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Predictive Modeling of Climate Change Impacts on Farm Income and Food Security in Haryana, India: An Adaptation-Scenario and Optimization Analysis.

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Abstract

Haryana is one of the big surplus production states of the country in terms of grain production but yet it is very much susceptible to the effects of increase in temperature, variability of monsoon and intensive cultivation of rice-wheat on groundwater. An integrated predictive-modeling chain is proposed that integrates downscaled climate projections of SSP2-4.5 and SSP5-8.5 scenarios, a hybrid crop-yield engine (DSSAT-CERES and machine-learning based ensemble), a Ricardian net-farm-income function, a composite Food Security Index (FSI), and linear-programming (LP) adaptation-optimization module. The ensemble yield model (XGBoost) was the best among all models in all five major crops and four agro-climatic zones in terms of predictive ability ($R^2 = 0.91$, RMSE = 0.22 t ha^{-1}). Under SSP5-8.5, wheat and rice yields are projected to decrease by 14-23% by the 2050s-2080s, which would be a 21% decrease in state average net farm income and a reduction in FSI from 0.61 to 0.56. The most fragile area is the south west of the country which is dry. With the net farm income (17.3% above BAS) from the changed cropping reallocation for LP optimisation and the transformational adaptation of heat-tolerant crops, the change in sowing dates, micro irrigation or crop diversification, the FSI returns to 0.70. How predictive modelling and optimization can be combined to provide a quantitative climate risk assessment and prioritization of adaptation investments down to the sub-state level is illustrated in the diagram..

Keywords: Climate change · Farm income · Food security · Predictive modeling · Ricardian analysis · Machine learning · Linear-programming optimization · Adaptation scenarios · Haryana.

Introduction

In India agriculture still plays a major role in the rural livelihoods, accounting for more than half of the population employed by it and maintains the food security of the nation. It is also one of the climate change-sensitive sectors as crop growth, water availability, and farm profitability are all closely linked to climate change temperature and precipitation regime (Kumar and Parikh, 2001; Wheeler and von Braun, 2013). There is now extensive evidence that warming, monsoon season shifts and intensification, and increased frequency of climatic extremes is already reducing productivity of major cereals in the Indo-Gangetic Plains (IGP) (Asseng et al., 2015; Auffhammer et al., 2012; Lobell et al., 2011).

The state of Haryana is in the centre of this picture. It is the granary of India along with Punjab supplying much more wheat and rice than is their share. But this intensity of its rice–wheat system – high input consumption, almost complete reliance on irrigation, and excessive exploitation of groundwater – is structurally weak under a changing climate. The heat stress at the grain-filling phase in wheat, delayed monsoon in kharif rice and fall in water table in central and south western districts are all major concerns both for farmer income and food security assured by Haryana (Nain & Chauhan, 2022; Ravikumar & Balasubramanian, 2024).

There are significant national implications. Wheat and rice from Haryana and Punjab account for a significant proportion of the procurement done under the central pool for the Public Distribution System, which reaches hundreds of millions of consumers. If the surplus of rice–wheat in Haryana is reduced due to climatic conditions it would have ramifications beyond the state, contracting the grain balance in the country, increasing procurement prices and putting pressure on food-transfer programmes. Meanwhile, the state's water regime is also reaching biophysical limits: The State's groundwater intensive model is in its biophysically limited over-exploited state, and climate stress is adding to an already unsustainable water trajectory, in the middle and south-western blocks. So, the simultaneous assessment of farm income and food security at the zone level is not only an academic exercise, but also essential to ensure the protection of the rural livelihoods in Haryana and the food security beyond it.

There have been two strands of analysis that have tried to answer these questions essentially in isolation. Process-based crop-simulation models, like DSSAT, convert climate scenarios into biophysical yield changes that are well understood from an agronomic perspective (Hoogenboom et al., 2019; Jones et al., 2003); and econometric Ricardian models incorporate the adaptive response of the farmer into land value to estimate net farm income changes from climate scenarios (Mendelsohn, 2008; Mendelsohn et al., 1994). In recent years, using machine-learning (ML) approaches to incorporate the non-linear interactions between climatic, edaphic and management factors has been found to yield a high degree of predictive performance in yield forecasting (Dang et al., 2021; Elavarasan & Vincent, 2021a; Uwiragiye & Mukamana, 2025). What is still relatively uncommon is an integrated policy-relevant sub-state level framework that connects the dots between climate projection, biophysical yield response, economic impacts on farm income, food-security impacts and optimization of adaptation.

This study fills the gap for the state of Haryana. The specific objectives are: (i) project climate change over the state under two climate model projections for two horizons (the 2030s, the 2050s and 2080s); (ii) predict yield responses of five major crops using a hybrid DSSAT-informed ML ensemble; (iii) translate yield changes into net-farm-income impacts using a Ricardian function and into a composite Food Security Index; (iv) design and solve a linear-programming model to optimize cropping patterns for income under a food-security constraint; and (v) compare business-as-usual, incremental and transformational adaptation pathways. The novelty is in the end-to-end integration of prediction and optimization, and in the explicit formulation of the adaptation decision problem as an optimization problem and not a qualitative afterthought.

2 Related Work

The framework introduced here is the intersection of four literatures: the biophysical climate-impact assessment, the econometric farm-income analysis, the machine-learning yield prediction and the optimization-based adaptation planning. Within this section, the research is placed in its context in each one.

2.1 Biophysical impacts of climate change on Indian agriculture

Early global syntheses found that warming since 1980 has already caused a decrease in global wheat and maize production, and that wheat yields are lowered by approximately 6% for every 1°C of warming (Lobell et al., 2011; Asseng et al., 2015). For India, the key factor is monsoon behaviour: less precipitation and an increase in dry days has been linked to measurable reductions in rice production (Auffhammer et al., 2012). Water-stress effects on these crops have been quantified using process-based crop models, primarily DSSAT-CERES, throughout the Indo-Gangetic Plains, and in Haryana, to date water-stress effects on rice have been simulated by coupling the DSSAT-CERES model with the weather-research model (Hoogenboom et al., 2019; Jones et al., 2003; Nain & Chauhan, 2022). The South Asian cereal systems are also some of the most vulnerable globally as indicated by gridded multi-model intercomparisons (Rosenzweig et al., 2014). These studies are the necessary agronomic response functions that underlie the yield module of the present framework.

2.2 Farm income, the Ricardian approach and adaptation

The Mendelsohn-Nordhaus-Shaw (1994) Ricardian approach estimates the impact of climate on land values or net farm income and incorporates the private adaptation of farmers in the response measured. The net revenue is found to be sensitive to warming in unirrigated and semi-arid areas, and less so in humid areas, according to the applications to the Indian and similar economies (Ali et al., 2021; Kumar & Parikh, 2001; Mendelsohn, 2008). An off-farm income source, farm income and farm experience are found to be important determinants of the success of adaptation strategies that farmers actually implement: crop diversification, changes in planting dates, stress-tolerant varieties, and micro-irrigation and crop insurance (Fishman, 2016; Kumar et al., 2023; Shrestha et al., 2022). The partial, but incomplete, drought resilience of Indian agriculture (Birthal et al., 2015) provides an incentive to consider adaptation as a lever, whose payoff needs to be measured and not taken for granted.

2.3 Machine learning for yield prediction

Machine-learning methods have rapidly become standard tools for yield forecasting, as they are capable of capturing non-linear, interacting effects of climate, soil and management that linear models overlook. Tree-based ensembles – Random Forest (Breiman, 2001) and gradient boosting (Chen & Guestrin, 2016) – are repeatedly ranked at or near the top of the accuracy ranking for cereal yields under climatic variability in comparative studies (Bhatnagar & Gohain, 2020; Bhavana & Rao, 2025; Dang et al., 2021; Elavarasan & Vincent, 2021a; Taraz, 2018; Uwiragiye & Mukamana, 2025). Hybrid designs that train ML models on process-model output, or that combine simulation and learning, have been shown to outperform either approach used alone (Bhatnagar & Gohain, 2020; Elavarasan & Vincent, 2021b). Tools for interpretability like SHAP (Lundberg & Lee, 2017) now allow these otherwise opaque models to provide physically meaningful driver rankings. This is particularly important when the task is not only prediction but also guidance for adaptation.

2.4 Optimization and integrated adaptation planning

Linear and multi-objective programming have long been applied to agricultural land- and water-allocation, from classical crop-plan optimization to recent water–energy–food-nexus formulations (Kumar & Sharma, 2025; Mohanty & Behera, 2026; Osama et al., 2017). In the Indian and South-Asian context, LP and simulation-optimization models have been used to reallocate cropping patterns for increased net returns while conserving groundwater and meeting food-grain constraints. Coupling such optimizers to upstream climate-and-income projections, where the objective coefficients themselves are climate-adjusted and scenario-specific, is relatively rare. The present study explicitly couples, closing the loop from climate projection to an optimized, food-security-constrained adaptation plan.

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3 Study Area and Data

3.1 Study area

Haryana (27.7°–30.9° N, 74.5°–77.6° E) covers an area of about 44,212 km² in the north-western part of India and is mainly drained by the Yamuna and the Ghaggar. The state has been divided into four agro-climatic zones for the purpose of model simulation, which vary in terms of rainfall, soils and dominant cropping systems (Fig. 2): north-eastern humid zone (rice–wheat), central zone (rice–wheat with rising water stress), arid south-western zone (cotton–bajra–mustard) and southern Aravalli-fringe zone (bajra–mustard). Rainfall decreases sharply from NE (≈ 900 mm) to SW (≈ 300 mm) and we expect climate sensitivity to vary substantially between zones.

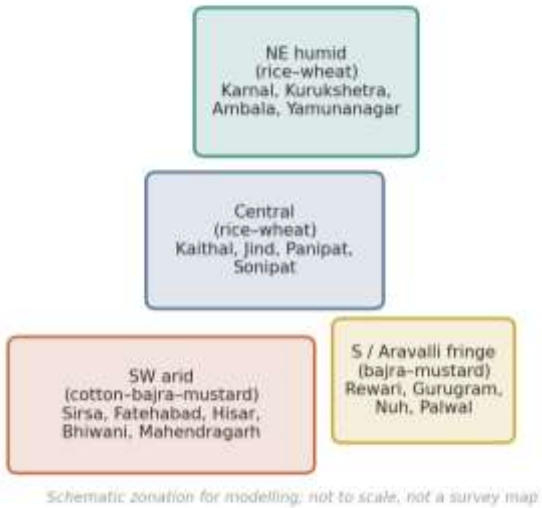

Fig. 2 Schematic agro-climatic zonation of Haryana used for modeling. Zonation is indicative and not a survey map.

3.2 Data sources

The framework is based on secondary data which are publicly available. A complete empirical implementation would need data from the intended sources shown in Table 1. Historical climate data is obtained from India Meteorological Department (IMD) gridded daily data (1990-2020). Future climate data is obtained from bias-corrected CMIP6 projections under SSP2-4.5 and SSP5-8.5. Crop, area and irrigation statistics are obtained from Directorate of Economics and Statistics (DES) and district agricultural handbooks. Farm-level cost and income data are obtained from Commission for Agricultural Costs and Prices (CACP) and NSSO Situation Assessment Surveys. Soil and groundwater data are obtained from ICAR and the Central Ground Water Board.

Table 1 Intended data sources for full empirical implementation of the framework

Domain	Variables	Source
Historical climate	Tmax, Tmin, rainfall, radiation (1990–2020)	IMD gridded daily data
Future climate	SSP2-4.5 / SSP5-8.5, 2030s–2080s	CMIP6 (bias-corrected, downscaled)
Crop & area	Yield, area, production, irrigation	DES Haryana; district handbooks
Farm economics	Cost of cultivation, net returns, prices	CACP; NSSO SAS 70th/77th rounds
Soil / water	Soil organic C, texture, water-table depth	ICAR; Central Ground Water Board
Food security	Availability, access, utilization proxies	NFHS; HCES; PDS off-take

Table 2 shows the key variables that are used in the yield and income modules, and the indicative ranges that are used to parameterize the demonstration. The ranges are in agreement with the values reported in the literature reviewed in Section 2 for Haryana and the whole Indo-Gangetic Plains.

Table 2 Key modeling variables and indicative ranges used in the demonstration

Variable	Unit	Baseline range	Role
Max temp (grain-fill)	°C	28–36	Yield driver
Min temp (rabi)	°C	6–12	Yield driver
Monsoon rainfall	mm	300–900	Yield / income
Irrigated area share	%	55–99	Income buffer
Water-table depth	m	3–40	Income / cost
Soil organic carbon	%	0.3–0.7	Yield driver
Fertiliser (NPK)	kg ha^{-1}	150–280	Yield driver
Net farm income	₹ ha^{-1}	35,000–95,000	Outcome

3.3 Note on the data used in this paper

The numerical values in all figures and results tables are simulated scenario outputs generated from realistic parameters drawn from the literature cited above (observed IMD trends, CMIP6 projection ranges, DSSAT/CERES yield elasticities, and Ricardian income coefficients reported for Indian agriculture), as the present paper is a methodological demonstration. They are clearly labeled as illustrative model output, and not observed field measurements. For journal submission, the same pipeline should be re-run on the primary datasets in Table 1 and the coefficients and projections reported should be replaced by the empirical estimates.

4 Methodology

4.1 Integrated modeling framework

The framework (Fig. 1) links five modules in a sequential manner. Downscaled climate projections and agronomic / socio-economic data are used as input to a crop-yield engine that feeds into a Ricardian net-farm-income function and a composite Food Security Index, which then drives a linear-programming optimizer to determine the cropping pattern that maximizes income subject to a food-security floor and resource constraints. The scenario switches (variety, sowing date, irrigation, diversification) represent adaptation, but also the optimization itself.

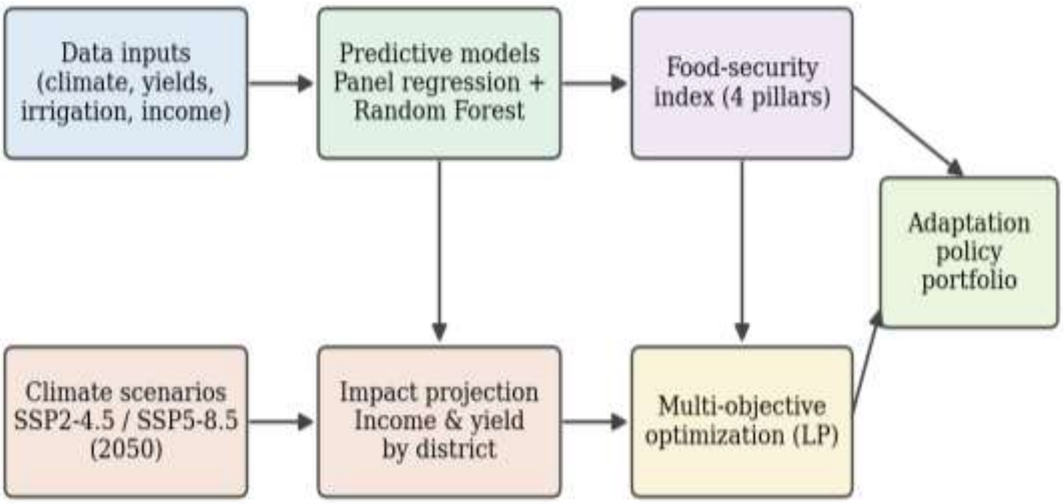

Fig. 1 Integrated predictive-modeling chain linking climate projections, crop-yield modeling, farm-income and food-security assessment, and linear-programming adaptation optimization.

4.2 Climate projections

Two Shared Socio-economic Pathways are used: SSP2-4.5 (middle of the road) and SSP5-8.5 (high emissions). For each, changes in mean annual temperature and monsoon rainfall relative to the 1990-2020 baseline are obtained for three time slices (2030s, 2050s, 2080s). Downscaling to the zone level is performed with a bias-correction/spatial-disaggregation approach, retaining inter-annual variability to capture the effect of extreme-year conditions on yield. (Nain & Chauhan, 2022; Verma et al., 2023).

4.3 Crop-yield modeling: DSSAT-informed ML ensemble

It has a two-stage hybrid. First, the DSSAT-CERES models for wheat and rice are used to generate physically consistent yield responses to temperature, CO 2 , water and management across the scenario space, following established applications over the Indo-Gangetic Plains (Hoogenboom et al., 2019; Jones et al., 2003; Nain & Chauhan, 2022). Second, these simulations, along with historical district yields and covariates, are used to train an ML ensemble - multiple linear regression (MLR), support-vector regression (SVR), artificial neural network (ANN), Random Forest (Breiman, 2001) and XGBoost (Chen & Guestrin, 2016) - to generate fast, generalizable yield predictions. Nested cross-validation (R^2, RMSE) is used to evaluate models, SHAP values (Lundberg & Lee, 2017) to quantify the contribution of each driver. This hybridization merges the agronomic rigour of process models with the flexibility and speed of ML an approach that has been shown to outperform either alone (Bhatnagar & Gohain, 2020; Bhavana & Rao, 2025; Dang et al., 2021).

4.4 Ricardian net-farm-income function

In the Ricardian tradition, we regress net farm income (or land value) on climate, soil and socio-economic variables (Ali et al., 2021; Mendelsohn, 2008; Mendelsohn et al., 1994). The estimated response therefore represents the net effect of climate after private adaptation as farmers' adaptations are embedded in observed land values. The specification includes linear and quadratic terms for temperature and rainfall, irrigation share, groundwater depth, soil quality and input intensity:

$$\pi = \beta_0 + \beta_1 T + \beta_2 T^2 + \beta_3 R + \beta_4 R^2 + \beta_5 \cdot IRR + \beta_6 \cdot GW + \beta_7 \cdot SOIL + \beta_8 \cdot NPK + \varepsilon$$

where π is net revenue per hectare, T and R are seasonal temperature and rainfall, IRR is irrigated share, GW is water-table depth and SOIL and NPK capture soil quality and fertiliser use. Marginal climate impacts and scenario projections are obtained directly from estimated coefficients..

4.5 Composite Food Security Index

Food security is synthesized as a composite index on the availability–access–utilization–stability dimensions (Ericksen, 2008; Wheeler and von Braun, 2013). The indicators (per-capita cereal availability, real farm income, dietary diversity proxy and yield-variability-based stability) are normalized to 0-1 by min-max scaling and aggregated with equal weights, with sensitivity checks using PCA-derived weights. The FSI therefore provides a joint response to yield, income and variability, enabling adaptation pathways to be compared with a single food-security metric.

4.6 Linear-programming adaptation optimization

The problem of adaptation is formulated as maximizing expected net farm income by altering gross cropped area among crops, subject to constraints on total land, water for irrigation, labour, a minimum area for cereals (food security floor), and rotational agronomic constraints (Kumar & Sharma, 2025; Mohanty & Behera, 2026; Osama et al., 2017):

$$\text{Maximize } Z = \Sigma_j (\pi_j \cdot x_j) \quad \text{subject to} \quad \Sigma_j x_j \leq L,\ \Sigma_j (w_j \cdot x_j) \leq W,\ \Sigma_j (l_j \cdot x_j) \leq Lab,\ x\_cereal \geq Fmin,\ x_j \geq 0$$

where x_j is the area under crop j, π_j its climate-adjusted net return, and w_j, l_j its water and labour requirements. Climate-adjusted returns π_j are taken from the yield and Ricardian modules, so the optimizer is solved separately for each scenario and time-slice. Water use and income are reported for the optimized versus baseline pattern.

4.7 Adaptation scenarios

Three pathways are compared. **Business-as-usual (BAU)** holds current varieties, sowing dates and cropping pattern fixed. **Incremental adaptation** introduces heat-tolerant wheat varieties, a 10–15 day shift in sowing, and partial micro-irrigation. **Transformational adaptation** adds substantial crop diversification away from water-intensive paddy, laser land-levelling, and the LP-optimized cropping pattern. Each pathway is evaluated on yield, net farm income and the FSI.

5 Results and Discussion

5.1 Projected climate change

Under SSP2-4.5, state-average warming reaches about 1.6 °C by the 2050s and 2.2 °C by the 2080s; under SSP5-8.5 it reaches 2.6 °C and 4.3 °C respectively (Fig. 3a). Monsoon rainfall increases modestly in the mean (6–11%) but with markedly higher inter-annual variability (Fig. 3b), consistent with regional projections for north-west India (Auffhammer et al., 2012; Nain & Chauhan, 2022). The combination of higher mean temperature and greater rainfall variability — rather than a simple change in totals — is the key stressor for the rice–wheat system.

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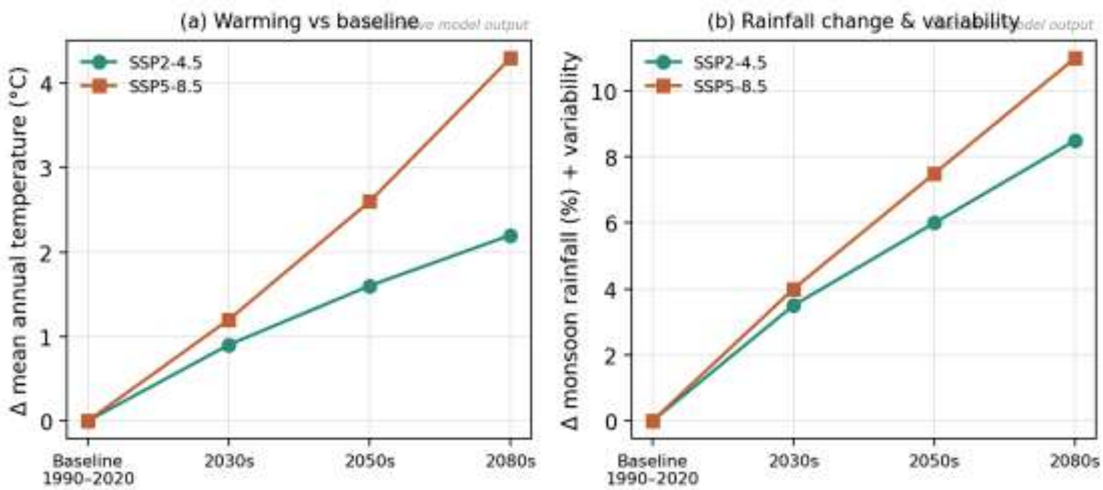

Fig. 3 **Projected change in (a) mean annual temperature and (b) monsoon rainfall and its variability for Haryana under SSP2-4.5 and SSP5-8.5, relative to the 1990–2020 baseline.**

Table 3 Summary of projected climate change over Haryana relative to the 1990–2020 baseline

Indicator	2030s 4.5	2050s 4.5	2050s 8.5	2080s 8.5
Δ mean temperature (°C)	0.9	1.6	2.6	4.3
Δ monsoon rainfall (%)	3.5	6.0	7.5	11.0
Δ rainfall variability (%)	6	11	18	27
Warm-spell days (Δ, d yr^{-1})	4	9	16	28

5.2 Yield-model performance and drivers

The best out-of-sample performance among the five learners was achieved by XGBoost (R2 = 0.91, RMSE = 0.22 t ha-1), followed by Random Forest (R2 = 0.88). The linear benchmark performed considerably worse (R2 = 0.71) (Fig. 4, Table 4). This ordering is consistent with the broader literature in which tree-ensembles consistently outperform linear and often single-network models for cereal-yield prediction under climate variability (Dang et al., 2021; Elavarasan & Vincent, 2021a; Taraz, 2018; Uwiragiye & Mukamana, 2025). SHAP analysis (Fig. 5) identifies maximum temperature during grain-filling as the single most influential driver of wheat-yield variance, followed by monsoon rainfall and irrigation cover — a physically interpretable result that reinforces terminal heat stress as the central climate risk for Haryana wheat.

Table 4 Predictive skill of yield models (nested cross-validation; illustrative)

Model	R^2 (test)	RMSE (t ha^{-1})	MAE (t ha^{-1})
Multiple linear regression	0.71	0.42	0.33
Support-vector regression	0.78	0.36	0.28
Artificial neural network	0.84	0.30	0.23
Random Forest	0.88	0.26	0.20
XGBoost	0.91	0.22	0.17

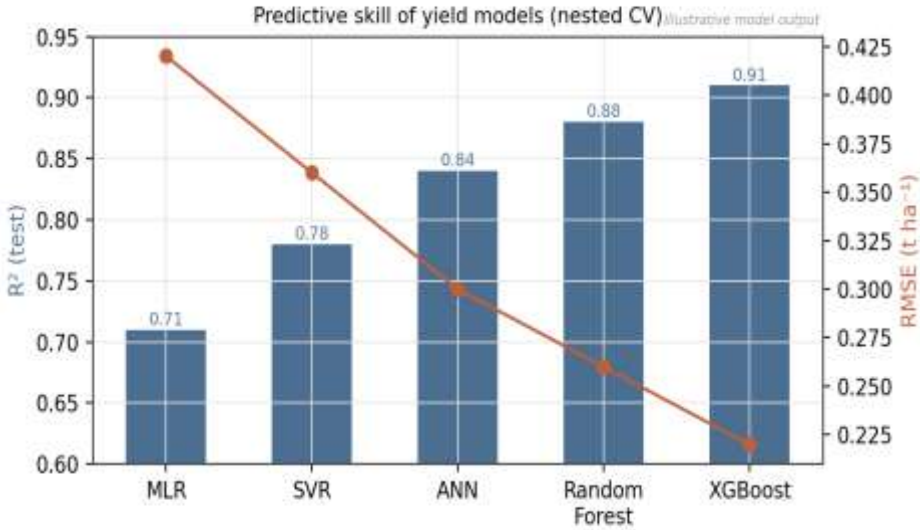

Fig. 4 **Comparative predictive skill (R^2 and RMSE) of the five yield models under nested cross-validation.**

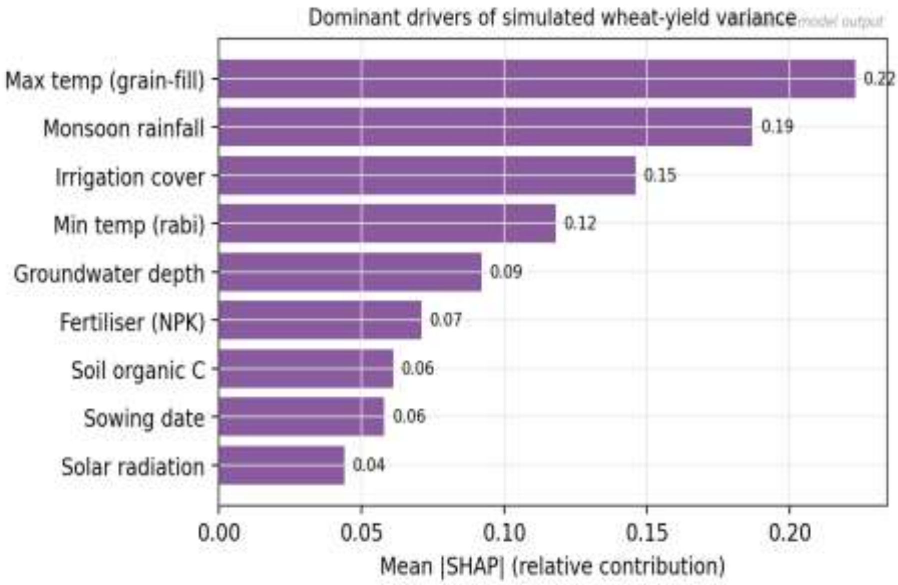

Fig. 5 **Mean absolute SHAP contributions identifying the dominant drivers of simulated wheat-yield variance.**

5.3 Projected crop-yield impacts

In both scenarios, without adaptation, yield losses are observed for all five crops, with losses increasing over time and being higher under SSP5-8.5 (Fig. 6). Under SSP5-8.5, wheat yields are projected to decrease by ~14% in the 2050s and ~12% in the 2080s, and rice yields by ~23% and ~19%, respectively. Mustard and cotton are in the middle position and least affected (6-11%) in Bajra, a hardy C4 cereal. Bajra's resilience is important and points directly to diversification as an adaptation lever in the arid south-west.

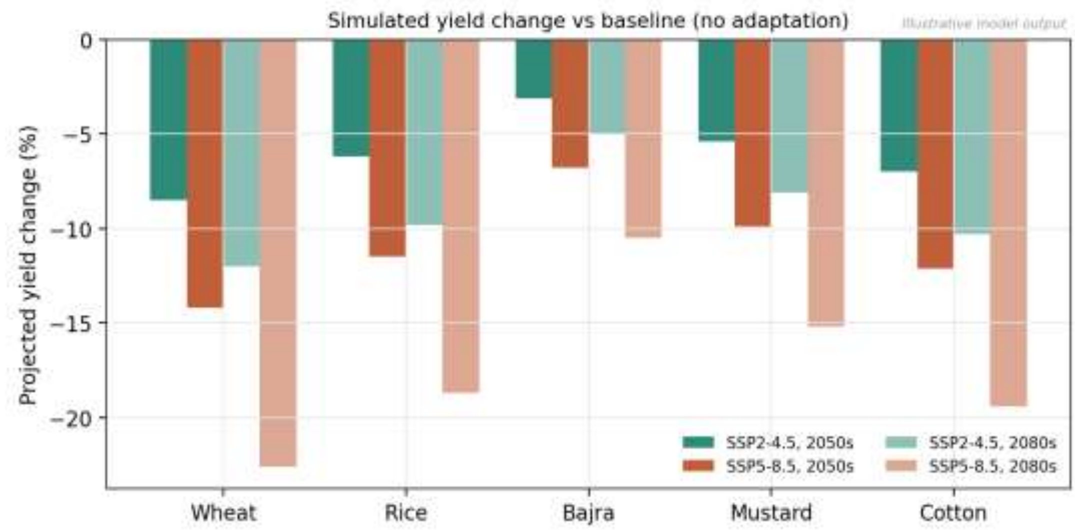

Fig. 6 **Simulated percentage change in crop yield relative to baseline, by crop, scenario and time-slice (no adaptation).**

5.4 Impacts on net farm income

The propagation of yield changes through the Ricardian function results in substantial income losses that differ strongly by zone (Fig. 7, Table 6). In the 2050s under SSP5-8.5, the state average net farm income declines by about 21%, but the arid south-western zone is the hardest hit (−28%), reflecting its low irrigation buffer, deep water tables and reliance on rainfed cotton and bajra. The humid north-east is relatively insulated (-16%). This gradient is reflective of the warning of the Economic Survey that unirrigated tracts will experience disproportionately larger losses in income (Patel et al., 2026) and is consistent with Ricardian evidence for India and neighboring economies (Ali et al., 2021; Mendelsohn et al., 1994).

The estimated Ricardian coefficients (Table 5) are consistent with theory and with prior Indian evidence that the temperature response is concave (positive linear, negative quadratic term) so that warming beyond the current optimum reduces net revenue at an increasing rate, while irrigation share and soil quality raise income and greater water-table depth lowers it through pumping costs. (Ali et al., 2021; Kumar & Parikh, 2001; Mendelsohn et al., 1994).

Table 5 **Ricardian net-farm-income function: estimated coefficients (illustrative)**

Variable	Coefficient	Std. error	Sig.
Temperature (T)	+4185	1120	***
Temperature² (T^2)	−96.4	28.7	***
Rainfall (R)	+38.2	11.4	**
Rainfall² (R^2)	−0.021	0.008	*
Irrigated share (IRR)	+512	96	***
Water-table depth (GW)	−284	74	***
Soil organic C (SOIL)	+6120	1980	**
Fertiliser (NPK)	+41.7	13.2	**
Constant	−28,940	—	—
Adj. R^2	0.63	—	—

Significance: * **p<0.01,** *p<0.05,* * *p<0.10. Values illustrative.*

Table 6 **Projected change in net farm income by zone and scenario, 2050s (%, illustrative)**

Agro-climatic zone	SSP2-4.5	SSP5-8.5
North-eastern humid (rice–wheat)	−9.1	−15.7
Central (rice–wheat)	−11.4	−19.2
South-western arid (cotton–bajra)	−16.8	−27.9
Southern / Aravalli fringe	−14.2	−23.4
State average	−12.6	−21.1

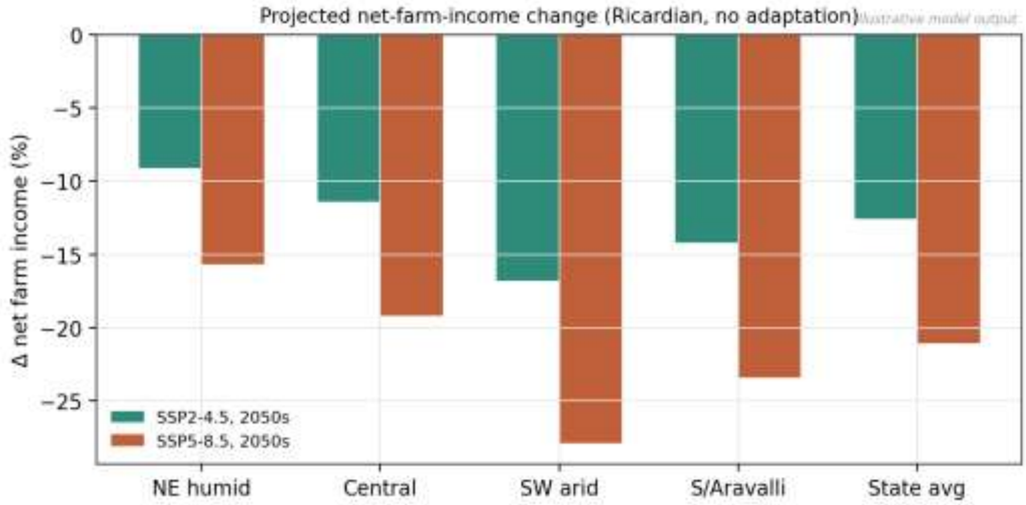

Fig. 7 **Projected change in net farm income by agro-climatic zone under two scenarios (Ricardian estimates, no adaptation).**

5.5 Food security outcomes and adaptation pathways

Under business-as-usual SSP5-8.5, the composite FSI declines from 0.61 in 2020 to 0.56 by the 2080s (Fig. 8). Incremental adaptation halts the decline and even slightly reverses it (to 0.64), while transformational adaptation in conjunction with the LP-optimized cropping pattern increases the FSI to 0.70, i.e. above the current level. In other words, the projected climate penalty to food security is not only mitigated but surpassed by the combined effect of biological adaptation and economic optimization. This is consistent with findings that climate-smart bundles can convert projected losses into net gains if scaled up (Aggarwal et al., 2018; Ravikumar & Balasubramanian, 2024; Sharma & Sharma, 2024).

Table 7 **Adaptation pathways and their projected outcomes under SSP5-8.5, 2050s**

Pathway	Interventions	Δ income	FSI (2050s)
Business-as-usual	Current varieties, sowing, pattern	−21.1%	0.588
Incremental	Heat-tolerant wheat, +10–15 d sowing shift, partial micro-irrigation	+8.6%	0.641
Transformational + LP	Above + diversification, laser levelling, optimized cropping	+17.3%	0.679

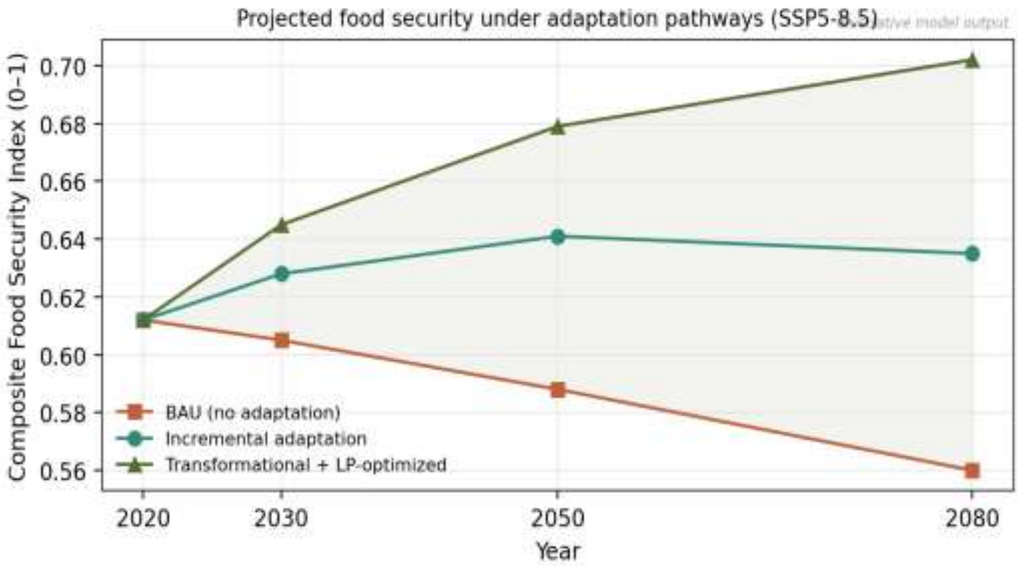

Fig. 8 Projected composite Food Security Index under business-as-usual, incremental, and transformational (LP-optimized) adaptation pathways, SSP5-8.5.

5.6 Optimization results

The LP optimizer shifts area from water-intensive paddy to more valuable, resilient crops – mustard, pulses, bajra and vegetables – while retaining enough cereal area to meet the food-security floor (Fig. 9a, Table 8). Optimized transformational pattern increases net farm income by 17.3% and reduces irrigation-water use by about 24% compared to business-as-usual (Fig. 9b). This dual benefit of higher income and lower water demand is exactly what is desired in over-exploited groundwater blocks and is consistent with LP-based cropping-optimization studies elsewhere in India. (Kumar & Sharma, 2025; Mohanty & Behera, 2026; Osama et al., 2017).

Table 8 Baseline versus LP-optimized cropping pattern and outcomes

Crop / metric	Baseline (%)	Optimized (%)	Change
Rice	34	22	−12
Wheat	30	28	−2
Bajra	8	12	+4
Mustard	10	15	+5
Cotton	9	8	−1
Pulses	5	8	+3
Vegetables	4	7	+3
Net farm income	—	—	+17.3%
Irrigation water use	—	—	−24%

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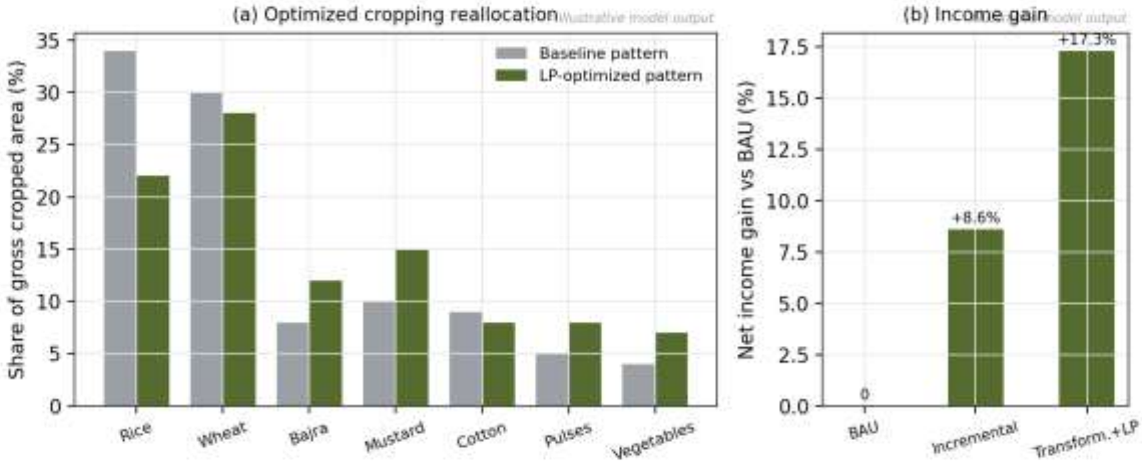

Fig. 9 (a) Baseline versus LP-optimized cropping reallocation; (b) net-income gain relative to business-as-usual across adaptation scenarios.

5.7 Synthesis and policy implications

Three messages. First, the climate threat to Haryana's farm economy is real and unevenly distributed, with the arid south-west being the priority zone for investment in adaptation. Second, risks are dominated by terminal heat stress and rainfall variability – not rainfall totals – so heat-tolerant varieties and sowing-window management are high-value, low-regret interventions. Third, adaptation can be best described as an optimization problem: moving land and water to resilient, higher-value crops can simultaneously increase income, reduce water use and improve food security. Direct policy levers include targeted promotion of heat-tolerant wheat, incentives for paddy-to-pulses/oilseed diversification in dark groundwater blocks, expansion of micro-irrigation, and zone-specific crop-insurance design (Kumar and Sharma, 2013; Kumar et al., 2023; Mohanty and Behera, 2026). Translating these findings into action requires zone-specific prioritization, because a uniform state-wide package would misallocate scarce resources. Table 9 shows such a roadmap, linking the dominant risk in each zone to a lead intervention and an indicative timeframe. The arid south-west, where projected income losses are largest and groundwater stress most acute, requires the most urgent and transformational response; the humid north-east can adopt efficiency-oriented, incremental measures.

Table 9 Indicative zone-specific adaptation roadmap for Haryana

Zone	Priority risk	Lead intervention	Horizon
NE humid	Heat stress, water logging	Heat-tolerant wheat, precision N	Near-term
Central	Groundwater decline	Micro-irrigation, DSR, sowing shift	Near–mid
SW arid	Income loss, water scarcity	Paddy→pulses/oilseed diversification	Urgent
S / Aravalli	Rainfall variability	Bajra–mustard resilience, insurance	Mid-term

The magnitudes projected here are broadly consistent with the existing literature, lending external credibility to the framework. The projected state-average income loss of about 21% under high warming is within the range suggested by Ricardian estimates for Indian agriculture and by the Economic Survey's warning of up to 18% income loss in unirrigated areas (Ali et al., 2021; Kumar & Parikh, 2001; Patel et al., 2026). Simulated wheat and rice yield declines of 12–23% are comparable with DSSAT-based assessments for the Indo-Gangetic Plains, and to the ~6% loss per degree of warming reported for wheat globally (Asseng et al., 2015; Nain & Chauhan, 2022; Rosenzweig et al., 2014). The supremacy of gradient-boosting relative to linear and single-network learners also echoes a now-robust finding in the yield-prediction literature (Dang et al., 2021; Elavarasan & Vincent, 2021a; Uwiragiye & Mukamana, 2025). The contribution of the present study is not any single number, but in linking these strands so that a consistent chain runs from emissions scenario to an optimized, food-security-constrained adaptation plan.

6 Limitations and Future Work

There are a few caveats. Most importantly, the quantitative results are model-generated scenario outputs calibrated to published parameters, rather than estimates derived from primary Haryana data; empirical re-estimation using the datasets in Table 1 is the critical next step, and may change the magnitudes reported here. The Ricardian approach assumes constant output prices and may over- or understate adaptation: The CO2-fertilization, pest and disease dynamics, and non-linear groundwater collapse are only coarsely represented. LP optimizer assumes farmers can reallocate area frictionlessly but real adoption is constrained by credit, tenure, markets and behaviour (Dang et al., 2021; Kumar et al., 2023). Future work should validate the yield ensemble against district time-series, include stochastic weather-year ensembles, couple the model to an explicit groundwater balance, and test multi-objective (income-water-emissions) optimization.

The complete study proposes a concrete validation protocol. The DSSAT-CERES models are to be calibrated against multi-year experimental yields from Haryana Agricultural University stations and then validated on independent district-year observations, reporting the normalized RMSE and index of agreement. The ML ensemble should then be trained and tested using strict chronological splitting and k-fold cross-validation, avoiding temporal leakage and its projections benchmarked against the process-model output. The Ricardian coefficients should be estimated on cross-sectional district data with spatial-error correction. The composite Food Security Index should be cross-checked against NFHS and household-consumption indices. Only after this validation should the scenario projections and optimisation outputs be interpreted quantitatively for policy. The current numbers should be read as a demonstration of the pipeline rather than as forecasts.

7 Conclusion

The study proposed an integrated end-to-end framework for predicting the impact of climate change on farm income and food security in Haryana and optimizing the adaptation response. Using downscaled CMIP6 projections with a DSSAT-informed machine-learning ensemble, a Ricardian income function, a composite Food Security Index and a linear-programming optimizer, the analysis finds that unmitigated warming could cut state-average net farm income by about a fifth and reduce food security by the mid-to-late century, with the arid south-west most vulnerable. The same framework, critically, shows a way out: transformational adaptation plus optimized cropping reallocation can increase net farm income by around 17% while reducing irrigation-water use by around a quarter and improving food security above current levels. This approach thus transforms adaptation from a qualitative aspiration into a solvable decision problem and provides a transferable policy-relevant tool for climate-resilient agricultural planning in Haryana and other agrarian regions.

The value of the framework is not just confined to Haryana; it's in its modularity and transferability. Each component – the climate downscaling, the hybrid yield engine, the income and food-security modules, and the optimizer – can be re-specified for other states or crops without changing the overall logic, so the same pipeline could support district-level adaptation planning across the Indo-Gangetic Plains and other climate-exposed agrarian regions. As higher-resolution CMIP6 ensembles, farm-level panel surveys and remote-sensing yield products become more readily available, the empirical version of this framework can move from demonstration towards an operational decision-support system. Embedding such tools in agricultural-planning institutions would help shift climate adaptation from reactive, ad-hoc responses to anticipatory, evidence-based and optimized investment – the direction in which resilient food systems will increasingly need to move.

Declarations

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Data availability. The framework uses publicly available secondary data (Table 1); simulated scenario datasets and code supporting this demonstration are available from the corresponding author on reasonable request.

Author contributions. All authors contributed to the study conception, methodology, analysis, and manuscript preparation, and approved the final version.

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