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Carbon Aware Crop Planning Through Integrated Optimization of Yield, Emissions and Resource Demand

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Abstract - The greenhouse-gas (GHG) emissions, water use and fertiliser demand of a farm is largely dependent on crop choice and crop management, but plans are typically developed for profits only. In this paper, a carbon-aware crop-planning framework is introduced that allocates cropping systems to individual parcels using a mixed-integer linear programming approach. A database of 100 ha is created at the parcel level, with soil and water-access constraints, and a library of 13 cropping systems is used, where income and emissions (IPCC based accounting of the methane, nitrous oxide, fertiliser manufacture, fuel and pumping energy) are calculated at the parcel level, as is irrigation water, N, energy and labour. Three goals are optimised (maximise net income, minimise emissions and minimise a composite resource-demand index (RDI)) under land, water, food-energy, labour, rotation, and market constraints. The Pareto set was obtained using the ε-constraint method (19 non-dominated plans), a carbon-price sweep, a strong max–min plan for dry year and an emission-factor sensitivity analysis. The profit maximising plan increased the net income by 40 % and reduced emissions by 12 % as compared with the current practice one, while a balanced (knee) plan reduced emissions by 38 %, irrigation water by 37 % and the RDI by 26 % and increased the net income by 24 %. Planting of direct-seeded rice and drip irrigation of sugarcane and vegetables took the place of flooded rice and flood-irrigated sugarcane, while dryland millet–pulse systems were introduced. The robust plan was able to meet the demand of the plan, while the reference plan and the profit maximising plan required 24 % and 12 % more water than was available in a dry year. A satellite-NDVI random-forest classifier accurately classified crop types with 86% pixel accuracy, yet crop-type maps mis-estimated emissions of plans by up to 34 % because of water and nutrient management being mis-estimated.

Keywords - Carbon-Aware Agriculture, Crop Planning, Multi-Objective Optimisation, Greenhouse-Gas Emissions, Water–Energy–Food Nexus, Remote-Sensing Verification.

I. INTRODUCTION

Agriculture is a significant contributor of anthropogenic GHGs and a large potential for mitigation, either by changing crop, soil management, nutrient management or water management [1]. Studies around the world indicate that emissions from crop production come from a variety of different processes including methane from flooded rice, nitrous oxide from N fertiliser, energy use for machinery and irrigation [2]. Foods can be highly diverse in terms of their emission intensity, and the intensity of emissions can differ between producers of the same product, so farm actions can have a significant impact on emissions [3]. A study of the dominant emission source reveals that there is a difference between the dominant emission source of cereal crops, with methane emissions being dominant in paddy fields and emissions relating to fertiliser used in the upland cereal crops.

Therefore, crop planning, or deciding what to grow on which land and by which practices, is a climate decision, as well as an economic one. This has lead to a long list of models that have been developed to support cropping-plan and rotation decisions, from linear programming to simulation and heuristics, but a review of that literature reveals that less attention is paid to environmental objectives than to economic objectives [5]. For the crop planning, a number of multi-objective methods have been suggested, using evolutionary algorithms as a trade-off between profits and labour etc. [6] and for the overall design of a farming system [7]. Three limitations remain. First, many models are developed at the farm level, thus overlooking the spatial variability of soil and water availability, influencing crop and practice feasibility on a specific parcel. Second, emissions are generally expressed in a single factor per crop, so the impact of management options like water regime in rice, irrigation method in sugarcane or use of legumes in rotation are concealed. Thirdly, resource demand (water, nitrogen, energy, labour) is generally taken as constraints instead of an aim, although some farmers and planners are concerned about reducing the total stress on resources.

This paper develops a carbon-aware crop-planning framework that addresses these gaps. The contributions are:

- a parcel-level formulation in which each parcel receives one cropping system, with eligibility rules that depend on soil and water access
- bottom-up emission and resource accounting of each parcel–system pair, including management variants of rice and sugarcane
- a three-objective formulation (income, emissions and a composite resource-demand index) solved exactly by mixed-integer programming with the ε-constraint method [8], together with a carbon-price analysis and the marginal abatement cost of crop re-allocation
- a robust plan for dry-year conditions; and
- an experiment on verifying the implemented plan by satellite NDVI, which shows what remote sensing can and cannot confirm about emissions.

II. LITERATURE SURVEY

Planning for agricultural crops has become more concerned with the efficient use of resources and environmental protection and increased productivity. Traditional approaches to crop allocation have focussed mostly on maximizing yield and profit in the farm, rather than the interplay between greenhouse-gas (GHG) emissions, irrigation water use, fertilizer use and energy use. Integrated optimisation has thus proven to be a convenient tool for assessing cropping options for situations where land, water, labor and markets are limiting factors. The literature on carbon-aware crop planning mainly falls under two categories: multi-objective agricultural optimisation, agricultural emission assessment, resource-efficient cropping systems, and remote-sensing-based crop monitoring [8].

Multi-Objective Optimisation for Crop Planning

The mathematical optimisation has been widely used to obtain appropriate crop combinations under agricultural resource limitations. Linear programming and mixed integer linear programming (MILP) have been used for land allocation, crop rotation, production schedule and irrigation planning. MILP is suitable when making a selection of crops involves discrete decisions, suitability of the parcels, and operational restrictions. In multi-objective optimisation, these formulations are extended to account for conflicting objectives such as: net income, water consumption, production requirements, and environmental impacts. The ε-constraint method is a systematic approach to obtain Pareto-optimal solutions of a set of objectives by maximizing one objective while setting the other to predefined levels. However, finding economically viable crop plans that will not only reduce emissions but also reduce overall resource demand is a great challenge, especially if more than one of the agricultural constraints is at play [9].

Greenhouse-Gas Emission Assessment in Agriculture

Throughout the production process multiple emission sources need to be taken into account for the agricultural emission assessment. The emissions of CH4 are of major interest for the flooded rice systems, and the emissions of N2O with N fertilization and soil processes. Other emissions include emissions from the production of fertilisers, agricultural machinery, fuel use and energy use during irrigation. The Intergovernmental Panel on Climate Change (IPCC) offers reliable methodologies that can be used to calculate agricultural GHG emissions based on activity data and sector-specific emission factors. These accounting processes can be incorporated into crop-planning models to assess the environmental impacts at the same time as the economic ones [10]. However, these emission estimates may differ depending on water management, fertiliser use, soil properties and pumping needs. Therefore, relying exclusively on crop identity to determine a crop's environmental impact can lead to a misrepresentation of the environmental impact of the actual crops grown on a given parcel.

Resource-Efficient Cropping and Climate Resilience

Water availability and energy use are now among the factors being taken into account when planning sustainable crops. Balancing profitability with environmental outcomes was achieved by Annetts and Audsley who developed a multiple objective linear programming framework for environmental farm planning. Recent studies have focused on combining water availability, agricultural benefits and food–energy–water linkages. 2024 research on multi-objective cropping-pattern

optimisation revealed the potential of linear programming in finding other cropping patterns when there are multiple goals such as water and income. Climate-aware crop planning additionally requires evaluating dry-year conditions, uncertain water supplies, and changing production requirements [11]. However, simultaneous consideration of emissions, irrigation water, nitrogen, energy, and labour within a unified parcel-level optimisation framework remains an important research direction.

Remote Sensing and Research Gap

Monitoring and spatial crop classification has been aided by satellite-based vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) Crop type classification has been carried out with the help of Random Forest classifiers, using remotely sensed observations, which enable the assessment of patterns in agricultural land use. However, crop classification is used to identify the classes of vegetation or crops but cannot directly set the rates of fertiliser application, irrigation methods, pumping energy or soil-management practices that cause agricultural emissions. To estimate agricultural emissions within the IPCC guidelines, there are established procedures, however it is necessary to have activity data as well as emission factors to be able to evaluate at the parcel level [12].

The literature reviewed highlights three key research gaps: lack of integration of economic, emission and composite resource-demand objectives; lack of consideration of dry-year feasibility at the parcel-level level of crop allocation; the failure to account for management-dependent emissions with a crop-type classification alone. The framework proposed in this paper aims to fill these gaps by combining multi-objective optimisation with MILP, Pareto generation with ε-constraint, robust dry year planning, and emission-factor sensitivity analysis. These components can be integrated to help guide the selection of a crop plan that integrates farm profitability, environmental performance, and resource availability [13].

III. MATERIALS AND METHODS

Framework

The development of the carbon-aware crop planning framework is depicted in **Fig. 1**, which brings together spatial data and parcel data together with crop and management information. The parameter estimation module calculates resource requirements, greenhouse-gas emissions, net income and crop yield. The multi-objective optimisation model calculates these estimates under the constraints of land, water, labour, food-energy, rotation and market. Optimisation maximises net income, whilst also minimising resource usage and emissions. The framework is likely to provide three main products: an optimum crop allocation plan by parcel, trade-off analysis among conflicting outputs, and decision support for sustainable agricultural planning. The framework that emerges is useful for making decisions related to cropping systems with lower environmental impacts and higher climate resilience.

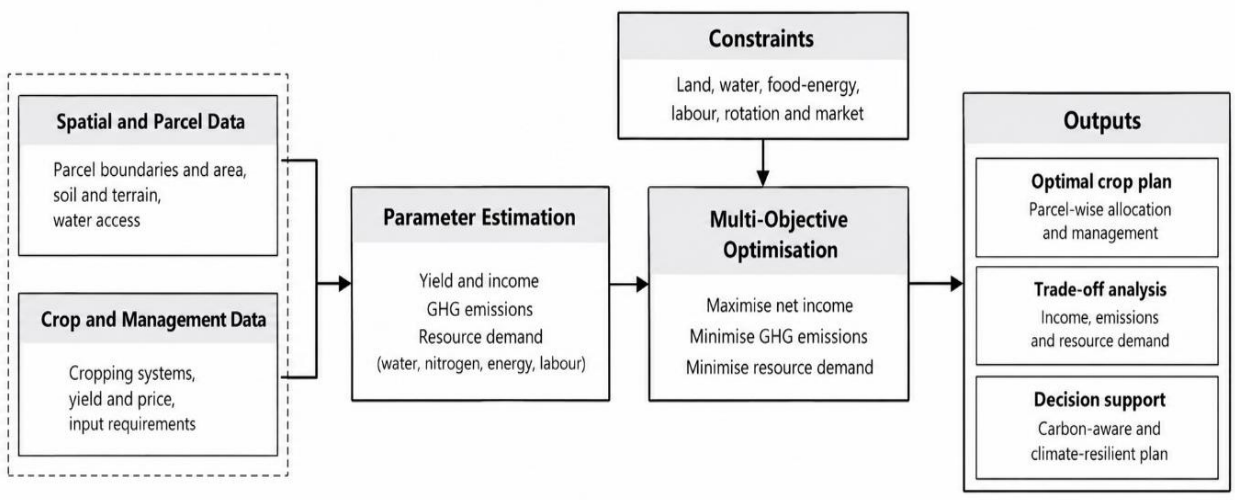


Fig 1. Architecture of the Proposed Carbon-Aware Crop Planning Model.

Farm, Parcels and Cropping Systems

The study farm cluster, representative of a producer organisation in a semi-arid tropical region of southern India, consists of 100 one-hectare parcels in a 10 × 10 grid. Soil (sand, loam or clay) was generated as a spatially correlated field, and water access varied from canal command on the western side through borewell irrigation to rainfed parcels on the east as shown in **Fig. 2**. In the dataset there were 25 sand, 40 loam and 35 clay parcels, and 44 canal, 25 borewell and 31 rainfed parcels. A library of 15 crop cycles (**Table 1**) was combined into 13 annual cropping systems: double-crop flooded rice (S1); rice with a black gram follow-on in three water-management variants, continuous flooding (CF, S2), alternate wetting and drying (AWD, S3) and direct-seeded rice (DSR, S4); maize–groundnut (S5); maize–black gram (S6); cotton (S7); flood-irrigated (S8) and drip-irrigated sugarcane (S9); tomato–ragi (S10); brinjal–black gram (S11); and two dryland systems, ragi–horse gram (S12) and sorghum–black gram (S13). Eligibility depends on the parcel: rainfed parcels can host

only the dryland systems, and rice, sugarcane and cotton cannot be grown on sandy parcels. Yields are multiplied by 0.88 on sand, 0.90 on rainfed land and 1.04 for rice on clay, and sandy soils require 10 % more water.

Table 1. Crop-Cycle Data Per Hectare (Indicative Values; to Be Replaced with Local Data)

Crop cycle	Yield (t/ha)	Price (₹/t)	Cost (₹/ha)	Water (m^3/ha)	N (kg/ha)	Diesel (L/ha)	Labour (d/ha)
Rice, flooded (CF)	5.5	23,000	55,000	11,000	120	60	110
Rice, second crop (CF)	5.8	23,000	57,000	13,500	130	60	115
Rice, AWD	5.4	23,000	54,000	8,000	120	60	105
Rice, direct-seeded	5	23,000	46,000	7,500	110	60	70
Maize	6.5	22,000	52,000	4,500	150	55	70
Groundnut	2.6	60,000	62,000	5,000	25	45	95
Black gram	0.9	70,000	22,000	1,500	20	20	40
Cotton (seed cotton)	2.4	65,000	78,000	6,500	120	65	160
Sugarcane, flood	95	3,400	140,000	20,000	250	90	220
Sugarcane, drip	105	3,400	150,000	12,000	220	80	190
Tomato, drip	45	12,000	190,000	5,500	180	40	280
Brinjal, drip	38	14,000	150,000	5,000	150	40	240
Ragi	2.6	40,000	28,000	800	50	30	60
Sorghum	3	32,000	26,000	800	60	28	50
Horse gram	0.8	50,000	14,000	0	10	15	35

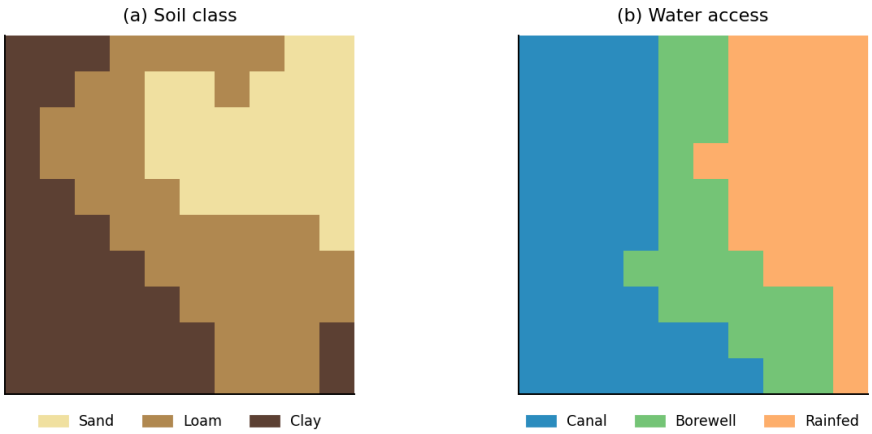


Fig 2. Simulated Parcel Attributes of The Farm Cluster: (A) Soil Class and (B) Water Access.

Income, Emissions and Resource Accounting

For parcel p and system s, comprising crop cycles c, the net income is the revenue less production cost and irrigation cost,

$$\pi_{ps} = \sum_{c \in s}\left(m_{pc} y_c p_c - k_c\right) - c_{w,p} V_{ps} \quad (1)$$

where m_{pc} is the soil and water-access yield multiplier, y_c the yield, p_c the price, k_c the non-irrigation cost, $c_{w,p}$ the unit cost of irrigation water for the parcel's source and V_{ps} the irrigation volume. Emissions follow an IPCC-style bottom-up accounting [9] that sums nitrogen-related, energy-related, methane and other contributions,

$$E_{ps} = \sum_{c \in s}\left[N_c\left(\varepsilon_p + \varepsilon_{N,c}\right) + d_c \varepsilon_d + \kappa_p V_c \varepsilon_g + o_c + E_{CH4,c}\right] \quad (2)$$

where N_c is the nitrogen applied (kg ha^{-1}), ε_p = 4.0 kg CO_2e per kg N the fertiliser-manufacture factor, d_c the diesel use (L ha^{-1}) with ε_d = 2.68 kg CO_2e L^{-1}, κ_p the pumping energy per m^3 of water (0.03 kWh m^{-3} for canal, 0.245 kWh m^{-3} for

borewell parcels), ε_g = 0.71 kg CO_2e kWh^{-1} the grid factor, and o_c the emissions of other inputs such as pesticides. Soil nitrous oxide is obtained from the emission factor EF_N (1.25 % of applied N for upland crops including indirect emissions and 0.75 % for flooded rice) and the global warming potential of N_2O (273 over 100 years),

$$\varepsilon_{N,c} = EF_N \cdot \frac{44}{28} \cdot GWP_{N2O}, \quad E_{CH4,c} = EF_c t_f SF_w GWP_{CH4} \tag{3}$$

The second expression is the IPCC form for rice methane [9]: a baseline daily emission factor EF_c (1.3 kg CH_4 ha^{-1} d^{-1}) multiplied by the length of the flooded period t_f (days), a scaling factor SF_w for water regime, and the methane global warming potential (27). The water-regime factor is 1.0 for continuous flooding, 0.52 for the multiple-drainage regime used for AWD, and 0.45 for DSR, which is an assumption based on the largely aerobic conditions of direct seeding. AWD and DSR are established ways to reduce water use in rice [10], and the adoption and economics of AWD have been studied for irrigated lowland systems [11]. Legume-containing systems receive a nitrogen credit of 15 kg N ha^{-1} for the following cereal. Soil-carbon sequestration, which can contribute to mitigation [12], was not credited, because the accumulation depends on long-term residue and tillage management that the annual model does not represent. Resource demand is aggregated into the RDI, the weighted sum of irrigation water V, nitrogen N, final energy En and labour L, each normalised by the value of the reference plan:

$$RDI = \sum_{r\in\{V,N,En,L\}} w_r \frac{R_r}{R_{r,ref}}, \quad (w = 0.40, 0.25, 0.20, 0.15) \tag{4}$$

so that the reference plan has RDI = 1 by construction. Final energy was computed from diesel (38.6 MJ L^{-1}) and electricity (3.6 MJ kWh^{-1}). Yield-related outputs reported besides income are the rice-equivalent yield (revenue divided by the paddy price) and the food energy produced (Mcal).

Optimisation Model

Let $x_{ps} \in \{0, 1\}$ indicate that system s is allocated to parcel p. The plan must assign exactly one eligible system to each parcel,

$$\sum_s x_{ps} = 1, \ \forall p, \quad x_{ps} \in \{0,1\}, \quad x_{ps} = 0 \ if \ (p,s) \ not \ eligible \tag{5}$$

and the three objectives are expressed with the parcel–system coefficients,

$$max\ I = \sum_{p,s} \pi_{ps} x_{ps}, \quad min\ E = \sum_{p,s} E_{ps} x_{ps}, \quad min\ RDI = \sum_{p,s} \rho_{ps} x_{ps} \tag{6}$$

with ρ_{ps} the RDI contribution of the pair. Farm-level constraints were: irrigation withdrawal not above 90 % of the reference demand (a water-scarcity assumption), food energy not below 90 % of the reference, labour not above 115 % of the reference, at least 15 ha of legume-containing systems, between 20 and 40 ha of rice (a staple-food and procurement commitment and a policy cap), at most 25 ha of sugarcane (mill contract) and at most 20 ha of vegetables (market saturation). The ε-constraint method [8] maximises income while bounding the other objectives and was applied on a grid of nine emission and seven RDI bounds,

$$max\ I(x) \quad s.t. \quad E(x) \le \varepsilon_E, \quad RDI(x) \le \varepsilon_R, \quad x \in X \tag{7}$$

and the non-dominated plans were filtered from the solutions. The knee plan, considered a balanced compromise, is the Pareto plan with the smallest Euclidean distance to the ideal point in the objective space normalised over the front,

$$\delta_i = \sqrt{\left(\frac{I_{max}-I_i}{I_{max}-I_{min}}\right)^2 + \left(\frac{E_i-E_{min}}{E_{max}-E_{min}}\right)^2 + \left(\frac{R_i-R_{min}}{R_{max}-R_{min}}\right)^2} \tag{8}$$

The effect of an internal carbon price λ (₹ per t CO_2e) was studied by solving the single-objective problem max $I - \lambda E$ for a range of prices, and the marginal abatement cost (MAC) of re-allocating crops was obtained from the slope of the income–emission frontier,

$$MAC = -\frac{\Delta I}{\Delta E}, \quad max\ I_\lambda = I - \lambda E \tag{9}$$

Uncertainty in weather was treated by a scenario-based robust plan that maximises the worst-case income over a normal and a dry scenario (yields reduced by 4–15 % depending on the crop and irrigation demand increased by 12 %), requires the dry-year water demand to remain within the available supply and the dry-year food energy to stay above 85 % of the reference, and does not allow emissions above those of the knee plan [14]:

$$max\ t \quad s.t. \quad I_s(x) \geq t,\ s \in \{normal, dry\}, \quad V_{dry}(x) \leq W_{cap}, \quad E(x) \leq E_{knee} \tag{10}$$

All models were mixed-integer linear programs of about 1,000 binary variables and were solved with the HiGHS solver [13], taking from a fraction of a second to a few seconds each. The sensitivity of plan emissions to emission-factor uncertainty was assessed by recomputing the knee plan with varied factors. The reference plan, representing current practice, assigned systems randomly with typical area shares (flooded rice about 20 %, sugarcane about 9 %, dryland about 41 %), and is deliberately not optimised.

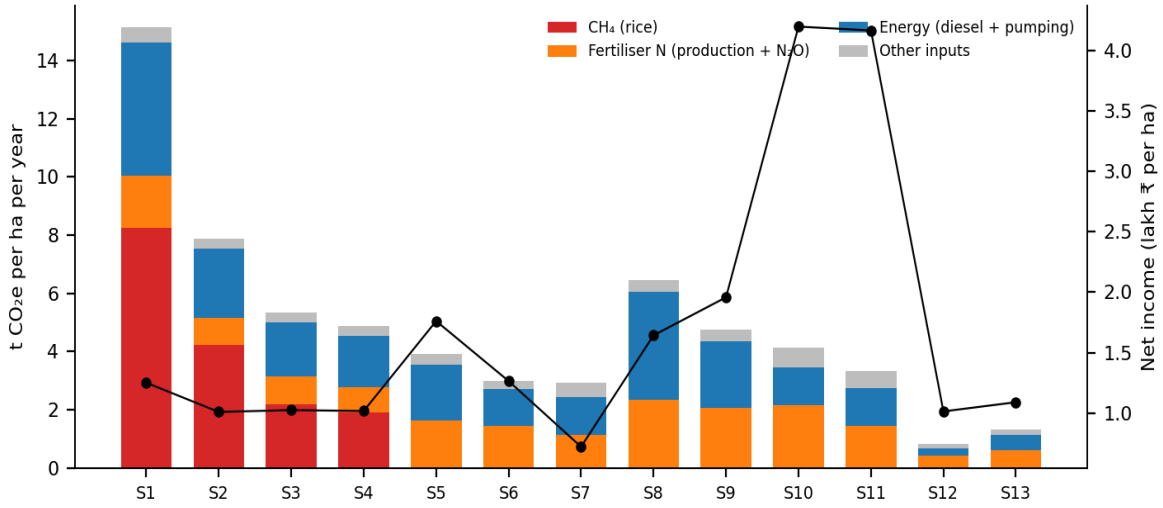


Fig 3. Emissions by Source and Net Income Per Hectare of Each Cropping System on A Loam Parcel Irrigated by Borewell.

Verification By Satellite NDVI

A carbon-aware plan is only useful if its implementation can be checked. Crop type can be mapped from the temporal profile of the normalised difference vegetation index, NDVI = ($\rho_{NIR} - \rho_{red}$) / ($\rho_{NIR} + \rho_{red}$) [15], which for the Sentinel-2 mission is available at 5-day revisit with 10-m resolution [16]. Time series with a 5-day step were simulated for six crop classes (rice, maize, cotton, sugarcane, vegetables and dryland millet) as double-logistic phenology curves with random timing and amplitude shifts, measurement noise and cloud gaps (50 % of observations during the monsoon, 15 % otherwise) filled by linear interpolation. A random forest of 300 trees [17] was trained on 70 % of 1,800 pixels and tested on the rest; the parcels of each plan were then classified by a majority vote of 15 pixels, and plan emissions were estimated from the classified crop types using default practices (flooded rice, flood-irrigated sugarcane). Overall accuracy and the macro F1 score were reported:

$$F_1 = \frac{2}{C}\sum_{k=1\ldots C} \frac{P_k R_k}{P_k + R_k} \tag{11}$$

IV. RESULTS AND DISCUSSION

Emission and Income Profile of The Cropping Systems

For the reasons described in **Fig. 3**, a single emission factor per crop is not suitable. The double flooded rice (S1) produced 15.1 t CO2e/ha/year with the majority being methane for a borewell-irrigated loam parcel, while the single flooded rice–pulse system (S2) produced 7.9 t/ha/year. The AWD (S3) and DSR (S4) variants had emissions of 5.3 and 4.9 t, respectively, due to the fact that the water regime scales methane production. The largest emitters apart from rice (6.5 t) were sugarcane, which was flood-irrigated (S8), and which emitted 6.6 t, and drip irrigation (S9), which emitted 4.8 t. The dryland systems released the least (0.8 and 1.3 t) and received the least as well. In terms of income, the horticultural systems (S10, S11) and drip sugarcane were most profitable, at 4.2, 4.2 and 2.0 lakh ₹ per hectare, against 1.0 lakh for flooded rice–pulse, which indicates a large scope for emission reduction without income loss, provided that markets, labour and water allow the shift.

Pareto Set and Trade-Offs

A total of 19 non-dominated plans were obtained from the ε-constraint procedure and are indicated in **Fig. 4**. The extreme plans were profit maximising plan, minimum emission plan and minimum resource plan (RDI 0.61). We were able to calculate and dominate the reference plan which represents current practice: income ₹133.8 lakh, emissions 334 t, RDI 1.00, so the profit maximising plan already increased the income by 40 % and reduced the emissions by 12 % and the amount of water used for irrigation by 10 %. This win–win segment is the first part of the front: the first emission reduction

was achieved with higher income, by adapting their systems to fit new contexts, and to be more profitable. Outside of that the goals are contradictory. The cuts in emissions of the knee plan and the minimum-emission plan were 38 % and 49 % respectively compared to the reference plan, with the minimum-emission plan earning an income of ₹112.6 lakh, 16 % lower than that of the reference plan. Emissions and resource demand were positively related for most of the front: Less water, nitrogen and energy usage leads to lower emissions, but they were not equal: the minimum-resource plan has higher emissions of 176 t than the minimum-emission plan of 169 t, as it trades emissions for lower water and labour demand (e.g., 16 ha maize–black gram).

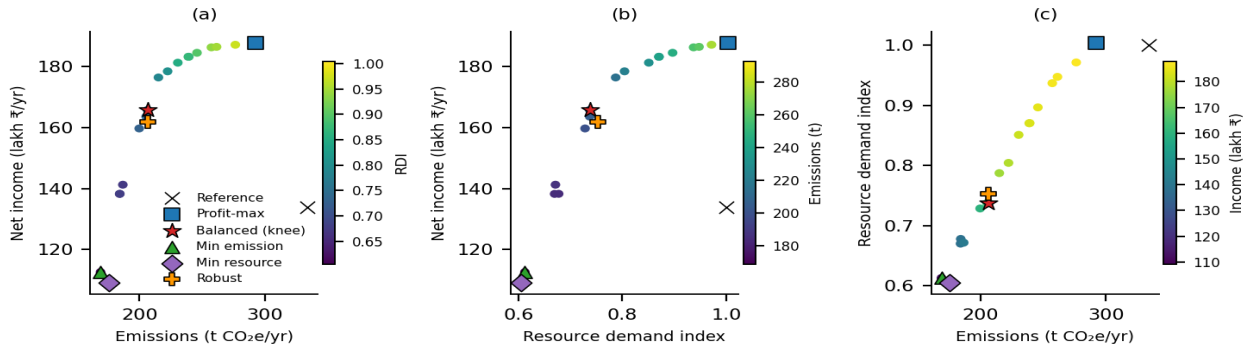


Fig 4. Multi-Objective Trade-Off Analysis of Crop Planning Solutions.

Table 2. Reference and Selected Plans (Annual Totals for the 100-Ha Farm Cluster; Income in Lakh ₹)

Plan	Income	Emissions (t CO_2e)	RDI	Water (10^3 m^3)	N (t)	Energy (GJ·10^3)	Labour (10^3 d)	Food energy (% ref.)
Reference	133.8	334	1.00	769	12.9	545	15.0	100
Profit-max	187.7	292	1.00	690	15.1	487	17.3	114
Balanced (knee)	165.8	206	0.74	484	11.2	338	14.4	90
Min emission	112.6	169	0.61	419	9.0	287	11.5	90
Min resource	109.2	176	0.61	392	9.7	292	10.7	90
Robust	161.8	206	0.75	513	11.0	353	14.3	93

Carbon Price and Marginal Abatement Cost

Fig.5a presents the income–emission frontier when the resource index is not constrained, and **Fig.5b** the marginal abatement cost, which is the loss of income per tonne of CO2e avoided. The cost becomes very high when the emissions are reduced, the reduction from the profit maximising plan costs about ₹2,820.212 to ₹5,170.911 per tonne, but rises to ₹16,849.282 after a few steps and to ₹181,949.935 per tonne close to the minimum emissions plan, which is much higher than the current carbon prices being discussed. A moderate value of internal carbon price thus has a relatively small effect on the optimal plan (**Fig.5c**, **Table 3**). This cost ₹10,000 per tonne and emissions decreased only 13 % compared to the zero-price plan by shifting the rice area from 17 to 20 ha of DSR or AWD, modest increases in drip sugarcane (22 to 23 ha) and minor adjustments in other activities, with a 0.7 % of income cost. This means that crop re-allocation is a sensible measure of mitigation for the 'flat to cheesy' part of the curve but other measures are required to achieve deeper cuts, including methane-reducing water management, nitrogen use efficiency, solar pumping, soil-carbon practices and compensation payments.

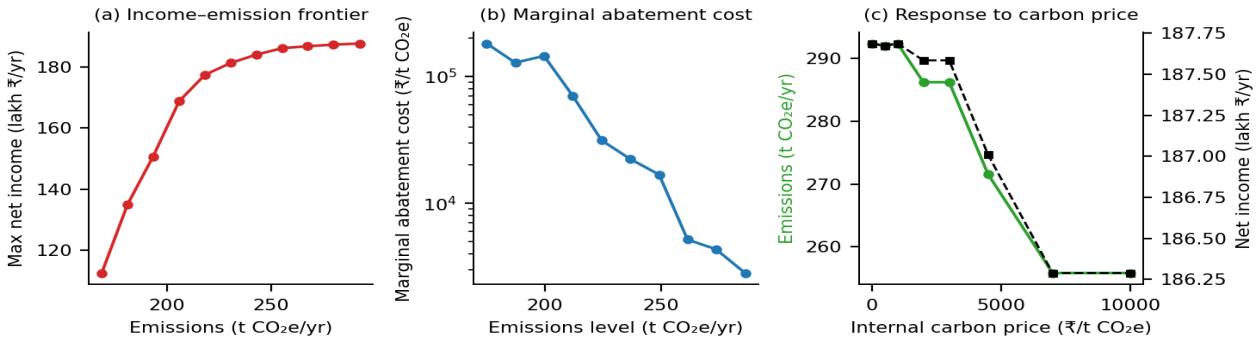


Fig 5. (a) Income–Emission Frontier, (B) Marginal Abatement Cost of Crop Re-Allocation (Logarithmic Scale) and (C) Response of The Optimal Plan to An Internal Carbon Price.

Table 3. Response of the Optimal Plan to An Internal Carbon Price

Price (₹/t CO_2e)	Emissions (t)	Income (lakh ₹)	Rice area (ha)	DSR/AWD (ha)	Drip cane (ha)
0	292	187.7	20	17	22
500	292	187.7	20	17	22
1,000	292	187.7	20	17	22
2,000	286	187.6	20	18	23
3,000	286	187.6	20	18	23
4,500	272	187.0	20	18	23
7,000	256	186.3	20	20	23
10,000	256	186.3	20	20	23

Composition and Spatial Pattern of The Plans

The system mix in **Fig. 6** explains the differences. The reference plan used flooded rice (20 ha), flood-irrigated sugarcane (9 ha), cotton (6 ha) and mainly dryland systems (41 ha). The profit-maximising plan cut flooded rice to 3 ha, kept most of the compulsory rice area as DSR (16 ha), shifted sugarcane to drip (22 ha) and added tomato–ragi (16 ha). The knee plan used DSR (20 ha), drip sugarcane (15 ha), brinjal–black gram (14 ha) and the dryland systems (48 ha), and the minimum-emission plan placed 62 ha under ragi–horse gram. DSR supplied the whole rice area in the knee, minimum-emission and minimum-resource plans and most of it in the profit-maximising plan, whereas AWD was used on only 1 ha, because in the assumed data DSR has lower cost, water demand and methane scaling than AWD, with only a modest yield penalty; if its yield penalty or its methane benefit were less favourable, AWD would enter. This result is therefore sensitive to the DSR parameters, which are among the least certain, and field trials should be used to calibrate them.

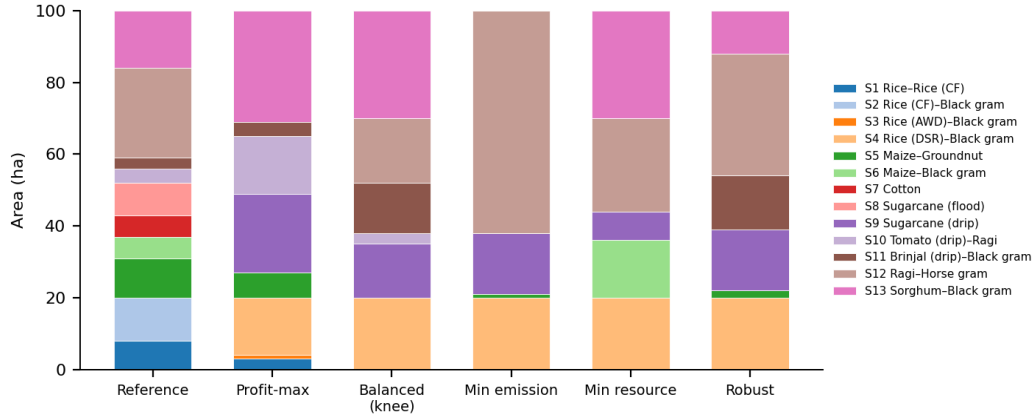


Fig 6. Area Allocated to Each Cropping System Under the Reference and Optimised Plans.

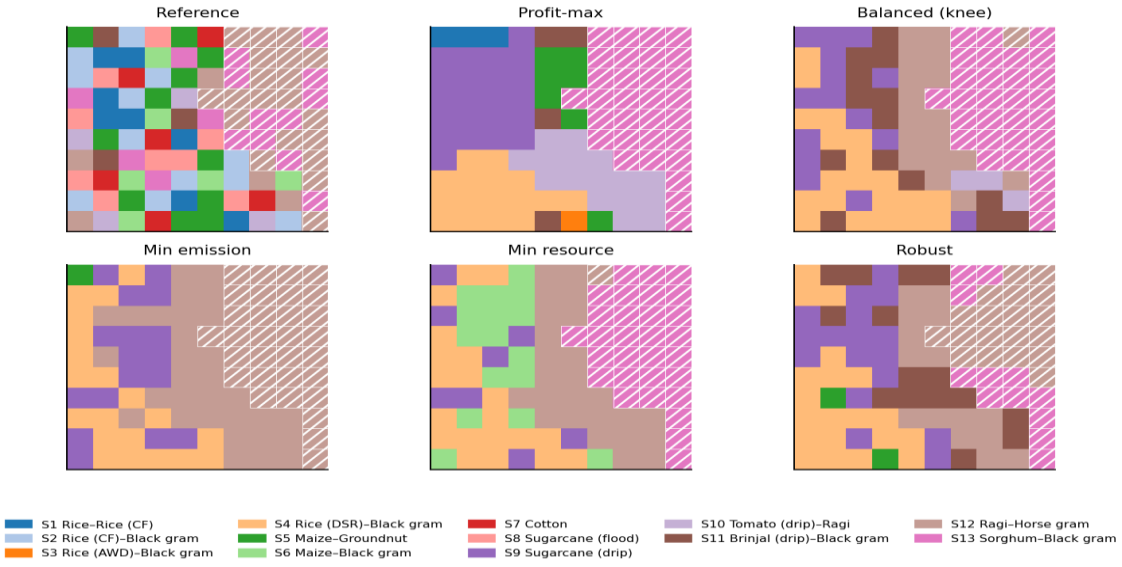


Fig 7. Parcel-Level Crop Allocation Patterns Under Six Optimisation Strategies.

The spatial maps in **Fig. 7** show how the plans respect parcel attributes. Rainfed parcels (hatched) received dryland systems in all plans, sandy parcels were never given rice, sugarcane or cotton, and water-demanding systems could be placed only on irrigated parcels. Such parcel-level maps are the form in which the plan can be communicated to farmers and tested against satellite observations.

Resource Demand and Yield

Fig. 8 compares the plans on all indicators. The knee plan used 37 % less irrigation water, 13 % less nitrogen and 38 % less energy than the reference, with an RDI of 0.74, while labour was 4 % lower and food energy was 90 % of the reference, the lowest level that the food-energy constraint allows. In terms of yield, the rice-equivalent yield of the knee plan was 1118 t against 970 t for the reference (15 %), and the profit-maximising plan achieved 1324 t. Higher yield value and lower emissions are therefore compatible here, because the high-value horticultural and drip-sugarcane systems produce more value per unit of emission than flooded cereals. The minimum-emission and minimum-resource plans reduced the rice-equivalent yield to 787 and 756 t, which shows the yield cost of extreme resource saving.

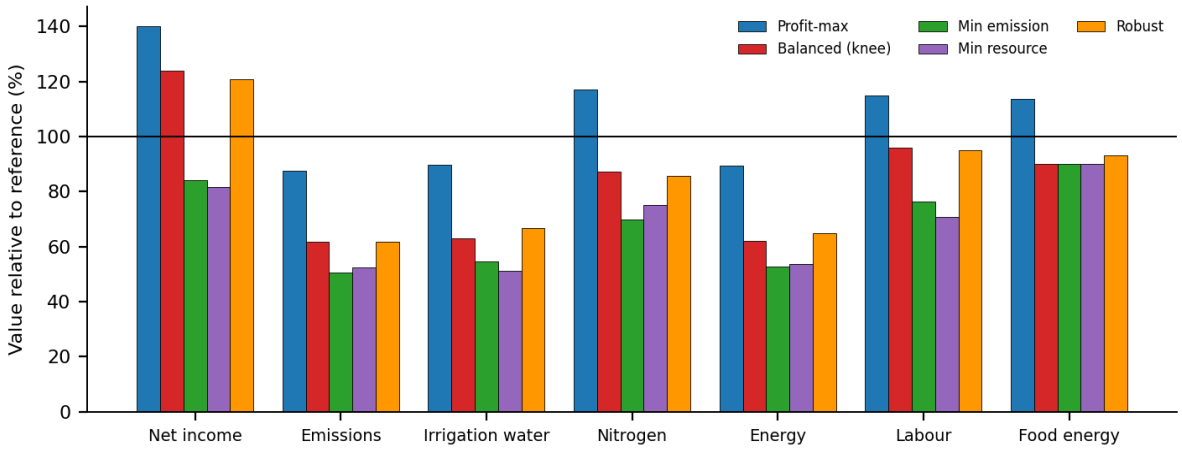


Fig 8. Indicators of the Optimised Plans Relative to The Reference Plan (100 %).

Robustness to a Dry Year

When the plans were evaluated under the dry-year scenario given in **Fig.9**, the reference plan needed 124 % and the profit-maximising plan 112 % of the available water, i.e. both exceeded the supply by 24 % and 12 %, which would force unplanned deficit irrigation and yield losses that the model does not capture. The knee plan required 78 % and the robust plan 83 % of the supply, so both remained feasible. Dry-year income fell by 15 % for the reference plan, 14 % for the profit-maximising plan, 12 % for the knee plan and 12 % for the robust plan. The robust plan is similar to the knee plan, with more ragi–horse gram and less sorghum–black gram on the dryland parcels and emissions kept at the knee level; it accepted a 2.4 % lower normal-year income in exchange for a dry-year food-energy supply of 86 % of the reference, compared with 83 % for the knee plan, which would violate the 85 % requirement. The low-water, low-emission plans are thus also the more drought-resilient ones, a co-benefit of the carbon-aware approach, although the income advantage in the dry year is modest compared with the avoided water shortfall.

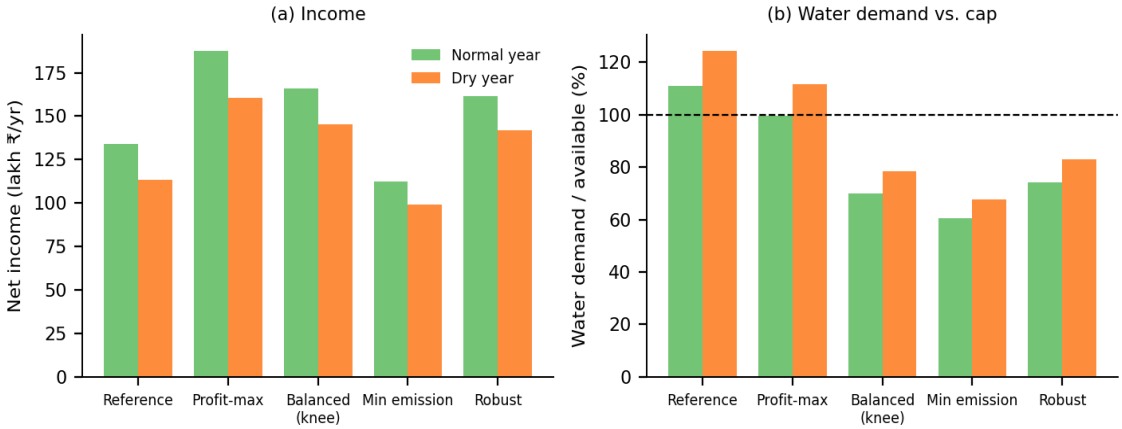


Fig 9. Normal and Dry-Year Performance of The Plans: (A) Net Income and (B) Irrigation Demand Relative to The Available Water (Dashed Line: 100 %).

Sensitivity to Emission Factors

Emission factors are uncertain, so the emissions of the knee plan were recomputed with varied factors as depicted in **Fig.10**. Uncertainty in the nitrous-oxide factors (±50 %) changed plan emissions by ±14 %, the largest effect, followed by the methane baseline (±5.5 %, because rice occupies only the 20-ha minimum) and fertiliser production (±5.4 %), whereas the grid factor mattered little (±2.0 %). The AWD scaling factor had no effect because the plan does not contain AWD. These variations are smaller than the difference between the knee plan and the reference (38 %), so the ranking of plans is robust, though the absolute emissions are not known with great precision. As nitrogen-related emissions dominate, improvements in nitrogen management (split application, fertigation, legume rotation) would be the most valuable complement to crop re-allocation.

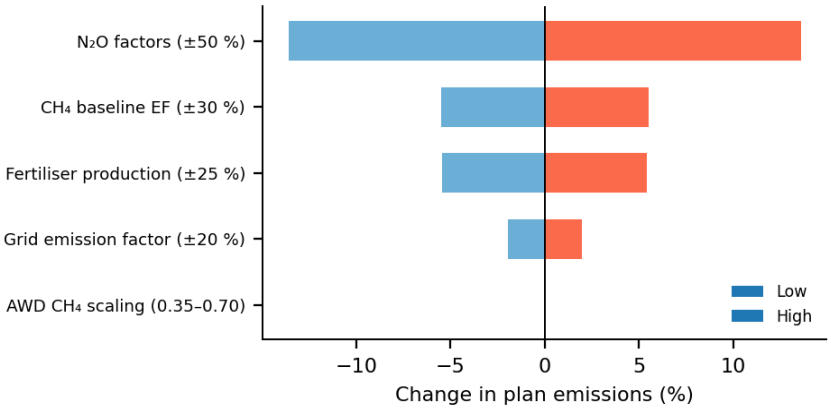


Fig 10. Sensitivity of the Emissions of The Balanced (Knee) Plan to Emission-Factor Uncertainty.

Verification of the Plan from Satellite NDVI

Fig. 11a shows the simulated NDVI profiles of the six crop classes. Sugarcane and cotton are readily distinguished by their long seasons, and dryland millet by its low peak, whereas rice, maize and vegetables, which share the monsoon window, overlap. The random-forest classifier reached an overall pixel accuracy of 0.86 and a macro F1 of 0.86; the class-wise recalls were rice 0.78, maize 0.67, cotton 1.00, sugarcane 1.00, vegetables 0.78, dryland 0.96 (**Fig. 11b**). With a majority vote over the pixels of a parcel, the crop was identified correctly in all parcels of every plan tested (**Table 4**), so that compliance with the planned crop allocation could be checked at parcel level. However, estimating plan emissions from the classified crop types and default practices produced large errors, because the maps cannot tell direct-seeded from flooded rice or drip from flood-irrigated cane: the estimated emissions differed from the true ones by -13 % for the reference plan (where the default single-crop rice practice understates double-cropped rice), but by 11 % for the profit-maximising plan, 30 % for the knee plan and 34 % for the minimum-emission plan, so the low-emission practices were not credited. This is a significant result for the design of carbon programmes: crop-type mapping verifies the crop plan, but verifying emission reduction also requires observations of water management (for example flooding detection from radar time series), irrigation method and fertiliser records, with spot checks in the field.

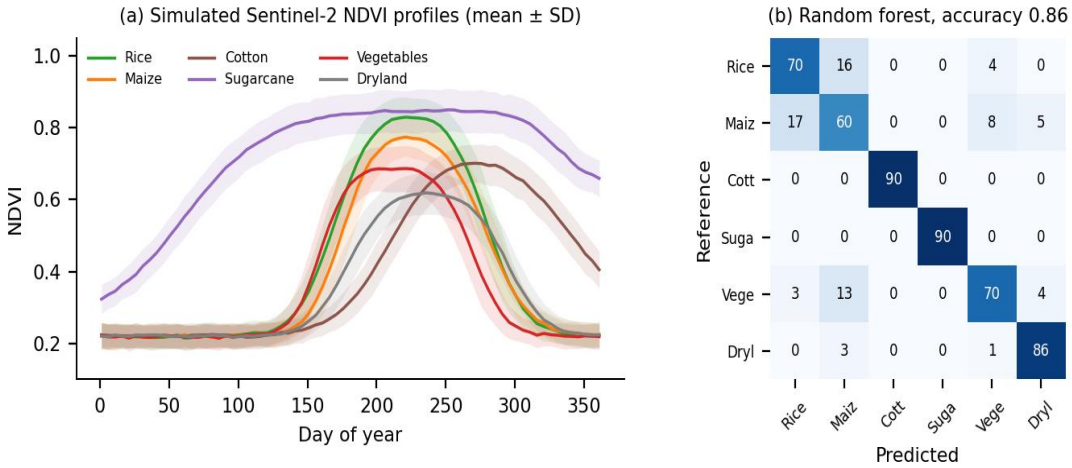


Fig 11. (a) Simulated NDVI Profiles of The Crop Classes (Mean ± SD) And (B) Confusion Matrix of The Random-Forest Classifier on The Test Pixels.

Table 4. Verification of the Crop Plans by Parcel-Level NDVI Classification and The Resulting Emission Estimates (t CO_2e)

Plan	Parcels Correct (%)	True Emissions	Estimated From Crop Map	Error (%)
Reference	100	334	291	-13
Profit-max	100	292	324	+11
Balanced (knee)	100	206	268	+30
Min emission	100	169	226	+34

First, the first part of the available emission reduction is economically free, since current mixes are not on the efficient frontier; extension services should therefore aim first at re-allocating crops and improving water management where it also raises income, but must check market and labour feasibility, which the model represents only through caps. Second, beyond this region, abatement is costly, so carbon payments or green procurement premiums of the order of thousands of rupees per tonne would shift decisions only slightly, and mitigation beyond the knee needs complementary measures. Third, collective planning at parcel level matters because water access and soil determine which low-emission options are feasible; a producer organisation can allocate high-value, low-emission systems to the parcels that suit them and share the market risk. Fourth, verification has to be designed along with the plan: crop maps from satellites are cheap and accurate enough for monitoring compliance, but credits for low-emission water and nutrient management require additional evidence.

Data are indicative or synthetic, and a single-year, annual-system model cannot represent crop sequences across years, soil-carbon change, residue management or price dynamics. Prices and yields are deterministic except for the dry-year scenario. The system library is small, and farmers' risk attitudes, credit, machinery and labour peaks are only represented by aggregate constraints. Emission factors are adapted default values; for rice in particular, region-specific measurements are needed. The NDVI experiment uses simulated profiles and cannot capture all the spectral confusion or cloud problems of real imagery, and further sensors (radar, thermal) were not modelled. Future work will calibrate the model to a real producer organisation, add multi-year rotations and soil carbon, include price and yield uncertainty in a stochastic programme, combine the plan with the solar-pumping and irrigation-scheduling optimisation, and test the satellite verification on real fields with water-regime detection.

V. CONCLUSION

By separating income from emissions and the demand for resources and introducing a framework as a mix of integer crops, transparent crop plans and comparisons can be designed. In the 100-ha demonstration cluster, the use of direct seeded rice, drip systems, horticulture and dryland millet-pulse rotations in place of flooded rice and flood-irrigated sugarcane, led to a reduction in emissions by 38 %, irrigation water by 37 % and the resource-demand index by 26 %, while increasing net income by 24 % from current practice. The profit maximizing plan is itself less emitting than the reference, so the first 12% of the abatement was costly but not excessive, but the rest of the abatement that is required is very costly, and far more than could compete with realistic carbon emissions prices. The balanced plan would also have been possible if the reference and profit-maximising plans were not. Crop-type mapping from NDVI verified the crop allocation but could not verify low-emission practices, and misestimated plan emissions by up to 34 %, which requires monitoring of water and nutrient management. The data in this paper are indicative, so the next step is to apply the framework to measured farm data and to extend it to multi-year rotations and stochastic conditions.

CRediT Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Gaurav Lazaro and Nandhini Priya T; **Methodology:** Nandhini Priya T; **Software:** Nandhini Priya T; **Data Curation:** Nandhini Priya T; **Writing-Original Draft Preparation:** Gaurav Lazaro and Nandhini Priya T; **Visualization:** Gaurav Lazaro; **Investigation:** Gaurav Lazaro and Nandhini Priya T; **Supervision:** Gaurav Lazaro and Nandhini Priya T; **Validation:** Gaurav Lazaro and Nandhini Priya T; **Writing- Reviewing and Editing:** Gaurav Lazaro and Nandhini Priya T; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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