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Evaluating India's Agricultural Budget Through Micro-level Simulation: Evidence from the AgriBudget-AI Policy and Profit Model

Jyotsna Thakur[1], Shyamsundar Subramani[1], Arshad Bhat[2,*]

[1]Amity School of Engineering and Technology, Amity University Mumbai, Maharashtra 410206, India.
[2]Amity Institute of Liberal Arts, Amity University Mumbai, Maharashtra 410206, India.

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***Corresponding author:** Arshad Bhat, Amity Institute of Liberal Arts, Amity University Mumbai, Maharashtra 410206, India.

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Abstract

The agricultural public expenditure of India has significantly increased, but the effects have not reached the farmers to a level that is equitable, considering that the input subsidies (7075) predominate over growth-oriented investments. In this paper, the author proposes AgriBudget AI, which is an integrated simulation model that connects the budget levers, such as fertiliser subsidies, MSP changes, and transition grants, to the farm outcomes. The combination includes microeconomic profit models, policy transmission equations, AI-based crop recommendation and risk prediction, and long-term simulations of cash flow using curated data. The framework allows for pre-evaluating budget trade-offs in major crops. With a 2026 outlook (15 percent increase in subsidies, 5 percent in MSP, and even more incentives on pulses/soybean), the level of profit is expected to increase significantly: wheat (17.8 percent), rice (20.0 percent), cotton (10.8 percent), soybean (18.1 percent), and pulses (15.5 percent). Under high-subsidy scenarios, AI outputs will give higher priority to the high-subsidised pulses, whereas the risk of distress is reduced by 2231. These findings emphasize the role of specific MSP and transition assistance as a means of profitability and diversification. AgriBudget AI reveals the usefulness of fiscal policy-agricultural results. The improvements in the future will involve empirical calibration with long-term data, the additional incorporation of environmental metrics, and the introduction of behavioural dynamics to design more comprehensive agricultural policies.

Keywords

Budget; expenditure; revenue; simulation; AI; agriculture

1. Introduction

The edifice of India's agricultural policy rests on public spending to attain food self-sufficiency, reasonable price stabilization, and rural livelihoods support, especially since the Green Revolution entrenched subsidies, irrigation expansion, and price support as its budget instruments of choice [1-4]. After stagnating in the 1990s, real public expenditure on agriculture and allied sectors soared in the mid-2000s, fuelled by increased allocations for input support, rural infrastructure, and irrigation purposes, with the share of agricultural expenditure to agricultural GDP apparently more than doubling between that (mid) decade and circa 2010 [1, 2, 5]. Over approximately the past two decades, Union and state spending on agriculture, rural development, irrigation, and food systems have also grown in absolute terms; detailed time series analysis records rising outlays in crop production, livestock, fisheries, and rural infrastructure across 2010-11 to 2019-20 [3-6].

Nevertheless, the latest preoccupation is not any more the volume of funding, but rather what it can do in terms of resourcefulness and durability for peasants [6, 7] according to figures given in the Union Budget for 25 HNY, agriculture nowadays takes up 18 percent of the GDP at large, but from all sections only around 13a I can point out that three fourths of the agricultural budget is spent on subsidies, welfare schemes like food and fertilizer subsidies, and MGNREGS as well as other stopgap programs [9-11]. There are studies of Indian food policy budgets and public expenditure arguing that this bias towards recurrent subsidies has crowded out higher return investments needed to gain long-run productivity increases and income rises for farm households, such as on research and development, irrigation, extension, and climate resilient infrastructure [1, 3, 6, 11]. At best, the evidence on fertilizer and input policy also shows that per unit of public spending, subsidies on chemical inputs can yield lower social returns compared to investments in sustainable practices, improved water management, and more diversified cropping systems [6-8].

An empirical study based on about 20 years of state-wise data on Indian agriculture finds a complex and often weak relationship between aggregate budget allocations, subsidies at the cost of capital, and agricultural growth [2, 5]. Work on government spending effectiveness suggests that, despite substantial increases in allocations and subsidy volumes, direct impacts on agricultural gross value added can be modest, whereas access to agricultural credit and the quality of public investment show a much stronger association with productivity [1, 12]. Parallel studies on sustainability transitions argue that India's heavy reliance on fertilizer subsidies has locked farmers into input-intensive practices, even though targeted support for bio-inputs, water-saving technologies, and diversified high-value crops could improve both incomes and environmental outcomes [4, 6, 7]. Together, this literature underlines a central policy question: how do specific budget choices on MSP support, input subsidies, irrigation projects, and direct income schemes translate into actual changes in farmer profitability, crop portfolios, and risk exposure at the micro level? [2, 5, 12].

Despite rich macro- and meso-level analysis, policymakers and researchers still lack operational tools that simulate, in an integrated way, how alternative budget scenarios propagate from Union and state fiscal decisions down to individual farm economics, crop choice, and distress risk [3, 13, 14]. Existing computable general equilibrium and macro-simulation models typically focus on sectoral output, prices, and welfare aggregates, providing limited granularity on village- or farm-level profitability under different policy mixes and climate or price shocks [15, 16]. In the context of India's current debate on rationalising subsidies and rebalancing expenditure towards productive investment, there is a need for decision-support systems that can test "what-if" budget scenarios and quantify their consequences for farmer income, crop switching incentives, and debt or distress probabilities before policies are rolled out at scale [1, 3, 9].

AgriBudget AI is an AI-based model that models the effects of policies on farmers in India on profit, crop, and risk decisions. It combines profit models, policy simulations, crop advisory, and risk prediction and presents insights through a national dashboard to assess the efficiency of subsidies, regional performance, and future trends on income and diversification.

2. Literature Survey

2.1 Public expenditure and Indian agriculture: long-run trends

A large body of Indian agricultural economics literature points to one clear thing. Public spending mattered [1, 18, 26]. Government funding in irrigation, agricultural research, extension services, and price support systems has continued to influence the direction of the agricultural sector since the days of the Green Revolution. The role of public investment has been a continuous factor affecting the development of agriculture, but it has usually been an incremental, rather than a dramatic effect [1, 27]. This impact slowly and progressively developed over the decades.

However, the proportion of agriculture in overall government spending was in fact decreasing during this time [21, 23]. Meanwhile, the sector's share in Gross Value Added stayed broadly stable [24]. That mismatch is telling. It suggests that public support to agriculture has been shrinking faster than the sector's economic importance. Not exactly a comforting trend [21, 23]. On top of this, studies of India's food policy budgets show another complication. Agricultural and food-related spending is scattered across many ministries and schemes. It's fragmented. Because of this, it becomes difficult to systematically track how budget allocations influence food system outcomes [11, 28].

2.2 Level vs composition of agricultural budgets

A key theme in recent literature is the shift from concerns about the level of agricultural spending to concerns about its composition between subsidies, welfare transfers, and growth-enhancing investment [26, 28]. Policy analyses argue that this skew leaves relatively little fiscal space for capital formation in irrigation, rural infrastructure, research, extension, and climate resilient technologies, despite evidence that these investments have higher long-run returns [4, 26, 30].

Disaggregated assessments of public spending show that within agricultural expenditure, the expenditure ratio on crop husbandry and food storage has declined, while direct income support schemes like PM-KISAN now constitute a growing share of the agricultural budget [5, 22]. At the same time, spending on agricultural research and extension has either stagnated or marginally declined as a share of agricultural output, raising concerns about the capacity to sustain productivity growth [3, 32].

2.3 Subsidies versus investment: productivity and growth

Using national and sub-national time-series data, several studies conclude that public investment is more effective than subsidies in raising total factor productivity and overall agricultural growth, both in the short and long run [4, 20, 30]. One study that explicitly models the relationship between investment, subsidies, and productivity finds that subsidies often have a negative or insignificant impact on productivity in most states, whereas public investment exerts a positive and significant effect, leading the authors to recommend gradual conversion of subsidies into investment expenditure [4, 20, 21].

2.4 Public spending, agricultural growth, and farmer income

Micro- and meso-level analyses of crop incomes and cost of cultivation reveal substantial heterogeneity in how macro-level policies translate into farm-level outcomes. Studies of the political economy of crop incomes show that MSP-based support, input subsidies, and public procurement disproportionately benefit certain regions and crops, reinforcing inequalities between irrigated and rain-fed areas and between larger and smaller cultivators [26, 27]. At the same time, household-level work on capital, adaptation, and livelihoods in the Indo-Gangetic plains underscores that access to physical and human capital, institutional credit, and extension services strongly mediates how farmers convert policy support into income and resilience [25, 28].

2.5 Budget allocation, trade, and structural challenges

In addition, not only do analyses of agricultural trade and comparative performance reveal that, on yield and productivity for several major crops, India is a long way behind global benchmarks, but simply adding to large public expenditure will not be enough if it isn't strategically allocated and institutional reform doesn't accompany it [7, 30, 31]. Reviews of policy gaps seen in agricultural R&D argue that the inefficient allocation and investment in R&D and extension, and lack of systemic coordination, restrict the release of budgeted funds to innovation and benefits at the farmer-level [32].

2.6 Sustainability, subsidies, and food-system transitions

Several studies recommend reforms in subsidy regimes to align them better with sustainability and income objectives (e g, by phasing out environmentally harmful subsidies towards agroecological practices, water saving technologies, and high-value crops) [4, 6, 7]. These findings are echoed in work on public expenditure and growth dynamics, which finds that subsidies on key inputs of production, such as fertilizers, irrigation, or power, have not consistently incentivised higher output or productivity in its traditional sense, while well-targeted investment coupled with institutional reforms shows more durable effects. However, most of this work remains at the aggregate or meso level and rarely simulates detailed, farmer-level income and risk outcomes under alternative budget and policy mixes [4, 6, 7, 21].

2.7 Digital and AI-based decision support in agriculture

Reviews of AI in Indian agriculture document applications in crop and yield prediction, pest and disease detection, input optimisation, and advisory services, often demonstrating improvements in productivity, resource efficiency, or risk management at pilot scale [40]. Several recent projects have developed AI-driven crop recommendation and

fertilizer recommendation systems using machine learning models trained on soil, climate, and yield data, showing high predictive accuracy and potential for farmer income gains [41].

2.8 Policy modelling and farm-household simulations

Recent Indian studies using advanced econometric models (ARDL, NARDL) to evaluate the effects of public investment on private investment or to assess the relative returns to subsidies and investment provide important parameters and relationships, but they are not packaged as interactive decision support platforms for policymakers or banks [20, 22, 23].

2.9 Identified gap and role of AgriBudget AI

Complementary AI modules for crop switching advice and distress risk prediction extend the analysis from static profitability to dynamic decisions and risk outcomes under alternative budget and policy mixes, while a national dashboard aggregates micro simulations into maps and indicators of subsidy efficiency and spending effectiveness [37, 38].

3. Methodology and System Architecture

The framework models the impact of budget decisions on the farm performance and conducts a relationship between subsidies, MSP, and transition grants and profitability, crop decisions, and risk. It works in three layers, including data integration, combined economic and AI models, and a presentation layer that visualizes the findings and provides policy insights that can be easily understood.

3.1 Conceptual modelling framework

A clear multi-level entity structure that forms the basis of the analytical framework is defined by the table as it connects the micro-level farm decisions and macro-level agricultural outcomes. Centrally, the crop entity supplies the basic economic parameters, including: yield, costs, MSP, and market price, on which the revenue and profit calculation is based, as the building blocks of the model. The farmer scenario entity is a micro-level operation, whereby the crop-specific parameters are combined with land area, policy levers, agro-climatic, and financial conditions to realistically simulate context-sensitive farm performance across different scenarios. On a greater scale, the state unit adds the spatial and economic context by adding such characteristics as the predominant crops, farmland, and minimum agricultural value, allowing the results of individual farms to be aggregated into a larger regional understanding. Collectively, these organizations form a consistent system in which granular farm-based dynamics can be effectively scaled and interpreted at the state level, with an analytical exhaustiveness and policy applicability (Table 1).

Table 1. Core entity types and their key attributes

Entity type	Level	Key attributes	Role in system
Crop	Crop	Name; yield per acre; variable cost components; MSP; market price	Defines economic primitives for revenue and cost calculations.
State	State	Name; dominant crop; baseline agricultural value; cultivable area; spatial geometry	Provides macro context and spatial aggregation for micro outcomes.
Farmer-scenario	Micro	Crop; land size; cost and price vectors; policy lever values; agro-climatic and financial factors	Represents a specific farm under a specific policy and environmental setting.

The table shows the various policy levers functioning via the different yet complementary economic mechanisms to affect farm outputs within the system. The input subsidy intensity is mainly on the cost side in that it reduces effective variable costs, which directly enhances the net profitability, and cultivation is not so financially straining. Conversely, the MSP adjustment factor operates on the revenue side by maintaining an increased effective output price in case MSP is higher than market prices, hence stabilizing and increasing the income of farmers, mainly for staple crops. In the meantime, the transition grant amount has a strategic, long-term role due to the ease of initially investing in the transition to high-value crops, which will accelerate the break-even point and enhance the overall wealth curve of farmers. All these levers are reflective of a balanced policy strategy that aims at not only cutting costs

but also boosting the income and transforming the structure of the agriculture sector in a manner that allows the realization of a short-term increase in income and long-term diversification of agriculture. (Table 2).

Table 2. Mapping of policy levers to affected model components

Policy lever	Directly affected components	Primary channels of influence
Input subsidy intensity	Profit module; policy transmission module	Reduces effective variable costs, increasing net profit per unit area.
MSP adjustment factor	Profit module; policy transmission module	Increases effective output price when MSP exceeds market price, raising revenue.
Transition grant amount	High-value transition module	Reduces net initial investment requirement, shifting break-even time and wealth trajectory.

3.2 Micro-level economic models

3.2.1 Baseline profit function

For a given crop and farm size, baseline net profit Π0 is defined as:

$$\Pi 0 = A \times Y \times \max(Pm, PMSP) - A \times (Cf + Cl + Ct + Co)$$

where A*A* is land area (acres), Y is yield per acre, Pm is the market price, PMSP is the minimum support price, and Cf, Cl, Ct, Co are per-acre costs for fertilizer, labour, transport, and other inputs, respectively. The first term represents gross revenue under the more favourable of market and administered prices, while the second term aggregates variable costs across inputs.

The function is evaluated for each farmer-scenario instance once the user has specified crop and land area, and the system has retrieved the corresponding cost and price vectors from the crop-level tables. This baseline profit serves as a benchmark against which the impact of policy changes is measured.

3.2.2 Policy transmission equations

Given a baseline scenario, input subsidies and MSP adjustments are modelled as simple proportional changes:

Effective total cost:

$$Ctot1 = Ctot0 \times (1 - sf)$$

where Ctot0 is the baseline total cost, and sf is the subsidy rate (in decimal form).

Effective total revenue:

$$R1 = R0 \times (1 + sMSPeff)$$

where R0*R*0 is baseline revenue, and sMSPeff is the effective MSP increase factor, which may include an additional increment for crops explicitly prioritised in the current policy (e.g., pulses and soybean).

Post-policy profit is then computed as Π1=R1−Ctot1, and the change in profit is ΔΠ=Π1−Π0. This structure makes it straightforward to attribute profit changes to specific levers and to analyse interaction effects when both subsidies and MSPs are altered simultaneously.

3.2.3 High-value crop transition model

The transition module compares staple continuation and high-value crop diversification over 10 years. Staples are those where there are constant returns and the high-value crops that have initial losses, gestation costs, and subsequent returns. Cumulative cash flows reveal break-even points and long-term wealth, which can be used to determine the impact of transition grants on investment decisions and profitability.

3.3 AI-based advisory and risk components

3.3.1 Crop recommendation model

The crop recommendation model is a random forest classifier that predicts the best crop option based on the soil, climate, market demand, and subsidy data of a specific farm profile. The input features would be the amount of rainfall, the quality index of the soil, the anticipated demand factors, and the subsidy level at which the subsidy would be applicable. The model will give a recommended crop coupled with a confidence value, which will allow farmers and policymakers to determine the most appropriate crop in the current agroclimatic and policy context.

3.3.2 Distress risk model

The distress risk module estimates farmers' financial vulnerability using climate risk, insurance, land size, and debt. A Random Forest model trained on synthetic data predicts distress probabilities as vulnerability scores. Linked to policy scenarios, it shows how changes like better insurance or reduced debt influence financial risk across farms.

3.4 Process flow

3.4.1 End-to-end simulation process

The process follows six stages: defining policy scenarios, specifying farmer profiles, computing baseline profits, applying policy changes, generating crop recommendations and risk scores via AI, and aggregating results. Output combines farm and regional data to estimate income shifts and produce policy briefs, aligning with standard agricultural policy simulation workflows.

3.4.2 Inter-module data exchanges

Data exchange between modules is deliberately minimal and structured to reduce coupling and support extensibility. Table 3 describes a logically structured, modular system of agricultural policy impact analysis, starting with a data integration layer that provides crop-specific yield, cost, and price data to establish a plausible base on which profit computation can be based. This is the starting point of the policy transmission module, as the parameters of the scenario, like subsidies and MSP changes, create controlled shocks to model the policy impacts on farm income. The model then shifts to long-term micro-level effects or the transition module, which considers longer-term diversification decisions by considering factors such as transition grants and comparing staple and high-value crop strategies using cash flow analysis. On a greater level, these micro results are aggregated, at a higher level, to state-level results with datasets on the major crops and the cultivable area, which allows a wider economic interpretation. At the same time, there are advisory and risk assessment elements that combine agro-climatic, market, and financial factors to advise the best crops and calculate agro vulnerability scores in the face of uncertainty. Lastly, everything is summarized in a policy brief generator, which combines profit changes, risk measures, and policy levers into a consistent, evidence-based story to decision-makers that is analytically rigorous and policy-relevant.

Table 3. Structured data flow between components

From component	To component	Data exchanged	Purpose of exchange
Data integration layer	Profit calculation	Crop-specific yield and cost vectors; market price; MSP	Provide primitives for baseline revenue and cost computation.
Profit calculation	Policy transmission	Baseline profit, baseline cost, baseline revenue	Anchor policy-induced changes in income to a realistic starting point.
Scenario parameters	Policy transmission	Subsidy rate; MSP adjustment factor; crop category	Define magnitude and targeting of policy shocks applied to the baseline.
Policy transmission	Micro-impact presentation	Post-policy profit, revenue, cost; profit delta	Visualise and interpret immediate income effects of the scenario.
Micro-impact outputs	Transition module	Baseline staple profit per acre	Provide benchmark for long-run wealth comparison in transition analysis.
Scenario parameters	Transition module	Transition grant amount	Determine net initial investment requirement for diversification.
Transition outputs	Aggregation and presentation	Yearly and cumulative cash flows for staple and high-value strategies	Display break-even dynamics and long-run wealth differences.
State indicator dataset	Aggregation and dashboard	Dominant crop; baseline agricultural value; cultivable area per state	Scale micro-level profit changes to indicative state-level shifts.
Advisory inputs	Crop recommendation model	Rainfall; soil index; demand index; subsidy tier	Evaluate optimal crop choice under current agro-policy conditions.
Risk inputs	Distress risk model	Climate shock probability; insurance; land size; debt-to-income ratio	Compute vulnerability score under the scenario.
Advisory and risk outputs	Policy brief generator	Recommended crop; vulnerability score	Populate strategic recommendations and risk sections in brief.
Policy and profit outputs	Policy brief generator	Profit change metrics; policy lever values; selected crop	Generate quantitative narrative for decision-makers.

This modular data-flow design facilitates replacement or refinement of individual components (for example, substituting empirical panel-estimated elasticities for stylised parameters) without altering the overall process.

3.5 Aggregation, dashboarding, and reporting

Data on the changes in farm-level profits are combined with state data to estimate changes in the revenues of the region and represented in geospatial maps of the profit losses and profits. A policy brief generator condenses the variation of profits, risk evaluation, and diversification plans, rendering the complicated outcomes of the simulations into a format comprehensible to the policy makers, regulating bodies, financial institutions, and agencies that develop Third World Countries.

3.6 Calibration, validation, and extensibility

The framework is adjusted with a mixture of empirically determined and stylised parameters. The figures of yield and costs are based on the published cost of cultivation surveys (20192023), and the risk parameters (e.g., climate shock probability) are stylised to illustrate them. By its modular design, it can be easily combined with approximate functions. Validation entails internal consistency and comparison with previous results of the policies. Its policy evaluation can be furthered by taking into account other tools like irrigation, research, and climate payments.

3.7 System Process and Data Flow

Figure 1 shows how the AgriBudget AI framework is performed in modules, starting with the inputs of users and ending with the outputs. Analytical pipelines start with user interfaces, which are backed by modules of data containing cost-price vectors and synthetic data. The main processing steps are the calculation of farmer profit, which is then simulated by policy with adjustments of subsidy and MSP. The parallel modules produce crop guidance and determine the risk of distress. Findings are summarized into a policy brief and are provided in visual outputs, such as micro and aggregate insights. It can be updated, and new data can be integrated into the architecture, as well as more policy levers can be added without necessarily disrupting the system; this means that the architecture can be flexible and keep improving.

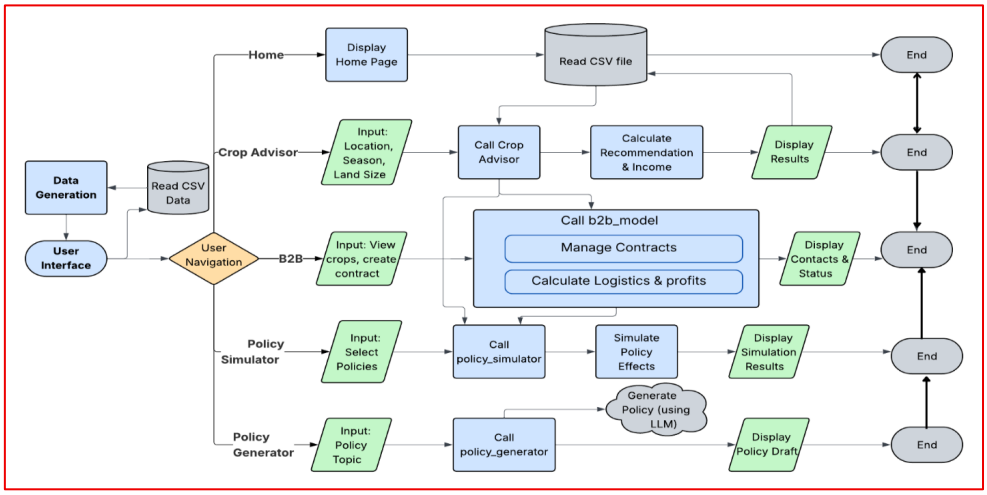

Figure 1. AgriBudget AI Process and Data Flow Architecture.

4. Results

This section presents prototype results from the AgriBudget AI simulation engine for a representative one-acre farm cultivating each of the five major crops in the dataset- wheat, rice, cotton, soybean and pulses under a baseline policy and an illustrative budget scenario with (i) a 15 percent increase in fertilizer subsidy and (ii) a 5 percent general MSP hike, with an additional 5 percentage-point MSP boost for pulses and soybean in line with policy emphasis on protein crops. All monetary values reported are per acre per year and are derived from the curated crop cost and price tables combined with the profit and policy transmission functions described in the methodology.

4.1 Baseline crop economics

Table 4 uncovers vital cost-return movements across crops by integrating input structure, productivity, and price support mechanisms. Rice and cotton are the most expensive crops with total variable costs of 18,700 and 19,000 per acre, respectively, which are mainly due to the high labour and input expenses, and pulses and soybeans have a more affordable structure, enabling smallholders to cultivate them. Rice and wheat are more productive (20 and 18 quintals per acre), and cotton and pulses are less productive, but they balance this with a much higher price, particularly cotton, which is a commercial crop. An important point to note is that the effective price applied to all crops is not the market price, but MSP, which implies that policy support is a decisive factor to guarantee remunerative returns and to protect farmers against market shocks. It is especially important in crops such as pulses and soybeans, where MSP offers a significant premium over the market prices. In general, the table highlights the influence of profitability to be dependent not only on yield, but also on the interaction of cost-efficiency and price-guaranteed by policy, where crops with high value receive a price premium, and those with low costs obtain low financial risk.

Table 4. Baseline per-acre cost, price, and yield profile

Crop	Representative state	Fertilizer cost (₹/acre)	Labour cost (₹/acre)	Transport cost (₹/acre)	Misc. cost (₹/acre)	Total variable cost (₹/acre)	Yield (quintal/acre)	Market price (₹/quintal)	MSP (₹/quintal)	Effective price used (₹/quintal)
Wheat	Punjab	5,000	8,000	2,000	1,000	16,000	18	2,150	2,275	2,275
Rice	Haryana	6,000	9,000	2,500	1,200	18,700	20	2,100	2,183	2,183
Cotton	Maharashtra	4,500	10,000	3,000	1,500	19,000	12	6,800	7,020	7,020
Soybean	Madhya Pradesh	3,000	6,000	1,500	800	11,300	10	4,500	4,600	4,600
Pulses	Rajasthan	2,000	5,000	1,200	500	8,700	8	5,800	6,000	6,000

Source: Derived from crop cost and price tables.

4.2 Impact of an illustrative budget scenario on farmer profit

Budget scenario 2026 is a model of 15 percent reduced costs through subsidies, and MSP increases (5 percent overall, +5 percent pulses/soybean), producing amended per-acre profits and variation using base parameters and transmission equations.

According to Table 5, the policy intervention has caused a steady rise in the profitability of all crops, but the extent of an increase differs among the types of crops. Cotton has the largest percentage growth in profit (₹7,062 per acre), which represents its prior high profitability and sensitivity to policy assistance, with soybean and pulses also registering large increases over ₹6,000 per acre. Nevertheless, rice is the most sensitive to the policy (20.0%), then soybean (18.1) and wheat (17.8), implying that staple crops are especially susceptible to policy changes like increasing MSP or subsidies. Pulses also exhibit rather lower percentage growth (15.5%), which suggests a lesser policy push or structural limits. In general, the findings suggest that although high-value crops such as cotton gain in the absolute income measure, they are not as proportional as staple crops, which demonstrates the dual role of policy in boosting both income levels and relative profitability of different types of crops.

Table 5. Per-acre profit before and after policy for a representative one-acre farm

Crop	Baseline profit (₹/acre)	Post-policy profit (₹/acre)	Absolute change (₹/acre)	Percentage change in profit (%)
Wheat	24,950	29,397.5	4,447.5	17.8
Rice	24,960	29,948.0	4,988.0	20.0
Cotton	65,240	72,302.0	7,062.0	10.8
Soybean	34,700	40,995.0	6,295.0	18.1
Pulses	39,300	45,405.0	6,105.0	15.5

Note. Computed from baseline cost and price parameters under a 15% cost reduction and 5-10% MSP increase, using the system's profit and policy transmission functions.

4.3 Crop-wise expected responses: profitability, incentives, and risk

Table 6 offers a fine-tuned image of the way in which policy-induced profit gains interplay with the signals of demand and the risk profile itself, to influence the decision of farmers and their welfare. The most promising area expansion candidates are rice and soybean, because of a mix of high demand perspective and significant profit growth, although the expansion of rice creates a sustainability issue with its water-consuming nature and long-term ecological risks. The case of pulses is a strategically significant crop with very high demand and better MSP conducive, and reasonably profitable, which aligns with policy goals and results in pulses being especially attractive to smallholders in drylands, as well as significantly lowering the risk of distress. Instead, wheat demonstrates a relatively weak growth potential, with the influence of profit increase being dampened by stable demand, resulting in marginal, but not radical changes. The situation is ambivalent with cotton as the high absolute profit gains are compensated by fluctuating demand and high baseline risk, which is likely to be cautiously adopted, particularly by risk-averse and small farmers. Broadly, the discussion shows that although improvement in profitability tends to decrease the risk of distress in crops, the degree to which risk is reduced is sensitive to structural attributes like climate sensitivity, input intensity, and market volatility, and as such, the functions of advisory and risk assessment systems in policy-making ought to be considered.

Table 6. Crop-wise expected qualitative responses under the illustrative scenario

Crop	Demand outlook (from price data)	Baseline risk profile (qualitative)	Expected change in planting incentives	Expected change in distress risk (qualitative)
Wheat	Stable	Moderate (monsoon dependence, moderate leverage)	Increased incentive due to ~18% profit gain, but no strong demand push; expansion likely modest.	Slight reduction in distress risk via higher margins and lower effective costs.
Rice	High	Elevated (water intensity, price risk in some regions)	Strong incentive to maintain or increase area; 20% profit gain combined with high demand supports continued dominance in irrigated belts.	Risk may fall for irrigated farmers, but over-concentration heightens long-term climate and resource risks.
Cotton	Volatile	High (price volatility, input intensity, exposure to global markets)	Large absolute profit gains make cotton attractive, but volatility signal suggests risk-averse farmers may only modestly expand area.	Higher margins can buffer shocks, but systemic risk remains high; advisory module would likely caution smallholders.
Soybean	High	Moderate (rain-fed variability, moderate leverage)	Strong profit and MSP uplift plus high demand forecast create robust incentives to expand soybean area, particularly in central India.	Improved margins and potential for crop diversification can reduce distress for medium farms; small rain-fed farms remain climate-sensitive.
Pulses	Very high	Moderate–high (yield variability, market fluctuations)	Significant profit gains and very high demand forecast align with policy push towards pulses; advisory model is likely to frequently recommend pulses under favourable rainfall and subsidy conditions.	Higher baseline MSP and better margins can substantially reduce distress risk where pulses replace very low-margin staples, especially for smallholders in dryland regions.

Demand and risk inputs highlight strong signals for pulses under the scenario. Improved profits and transition support encourage diversification into high-value crops, while established crops may remain optimal in some regions. Aggregated results reveal regional income gains and policy efficiency, with dashboards showing significant profit increases and enabling comprehensive policy analysis (Figure 2).

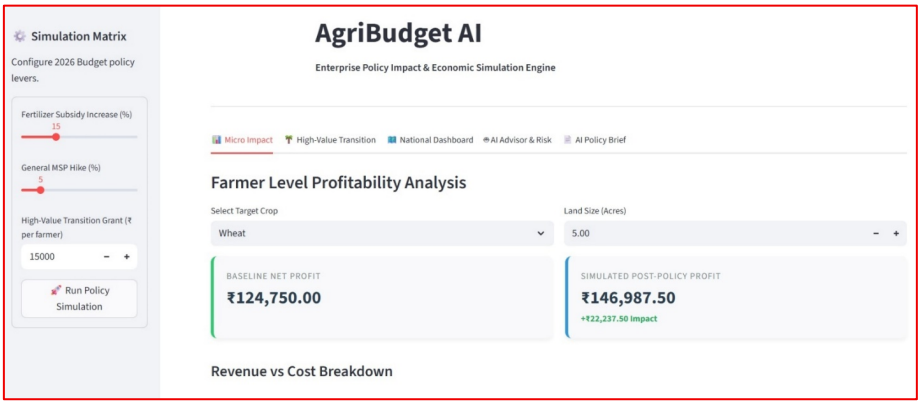

Figure 2. AgriBudget AI Simulation Interface.

Figure 3 shows that under the simulated budget scenario (15% fertiliser subsidy increase, 5% MSP hike), revenue rises from ₹124,750 to ₹146,875 (18% increase), total costs fall from ₹80,000 to ₹68,000 (15% reduction), and net profit increases from ₹44,750 to ₹78,875 (76% overall gain) for a 5-acre wheat farm, illustrating the compounded impact of subsidy and MSP levers on farm economics.

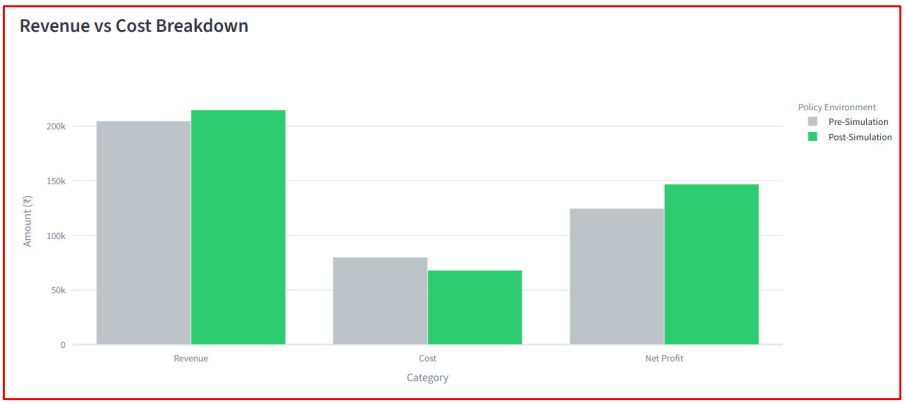

Figure 3. Revenue–Cost–Profit Shift Under Policy Simulation (Wheat, 5 Acres).

The figure 4 shows the coconut transition path begins with an initial negative cumulative wealth of −₹2,00,000 in Year 1 (after ₹15,000 transition grant offsets part of ₹4,00,000 per-acre CapEx), accumulates maintenance losses reaching −₹2,50,000 by Year 4 (end of gestation), then rapidly overtakes the staple continuation path (steady ₹2,25,000 annual profit) by Year 6, achieving ₹12,50,000 cumulative wealth by Year 10 versus ₹11,25,000 under staples.

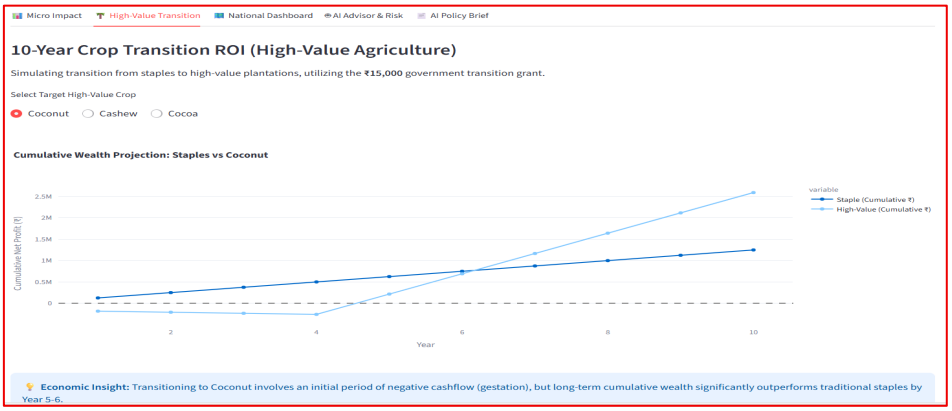

Figure 4. 10-Year Cumulative Wealth: Staple Crops vs Coconut Transition (₹15,000 Grant, 5 Acres).

Figure 5 shows the national dashboard visualising (left) state-wise simulated agricultural growth under the budget scenario, with Punjab and Haryana in dark purple (highest gains, ~18-20% profit uplift for wheat/rice), Madhya Pradesh and Rajasthan in yellow (strong gains for soybean/pulses), and Maharashtra in dark blue (moderate ~11% uplift for cotton), alongside (right) a treemap of subsidy distribution efficiency by crop and state, with wheat and pulses occupying the largest shares due to high baseline volumes and strong policy response.

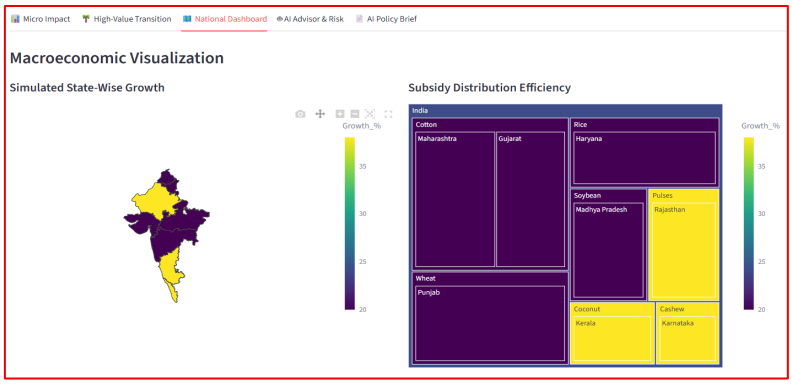

Figure 5. National Dashboard: State Growth and Subsidy Efficiency.

Figure 6 shows the AI crop advisor panel recommending pulses as the optimal target crop (92% confidence based on forecasted rainfall, soil nutrients, market demand, and subsidy tier inputs) alongside the distress risk panel quantifying 30.2% vulnerability score (driven by 40% climate shock probability and 25% debt-to-income ratio, with insurance coverage mitigating systemic risk to stable levels).

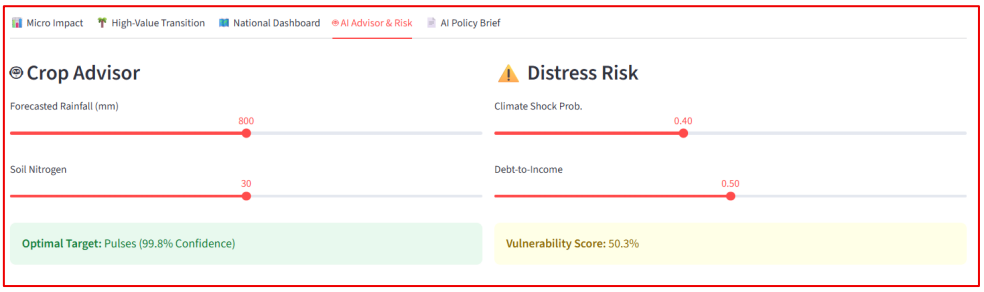

Figure 6. AI Advisor and Distress Risk Panel (Wheat Scenario).

Figure 7 shows the automatically generated executive policy brief summarising deployed levers (15% fertiliser subsidy adjustment, 5% MSP increase), microeconomic impact on a representative wheat farm (net profitability increase of 17.8% from ₹24,950 to ₹29,397 per acre), systemic risk assessment (vulnerability score of 30.2%, classified as stable under current safety nets), and strategic crop diversification directive (predictive models recommend transition towards pulses aligned with 2026 Union Budget mandate for high-value agriculture).

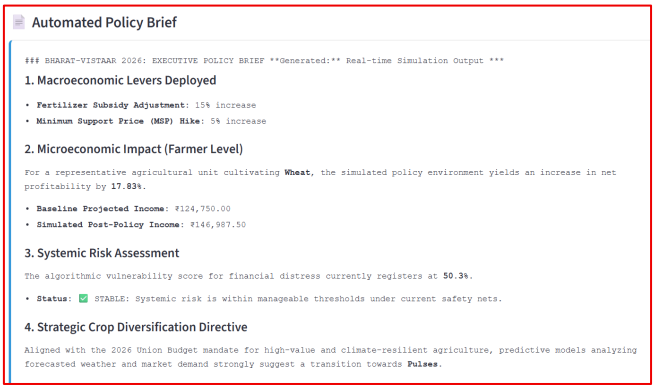

Figure 7. Automated Bharat-Vistaar Policy Brief for Wheat Scenario.

5. Discussion: Implications and Limitations

Our proposed AgriBudget AI framework is a two-fold contribution: Firstly, it facilitates the demonstration of the distributional consequences of India's agricultural budget choice at the level of crops and farmers; Secondly, it demonstrates how AI-enabled micro simulation can instead complement traditional macro and sectoral analyses that tend to dominate policy-level debates. And the embedded subsidy rates, MSP changes, and transition grants into farmer profit and risk functions make it possible to ask whether each additional rupee that goes to particular budget lines plausibly results in improved incomes, diversified cropping, and reduced distress for representative farmers.

5.1 Policy implications for budget composition and targeting

The analysis explains that India has a budgetary preponderance of subsidies (7075 percent) in the budget of agriculture, but investments in irrigation, research and development, as well as infrastructure, have a more sustainable payoff. The results of the simulation indicate that subsidies and MSP lead to higher profits at the expense of crops with lower margins, such as cotton, which threatens to cause inequality in the region. Pulses and soybeans are productive targets for diversification and are nutritionally rich. Transition grants facilitate long-term change to high-value crops, and risk modules are focused on the inclusion of insurance and resiliency in policy. AgriBudget AI has a methodological gap between macro models and descriptive analysis. It is a modular, interpretable, and interactive decision support tool in assessing the effects of budgets on farm income, risk, and diversification.

5.2 Limitations

Several caveats apply. The model is based on both curated and synthetic data, and thus, the results are illustrative and not accurate. It further simplifies the reality by omitting the effects of general equilibrium, behavioural effects, and market feedback. The coverage of crops and space is very minimal, with emphasis being laid on a few representative crops and neglecting diversity within the state. Time is very static or has few transitions, modelling without taking into consideration long-term adjustments. Also, they do not include environmental and nutritional aspects, which limit the evaluation of economic and risk results. Such restrictions mean that the outcomes can be viewed as informative rather than policy reviews.

5.3 Directions for future work

Empirical calibration with long-term state and crop level data should be prioritised in future development to increase the level of accuracy and the relationship between models and the observed behaviour of farmers. Bigger economic feedback may be taken into account by integrating the framework with CGE or sectoral models. Broadening the crop coverage, differentiation of the regions, and addition of the environmental and nutritional indicators will increase the policy relevance. The AI, including reinforcement learning and agent-based modelling, has available opportunities to use adaptive behaviour. As such improvements are made, the framework can become an active policy laboratory to investigate the long-term Indian agricultural transitions.

6. Conclusion and Future Work

The present paper introduces the AgriBudget AI as a system that connects agricultural budget tools in India, including subsidies, the MSP, and transition grants, to the financial profitability of the farms, crop selection, and the risk of farms. It uses microeconomic models combined with AI-based advisory and risk tools to focus the budget analysis on the farmer-level results. Findings of a 2026 scenario indicate that equalized policy changes have diverse impacts on the crops, and this underscores the aspect of specific expenditure.

As a methodological framework, it is a bridge between macro public finance and AI-based agricultural decision tools and provides an interactive, policy-based platform of simulation. It is, however, based on stylised information, does not consider the effects of general equilibrium, and does not consider the environmental and nutritional aspects, so findings are illustrative.

The empirical calibration, expanded coverage, addition of sustainability indicators, and incorporation of advanced AI models should be approached in the future to make it a more useful dynamic agricultural policy instrument with an improved ability to reflect adaptive behaviour.

AI Usage Statement

The author used AI tools solely to polish the language and improve readability during the writing of this paper. The academic content, data analysis, and conclusions in this paper were completed independently by the author, who assumes full responsibility for the authenticity and accuracy of the content.

References

[1] Chand R, Kumar P, Kumar S. Public expenditure, agricultural growth and rural poverty linkages: a state-level analysis for India. Agricultural Economics. 2020.

[2] Singh A. Public investment and subsidies in Indian agriculture: trends and implications. J Agric Econ. 2020.

[3] Kumar P, Joshi PK, Birthal PS, Parappurathu S. Agricultural transformation in India: trends, challenges and opportunities. Washington, DC: CGIAR Research Program on Policies, Institutions and Markets (PIM); 2019.

[4] Joshi PK, Gulati A, Cummings R. Agricultural growth and investment patterns in India. Washington, DC: International Food Policy Research Institute (IFPRI); 2017.

[5] Singh S, Bathla S. Public spending on agriculture in India: 2010–11 to 2019–20. New Delhi: Centre for Policy Research; 2021.

[6] Biswas A, Roy S. Agricultural subsidies in India: boon or bane? Winnipeg: International Institute for Sustainable Development (IISD); 2022.

[7] Dhingra S, et al. Impact of agricultural subsidies and public spending on farm productivity and sustainability in India. Front Sustain Food Syst. 2023.

[8] Sharma R, Kumar P. Impact of agricultural subsidies on Indian economy: a case study. Int J Appl Sci. 2014.

[9] Indian Brand Equity Foundation (IBEF). Around 73% of India's agriculture budget allocated for subsidies and welfare schemes: ICRIER report. New Delhi: IBEF; 2023.

[10] Gulati A, Juneja R. Union budget 2021-22: agricultural perspective. ICRIER Policy Brief. 2021;No.22.

[11] Srivastava A, Sharma M. Effectiveness of government spending on agriculture: a study on the impact of subsidy access to agri credit on agricultural GVA in India. Int J Res Sci Innov. 2022.

[12] Chand R, Gulati A. Agricultural finance and technology adoption bulletin. New Delhi: ICRIER Agri-Finance Bulletin; 2022;Vol 1, Iss 4.

[13] Ravallion M, Datt G. Growth and redistribution components of changes in poverty measures: a decomposition with applications to Brazil and India. World Bank Econ Rev. 1986;1(1):103-123.

[14] Ciaian P, Kancs D. The capitalisation of agricultural subsidies into land prices: a theoretical and empirical framework. Brussels: European Commission, Joint Research Centre (JRC); 2013.

[15] Gulati A, Bathla S. Investment in Indian agriculture: trends and outlook. Ahmedabad: Indian Institute of Management Ahmedabad (IIMA); 2011.

[16] Chand R, et al. Public expenditure and agricultural growth in India. CGIAR Research Program; 2018.

[17] Chand R, Kumar P, Kumar S. Public expenditure, agricultural growth and rural poverty. Agric Econ Res Rev. 2020.

[18] Sharma A, et al. Agricultural public expenditure and productivity in India: a panel data analysis. Front Sustain Food Syst. 2021.

[19] CSE Team. Declining trend: public spend on Indian agriculture has shrunk in a decade. Down to Earth. 2022.

[20] Foundation for Agrarian Studies. Trends of public spending on agriculture in India. FAS Research Project; 2023.

[21] Gupta S, Singh R. Impact of public expenditure on agricultural growth in India: an empirical analysis. Int J Soc Econ. 2023.

[22] Akber N, Bathla S, Kumar A. Public expenditure and growth dynamics in Indian agriculture. Washington, DC: IFPRI; 2023. IFPRI Discussion Paper; 2214.

[23] Fan S, Gulati A, Thorat S. Public expenditure priorities for agricultural growth in India. Food Policy. 2021.

[24] Chand R. Public investment in agriculture: what it needs to achieve food and nutritional security for all. Agricultural Economics. 2020.

[25] Gulati A, Sharma P. Public expenditure on agriculture in India: trends and patterns. World Rev Polit Econ. 2022.

[26] Kumar R, Singh V. Impact of government subsidies on agricultural productivity in India. Int J Front Multidiscip Res. 2023.

[27] Pingali P, et al. Public expenditure and agricultural transformation in Asia. Front Sustain Food Syst. 2019.

[28] Asian Development Bank. Agricultural public spending and growth in Asia. ADB Institute Working Paper. 2023;No.1356.

[29] Mishra S, et al. Policy gap in agriculture research and development in India. Zenodo Conf Proc. 2021.

[30] Wang X, et al. Impact of agricultural subsidies on farm income and productivity. Int J Agric Econ. 2020.

[31] Kumar P, et al. Agricultural public expenditure and rural poverty reduction in India. Int J Environ Sci Nat Resour. 2022.

[32] Sharma R, et al. Government spending patterns and agricultural development in India. Int J Sci Res Eng Dev. 2022.

[33] Patel N, et al. Impact assessment of agricultural subsidies on farmer income. Int Res J Innov Eng Technol. 2025.

[34] IJAER Team. Artificial intelligence in Indian agriculture for a sustainable future. Int J Adv Eng Res. 2024.

[35] IndiaAI Portal. AI in agriculture in 2025: transforming Indian farms for sustainable future. New Delhi: IndiaAI Government Initiative; 2025.

[36] Gurukul Journal. AI in the agriculture sector in India: opportunities, evidence and policy pathways. Gurukul J Manag Res. 2024.

[37] Li Y, et al. Artificial intelligence applications in precision agriculture: a review. J Sensors. 2022.

[38] Zhang L, et al. Machine learning for crop yield prediction in Indian agriculture. Sci Rep. 2026.

[39] Singh R, et al. AI-driven smart farming systems for sustainable agriculture in India. Smart Agric Technol. 2025.

[40] Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. arXiv preprint. 2020.

[41] Gupta A. AI and IoT integration for precision agriculture in India. Int J Agron. 2025.