in Section 2.4. For all scenarios and constraint setups, the toolkit targeted food self-sufficiency based on forecast demand over the model horizon. The *Local-Marginal and Global-Consolidated* constraints formed the respective upper and lower bounds on the total production envelope. Sets of scenarios for these constraints are illustrated in Fig. 3. The total crop demand scenario was derived from a combination of published statistics and measured elasticities (Kumar et al., 2011). Where incomplete, data has been adjusted to best model those specific crop categories applied in this case-study. Demand for each crop commodity over the horizon 2015–2025 was translated into a trend in per capita demand, projected forward on trend to 2030 and fixed to constant at that level from 2030 to the end of the model horizon. Total demand (kt) in each future year was calculated by multiplying projected per capita demand to total population

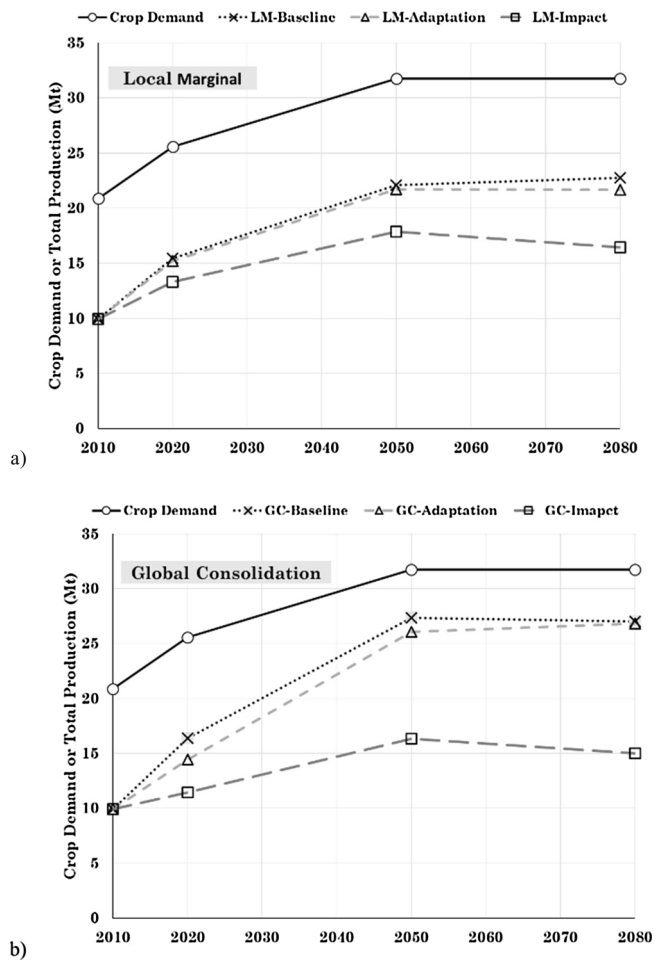

Fig. 3. Baseline and adaptation growth pathway scenarios for a) Local-Marginal (LM) and b) Global-Consolidated (GC) systems relative to target crop demand. Crop demand curve describes projected food crop demand for Bihar, India; Baseline curve indicates food production under current climate; Impact curve indicates food production under climate change scenario without any technology interventions and adaptation curve indicates food production under climate change scenario with technology interventions. For more details of local marginal (LM) and global consolidation (GC) scenario please see materials and methods.

projections based on Bihar-specific projection (Population projections for India and States 2001–2026, May 2006) to 2026 indexed to total India population projection for remainder of horizon (World population prospectus, 2016, https://esa.un.org/unpd/wpp/).

Fig. 3 shows that the targeted self-sufficiency in the crop demand is not achievable under the constrained growth pathway (Local Marginal, LM) as well as under the most relaxed growth pathway (Global Consolidation, GC). The gap in the total production and demand is more and remains same with the time as compared with the global consolidation pathway where it becomes narrower with time. Total population in the study area (Bihar) is already high and is projected to continue to grow in future. Only after 2050, food demand will not increase significantly because of low expected population growth in the state. Disaggregated analysis of individual crop showed that maize and pulses production can satisfy their demand under LM and GC scenarios, however, major crops like rice, wheat and mustard production cannot fulfil their total demand of the study area (for more information please see Appendix III – Table S1 in the Supplementary file). The profile of each set of pathways is largely dictated by the constraint on the rate of land-use change (set at 250 kha yr^{-1} over the horizon) coupled with the allowance of higher-yielding high-level climate-smart technologies in the *GC* case.

Impact scenarios measure the effect of forecast climate change on the baseline pathways if the land-use pattern was fixed at baseline levels in each period. In this case the level of impact largely reflects the forecast impact on yields, dominated by forecast reductions in wheat and rice yields by approximately 3% in 2020–6% in 2080 across all the scenarios (Table 2, Shirsath et al., 2017). Relative to this impact scenario, adaptation takes place through shifts to more climate-tolerant rice, wheat, and maize crops. An interesting result of the analysis presented in Fig. 3 is that the gap between impact and baseline scenario for the GC is significantly greater than for the LM scenario, both in absolute and proportional terms though there is an absolute lower production to meet crop demand under climate change of the global consolidated scenario. This suggests some inherent resilience of farm margin to climate change in the local, marginal configuration of production under baseline technologies. Flexibility in technology adoption and economy of scale under GC scenario leads to high agricultural growth compared to LM scenario.

We recognise the sensitivity of these results – and onward analysis of adaption costs shown below – on the climate scenario applied. The default scenario reported throughout is RCP 8.5, however we have explored other scenarios for their impact on modelled total production, cropping area and aggregate yields. Across the range of scenarios RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 the total production (kT) will be 99,828.21, 9817.60, 9817.10 and 15,211.97, respectively in 2020s. In 2050s it will be 9463.92, 9162.18, 9521.26 and 21,696.72 and 9079.16, 9277.80, 9421.73 and 21,652.26 in 2080s, respectively across the range of climate scenarios.

3.3. Marginal cost of adaptation

Table 3 presents marginal cost of adaptation to climate change measured as the additional cost relative to baseline growth for the *LM* constrained system. This omits the residual differences in production relative to baseline which represents additional costs and benefits through income and consumption. Under the adaptation scenario increase of +14.5% total kt production in 2020, +21.3% in 2050 and

Table 3
Modelled cost of production and investment under baseline and adaptation scenarios for *Local-Marginal*[a] configuration (Note: Years refer to weight of each position in interpolated cost profile).

Scenario		Units yr	2010 5	2020 20	2050 30	2080 15mmm	Total	NPV
Baseline	Production	₹bn	108.9	133.5	162.4	172.4	10670.7	4323.9
	Investment	₹bn	–	25.3	32.6	14.3	72.1	41.5
Adaptation	Production	₹bn	108.9	141.0	180.6	193.7	11687.4	4672.8
	Investment	₹bn	–	32.5	43.3	20.9	96.6	54.5
Margin	Production	%	–	5.6%	11.2%	12.4%	9.5%	8.1%
	Investment	%	–	28.4%	33.0%	46.2%	34.0%	31.5%

[a] *Note*: For more details of local marginal (LM) scenario please see materials and methods.

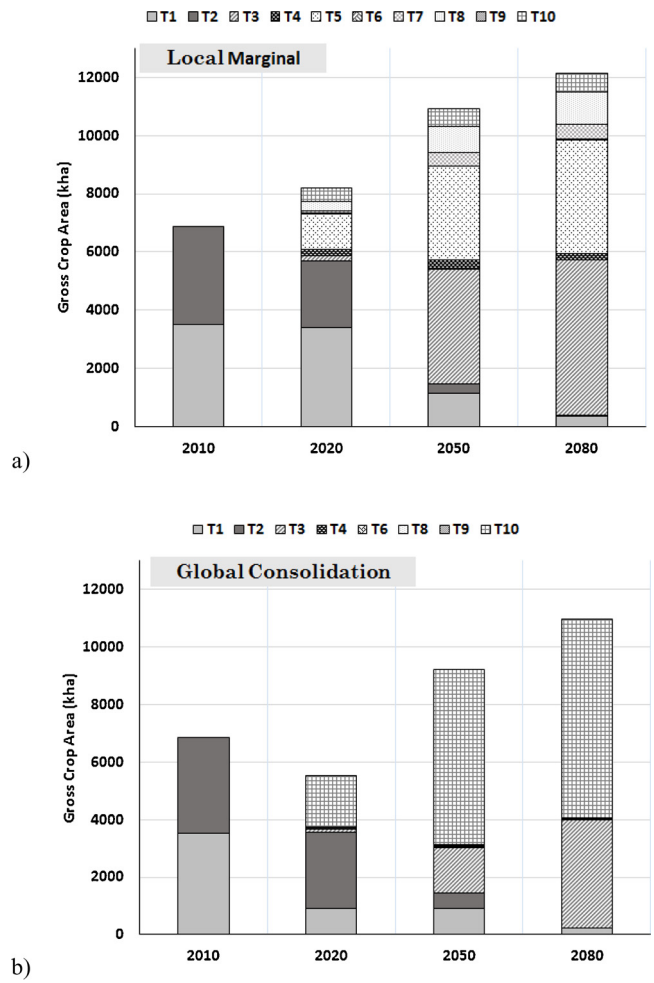

Fig. 4. Technology portfolios for growth pathways under a) Local-Marginal and b) Global-Consolidated constrained systems. T represents technology package, T1 and T2: current rainfed and irrigated technology; T3: improved rain fed technology; T4–T6: different levels of intensification technology (low to high); and T7–T10: different levels of climate smart technology (low to very high). For more details on technology portfolio, please see Table 2 and Shirsath et al. (2017).

+31.8% in 2080 were observed over the climate change impact scenario (Fig. 3). Results show that investment requirement for adaptation to climate change is rapidly increasing over the time. For instance, investment in adaptation activities has increased from 33.0% in 2050 to 46.2% in 2080 compared to baseline (Table 3). The change in total production in adaptation scenario over baseline in 2050 is about 11.2% and same change in 2080 is 12.4% leading to marginal change of 1.2%. Here, we must note that these results were not robust across configurations (Table 3).

Given the magnitude of underlying growth targets, irrespective of additional climate change impacts, we consider adaptation only in the context of incorporating climate change scenarios explicitly when developing wider growth strategies, not as a separate climate margin. Subsequent discussion of prioritization refers only to *adaptation* scenarios in their absolute, highlighting promising crops and technologies to support climate-proofed growth in agricultural output.

3.4. Crop and technology prioritization

Fig. 4a and b demonstrates the progressive shift in technology composition throughout the adaptation growth pathway for the LM and GC scenarios, respectively. Fully consolidated growth (*GC*) allows the allocation of high-level climate smart technologies (T7 to T10) to all land units, irrespective of farm-size constraints. Cost-efficiency is not a factor in these scenarios given that all targets were well above the technical potential of production. As a result, the system prioritizes investment based only on marginal yield gains per unit land-change and hence the *GC* system in Fig. 4b proposes investment only in high-level climate smart technology (T10) in the period to 2020. By comparison, the *LM* system employs a much more diverse portfolio of technologies including input intensification (T3, T5) on medium-sized farms, low-level climate smart technology on marginal farms and an early breakthrough of improved rainfed production. In both the cases 2080 represents a maximum feasible production configuration given the respective constraints on technology application. Marginal changes in Fig. 4 over the period 2050–80 correlate with the flat profiles observed in Fig. 3 over the same period. Land and seasonal water constraints are largely binding by 2050 at the allowed rate of expansion.

Crop selection decisions are much more closely aligned between the *LM* and *GC* configurations, being driven largely by common yield and sensitivity to yield. Growth in wheat and rice dominates due to significant gap to demand targets. However, when the crop demand constraints are not applied, Maize remains the best choice in many land units because of its higher productivity than rice or wheat. Under the crop demand constrained scenario, the self-sufficiency in maize is achieved early because of limited growth in its demand and selection of high yielding technology options by the model. The self-sufficiency achieved through a reduction in maize production compared to previous scenario (demand unconstrained scenario) under falling growth rate of crop demand of the cereals. The most significant difference is the delayed onset of expansion in pulses and oil-crops under the *GC* configuration, as pathways focuses on developing concentrated high-level climate smart rice and wheat production (for more information please see Appendix III – Table S2 in the Supplementary file). It must be noted that in the Fig. 4, the increase in the crop area under both the configurations indicates increased cropping intensity in the Bihar.

In addition to new technologies, increase in aggregate production requires surplus land, water and labour resources in the system. In Fig. 4a and b we observe a significant increase in gross cropping area of 2010 levels by 2080. Water constraints form a primary limit on production, in particular for rice, with kharif-season water resource being the binding constraint on production in 2080 for 36 out of 38 districts in the model. However, technology portfolio (T10) can help to minimize water related constraints by introducing water efficient technologies thereby increase gross cropped areas. Therefore, these location-specific surpluses and resource-constraints drive the place-specific priorities for the adaptation growth pathway. However, the decrease in cropping area under global consolidation scenario in 2020 are attributed the fact that crop demand targets are being achieved through the most efficient technologies under the most productive land-units which otherwise was constrained in the marginal scenarios.

Table 4 highlights the potential agricultural growth across the 38 districts of Bihar for each period for the *LM* system. This Table is sorted on 2010–20 production growth to highlight priority districts for investment in the short term. Results show both spatial and temporal distribution of land area that can be allocated under various crops in different time periods. The state level aggregated crop production shortfall and area under crops in both the scenarios is given in Tables S1 and S2 of Supplementary file. Crop wise disaggregated analysis (not presented here) shows that five districts (Supaul, Aurangabad, West Champaran, Bhabua and Araria) can significantly increase in the wheat production with exception of Aurangabad. Whilst West Champaran, currently the second largest mustard producer, is identified as a location for significant increase in the output of wheat and rabi maize production. Aurangabad, Bhabua and Supaul are projected to be producing ~20% more rice compared with the baseline production levels. In general, for the top five districts, gram and lathyrus are identified as priority crops in 2080s.

The changes in the total crop area allocation across districts of Bihar

Table 4
Total Crop Area Allocation across districts of Bihar under Local-Marginal[a] system. (Note: values represent additional investment area in kha).

District	2010 to 2020	2020 to 2050	2050 to 2080	Total
Supaul	278	-176	68	170
Aurangabad	143	-7	75	211
West Champaran	140	386	-221	305
Bhabua	134	7	-62	80
Araria	124	233	-77	280
East Champaran	116	86	-97	105
Rohtas	113	321	-355	79
Purnia	96	257	-199	154
Banka	88	215	-76	228
Muzaffarpur	85	136	-26	194
Madhubani	78	241	2	322
Gaya	74	172	-154	92
Gopalganj	73	115	-103	85
Buxar	72	90	-79	84
Nalanda	72	23	79	173
Patna	71	15	68	155
Madhepura	61	165	-133	92
Bhojpur	55	136	-36	156
Nawada	52	148	-148	52
Siwan	50	127	-53	124
Katihar	45	239	-81	203
Munger	44	8	-33	20
Jamui	38	137	26	201
Bhagalpur	38	139	-67	110
Samastipur	35	323	-290	67
Kishanganj	34	198	-37	195
Arwal	31	13	-42	3
Saran	31	168	-136	64
Saharsa	30	161	-59	133
Darbhanga	28	245	-183	90
Begusarai	28	114	-61	80
Sitamarhi	26	151	-40	137
Lakhisarai	26	45	-10	60
Vaishali	20	150	-91	80
Sheikhpura	20	13	-3	30
Khagaria	19	86	-61	44
Sheohar	15	22	-16	21
Jehanabad	13	93	-85	21
Total	**2500**	**5000**	**-2799**	**4701**

[a] *Note*: For more details of local marginal (LM) scenario please see materials and methods.

results in change in the effective returns (to unit land-use change) under climate impacts. Marginal yield changes are +28, +7 and −10% for the period 2010–2020, 2020–2050 and 2050–2080, respectively, over the previous time. Yield gains diminish towards the end of the century under the current available technologies.

3.5. Trade-off analysis

We conducted trade-off analysis under the local marginal (LM) scenario between (i) minimizing emissions (*Min.Emissions*), (ii) maximizing the total production (*Max.Prod*), and (iii) maximizing the total NPV of farm margin (*Max.NPV*). Fig. 5 presents trade-off between production and emission intensity in the different time periods. Results shows that there is a large trade-off between production and emissions (CO_2 eq.) across the time period. The production gaps between max. production and min. emissions are about 7, 19 and 21 million tons in 2020s, 2050s and 2080s, respectively. The gap in emission intensities of maximization of production and NPV of farm margin against minimization of emission is large in 2020s. The gap in emission intensities of maximization of production and minimization of emission is minimum in 2080s, however, the gap still remains appreciable between maximization of NPV of farm margin and minimization of emission. There is yield penalty for minimizing emissions, however, emission intensity (CO_2 eq kt^{-1}) can significantly decrease with increase in total production overtime. The widening gap in production and narrowing gap in emission intensity over time indicates the selection of more high yielding but emission-efficient technologies by the model. With changed landuse (crop-technology combination) the production and emission changes are not proportional.

The change in crop area becomes appreciable only after the 2020s

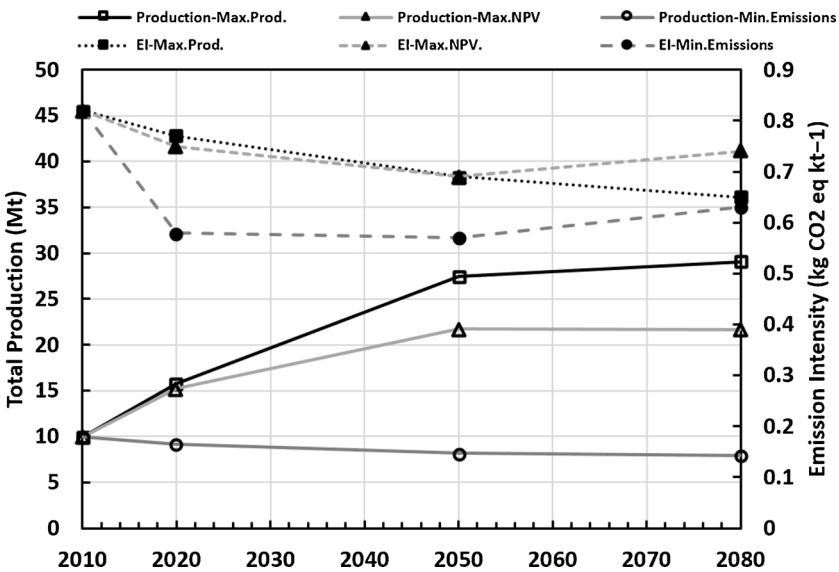

Fig. 5. Trade-offs between crop production and emission intensity for local marginal (LM) scenario. Trade-offs are presented for three competitive objectives viz., minimizing the emissions, maximizing the total production and maximizing the NPV of farm margin. For more details of local marginal (LM) scenario please see materials and methods.

(Table 5), although, Max.Prod. and Max.NPV scenarios show distinct shifts in their technology portfolio (Fig. 6). The Min.Emissions scenario remains dominated by the current level of the technologies, however, it should be noted that this scenario still targets minimum production levels specified in the model.

The emission intensity at 2010 (baseline) is about 0.82 kg CO2eq kt^{-1} which can be reduced to 0.63 kg CO2eq kt^{-1} under the Min.Emissions scenario; it remains highest at 0.74 kg CO2eq kt^{-1} in the Max.NPV. scenario (Fig. 5). The Max.Prod. scenario has a slightly higher emission intensity (0.65 kg CO2eq kt^{-1}) than the Min.Emissions scenario (Fig. 5).

In general, maize (all seasons) and pulses showed highest gains in crop area and production over the baseline. The Max.Prod and the Max.NPV scenario are resulting in the same level of emission intensities (Fig. 6) until 2050s, however, the production gap for these scenarios is 0.5 Mt and 5.7 Mt at the 2020s and the 2050s, respectively. This shows that for attaining food security at the state level while keeping emission intensity same the crop-technology portfolio of the Max.Prod. is the best suited. Emission intensities after 2050s increase slightly as a result of stabilized production profiles (Fig. 5). The trade-off analysis shows several possibilities of the crop technology portfolios depending on the system level objectives. Distinct variation was observed in the crop and technology portfolios at the land unit scale.

3.6. Sensitivity to rate of land-use change

A limited sensitivity analysis was carried out looking at variations in production growth, crop-technology configurations and costs with the maximum annual rate of area undergoing land-use change in each year. This was implemented by applying scalar multipliers to Eq. (8). Rates of annual land-use change were varied in the range 50–300 kha yr^{-1} around the baseline assumption of 250 kha yr^{-1}.

Table 5
Change in land use and total production for local marginal (LM) scenario. Land-use change and change in total production are presented for three competitive objectives viz., minimizing the emissions, maximizing the total production and maximizing the NPV of farm margin over the baseline.

Crop/Period	2020			2050			2080		
	Max.Prod.	Min.Emissions	Max.NPV	Max.Prod.	Min.Emissions	Max.NPV	Max.Prod.	Min.Emissions	Max.NPV
Change in crop area over baseline									
Rice	0.22	-0.65	0.13	0.46	-0.83	0.02	0.04	-0.83	-0.08
Maize (Kharif)	0.63	0.41	0.58	5.99	1.89	5.27	11.88	2.01	7.95
Wheat	0.27	0.58	0.09	0.25	0.09	-0.22	0.17	0.20	-0.20
Gram	0.63	0.63	0.63	6.02	4.82	6.04	17.36	1.72	11.12
Lentil	0.63	0.52	0.63	2.74	5.38	6.04	-0.63	5.87	12.82
Lathyrus	0.63	0.61	0.63	5.80	0.71	5.91	11.67	1.01	-0.68
Mustard	0.51	0.49	0.63	0.91	4.22	5.83	-0.06	2.17	4.80
Maize (rabi)	0.63	0.03	0.40	5.26	-0.03	-0.45	4.05	-0.03	-1.00
Mung bean	0.33	0.63	0.63	-0.83	3.00	5.89	-1.00	2.22	10.18
Maize (Summer)	0.63	0.39	0.59	5.97	-0.71	1.22	6.82	-0.42	-1.00
Change in production over baseline									
Rice	0.67	-0.66	0.67	0.97	-0.84	0.72	0.62	-0.82	0.66
Maize (Kharif)	3.45	1.03	3.38	17.63	2.80	16.36	27.47	2.55	20.09
Wheat	1.29	1.24	1.10	0.90	0.52	0.52	0.72	0.59	0.41
Gram	1.06	1.12	1.74	10.24	6.15	13.21	33.13	1.33	24.42
Lentil	0.79	0.81	1.33	3.93	5.91	10.95	-0.58	6.47	20.66
Lathyrus	0.97	0.97	0.81	9.25	1.27	9.08	19.18	1.81	-0.48
Mustard	2.07	0.59	2.24	3.20	3.28	18.15	1.95	1.06	13.44
Maize (rabi)	5.40	0.34	4.88	19.86	0.54	1.37	18.00	0.47	-1.00
Mung bean	0.03	-0.11	0.51	-0.92	1.37	6.16	-1.00	1.00	10.42
Maize (Summer)	5.03	2.15	4.51	22.75	-0.79	7.14	22.89	-0.60	-1.00

Number indicates ratio of change of crop area/production over the baseline area/production.

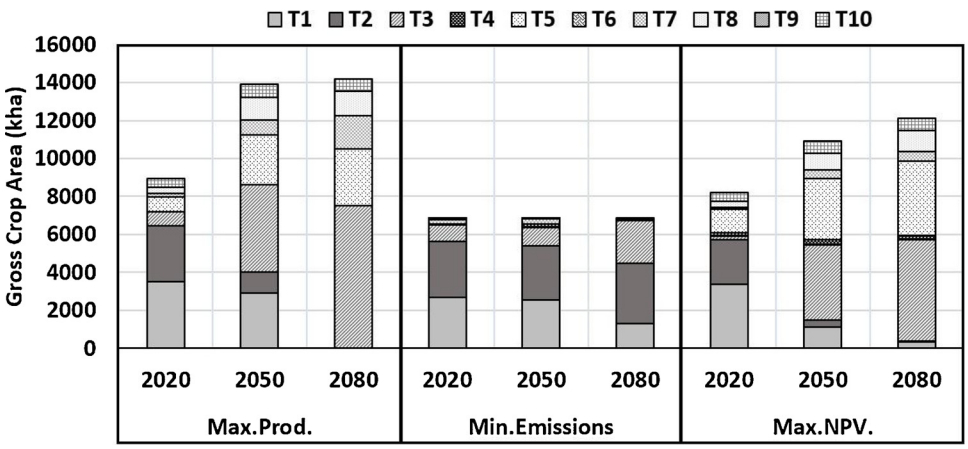

Fig. 6. Crop area under different technologies for local marginal (LM) scenario at minimizing the emissions, maximizing the total production and maximizing the NPV of farm margin. T represents technology package, T1 and T2: current rainfed and irrigated technology; T3: improved rainfed technology; T4–T6: different levels of intensification technology (low to high); and T7–T10: different levels of climate smart technology (low to very high). For more details on technology portfolio, please see Table 2 and Shirsath et al. (2017).

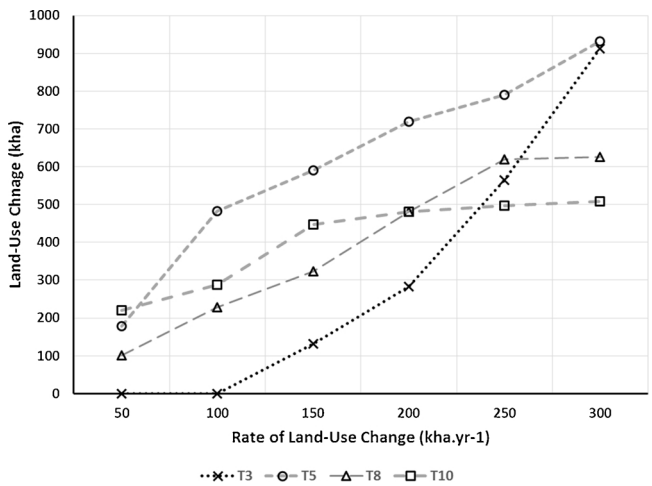

Fig. 7. Sensitivity of technology uptake for period 2010–20 to rate of land-use change (Note: *Other technologies removed as they contribute only marginal levels of technology land-use change*). T represents technology package, T1 and T2: current rainfed and irrigated technology; T3: improved rainfed technology; T4–T6: different levels of intensification technology (low to high); and T7–T10: different levels of climate smart technology (low to very high). For more details on technology portfolio, please see Table 2 and Shirsath et al. (2017).

As the rate of land-use change is increased from an initial low level we can identify priorities by the stage at which they enter the portfolio. Sensitivity to the rate can be considered an approximate sensitivity to the level of investment. Fig. 7 demonstrates sensitivity of technology investment for the period 2010–20 as a function of the allowed rate of land-use change for the *Local-Marginal* configuration. Priorities can be inferred both from the absolute level and gradient of investment observed at each rate. Moderate intensification is a clear priority at lower rates, whilst improved rainfed technologies become increasingly important as the rate of land-use change increases.

4. Discussion

4.1. Spatial and temporal prioritization of CSA technologies

The CSAP toolkit tested and evaluated here can identify location specific technological options and prioritize them for climate change adaptation in agriculture. A range of CSA technologies are prioritized based on crop and cropping systems, resource availability and current/future climatic conditions. The CSAP toolkit's potential of identifying adaptation domains and establishment of out-scaling potential for a range of technological options serves multiple objectives of climate change adaptation and mitigation in agriculture. Location and time period specific technological options provided by this toolkit can help development actors to decide which options to promote where and when. Results show that this toolkit can conduct an ex-ante impact assessment of with/without adaptation under current and future climate scenarios which is very important to avoid maladaptation of any CSA technology. By coupling with future scenario, the toolkit can identify suitable options that can avoid maladaptation, potentially leading to decisions that are informed by CSAP outputs. This CSAP contributes to growing literature on climate change adaptation and mitigation planning through data based modelling approach.

4.2. Investment prioritization on CSA

A combination of biophysical, social and economic indicators used for prioritization of CSA options allow key stakeholders to assess technologies against various end-users' goals (Andrieu et al., 2017; Campbell et al., 2016). National Adaptation Plan (NAP) and Intended Nationally Determined Contributions (INDC) of developing countries emphasise the importance of decision support tools in targeting adaptation investments. Identifying which interventions to choose from a portfolio that includes weather insurance, groundwater management, inter-cropping and community-managed seed banks, among many others, requires time and careful analysis by policymakers. The CSAP toolkit can generate this information for policymakers that substantially can increase their ability to make better decisions under existing and future uncertainties.

Our test and evaluation of CSAP in Bihar, India show that this toolkit provides enough information such as type and level of technology use in different crops and total food production under various portfolios of CSA options in different time period. This information can be used for prioritizing CSA investment for particular location and crop/cropping system (e.g. Shirsath et al., 2017). We estimated technology input and output values based on available price information and discount factor for different period of time. The resulting analysis provides information about investment requirement on particular portfolio of CSA options to achieve target level of production under baseline and future scenarios. The toolkit provides enough information to prioritize investment for the short-term (2020), while locating those priorities within a medium- (2050) and long-term (2080) agricultural growth pathway. Results show that investment requirement for adaptation to climate change is rapidly increasing over the time. For instance, investment in adaptation activities has increased from 33.0% in 2050 to 46.2% in 2080 compared to baseline. However, change in total production is marginal between 2050 and 2080. This change in total production for adaptation scenario over baseline in 2050 is about 11.2% and same change in 2080 is 12.4%.

4.3. Adaptation benefits

This toolkit incorporates dynamic investment constraints to assess the impact of particular crop-technology activities at different farm size and rate of land use change. The accessibility of various farm size categories to specific technologies is determined by their investment capacity. Results indicate that economy of scale in CSA technology implementation can be achieved when farm-size no longer plays a role in limiting technology adoption. Similarly, land use change applied in the toolkit accounts large transaction cost for shifting in crop production with new technologies. The changes in the total crop area allocation results in change in the effective returns (to unit land-use change) under climate impacts. Period-on-period yield changes under climate scenario RCP 8.5 are +28%, +7% and −10% for the periods 2010–2020 (vs. baseline), 2020–2050 and 2050–2080, respectively, over the previous time. However there are less significant impacts for some other scenarios explored, RCP 6.0 reporting only −1%, −3% and −1% for the same period-to-period shifts. Yield gains diminish towards the end of the century under the current available technologies. With surplus production potential exhausted and the onset of significant climate change, returns to the final stage of investment on remaining rainfed land fail to maintain yield levels. The system has a deficit of adaptive capacity, in terms of resources and technologies available to it. This indicates that a transformational adaptation is required over time to achieve more benefits from CSA.

This toolkit has also provided results of trade-off analysis between investment requirement for different crop technology portfolios and return to investment. High level of technology intervention (i.e. more climate smart technologies) for adaptation to climate change require more investment, however net return increases at high level of CSA intervention due to a significant improvement in production both in current and future climate.

4.4. Scope and limitations of the CSAP toolkit

The development of dynamic models, such as that demonstrated here, provide valuable tools by integrating climate-change forecasts, socio-economic datasets and biophysical models into the design of wider sectoral growth pathways. The toolkit presented here can also be used to design growth pathways with due emphasis on ecological services. The toolkit has capabilities understand the effects of agricultural production systems on environment through analysis of GHG emissions from agriculture and resources use efficiencies of inputs applied. On the other hand, it also factors in the effects of the changes in the environmental systems on the agricultural production through detailed biophysical modelling. For example, the toolkit can be used to understand the water, energy, emissions and food nexus in agro-ecological systems wherein these components are fully interconnected, and cannot be treated separately which will otherwise lead to undesired effects on the other. Application of one such modelling framework for agricultural production in Arizona is demonstrated using similar modelling framework by Berardy and Chester (2017). The toolkit presented here treats the agro-ecological systems in holistic manner wherein we can maximize the synergies and minimize the trade-offs through multi-objective optimization.

The analysis using CSAP toolkit considers biophysical, socio-economic and climatic factors and scenarios. As it's a bottom-up approach the analysis often starts from smallest homogeneous parcels called "land-units", getting the datasets at land-unit scale remains the most critical issue; the methods, techniques and analysis using CSAP toolkit poses challenges in data scarce conditions. The CSAP modular framework and database creation methodology currently works in decoupled fashion, this means the location specific peculiarities can be addressed but the changes need to be translated manually in model indexing and databases. Further, our analysis of adaptation was also constrained by our model of climate change impacts. We only considered crop-specific impacts on average yields. We did not consider: (i) technology-specific climate impacts wherein technologies could be differentiated based on the sensitivity of their yields to the forecast climate change; or (ii) crop and technology-specific yield variability in the short-term as a function of underlying drought and flood year likelihood. The modelling framework outlined here is however capable of handling both these forms of crop and technology differentiation.

5. Conclusions

The objective of developing this toolkit was to provide a relatively simple and quantitative framework for prioritization of climate smart interventions using detailed biophysical and socioeconomic datasets at subnational and local level. In its current formulation CSAP is flexible in its capability to model agricultural production at a wide range of spatial and temporal scales. This work develops a dynamic, spatially-explicit optimization model to explore a range of agricultural growth pathways coupled with climate-adaptation strategies. Integrating detailed bottom-up biophysical, climate impact and agricultural-emissions models, this tool is capable of supporting multi-objective analysis of agricultural production in relation to food self-sufficiency, incomes and mitigation targets. CSAP supports climate-proof agricultural development by providing a means for carrying out detailed scenario analysis in the context of climate adaptation, providing valuable bottom-up evidence to support top-down estimates of the costs of climate change adaptation.

The CSAP toolkit allows the user to identify robust decisions under a set of uncertain circumstances. It is then possible to carry out trade-off analysis of alternative climate smart agriculture development pathways. Based on the dynamic pathways, the toolkit can support decisions on which crops to cultivate; which climate-smart agricultural technologies and practices to invest in; where to target that investment; and when those investments should be made. The toolkit prioritises investment decisions for the short-term (e.g. to 2020), while locating those priorities within a medium- (2050) and long-term (2080) agricultural growth pathway. The trade-off analysis showed several possibilities for the crop technology portfolios depending on the system level objective. The tool constrains the adaptation options to a limited set of viable alternatives and provides the critical trade-off information required to support the prioritization decision. For Bihar, the CSAP results show that investment requirement for adaptation to climate change is rapidly increasing over the time. For instance, investment in adaptation activities has increased from 33.0% in 2050 to 46.2% in 2080 compared to baseline.

Most importantly, CSAP can bring analytical rigor in the planning process and in solving developmental problems, in particular supporting developing countries in their preparation of National Adaptation Programmes of Action (NAPA) and Nationally Appropriate Mitigation Actions (NAMAs) under the UNFCCC framework. The CSAP toolkit has the capability to generate information for policymakers which may help them to make better decisions even under existing and future uncertainties. The methods, techniques and analysis using CSAP toolkit poses challenges in data scarce conditions. Besides, the CSAP modular framework and database creation methodology currently works in decoupled fashion, the development of generic software with dynamic feedback loops to the databases and scenario analysis within a single framework, is a goal of future research.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecolmodel.2018.04.008.

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