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Optimum Designing and Field Validation of a Multi-Objective Integrated Farming System in Indian North-Western Himalayas

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ABSTRACT

Multi-criteria decision making (MCDM) technique – compromise programming – was utilized to optimize an integrated farming system (IFS) operated by a representative small sized farm of Indian north-western mid-Himalayas (INWH). The optimization was undertaken to provide a better alternative for formulation of an IFS individually for such variable sized farms that are the majority, especially in INWH, as compared to non-mathematical fixed farm-size simulations that have been adopted in India, which follow a one-size-fits-all approach. The optimal IFS aimed to maximize farm income and food energy while minimizing soil loss – conflicting decision criteria chosen and prioritized by the farmer within constraints such as production input-output ratios, available resources, and preferences for local production to meet family needs. Optimization of selected farmers' IFS revealed potential to achieve better values of their farming attributes, more so revealed by its on-field implementation. Implementation of the formulated IFS plan, comprising crop cultivation and animal husbandry components, on the farm continuously for three years could achieve higher average farm income of >10% and food energy production of >1% compared to potential of 10.9% and 0.4% as per the optimal IFS plan, respectively. The success of the implemented IFS model based on the formulated index indicated that it has at least 67% probability of achieving its potential. Formulating farmer-specific IFS with MCDM, considering local needs and traits, helps small farms identify the best options across criteria, enabling them to move beyond subsistence and failure-prone farming.

1 | INTRODUCTION

Small and marginal farmers, comprising 86.1% of India's farming community but owning just 46.9% of operational land (Kumar and Pathak, 2024), form the backbone of the rural economy. Yet, they struggle to generate stable and adequate supplies of food, nutrition and cash. Their challenges are compounded by reliance on monsoons, persistent land degradation, dependent on labour-intensive practices, and the ongoing impacts of climate change. To sustainably improve their livelihoods, there is an urgent need to focus on farming systems that promote economic stability, soil sustainability, environmental quality, and ecological balance even in less favourable regions. With land per capita shrinking due to population growth, India has limited potential for expanding agriculture horizontally. Thus, vertical intensification, integrating diverse farming components, becomes essential to ensure consistent income for farm families. The Integrated Farming System (IFS) achieves this by linking various bio-systems, where outputs or by-products from one enterprise serve as inputs for another (Gill *et al.,* 2009). This synergy makes IFS a viable pathway for meeting rising demands for food and nutrition, while also providing income stability for small and marginal farmers who operate under resource constraints.

The scientific community widely endorses IFS as a suitable approach for these households (Dagar, 2014). Small landholders often focus on cereal crops that are highly vulnerable to climate variability. Failure of monsoon rains can quickly jeopardize family sustenance (Kumar *et al.,* 2013). Compared to mono-cropping IFS leverages synergies among multiple components, yielding more output with fewer inputs, conserving resources, and reducing production costs—thus improving both productivity and income (Akter *et al.*, 2024; Edwards *et al.*, 1988). IFS also emphasizes by-product utilization, enhancing the profitability and feasibility of resource-constrained farming (Behera and France, 2016). IFS encompasses a suite of practices designed to achieve sustained production, high profits, and minimal negative environmental impacts, while improving the living standards of small and marginal farmers (Gupta *et al.*, 2012; Lal and Miller, 1990; Kumar *et al.*, 2013). Mimicking natural diversity, IFS incorporates crops, animals, poultry, fish, and various plants to maximize year-round resource use (Kumar *et al*., 2015). When well-planned, integrating multiple enterprises with cropping offers greater returns than monoculture, which is especially crucial for resource-limited farmers (Gill *et al*., 2009). The benefits of IFS are multidimensional: it enhances food security, environmental sustainability, resource conservation, and social acceptability (Akter *et al.*, 2024; Chuanrum and Shrestha, 2024; Tipraqsa *et al*., 2007). Notably, IFS can address soil fertility depletion, thus supporting both productivity and sustainability (Gowing *et al*., 2020).

The IFS adoption is recommended for various Indian agro-ecologies (Balamatti and Shamaraj, 2017; Basavanneppa and Gaddi, 2017; Gill *et al*., 2009; Pankaj, 2018; Sahoo *et al*., 2015; Surve *et al*., 2014; Tanwar *et al*., 2018). Multiple regional case studies (Behera and Mahapatra, 1999; Bisht, 2011; Bohra *et al*., 2014; Gill et al., 2009; Goverdhan *et al*., 2020; Kumar *et al.*, 2012; Makdoh et al., 2014; Mohanty et al., 2016; Rautaray *et al.*, 2005; Sahoo and Behera, 2017; Sekar *et al*., 2001; Sharma *et al*., 2014; Sheokand *et al*., 2000; Singh *et al.,* 2012) inform policy and practice, and IFS has become a government focus for small and marginal farmers, aiming at livelihood security and a new Green Revolution. However, despite research efforts, many IFS findings have not translated into actionable recommendations for stakeholders (Dagar, 2014). A key limitation is the often rigid design of case studies—using fixed enterprise sizes and discrete landholding classes—while actual farm sizes and component mixes vary widely. Moreover, IFS is not prescriptive but must be tailored to local ecological and socioeconomic conditions (BAA, 1996; IACPA, 1996; Morris and Winter, 1999; FAO, 2001; Singh *et al.,* 1998; Yamin *et al*., 2010). Effective IFS planning requires a holistic, multidisciplinary, and context-specific approach, considering the entire farm unit and local resource and market realities. Given the complexity of farming systems—comprising soil, crops, animals, machinery, labour, capital, and family management—a decision-making tool capable of optimizing multiple, sometimes competing objectives is essential. Multi-Criteria Decision Making (MCDM) techniques enable simultaneous optimization of several goals ranked by farmers according to their needs and preferences. MCDM can determine optimal resource allocation (for example, ideal land area for each IFS component) tailored to specific farm constraints, objectives, and priorities-offering a precision lacking in previous simulation studies, which often ignored the realities of farm-level resource constraints and priorities.

HIGHLIGHTS

- Optimized Integrated Farming System (OIFS) using a multi-criteria decision-making technique boosted the farmer's annual net income by about 10%.
- Three years of field implementation of OIFS closely matched model predictions, with a success index indicating about a 67% chance of reaching projected gains.
- Scaling up, farmer-specific, multi-objective optimization approach can improve rural livelihoods and resilience in the Himalayan region.

Globally, few IFS case studies have employed optimization techniques (Groot et al., 2012; Liang et al.,2018;Rundengan, 2014), and such research is almost non-existent in India (Mandal et al., 2017). Notably, only Groot et al. (2012) implemented an optimized, multi-objective 96 ha mixed organic farm in the Netherlands. No study has yet developed and tested an optimal IFS in the Himalayan agro-ecosystem, tailored to a farmer's objectives, enterprise preferences, and real resource constraints. The objective of the present study is to optimally enhance an existing IFS for a small farmer in the Himalayan foothills, using an MCDM technique that accounts for the farmer's diverse and prioritized objectives, resource limitations, and enterprise preferences. The study also compares the actual outcomes of this implementation with the MCDM-generated recommendations.

2 | MATERIALS AND METHODS

2.1 | Study Area

The Indian North-Western Himalayan (INWH) region spreads to an approximate area of 33.13 million ha, which is about 10% of India's total geographical area. The region itself supports 2.4% (29.5 million) of the country's human population. The region accounts for only 3.7% (18.8 million) of the total livestock population of the country; however, animal husbandry is an integral part of hill agriculture as it is required for various purposes – milk, meat, wool, fur, hide, manure, and transportation. The major portion (76%) of the INWH region's population lives in rural areas. Agriculture and allied sectors provide direct employment to about 70% of the workforce. The net sown area of the region is only 12% (2019/20) of reported geographical area, ranging from 10% in Himachal Pradesh (HP) to 13% in Jammu & Kashmir (J&K) among the three, including Uttarakhand (UK), INWH states (GoI, 2022), which is low in comparison to that of the country (43%). Out of the net sown area of the INWH region, 34% is rain-dependent (ICAR-IASRI, 2024). However, agriculture is the backbone of the region as agriculture and livestock contribute 11.04% to 17.12% of the total Gross State Value Added (GSVA) of Agriculture and Allied Sector in total GSVA of the State at current prices (2021/22) across three states (GoI, 2022).

The average landholding per farmer in the region ranges from 0.59 ha (Jammu & Kashmir) to 0.95 ha (Himachal Pradesh), which is below the national average of 1.08 ha (2015/16). Despite sparse population, pressure on agricultural land remains high due to only 12% of land being cultivated, leading to small land holdings. Over the years, the share of small and marginal farmers increased from 87-94% in 2005-06 to 89-95% by 2015/16. The share of total cultivated area owned by marginal and small farmers grew from 52%-70% in 2005/06 to 56%-73% in 2015-16 (ICAR-IASRI, 2024). The states within the INWH region have higher cropping intensity than India overall, reaching between 151% and 168% in 2019/20 (GoI, 2022), with a national average of 142%. Since agriculture is the primary livelihood for most residents, land use is highly intensive. Despite this, natural factors lead to land productivity remaining below the national average.

The main features of hill and mountain farming in INWH states include small, fragmented land holdings, sloping farmlands, rainfed agriculture, poor water management, and socio-economic challenges faced by farmers. The Himalayas are naturally susceptible to soil erosion due to fragile geology, steep slopes, and intense storms. Rainwater-induced soil erosion is a significant issue, with rates exceeding 10 Mg ha^{-1} yr^{-1}. Recent data show that the UK has the highest land area affected by water erosion (21%), followed by HP (18%) and J&K (9%). Erosion causes annual crop yield losses between 10% (J&K) and 20% (UK) in rainfed cereals, oilseeds, and pulses, mainly because of steep terrain and poor management practices (Sharda *et al*., 2010), resulting in reduced crop productivity (Sharda & Dogra, 2013). Overuse of natural resources has led to severe land degradation and paradoxical water scarcity despite the region's abundant water resources. The Himalayas, often called the “Water Towers of the Earth” (Messerli & Ives, 1997), supply nearly half (47%) of India's usable surface water through the Indus and Ganga-Brahmaputra-Meghna basins (Kumar *et al*., 2005). However, local communities face water shortages because ongoing mismanagement of catchment areas has decreased the perennial flow of natural springs and streams over time (Banskota & Chalise, 2000; Rawat, 1988; Sharda, 2005; Valdiya & Bartarya, 1991). About 78% of the region's total cropped area, where agriculture is the main source of local economic growth, relies on rainwater because of water scarcity, leading to less than optimal food production and increased poverty (Dogra *et al*., 2014).

2.2| The IFS Farmer

Ashti watershed (473 ha), located between 770 47' 18" and 770 49' 48" E and 300 39' 10" and 300 40' 35" N (Fig. 1 & 2) in Dehradun district, in the north-western mid-Himalayas of the Indian state of Uttarakhand and representing major Agro-ecological Zone 14—namely Western Himalaya was selected by ICAR-Indian Institute of Soil and Water Conservation (formerly CSWCRTI), Dehradun, for development as a model watershed during the XI Plan under the National Watershed Development Project for Rainfed Areas (NWDPRA) funded by the Ministry of Agriculture, Govt. of India. The watershed features mountainous terrain with undulating topography and steep slopes (average slope 67%). It drains into the river Tons, a tributary of the Yamuna river in the Ganga-Brahmaputra-Meghna basins. The watershed has a well-developed drainage network. Soils in the watershed are light-textured, primarily gravelly sandy loam to silty clay loam, with high bulk density, infiltration, and permeability rates. Water-holding capacity is very low, with low available nitrogen and medium to high levels of phosphorus and potassium. Organic carbon content is very high in most soils due to frequent application of partially decomposed farmyard manure (FYM) and low temperatures. The annual rainfall is approximately 1600 mm, with most of it (75-80)% falling during the monsoon season (June-September). The area also experiences high-intensity storms and occasional cloud bursts. Snowfall occurs occasionally in the higher elevations. Winter season rainfall generally does not meet the water requirements of crops (CSWCRTI, 2009).

In 2014, a farmer from Tangri village in the Ashti watershed was selected for the study. Tangri had 16 small-scale farming families, each with plots no larger than 1.0 ha, from resource-poor backgrounds. The farmer’s farm spans 0.67 ha, with 0.18 ha (26%) irrigated by seasonal streams and 0.49 ha (74%) relying on rainfall. Water supply depends on rainfall. His land is highly fragmented, with 30 small fields averaging 0.023 ha, mainly in Tangri and Jamuwa (see Fig. 3). He grows cereals, pulses, oilseeds, vegetables, and fodder. His livestock includes 8.1 SLU, comprising buffaloes, cows, bullocks, calves, and goats. His family has ten adults—five men, five women over 20—and seven children, with some working outside as teachers or students, while others are farm laborers. Farming is his main occupation, and he earns extra as a temporary laborer in road work during the off-season.

2.3 | Data Collection and Computations

All relevant data needed to create an optimal IFS plan (OIP), based on the existing/suboptimal IFS plan (ESIP) using an MCDM technique, was gathered from the farmer. Primary quantitative data for the selected farmer, required to outline the current IFS on his farm and its details, was collected through personal interviews and recorded on well-structured questionnaires. This data was collected during 2013-14 from the farmer, representing an average of the past three years. For data collection, his farm's production enterprises—such as cultivated cropping sequences in a year and owned livestock—were first listed. For crops, the sowing and harvesting dates were recorded to determine the land requirement period for each crop during the year. Data on cropping season-wise area allocation of rainfed and irrigated land for each crop, along with human and animal labor (month-wise), seed, farmyard manure (FYM), fertilizers, and pesticides, as well as the average yields of main and by-products, were documented. Livestock (sheep/goats) were considered collectively as a single enterprise. To evaluate the economics of these enterprises, the prices of various inputs used and outputs produced were recorded. Input, output, and price data were collected as an average over the past five years.

To optimize the existing IFS according to the farmer's objectives—such as guiding improvement or optimization of farming attributes, decision criteria, as well as production enterprises' preferences and the farmer's actual resources and constraints—which greatly influence farming decisions—the following data collection and necessary calculations were undertaken.

- The farmer selected three decision criteria for optimization: net returns (farm income in Indian Rupees), nutrient energy (food production in Mcal), and soil loss (Mg). These criteria represented the farmer's objectives (Romero & Rehman, 2003), with each assigned a weight that sums to ten across all objectives. During the survey, the farmer recorded the importance of each objective: maximizing farm income (weight 5), maximizing food energy production (weight 4), and minimizing soil loss (weight 1) objectives.

FIGURE 1 Index map of District Dehradun in Uttarakhand State, India

FIGURE 2 Index map of Ashti watershed, District Dehradun in Uttarakhand State, India

- ·For each objective function, the respective coefficient of each production activity was calculated. A budgeting technique was used to determine the individual net returns of various crops (from main product only) and livestock (from cattle milk and goat meat) based on collected data. For crops, the estimates for this attribute or decision criterion were initially made based on the actual area cultivated for each, and then on a per-unit-area basis. For livestock, actual measurements of each animal (for goats and sheep, treated as one group) were used. The costs incurred for purchasing inputs for any production activity were not included in the net return estimation, as these costs were summed for all activities and separately accounted for in the net returns objective function of the MCDM model, following a linear programming approach by Sankhayan and Cheema (1991). Accordingly, the costs of fertilizers such as urea, DAP, and CAN were not used in calculating the net returns of crops for which they are applied. However, since pesticides were purchased in limited quantities only for the cultivation of tomato, their costs were included in the net return calculation for tomatoes. Similarly, this approach was applied for feed, which is purchased and fed only to lactating livestock. Food energy production from grains, seeds of cultivated cereals, pulses, and oilseeds; fruits, tubers, and corms of vegetables; livestock milk; and goat meat was calculated based on the standard nutritional values provided in Gopalan *et al.* (2012). Soil loss rates were not available for individual crops at the IFS location, particularly for rainfed crops like maize and finger millet grown during the rainy season. As a result, experimental data from similar nearby conditions were used as proxies. For irrigated crops, soil loss rates were considered negligible because they are cultivated under well-managed conditions (Sharda *et al*., 2010). The estimates for each production enterprise (net returns – INR ha^{-1}, food energy – 10^3 kcal ha^{-1}, and soil loss – Mg ha^{-1}) were used as coefficients per hectare in the formulation of the objective functions of the optimization model. For each livestock animal, these were represented as INR animal^{-1} and 10^3 kcal animal^{-1} for net returns and nutrient energy, respectively. It is also understandable that soil loss was assumed to be zero for each livestock animal.
- Quantitative data on utilized resources—including owned [rainfed/irrigated land, month-wise human (family) labor, drought animal power, farm-produced crop seeds, and farm equipment] and fodder (dry/green) harvested from various sources (crops, field bunds, community land, pastures, and forest) across different seasons—were collected. To identify the limited resources, the actual utilization of each resource across all

farm production enterprises was summed and compared to its respective total available resources owned by the farmer. This process helped identify resource constraints and formulate them for the MCDM model. Land constraints for crops were considered separately for rainfed and irrigated categories of cultivated land in each location and month, as the farmer practiced crop rotations that overlapped over time. These constraints were incorporated into the optimization model to ensure proper allocation of the limited cultivated land in each category. Each purchased input was regarded as a limited resource since the farmer did not own it, and purchased it using limited capital. The farmer used urea for all crops except wheat and peas. Fertilizers such as calcium ammonium nitrate (CAN) and di-ammonium phosphate (DAP) were used for tomato cultivation. Because these inputs were purchased and limited, they represented constraints for farming. The average input-output coefficients of these constraints were estimated using a budgeting technique based on the actual utilization of the limited resource for a crop production activity per hectare; for individual livestock, actual utilization served as the coefficients. In addition to the identified land resource and fertilizer constraints, such as summer+rainy season irrigated land at Jamuwa (month-wise), winter season irrigated land at Jamuwa (month-wise), summer+rainy season irrigated land at Tangri (month-wise), winter season irrigated land at Tangri (month-wise), and fertilizers [urea, DAP, and CAN], a simple land constraint was included for dairy activity in the optimization model (Sankhayan and Cheema, 1991). Other inputs were found to be non-limiting for achieving farming objectives due to their surplus availability. For example, human labor was not a constraint because of a large family size (1620 mandays/year). Similarly, fodder was not a constraint mainly due to good availability from nearby forests, and FYM was not a constraint because of the high livestock ownership (8.5 standard livestock units). These resources, which were not limited in production activities, were also valued and used to estimate the net returns of the activity, forming the coefficients for the net returns maximization goal function.

- An IFS can integrate bio-systems since the output of one can serve as the input for another, and vice versa. In the IFS of this study, the fodder produced by the crop component is the input for the livestock component, and the produced manure (FYM) is the input for the crops. These outputs are considered intermediate because they are consumed as inputs; therefore, they were not included in the net returns calculation. However, since costs were incurred in their production with the main outputs, they were included as costs whenever used as inputs for livestock and crops, respectively. For the same reason, the net returns of a fodder crop were considered negative, as it functions as an input for the livestock component of the IFS. Nutritional computation was not performed for any fodder because the goal was to maximize nutrient energy for the farm family.
- A set of capital constraints was used, including two based on the mentioned seasonal groups and one on the total capital limit. The optimization was conducted using the farmer's own capital, as he relied solely on his personal funds for farming activities. The coefficients for these constraints represented the cost per unit area for each production activity, excluding input purchase costs. (Sankhayan and Cheema, 1991).
- Two new production enterprises – paddy + fish inter-culture and drip irrigated tomato – were suggested to the farmer who agreed to include them in the OIP. Their costs and returns available from secondary sources were utilized for the analysis.
- Preferences regarding the farming enterprises (existing or any new), and their respective sizes (maximum/minimum/constant) in terms of area allocation/number recorded during survey were utilized as a set of constraints in the model. These preferences were for meeting the food and nutrition requirements of his large family from his own land, as well as the limitation of resources for allocation to high-input crops
- Technical restrictions formed the last set of constraints.

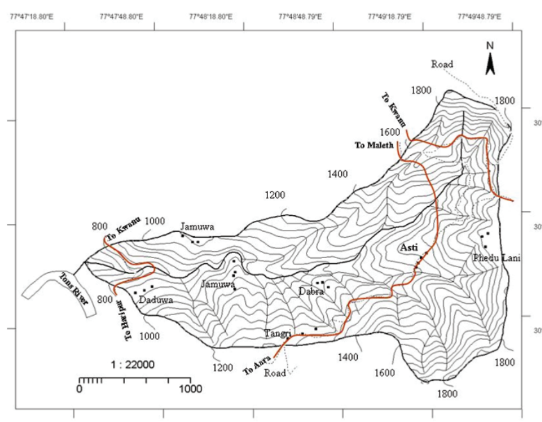

FIGURE 3 Map of Ashti Watershed

2.4| Optimization Model Formulation

Multi-Criteria Decision Making (MCDM) techniques have inherent properties which render them practically useful, e.g., multiple and conflicting criteria are explicitly accounted for, and rational, justifiable, and explainable decisions are provided (Belton & Stewart, 2002). MCDM has some desirable features that make it an appropriate tool for analysing complex natural resource management problems (Mendoza & Martins, 2006). Among MCDM techniques, compromise programming is a well-established mathematical programming technique, which has the inherent advantage of conceptual simplicity, especially for solving natural resources allocation problems (Romero &

& Rehman, 2003). Compromise programming (CP) allows handling of several objectives in those situations in which the existence of a high level of conflict between criteria does not permit simultaneous optimization of all the considered objectives (Raizada *et al*., 2008; Sankhayan, 1988). For optimization of IFS of the selected farmer, a multi-criteria optimization model was formulated following compromise programming, as given below, for simultaneously optimizing the farmer's three farming objectives as per his weight-based ranking of the objectives, his preferences for farming enterprises, and his resource constraints.

The model includes farming activities and constraints that characterize the farming enterprise of the selected farmer over a 12-month period. CP was utilized as the two objectives – maximization of farm income and food energy production - are inherently conflicting with the third objective of minimization of soil loss. In such cases, obtaining an ideal solution that simultaneously achieves the desired ideal values of the three objectives (indicated by individual optimization of each objective with no consideration of the other objectives in it) is difficult. The form of CP adopted for the study was as described in Dogra *et al.* (2014), as the best possible solution lies within the best compromise solutions defined by the two boundaries L_1 and L_∞. It is well established that L_1 and L_∞ matrices define the two boundaries of all the compromise solutions, and all other best compromise solutions fall between these two boundaries (Romero & Rehman, 2003). Therefore, two optimal solutions, termed as L_1 and L_∞, were generated by CP for the farmer's IFS.

Objective Functions

$$MaxFarmIncome = \sum_{c=1}^{C}\sum_{v=1}^{V} a_{cv}X_{cv} + \sum_{d=1}^{D} a_d X_d - \sum_{f=u,m,n}(1+i_r)p_f X_f - \sum_{r=y,w} i_r X_r \quad (1)$$

X_{cv} cultivated area allocated (ha) for crop *c* at location *v*
X_d livestock animal allocated *d* (unit)
X_f fertilizer f (u - urea, m - DAP, – CAN) quantity purchased for crops cultivation (kg)
X_f owned capital utilized (INR) except for purchasing in season *r* (*y* - summer+rainy, *w*- winter)
a_{cv} returns over variable cost other than of purchasing (INR ha^{-1}, from crop *c* at location *v*
a_d returns over variable cost other than of purchasing (INR) from livestock animal *d*
i_r rate of interest (%) charged on owned capital utilized during season *r* (*y*- summer+rainy, *w*- winter)
p_f price of a fertilizer *f* (u - urea, *m* - DAP, *n* - CAN) (INR kg^{-1})
c, d, v, f, r index of crops, livestock animals, location, fertilizers and cropping season, respectively
C, D, V number of crops cultivated/introduced, livestock animals owned, and locations, respectively

$$MaxFoodEnergy = \sum_{c=1}^{C} e_c X_{cv} + \sum_{d=1}^{D} e_d X_d \quad (2)$$

e_c nutrient energy (Mcal ha^{-1}) from crop c
e_d nutrient energy (Mcal) from livestock animal d

$$MinSoilLoss = \sum_{c=1}^{C} s_c X_{cv} \quad (3)$$

s_c soil loss (Mg $ha^{-1}yr^{-1}$) from cultivation of crop *c*

Constraints

The three objective functions were subjected to sets of six categories of constraints, *viz*. land, fertilizer, capital, individual crop's area, as well as animal's number as per farmers' preferences, and technical restrictions in the model, as they significantly affect production on the farm.

Land constraints set:

$$\sum_{c=1}^{C} X_{cv} \le L_{vmr} \quad (4)$$

L_{ymr} total irrigated/rainfed land *r* available (ha) for allocation at location V during month (*m*)

$$\sum_{d=1}^{D} l_d X_d \le L_d \quad (5)$$

I_d land required (ha) for animal shed of a livestock animal *d*
L_d total and available (ha) for animal sheds of *d* livestock animals

Fertilizer constraints set:

$$\sum_{c=1}^{C} z_{cfv} X_{cv} - X_f \le 0 \quad (6)$$

Z_{cfv} fertilizer *f* (*u* - urea, *m* - DAP, *n* - CAN) quantity required to cultivate crop *c* on a unit area at location *v* ($kgha^{-1}$)

Capital constraints set:

$$\sum_{c=1}^{C} k_{cr} X_{cv} + \sum_{d=1}^{D} k_{dr} X_d - X_r \le 0 \quad (7)$$

k_{cr} working capital required other than for purchasing during season *r* (*y* - summer+rainy, *w* - winter) to cultivate crop *c* on a unit area at location *v* ($INRha^{-1}$)
k_{dr} working capital required other than for purchasing during season *r* (*y* - summer+rainy, *w* - winter) for a livestock animal *d* (INR)

$$\sum_{f=u,m,n} p_f X_f + \sum_{r=y,w} X_r \le K \quad (8)$$

K total amount of own working capital actually utilized in a year for farming by the farmer for all crop and livestock production activities in the ESIP (INR)

Crop area restrictions set:

$$\sum_{c=1}^{C} X_{\mathrm{cv}} \leq T_{\mathrm{cv}} \tag{9}$$

$$\sum_{c=1}^{C} X_{\mathrm{cv}} = T_{\mathrm{cv}} \tag{10}$$

$$\sum_{c=1}^{C} X_{\mathrm{cv}} \geq T_{\mathrm{cv}} \tag{11}$$

T_{cv} area allocation (ha) restriction for crop c at location v

Animal number restrictions set:

$$\sum_{c=1}^{C} X_{\mathrm{d}} = B_{\mathrm{d}} \tag{12}$$

B_d number of a livestock animal d

After all the necessary data were generated, it was used in the optimization model. Optimal solutions, L_1 and L_∞, were obtained using software developed earlier (Cheema, 1992) and used for other studies, notably Raizada *et al*. (2008) and Dogra *et al*. (2014). The optimization exercise was done several times, as each generated OIP was discussed with the farmer, and his suggestions and preferences were incorporated in the input matrix for the optimization model to obtain the OIP that is as per the farmer's importance-ranked objectives, production enterprises' preferences, and his actual resource endowment and constraints. The final form of the matrix generated as per the above model had three objective functions, 31 production and non-production activities, and 94 constraints of various kinds. Before the implementation, the final optimal solutions, L_1 and L_∞, were discussed with the farmer for him to select one of these two OIP for implementation.

2.5 | Measurements of Success of Implemented IFS

Success of the implemented OIP was assessed based on cumulative comparison of values of its three objective functions to two different standards, namely (a) values of objective functions of farmer's ESIP, and (b) potential values of objective functions of OIP (*per se* before its implementation). For the measurement of success, two indicators were formulated. First indicator – Success Index – measured success of the implemented optimal IFS in the individual year of implementation:

$$Success\ Index = \sum_{i=1}^{n} w_i \left(\frac{v_i}{V_{is}}\right) \tag{13}$$

where,

V_i actual value of objective function i after implementation of the OIP on farmer's fields

V_{is} value of objective function i as per chosen standard s for measuring success

W_i weight assigned by the farmer to objective function i

n total number of objective functions optimized for the IFS

It measured how precisely the implemented OIP was able to generate higher farm income and nutrient energy (as "higher is better" is the universal norm for these two parameters) as well as lower soil loss (as "lesser is better" is the general norm for this parameter) as compared to the identified standards. Estimated value of the Success Index varied as per the standard based on which it was estimated.

The second indicator – Probability of Success – based on the estimated values of the first indicator (Success Index) over the years of implementation, estimated the probability of the implemented OIP being successful as per the two standards. As it was hypothesized that the implemented OIP would achieve higher values of farm income and nutrient energy, and lower values of soil loss as compared to the standard of ESIP values, therefore the implemented OIP was considered to be a success only if it happened accordingly, i.e., the Success Index has a value higher than 1.0. On the other hand, in case of second standard (expected values from OIP before its implementation), since it was hypothesized that the implemented OIP may or may not achieve the highest/potential values, therefore it was considered to be a success if values of the implemented OIP were higher than *or even equal to* those of the second standard i.e. the Success Index has a value higher than or equal to 1.0. Therefore, this indicator's value also varied as per the standard employed.

When the standard was ESIP values, number of years the value of Success Index was greater than 1.0 were counted for estimation of the probability of success:

$$Probability\ of\ Success = \frac{Number\ of\ years\ value\ of\ Success\ Index > 1.0}{Number\ of\ years\ of\ implementation} \tag{14}$$

When the standard was potential values of objective functions of OIP, the number of years the value of Success Index was equal to or greater than 1.0 were counted for estimation of the probability of success:

$$Probability\ of\ Success = \frac{Number\ of\ years\ value\ of\ Success\ Index \geq 1.0}{Number\ of\ years\ of\ implementation} \tag{15}$$

3 | RESULTS AND DISCUSSION

3.1 | Scope for Improvement in the Suboptimal IFS

Prior to the generation of two optimal solutions, L_1 and L_∞ using CP, the three decision criteria – net returns, nutrient energy from food, and soil loss - each expressed as an objective in the form of a mathematical function of decision variables - were individually optimized subject to same set of constraints using simple linear programming (LP). Thereby, three optimal plans were generated. From the values of the three decision criteria obtained from each LP optimal plan, a Payoff Matrix was generated for the farmer's farm (Table 1). The diagonal elements of the Payoff Matrix, called the Ideal Points, indicated the maximum scope (potential) of improvement of the value of an individual decision criterion. The minimum value of a decision criterion in the Payoff Matrix, called its Anti-Ideal Point, indicates the extent to which it will have to be sacrificed when optimization is done for another decision criterion as the objective function. In light of the above, farm income individually can increase by a significant 11% (its Ideal Point) over the ESIP; but if other decision criteria are optimized, then the range of change in its value will be a reduction by 1% (its Anti-Ideal Point) to an increase by 10%. Similarly, nutrient energy individually can be increased by only 1% (its Ideal Point). When other decision criteria are optimized, it will decrease by 0.2% to 2% (its Anti-Ideal Point). Individually, soil loss can be reduced significantly by 43% (its Ideal Point), otherwise it will be reduced by 2% (its Anti-Ideal Point) to 3% only. This indicated that there was a conflict among the decision criteria. If the farm income LP optimization plan is implemented, the nutrient energy production on the farm will be 0.2% less than that from ESIP, though soil loss will decrease (2%), which is desirable but not the best one as it is not its Ideal Point. If the soil loss LP optimization plan is implemented, farm income (1%) and nutrient energy (2%) will be even less than that from ESIP, and the lowest, being their Anti-Ideal Points. Implementation of nutrient energy LP optimization plan will increase farm income (10%) and decrease soil loss (3%), but they are not their Ideal Points.

TABLE 1 Payoff matrix of IFS farmer's decision criteria

Planning Situation	Decision Criteria Value		
	Net Returns (INR)	Nutrient Energy (Mcal)	Soil loss (Mg)
Before optimization	269,776	68,156	5.32
Payoff matrix			
Farm income (maximized)	**299,308** **(11)**	67,992 (-0.2)	5.24 (-2)
Nutrient Energy (maximized)	297,399 (10)	**68,519** **(1)**	5.17 (-3)
Soil loss (minimized)	266,150 (-1)	66,495 (-2)	**3.04** **(-43)**

Figures in parentheses are percentage change as compared to respective value before optimization.

The farmer selected the final form of the optimal solution L_1 for implementation as values of the decision criteria net returns and food energy of this solution were higher by INR 2373 (0.8%) and 233 Mcal (0.3%), respectively than of L_∞ solution. However, soil loss was 1 Mg (20%) higher from L_1 solution. The farmer, therefore, preferred to have more income and food energy from the IFS at the cost of higher soil loss (Table 2).

A comparison of decision criteria values of the ESIP against the same of the optimal solution L_1, i.e., the OIP (Table 3), indicated that the OIP could provide 10.9% (INR 29,302) significantly higher net returns of INR 299,078 (compared to INR 269,776) from the farm. Similarly, food energy can be improved, though marginally by 0.4% (68,443 Mcal compared to 68,156 Mcal). Further, these higher values can be achieved with 1.1% lower soil loss (5.26 Mg compared to 5.32 Mg) from the farm. The scope for improvement of last two decision criteria is lower than for net returns because of higher importance/weight given by the farmer to it, though many of the production enterprises are both a source of income as well as nutrition, which vary across the crops. Also, the scope for improvement is curtailed if the farmer's preferences and constraints are such that crops that are a better source of food energy are allocated a lesser area than higher income-generating crops in the OIP.

To examine the reasons for changes in decision criteria values due to optimization, the area allocations before and after optimization need to be reviewed (Table 4). In Jamuwa, among irrigated crops, ESIP allocated 10%, 40%, and 50% of the gross cropped irrigated area to clover, tomato, and pea crops, respectively. Conversely, in OIP, allocations of the gross cropped irrigated area of Jamuwa were 0% for clover, 47% for tomato, 47% for pea, and 7% for paddy+fish. For rainfed crops, ESIP allocated 10%, 7%, 33%, and 50% of the gross cropped rainfed area to ginger, chili, maize, and wheat, respectively. In contrast, the optimal OIP allocations were 8%, 8%, 32%, and 52% of the gross cropped rainfed area to these crops, respectively.

TABLE 2 Comparison of the compromise programming generated optimal solutions

Optimal Solution	Net Returns (INR)	Food Energy (Mcal)	Soil loss (Mg)
L_1	299,078	68,443	5.3
L_∞	296,704	68,210	4.4
Difference	2,373 (0.8)	233 (0.3)	0.9 (20)

Figures in parentheses are percent difference of L_1 from L_∞

For Tangri, the ESIP allocations from gross cropped irrigated area were 39%, 10%, 13%, 25%, and 13% for tomato, maize, potato+coriander, rapeseed, and pea crops, respectively. However, the OIP allocations differed—22%, 0%, 13%, 17%, 26%, and 22%—for tomato, maize, potato+coriander, rapeseed, pea, and tomato-drip, respectively, of the gross cropped irrigated area. For rainfed crops at the location, the ESIP allocations were 6%, 9%, 6%, 38%, 2%, 10%, and 30% for colocasia, chilli, ginger, maize, pigeonpea, fingermillet, and wheat, respectively, of the gross cropped rainfed area. In the case of OIP, the allocations were 4%, 8%, 7%, 42%, 2%, 8%, and 29% for colocasia, chilli, ginger, maize, pigeonpea, fingermillet, and wheat, respectively, of the gross cropped rainfed area of Tangri.

From these allocations, it is clear that for the OIP, area allocations increased for irrigated crops such as tomato and paddy+fish, at the expense of declining areas under clover and pea at Jamuwa. Similarly, there was an increase in area for tomato-drip and pea compared to tomato, as well as for maize and rapeseed at Tangri. For rainfed crops, the area allocated in the OIP increased for chili and wheat, with decreases in ginger and maize at Jamuwa, and similarly for ginger and maize compared to colocasia, chili, fingermillet, and wheat at Tangri. Overall, no area was allocated to clover at Jamuwa or to irrigated maize at Tangri (see Table 4). Higher areas were allocated to cash crops such as tomato and chili at Jamuwa, and pea and ginger at Tangri, compared to ESIP, although the areas for other cash crops like pea and ginger at Jamuwa, and tomato and chili at Tangri, decreased. The new production enterprises—paddy + fish intercultural cultivation and drip-irrigated tomato—were allocated 0.01 ha and 0.05 ha, respectively, by the OIP. The area under potato and coriander remained unchanged. For cereal crops, the area allocated to maize decreased while that for wheat increased at Jamuwa. At Tangri, the area for the remaining crops decreased, except for rainfed maize. Since net returns received the highest weight in the OIP, the area for less profitable crops decreased in favor of more profitable ones. A similar trend was observed for the next most important decision criterion, food energy, based on its assigned weight. Regarding the livestock component of the IFS, the farmer preferred to maintain the current number of livestock units (8.1 SLU), as they were deemed optimal for the farm's maintenance and meeting the family's needs.

TABLE 3 Comparison of decision criteria values before and after optimization

Decision Criteria	Optimization	Existing/ Suboptimal IFS	Optimal IFS	Expected change
New Returns (INR)	Maximized	269,776	299,078	29,302 (10.9)
Energy (Mcal)	Maximized	68,156	68,443	287 (0.4)
Soil Loss (Mg)	Minimized	5.32	5.26	0.1 (-1.1)

Figures in parentheses are percent difference of optimal IFS from existing IFS

3.2 | Resource Use Change

With optimization, there was a change in the use of purchased inputs, namely urea, DAP, and CAN fertilizers, included as constraints in the optimization model. The annual quantity of urea used increased slightly by 4% (3.27 kg), from 81.37 kg in the ESIP to 84.64 kg in the OIP. For DAP, although the increase was significant at 20%, from 24.86 kg to 29.83 kg in the respective plans, the actual increase in use was only 4.97 kg, similar to urea. In the case of CAN, utilization decreased by 16%, from 1.09 kg to 0.92 kg in the respective plans. The overall quantitative decrease was a small 0.17 kg. Therefore, the changes in fertilizer use proposed by the OIP were marginal. Even with these small changes in fertilizer utilization due to shifts in cultivated area allocations, there was a potential for an 11% increase in net returns, along with marginal but positive improvements in the other two decision criteria.

3.3 | Optimal IFS Implementation

The selected OIP was implemented by the farmer on his farm over three years (2014-15 to 2016/17) under the technical guidance of ICAR-IISWC. During the implementation period, yield data of the crops grown according to the OIP, as well as the owned livestock, were recorded (Table 5). The new production activity of paddy-fish interculture was not adopted or implemented by the farmer, although he initially agreed to adopt it, and it was considered for optimization. The location, Jamuwa, where this activity could be adopted, is situated a significant walking distance via footpath across the watershed landscape (Fig. 3) from Tangri, where the farmer resides. He expressed an inability to prevent fish from escaping the field to wild animals. Additionally, since paddy cultivation is a new intervention on a small area of 0.01 ha (the smallest among all optimal allocations), he did not implement this activity at any point during the three-year study. This indicates that small or marginal hilly farmers face difficulties in adopting new farming activities due to inherent constraints.

Over the recorded period, yields of chili and maize were higher than their average yields, while the yields of other crops ranged from higher to lower. During 2014/15, yields of most cultivated crops were either less than (for 10 crops) or equal to (for 5 crops) their respective averages.

Potato, coriander, rapeseed, fingermillet, colocasia, and wheat-Tangri had yields equal to their averages, while all other crops, except chili and maize at both locations, had lower yields (Table 5). The differences in yields for these crops ranged from (-)8% (wheat-Jamuwa) to (-)65% (tomato-drip). The low yields during this year were mainly attributed by farmers to poor rainfall. During 2014/15, there was an 18% rainfall deficit (ICAR-IISWC, 2014), primarily due to low rainfall (883 mm) during monsoon months (July to September 2014), compared to 1257 mm and 1123 mm in 2015/16 and 2016/17. Even irrigated crops experienced low yields due to limited water availability for irrigation. However, chili yielded significantly more than average, ranging from 52% to 116%, along with maize at 6% to 7%. Both crops performed well at both locations despite the low rainfall during the year. There was no change in yield for livestock products (milk and meat) during this period.

TABLE 4 Existing and optimal IFS plan cultivated area allocations

S.No	Production activity and location	Cultivation period months	Rainfed/Irrigated	Existing/Suboptimal IFS plan (ha)	Optimal IFS plan (ha)	Difference in plans (%)
			Jamuwa			
1	Clover	January-June	Irrigated	0.015	0.000	-100
2	Tomato	March-June	Irrigated	0.062	0.070	14
3	Ginger	April-October	Rainfed	0.025	0.020	-19
4	Chilli	April-October	Rainfed	0.018	0.020	8
5	Maize	May/June-October	Rainfed	0.082	0.080	-3
6	Paddy+Fish	May/June-July	Irrigated	-	0.010	NA
7	Pea	October-December	Irrigated	0.077	0.070	-9
8	Wheat	November-April	Rainfed	0.126	0.130	4
			Tangri			
9	Tomato	March-June	Irrigated	0.082	0.050	-39
10	Tomato-Drip	March-June	Irrigated	-	0.050	NA
11	Colocasia	March/April-Oct.	Rainfed	0.031	0.020	-35
12	Chilli	April-October	Rainfed	0.044	0.040	-9
13	Ginger	April-October	Rainfed	0.031	0.035	13
14	Maize	May/June-October	Irrigated	0.022	0.000	-100
15	Maize	May/June-October	Rainfed	0.196	0.215	10
16	Pigeonpea	June/July-Oct/Nov.	Rainfed	0.011	0.010	-8
17	Fingermillet	June-November	Rainfed	0.050	0.040	-19
18	Potato+Coriandor	July-September	Irrigated	0.027	0.030	12
19	Rapeseed	October-December	Irrigated	0.054	0.040	-27
20	Pea	October-December	Irrigated	0.027	0.060	123
21	Wheat	November-May	Rainfed	0.152	0.150	-1
			Total	1.130	1.140	

During 2015/16 and 2016/17, most crops had yields that were higher than or equal to the average yields (Table 5). In 2015/16, except for rapeseed (-14%), pigeonpea (-14%), and fingermillet (-13%) at Tangri, crop yields were higher at both locations. The increase ranged from 1% (ginger-Jamuwa and colocasia) to 60% (maize-Tangri). There was no change in the yields of potato+coriander intercropping and wheat-Tangri. Equivalent yields were also produced in intercrops in 2016/17. Additionally, there was no change in the yields of rapeseed, fingermillet, and colocasia. All other crops, except wheat-Tangri (-15%), had higher yields than their average yields. Higher yields ranged from 7% (pigeonpea, tomato-drip) to 80% (maize-Tangri). The higher-than-average yields over the two years were attributed to near-normal rainfall. Regarding livestock, buffalo yields were 4% and 21% higher than average during the two years, respectively. However, cow yields increased by 2% in 2015/16 but declined in 2016/17 due to the end of its lactation period. There was no change in meat yield from goats.

3.4 | Decision Criteria Values after Implementation

To estimate the year-wise net returns for each production activity of the implemented optimal IFS, the recorded yield data over the years were used. It was assumed that input utilization remained constant. Constant prices, used for optimal planning, were applied for net return estimations across the years. For nutrient energy, the energy per unit crop area or livestock unit, used in planning, was employed to estimate nutrient energy production from the yields. As a result, varying yields of the production activities led to different values of the two decision criteria over the years. Regarding soil loss, the values based on proxy experimental data used for optimal planning were assumed as soil loss estimates.

Farm income from the implemented OIP could not reach the potential 11% higher value during 2014/15 due to lower yields (-11% to -65%, Table 5) of cash crops like tomato, pea, and ginger, which occupied 31% of the gross cropped area, compared to the respective average yields at both locations (Table 6). The below-average yields were mainly caused by below-average rainfall (18% deficit), especially during the rainy season (30% less than 2015/16 and 21% less than 2016/17). Other external factors may also have contributed to the lower yields. Among cash crops and all crops, ginger yields the highest average net returns from both locations (INR 1,072,141 ha^{-1}), followed by tomato (INR 695,258 ha^{-1}) and pea (INR 232,741 ha^{-1}), each with their respective average yields. Although chili, a cash crop, had higher (52% to 116%) yields than the average during 2014/15 at both sites, it only partly offset income losses because it provides the lowest net returns (average INR 64,816 ha^{-1} across both locations) among cash crops, with area allocation at only 5% of the gross cropped area. Food crops grown on the farm, mainly for family consumption, also have monetary value. Among these, colocasia stands out with the highest net returns (INR 261,700 ha^{-1}), and it can supplement farm income, especially when cash crop returns are low, as its 2014/15 yield matched the average. Tuber colocasia, in addition to being a high-income cash crop, is a nutrient-rich food crop that can be stored for future use. Similarly, crops like potato+coriander (INR 220,776 ha^{-1}), rapeseed (INR 19,530 ha^{-1}), fingermillet (INR 13,635 ha^{-1}), wheat-Tangri (INR 7,924 ha^{-1}), as well as livestock like buffalo (INR 42,345), cows (INR 8,819), and goats (INR 17,986), can increase farm income. Although maize has a lower income value (average INR 25,188 ha^{-1}) than cash crops, it contributed to income maximization by yielding 6%-7% more than its average yield. Other food crops experienced yield decreases ranging from -8% (wheat-Jamuwa, INR 10,324 ha^{-1}) to -64% (pigeonpea, INR 136,669 ha^{-1}), which negatively affected farm income. Overall, the farm income was 25% below the ESIP target (Table 3). The low yields of cash crops also reduced total food energy produced on the farm during 2014/15, especially since ginger (average 18,427 $Mcalha^{-1}$) and tomato (average 7,957 $Mcalha^{-1}$) have higher energy values than most other food crops. Pea (average 4,632 $Mcalha^{-1}$) also saw a reduction in on-farm energy due to low yields at both locations. Although chili's yield increase of 116% could not fully compensate for the energy shortfall from other cash crops, it has a relatively low energy value (average 861 $Mcalha^{-1}$). Among food crops, pigeonpea, with a 64% yield decline (4,641 $Mcalha^{-1}$), reduced energy production. Similarly, wheat-Jamuwa (4,360 $Mcalha^{-1}$) showed a decline, whereas wheat-Tangri nearly maintained its potential energy output, with no change in yield. Other crops like colocasia (18,842 $Mcalha^{-1}$), potato+coriander (14,516 $Mcalha^{-1}$), maize (average 7,695 $Mcalha^{-1}$), fingermillet (4,264 $Mcalha^{-1}$), and rapeseed (3,246 $Mcalha^{-1}$), contributed to total energy production due to yields at or above average. Overall, food energy was only 1% below the ESIP target (Table 6). Since soil loss could not be measured at the IFS location, it was assumed that there was no change in this criterion's value, despite the low rainfall in 2014/15 and normal or above-normal rainfall in the other study years.

In 2015/16 and 2016/17, higher than average yields across all cash crops and most food crops resulted in more than 11% higher net returns during these years. Cash crops, especially those with high income values, contributed to increased farm income in 2015/16, with yield increases ranging from 1% to 26% on 36% of the cultivated land. Although the highest income cash crops like ginger and tomato showed slightly lower yields at Jamuwa (1% to 2%) compared to Tangri due to distance management issues, the yields of other cash crops still boosted net returns. Among food crops, colocasia (INR 261,700 ha^{-1}), potato + coriander (INR 220,776 ha^{-1}), maize (INR 25, 188 ha^{-1}), and wheat (INR 9, 124 ha^{-1}) saw yield increases of 1% to 60%, contributing to income growth. Milk yields from buffalo and cow increased by 2% to 4%, further supporting income gains, along with goats. Conversely, crops like rapeseed, pigeonpea, and fingermillet experienced decreased productivity (-13% to -14%), negatively affecting farm income. Overall, net returns rose by 23.5% in 2015/16. The following year, 2016/17, saw even higher crop yields (except for wheat at Tangri (-15%) and the cow (-100%), boosting farm income by 32.3% (see Table 6). High-value cash crops such as ginger (31% to 33%), tomato (7% to 29%), and chilli (31% to 59%) were significant contributors. In food crops, maize (53% to 80%), pigeonpea (7%), and wheat at Jamuwa (8%) stood out as main contributors. Intercropped potato and coriander, fingermillet, colocasia, and rapeseed also contributed additional yields. In energy terms, crops increased energy production by more than expected by 0.4% in both 2015/16 and 2016/17 thanks to higher yields for most crops. Although pea and chilli, ranked lower for energy production, showed yield increases of 3% to 59%, ginger and tomato at Tangri contributed more energy than in 2014/15 with increases of 15% to 33%. Maize, with high energy content, experienced yield increases of 24% to 80%. Colocasia and potato + coriander, ranked high for energy, also contributed positively, with yields matching average yields. The total decision criterion value increased by 2.7% in 2015/16, and in 2016/17, the increase was slightly higher at 2.8%, driven by yield increases across most crops. Over the three years of OIP implementation, farm income increased on average by 10.2%, and food energy production grew by 1.4%.

TABLE 5 Yields during Implementation of optimal IFS plan

Location-wise production activity	Average yield before 2014/15 ($Mgha^{-1}$)	Yield ($Mgha^{-1}$) under optimal IFS implemented during			Difference (%)		
		2014/15	2015/16	2016/17	2014/15	2015/16	2016/17
			Jamuwa				
Tomato	32.6	14.0	33.3	39.7	-57	2	22
Pea	9.8	8.4	11.5	10.6	-14	17	8
Ginger	29.1	19.8	29.3	38.0	-32	1	31
Chilli	3.2	6.9	3.3	4.2	116	3	31
Maize	1.7	1.8	2.1	2.6	6	24	53
Wheat	1.2	1.1	1.4	1.3	-8	17	8
			Tangri				
Tomato	35.3	14.9	40.7	45.5	-58	15	29
Potato+Coriander	14.0[#]	13.9	14.0	14.1	-1	0	1
	4.5[##]	4.5	4.5	4.5	0	0	0
Rapeseed	0.7	0.7	0.6	0.7	0	-14	0
Pea	10.0	8.9	12.3	11.9	-11	23	19
Chilli	2.7	4.1	3.4	4.3	52	26	59
Maize	1.5	1.6	2.4	2.7	7	60	80
Fingermillet	1.5	1.5	1.3	1.5	0	-13	0
Ginger	25.9	18.2	30.0	34.5	-30	16	33
Colocasia	19.4	19.4	19.5	19.4	0	1	0
Pigeonpea	1.4	0.5	1.2	1.5	-64	-14	7
Wheat	1.3	1.3	1.3	1.1	0	0	-15
Tomato-Drip	42.3	14.9	49.5	45.5	-65	17	7
Livestock							
Buffalo*	1,703	1,703	1,779	2,068	0	4	21
Cow*	548	548	557	0	0	2	-100
Goats*	30	30	30	30	0	0	0

*[#]Potato data row, [##]Coriander data row; *Litre; **kg*

TABLE 6 Decision criteria values of implemented optimal IFS plan

Particulars	Decision Criterion		
	Farm Income (maximization) ($INRyr^{-1}$)	Food Energy (maximization) ($Mcalyr^{-1}$)	Min Soil Loss (minimization) ($Mgyr^{-1}$)
Farmer assigned weight	5	4	1
Value from existing/suboptimal IFS plan	269,776	68,156	5.32
Potential value from optimal IFS plan	299,078	68,443	5.27
	(10.9)	(0.4)	(-1.1)
Value from implemented optimal IFS plan			
2014/15	201,433	67,334	5.27
	(-25.3)	(-1.2)	(-1.1)
2015/16	333,219	70,003	5.27
	(23.5)	(2.7)	(-1.1)
2016/17	356,906	70,069	5.27
	(32.3)	(2.8)	(-1.1)

Figure in parentheses is percent difference from respective suboptimal IFS value

3.5 | Success of Implemented IFS

To evaluate the overall benefit to the farmer across three decision criteria during different implementation years of the formulated OIP, and to estimate the probability of the OIP's future success on the farmer's field based on success in individual years, the Success Index was calculated using two standards for each year. Results showed that in the first year, the index ranged from 0.8 to 0.9 below 1.0 across both standards (Table 7), mainly due to significantly low yields in nine production activities, which affected farm income and food energy production. In the subsequent two years, the index increased to between 1.1 and 1.2, as poor yields occurred in one to three activities, while most remaining activities yielded well. Consequently, the success probability of the OIP was estimated at 67% under both standards, primarily due to poor rainfall—a factor beyond human control. Despite this 67% success chance, the potential of the OIP to enhance farm income and food energy output while reducing soil loss suggests that the farmer would benefit more from adopting the OIP over the ESIP in the future.

TABLE 7 Success index and probability of success of the optimal IFS plan

Year	Standard for measurement							
	Values of objective functions of existing/ suboptimal IFS plan				Expected Values of objective functions of IFS optimal plan			
	Farm Income	Food Energy	Soil Loss	Success Index	Farm Income	Food Energy	Soil Loss	Success Index
2014/15	0.75	0.99	1.01	0.9	0.67	0.98	1.00	0.8
2015/16	1.24	1.03	1.01	1.1	1.11	1.02	1.00	1.1
2016/17	1.32	1.03	1.01	1.2	1.19	1.02	1.00	1.1
Probability of Success (%)				67				67

4 | CONCLUSIONS

This study aimed to use a multi-criteria decision-making (MCDM) tool for a structured, systematic, and mathematical approach to optimize an integrated farming system (IFS). The optimization considered location- and farmer-specific conditions rather than fixed-size farm simulations often used in studies, especially in India, leading to a better (or new) IFS plan compared to the suboptimal existing one. The compromise programming method was employed to develop an optimal IFS plan (OIP) for a typical small farmer in the Indian north-west Himalayas, involving crop cultivation and animal husbandry. The OIP was designed to balance three conflicting but essential goals: increasing farm income, boosting food energy production, and reducing land degradation by minimizing soil loss for sustainability. The OIP was formulated based on crop and livestock input-output ratios, available resources, constraints, and farmer preferences to meet local family needs. After three years of implementing the OIP, using constraints specific to each location, farm income increased by 10.2% and food energy production by 0.4%. The overall results showed an average income increase of 10.2% and food energy increase of 1.4%. The OIP demonstrated the potential to improve the farmer's decision criteria compared to the existing system, especially as evidenced by field results. A formulated index from two different standards indicated that the OIP has a 67% chance of achieving or exceeding its potential to enhance the farmer's farming attributes.

Formulating such optimal IFS using multi-criteria decision-making tools can be a promising approach to support the Indian Government's focus on integrated farming systems. This can help marginal and small farmers, who are central to the Indian rural economy, move away from subsistence and high-risk farming due to limited resources and climate variability. Stakeholders need to advocate for policies supporting this. An individual farmer approach should be adopted in developing integrated farming systems, supported by policy proposals. Developing decision support systems (DSS) to provide customized IFS models tailored to specific farming conditions—especially under fluctuating input/output prices, technology, and policy changes—can enhance farmers' food production, net income, employment, risk management, and other benefits of IFS. Including environmental protection features, like soil erosion reduction and water conservation in IFS planning through optimization should be mandatory via appropriate policies, ensuring sustainability amid climate change. Generating optimal IFS models using suitable multi-criteria decision-making (MCDM) tools, combined with advanced mathematical methods such as multi-period programming—leveraging real-time data on input and output prices—and artificial intelligence (AI), can further amplify the benefits of IFS.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data is available with the corresponding author and will be provided as and when required.

AUTHOR'S CONTRIBUTION

Conceptualization: PD; Data curation: PD, ACR, SP, MM, NKS; Methodology: PD; Resources: ACR; Software application: PD; Validation: PD, ACR, SP; Visualization: PD; Writing – original draft: PD; Writing – review and editing: PD, ACR, SP, MM, NKS.

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