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AI-Based Intelligent Management System for Agriculture in Population Decline Regions: A Case Study of Maharashtra, India

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Abstract: Demographic shifts and population decline pose significant risks to agricultural workforce stability, particularly in labor-intensive crops like soybean. This research introduces an AI-Based Intelligent Management System to evaluate how agricultural operations can be dynamically redistributed during severe workforce-capacity reductions in population decline regions. Focusing on Kharif soybean cultivation in Yavatmal, Maharashtra, the study applies Mixed-Integer Linear Programming (MILP) to optimize the allocation of six fundamental agricultural tasks across human, mechanized, and AIassisted execution modes. Four simulated labor-availability scenarios (100%, 80%, 75%, and 70%) are assessed against three operational policies (Human-only, Fixed-allocation, and MILP-optimized). Based on publicly available regional agricultural statistics and documented agronomic assumptions, the experimental results indicate that while a 30% reduction in labor capacity causes unmet workloads under traditional models, the AI-based management system successfully maintains 100% task coverage by optimally shifting suitable tasks to AI and machine modes, albeit with a 22.4% increase in overall operational costs. This system serves as a preliminary decision-support tool for agricultural planning under constrained resource conditions.

Keywords: AI-Based Intelligent Management System, Population Decline, Agricultural Workforce Allocation, Mixed-Integer Linear Programming, Artificial Intelligence in Agriculture, Yavatmal.

I. INTRODUCTION

Agriculture remains the economic backbone of Maharashtra, India, with the Vidarbha region serving as a primary hub for soybean cultivation during the Kharif season. Yavatmal district, characterized by extensive agricultural tracts, relies heavily on manual labor for essential farming operations, from soil preparation to harvesting. However, population decline and demographic shifts—driven by factors such as urbanization, demographic aging, and shifting occupational preferences—necessitate the exploration of supplementary and automated farming techniques.

Artificial Intelligence (AI) and advanced mechanization offer promising solutions to mitigate labor shortages. AI-assisted systems, such as drone-based crop monitoring and precision spraying, alongside traditional mechanized equipment (e.g., tractors and mechanical harvesters), can execute specific tasks with high efficiency. The challenge lies in determining the optimal distribution of these execution modes across different agricultural tasks. Not all tasks are suitable for automation, and AI implementation is often constrained by high fixed costs and technical eligibility requirements.

This paper presents an optimization framework designed to allocate agricultural tasks among human workers, machines, and AI systems. By applying a Mixed-Integer Linear Programming (MILP) model to a case study of Yavatmal's soybean

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production, this study quantifies the economic and operational impacts of hypothetical labor reductions (down to 70% of baseline capacity) and demonstrates how algorithmic allocation can sustain agricultural output.

II. PROBLEM STATEMENT

Traditional agricultural planning assumes a consistent and sufficient supply of human labor. When labor capacity decreases, farmers face delayed operations, unmet workloads, and ultimately, reduced crop yields. Current decision-making processes lack a quantitative framework to dynamically redistribute specific farming tasks (such as sowing, irrigation, and monitoring) to alternative execution modes (machines or AI) based on cost, task suitability, and real-time resource availability. There is a critical need for an automated scheduling and allocation system that can minimize operational costs while guaranteeing complete task coverage under varying degrees of workforce capacity reduction.

III. RESEARCH OBJECTIVES

- To develop a data-driven AI-Based Intelligent Management System for soybean cultivation in population decline regions.
- To decompose agricultural operations into distinct tasks and evaluate their suitability for human, mechanized, and AI-assisted execution.
- To formulate a Mixed-Integer Linear Programming (MILP) model that optimizes task allocation based on cost, capacity, and eligibility constraints.
- To evaluate system performance across four hypothetical labor-capacity scenarios (100%, 80%, 75%, and 70%) using public data assumptions for Yavatmal, Maharashtra.
- To compare the proposed MILP allocation policy against baseline traditional policies to validate operational efficiency.

IV. LITERATURE SURVEY

The integration of technology in agriculture has evolved from basic mechanization to precision agriculture, and currently towards AI-driven automation Walter et al. (2017). Early research focused on autonomous crop production systems Blackmore et al. (2007), outlining the feasibility of replacing human labor with machines. More recent studies emphasize human-robot collaboration and the economic feasibility of AI in field operations Fountas et al. (2020).

While existing literature explores the isolated benefits of AI monitoring or automated harvesting, there is a distinct lack of comprehensive mathematical frameworks addressing the optimal economic distribution of human, machine, and AI resources at a granular task level under constrained labor scenarios. The research gap addressed here is the holistic, optimization-based allocation of a hybrid workforce in a developing agricultural context.

Table 1: Comparative Analysis of Existing Literature

Author & Year	Focus Area	Methodology	Identified Gap / Limitation
Blackmore et al. (2007)	Autonomous mechanization	Conceptual architecture	Lacks mathematical optimization for cost and capacity constraints.
Walter et al. (2017)	Smart farming sustainability	Review and policy analysis	Focuses on macro-trends rather than tasklevel execution.

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Fountas et al. (2020)	Agricultural robotics	Systems evaluation	Does not simulate variable human-labor reduction scenarios.
Proposed System	Hybrid workforce allocation	MILP Optimization model	Specifically addresses task allocation under quantified labor constraints.

V. WORKING OF THE PROPOSED SYSTEM

The proposed system processes inputs regarding task demand (hectares of soybean to be managed), resource capacities (available labor hours, machine availability), and cost parameters. The system decomposes the farming lifecycle into six primary tasks. An eligibility matrix dictates which modes (Human, Machine, AI) can safely and legally perform each task. The MILP engine then processes these constraints to output an optimal allocation plan.

System Workflow Architecture

[Public Agricultural Data & Operational Assumptions]
↓
[Task Decomposition & Mode Suitability Scoring]
↓
[Constraints Definition: Labor, Budget, Eligibility]
↓
[MILP Optimization Engine (Minimize Cost)]
↓
[Scenario Analysis (100%, 80%, 75%, 70% Labor)]
↓
[Output: Optimal Task-Mode Allocation Matrix]

VI. SYSTEM DESIGN AND METHODOLOGY

A. Data Collection and Assumptions

Due to the lack of granular, field-level digitized operational datasets for Yavatmal, the macroeconomic baseline was derived from the Directorate of Economics and Statistics (DES), Maharashtra. For the experimental model, a standard reference farm of 100 hectares is assumed. Operational parameters (hours per hectare, cost) are formulated based on standard agronomic practices for Kharif soybean.

Table 2: Dataset Registration and Assumptions Matrix

Parameter / Data Point	Value / Assumption	Source Context / Role
Reference Area (Demand)	100 Hectares	Standardized baseline for experimental model
Baseline Labor Capacity	2,000 Hours	Represents 100% capacity scenario
Task 1: Soil Prep Cost (H/M)	₹800 / ₹1500 per ha	Derived agronomic assumption
Task 5: Monitoring AI Cost	₹500 per ha	Drone/Software operational assumption

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B. Task Mode Eligibility

Let T be the set of tasks: {Soil Preparation, Sowing, Irrigation, Crop Protection, Monitoring, Harvesting}. Let M be the set of modes: {Human, Machine, AI}. Safety and technical feasibility act as hard constraints. For example, Harvesting is restricted to Human and Machine modes, while Crop Monitoring can be performed by Human or AI, but not traditional heavy machinery.

C. Mathematical Formulation (MILP)

The objective is to minimize total operational costs while ensuring all 100 hectares of task demand are met without exceeding available labor hours.

Decision Variables: x_{tm} : Area in hectares assigned to task t using mode m.

Objective Function:

Minimize Total Cost $Z = \sum_{t \in T} \sum_{m \in M} (C_{tm} \times x_{tm})$ where C_{tm} is the cost per hectare for task t using mode m.

Constraints:

1. Demand Fulfillment: For each task t, the total area processed must equal the farm size D.

$\sum_{m \in M} x_{tm} = D$, for all $t \in T$.

2. Labor Capacity: Total human labor hours used cannot exceed the scenario limit W.

$\sum_{t \in T} (L_{t,Human} \times x_{t,Human}) \leq W$ where $L_{t,Human}$ is the labor hours required per hectare for task t.

3. Non-negativity and Eligibility: $x_{tm} \geq 0$, and $x_{tm} = 0$ if mode m is not eligible for task t.

VII. RESULTS AND DISCUSSION

The methodology was implemented using Python, utilizing the Pandas library for data structuring and the PuLP library as the MILP solver. The experiment evaluated three policies across four workforce-capacity scenarios: 100% (2,000 hrs), 80% (1,600 hrs), 75% (1,500 hrs), and 70% (1,400 hrs).

A. Policy Comparison

Policy A (Human-only): At 100% capacity, human labor is sufficient. However, at 70% capacity, Policy A results in approximately 30 hectares of unmet workload, drastically threatening crop yield. **Policy B (Fixed-Allocation):** A static 50/50 split between human and machine modes. It survives the 80% scenario but is highly cost-inefficient when human labor is abundant.

Policy C (Proposed MILP): Dynamically shifts tasks. At 100% capacity, it maximizes cheap human labor. At 70% capacity, it shifts AI-eligible tasks (like monitoring) entirely to AI, and heavy tasks to machines, ensuring 0% unmet workload.

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Table 3: Experimental Results under Proposed MILP Policy (100 Hectares)

Labor Scenario	Available Hours	Unmet Workload (ha)	Total Cost (₹)	AI Utilization (%)
100% (Baseline)	2,000	0	₹425,000	0% (Cost prohibitive)
80% Reduction	1,600	0	₹468,500	25% of eligible tasks
75% Reduction	1,500	0	₹492,000	60% of eligible tasks
70% Reduction	1,400	0	₹520,300	100% of eligible tasks

B. Discussion of Findings

The results demonstrate that as human labor capacity drops by 30% (Scenario 4), the overall cost of cultivation increases by 22.4% (from ₹425,000 to ₹520,300). The MILP algorithm optimally prioritizes the transition of Crop Monitoring to AI (due to its relatively low AI transition cost per hectare compared to the high labor hours saved). Harvesting, which requires high machine costs, is only transitioned when absolute labor limits are reached. This confirms that the framework correctly balances cost minimization against strict capacity limits.

VIII. CONCLUSION

This research successfully formulated and executed an AI-Based Intelligent Management System for soybean farming in Yavatmal, Maharashtra, addressing the challenges of population decline regions. By utilizing a Mixed-Integer Linear Programming model, the study demonstrated that while hypothetical labor capacity reductions up to 30% pose severe risks to task completion under traditional policies, an optimized hybrid workforce can maintain 100% operational coverage. The inevitable increase in operational costs is minimized through algorithmic allocation, providing a critical decision-support mechanism for future agricultural resilience.

IX. FUTURE SCOPE

Future enhancements to the system include the integration of real-time sensory data and dynamic weather forecasting (e.g., IMD rainfall data) to adjust task schedules dynamically rather than statically. Expanding the dataset to include field-validated operational costs and executing multiobjective optimization (minimizing environmental impact alongside cost) will further strengthen the practical applicability of the framework for regional farmers and policymakers.

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