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RESEARCH PAPER

Eco-efficiency of Crop Production in Madhya Pradesh: A Directional Distance Function Approach

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Abstract: The growing global population presents a dual challenge: increasing crop production while minimizing environmental impact. To overcome this challenge, the eco-efficiency of crops must be improved. Measuring eco-efficiency—defined as the ratio of desirable output (crop production) and undesirable output (environmental degradation) to resource use (inputs)—is crucial for sustainable agriculture. This study assesses the eco-efficiency of crop production in Madhya Pradesh, India, using life cycle assessment (LCA) and data envelopment analysis–directional distance function (DEA–DDF). We obtained the input data for crops from multiple packages of practices from government sources for the 2021–2022 agricultural year. LCA quantified the environmental impact of crop production, while DEA–DDF evaluated efficiency by considering both economic output and environmental degradation. Our results indicate that rainfed wheat, maize, sorghum, and soybean exhibit production inefficiencies, with an average inefficiency of 0.22, suggesting a 22% potential for improvement. Inefficient decision-making units can enhance efficiency by optimizing input use, reducing environmental degradation, and increasing crop and residue output. The study also determines target values for input reduction and output improvement to guide sustainable agriculture. It helps optimise crop eco-efficiency by emphasizing resource-efficient and environmentally sustainable agricultural practices, thereby supporting long-term food security.

Keywords: Environmental Impact, Eco-efficiency, Data Envelopment Analysis, Directional Distance Function, Agricultural Impact

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1. INTRODUCTION

Agriculture is a significant source of global greenhouse gas (GHG) emissions, contributing substantially to climate change (Khangar and Mohanasundari 2025; Jimmy *et al.* 2017; Lynch *et al.* 2021), which, in turn, affects agricultural productivity (Adams et al. 1998; Taki *et al.* 2018). Since 2000, GHG emissions from global agrifood systems have increased by 9%, reaching 16 Gt CO_2 eq in 2020 (FAO 2022). Numerous studies have highlighted that agricultural practices, soil management, irrigation, and fertilizer use significantly influence emissions from crop production (Aryal *et al.* 2015; Kumar *et al.* 2021; Safa and Samarasinghe 2012; Syp *et al.* 2015; Vetter *et al.* 2017; Taki *et al.* 2018; Tayefeh *et al.* 2018). These emissions exacerbate environmental degradation (Khangar and Mohanasundari 2023, 2024; Nayak *et al.* 2023), posing challenges to achieving sustainability and food security. Agriculture not only contributes to climate change but is also adversely affected by it, as rising temperatures and extreme weather conditions reduce crop yields (Arora 2019; Kumar *et al.* 2024; Kumar, Ray, and Mohanasundari 2024; Malhi *et al.* 2021). This cyclical relationship underscores the urgent need for sustainable agricultural practices.

Given the growing global population, the challenge is to increase food production while minimizing environmental harm. This calls for the development of innovative production practices that optimize resource use. Enhancing crop eco-efficiency, which refers to producing more agricultural output with fewer inputs (such as water, energy, and fertilizers) while reducing environmental impacts, is crucial to achieving sustainability. Yet, farmers, especially in developing countries, face hurdles such as high input costs, low yields, land degradation, and inefficiencies in production, necessitating policy discussions on agricultural subsidies and sustainability measures (Manogna and Mishra 2020; Yadava 2017).

This study assesses the production–environmental efficiency of major crops in Madhya Pradesh using data envelopment analysis (DEA), a widely used tool for measuring eco-efficiency. The study extends the concept of technical efficiency by incorporating environmental impacts. While DEA traditionally measures technical efficiency, this study uses data envelopment analysis–directional distance function (DEA-DDF), which allows for the inclusion of undesirable outputs (e.g., emissions) and provides a broader measure of eco-efficiency in crop production. The study aims to provide insights into how different crop production systems vary in efficiency, thereby helping policymakers and stakeholders develop sustainable farming strategies. One of the core goals of this study is to contribute to the global movement toward sustainable agriculture by informing decision-making with evidence-based analysis. Notably, this study makes a fundamental contribution to achieving the United Nations Sustainable Development Goals (SDGs), particularly goals 2 (zero hunger), 12 (responsible consumption and production), and 13 (climate action).

This paper begins with a review of the environmental impact of agriculture and methods for measuring eco-efficiency, followed by a discussion of the empirical approach. The results highlight variations in eco-efficiency across crops, emphasizing the need for targeted interventions. The study concludes with policy recommendations, stressing the role of DEA in guiding sustainable agricultural practices. By promoting resource-efficient farming, this study contributes to the broader discourse on sustainable agriculture and environmental conservation. Through this research, we aim to contribute to the ongoing debate on sustainable agriculture and promote a more resilient and environmentally conscious approach to food production.

2. LITERATURE REVIEW

The literature review is structured into two main sections. The first section presents a methodological review of various eco-efficiency assessment methods, evaluating their theoretical foundations and practical applications. The second section examines past studies that have employed eco-efficiency and similar approaches to identify research gaps both in terms of methodology and the existing literature.

2.1. Methodological Review

DEA is a mathematical programming approach used to measure the relative efficiency of decision-making units (DMUs) by assessing the ratio of weighted outputs to weighted inputs (Allen *et al.* 1997; Iribarren *et al.* 2015). It eliminates subjectivity in eco-efficiency measurement (Masternak-Janus and Rybaczewska-Błażejowska 2017; Picazo-Tadeo *et al.* 2011; Sanjuan *et al.* 2011) and is recognized as an effective means of reducing environmental pressures. It is also widely accepted in policymaking (Kuosmanen and Kortelainen 2005). Developed initially to estimate firm efficiency (Cooper *et al.* 2011), DEA has been applied widely in agriculture to assess sustainability and efficiency (Toma *et al.* 2015), in conjunction with life cycle assessment (LCA).

In agricultural studies, emissions are often treated as inputs due to their controllable nature, following the arbitrary treatment of undesirable outputs by Dyckhoff and Allen (2001). While some researchers follow this approach

(Korhonen and Luptacik 2004; Zhang *et al.* 2008), Seiford and Zhu (2002) argue that it does not accurately represent the production process. The DDF in the DEA approach addresses this issue by considering undesirable outputs separately (Chung *et al.* 1997; Färe and Grosskopf 2004).

DEA has evolved to incorporate stochastic models and concepts of weak or marginal disposability (Amirteimoori *et al.* 2023). Hua and Bian (2007) identify six methods to handle undesirable factors: ignoring them, treating them as inputs, using nonlinear models (Färe *et al.* 1989), applying nonlinear monotone transformations and linear monotone transformations (Seiford and Zhu 2002), and lastly, employing the DDF approach. A challenge in eco-efficiency measurement is assigning weights to emissions, as default weight assignments may not be ideal (Tyteca 1996). To address this, Kuosmanen and Kortelainen (2005) employ DEA with constrained linear programming to assign soft weights.

2.2. Review of Past Studies

In agriculture, eco-efficiency is well substantiated, encompassing various crops, techniques, and horticulture (Picazo-Tadeo *et al.* 2011). Numerous studies have investigated the eco-efficiency of agricultural crop production using DEA (Cao *et al.* 2022; Coluccia *et al.* 2020; Huang *et al.* 2018) and stochastic frontier analysis (SFA) (Orea and Wall 2016; Song and Chen 2019). However, these studies explore eco-efficiency in agriculture only at the farm or crop levels, within specific geographic regions, and are thus limited in scope. Mohammadi *et al.* (2015) combined LCA and DEA to benchmark the environmental impacts of rice production by applying the constant returns to scale (CRS) model with a focus on reducing the input (environmental harm) at constant production yield.

In a comprehensive examination of eco-efficiency in rice production in China, Huang *et al.* (2022) integrated LCA and DEA, arriving at a combined eco-efficiency value of 0.51. In contrast, Aslam *et al.* (2021) reported eco-efficiency values of 0.88 and 0.90 for wheat and rice, respectively, in India, thus demonstrating a higher eco-efficiency compared to China. Pishgar-Komleh *et al.* (2020) added to this discourse by estimating a wheat production efficiency of 0.43 ± 0.23 in Poland. Notably, they argue that enhancing the performance of inefficient farms could lead to a remarkable 57% reduction in resource usage.

Adding to the regional perspective, Ding *et al.* (2024) investigated the eco-efficiency of grains in China, revealing values of 0.67 at CRS and 0.71 at variable returns to scale (VRS). Numerous studies, such as those conducted by Bagheri *et al.* (2020), Chaloob *et al.* (2018), Fusco *et al.* (2023), and Hsu *et* *al.* (2023), also examine the eco-efficiency of aggregate agricultural production across different regions. Evidencing results obtained using typical DEA models—such as the Charnes, Cooper, and Rhodes (CCR) model, based on CRS, and the Banker, Charnes, and Cooper (BCC) model, based on VRS (Kyrgiakos *et al.* 2023)—Fusco et al. (2023) measured the eco-efficiency of agricultural produce, combining it with soft weightages for emissions, highlighting significant territorial disparities in eco-efficiency across Italy. Northern regions in Italy demonstrated higher eco-efficiency, while southern regions showed greater scope for improvement.

We find that most studies in the agricultural context a) use a soft weightage system for emissions, considering them as an input and applying a classic DEA approach; b) consider only GHGs as environmental emissions; or c) use the DEA–DDF approach. Therefore, in this study, we combine the DEA with restricted weights for emissions and consider them as undesirable output. We use the analytical hierarchy process (AHP) to assign subjective weightage to emissions while distributing the weights. In this way, this study can demonstrate a more efficient production process and improved efficiency scores. Further, we integrate economic outcomes and environmental impacts assessed using the LCA into an eco-efficiency (EE) ratio. This ratio is determined using a weight estimation model based on DEA, which provides distinct weights for each emission category using AHP, considering the vast category of impacts.

Based on the identified literature gap, this study aims to measure the eco-efficiency of major crops, including irrigated wheat, rainfed wheat, direct-seeded rice, maize, sorghum, millet, and soybeans, in Madhya Pradesh, India. This study investigates which crop is the most eco-efficient in the state and what should be the target to make all the crops sustainable and eco-efficient.

3. DATA AND METHODOLOGY

This section outlines the regional input–output data sources and the methodological framework used to assess agricultural eco-efficiency. It details the analytical approaches employed to evaluate environmental emissions using LCA, measure efficiency performance using DEA–DDF, and assign subjective weights to emissions and inputs.

3.1. Data Sources

We collected the input data for the crops from multiple packages of practices (PoPs) from government sources, as shown in Table 1.

Table 1: Life Cycle Production Inventory Data Sources for Crops

Crop	Production input data source
Wheat	Package of Practice, Farmer Welfare and Agriculture Development Department, Madhya Pradesh (n.d.a)
Rice	Package of Practice, Farmer Welfare and Agriculture Development Department, Madhya Pradesh (n.d.b)
Maize	Package of Practice, Farmer Welfare and Agriculture Development Department, Madhya Pradesh (n.d.c)
Soybean	Package of Practice, National Food Security Mission (n.d.)
Sorghum	Indian Council of Agricultural Research –Indian Institute of Millets Research (ICAR-IIMR) (n.d.a)
Millet	ICAR–IIMR (n.d.b)

Source: Authors' compilation

Residue is also an output of agricultural practices. Therefore, in this study, DEA considers agricultural residue as an output. It further assumes that the residue is untreated and, therefore, not included in the LCA of crops. Since residue data are not readily available, we calculated the amount of residue by adopting the cool farm tool (CFT) model, which is represented by the following equation:

$$Q^{\mathrm{FU}}_{\mathrm{residue}} = \sum R_a + R_b$$

where $Q^{\mathrm{FU}}_{\mathrm{residue}}$ is the quantity of residue per functional unit (e.g., ha^{-1}), R represents the residue, with subscript "*a*" denoting above-ground residues and "*b*" denoting below-ground residues. The above-ground residue (R_a) was calculated as follows:

$$R_a = Y_{\mathrm{Crop}} * D_{\mathrm{Crop}} * \left[\frac{D_{\mathbf{Crop}}}{Y_{\mathbf{Crop}}}\right]$$

where "*Y*" represents crop yield, "*D*" refers to the dry matter fraction of the crop, and $\frac{D_{\mathbf{Crop}}}{Y_{\mathbf{Crop}}}$ is the ratio of above-ground residue dry matter to the harvested yield of the respective crop.

Residue below ground was assessed by the given equation:

$$R_b = R_a * \left[\frac{R_{\mathrm{biomass}}}{\mathrm{R_a}}\right]$$

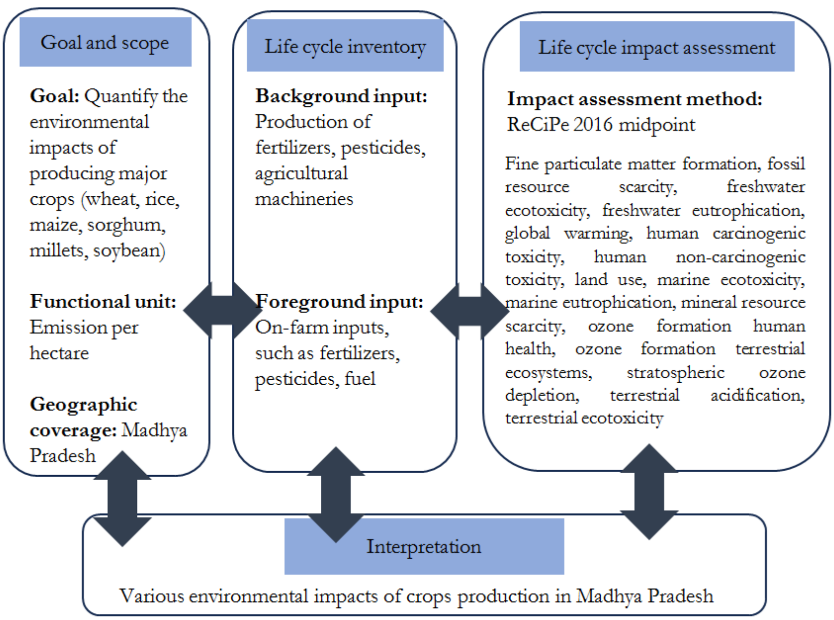
where the R_{biomass} refers to the ratio of the below-ground root biomass of the crop to the above-ground shoot biomass, which is assumed to be zero because the primary focus is on above-ground biomass. This study follows IPCC (2019) in calculating the ratio of the above-ground residue dry matter to the harvested yield for crops, as well as that of the below-ground root biomass to the above-ground shoot biomass of crops. The average output data of the crops has been obtained from the Indiastat database (n.d.).

3.2. Empirical Analysis

The empirical analysis follows a structured approach to assess agricultural eco-efficiency. First, we undertook LCA to quantify various environmental emissions resulting from agricultural activities. We then assigned subjective weights to these emissions to aggregate them into a single composite emission score. Similarly, inputs were weighted with equal importance to ensure a balanced evaluation. Finally, we performed DEA using these processed inputs and outputs to measure the relative efficiency of different production units or regions.

3.2.1 Life cycle assessment

Figure 1. Cyclical Impact of Climate Change on Agricultural Production



Source*:* Authors' compilation

We performed LCA for select major crops within the system boundary to calculate environmental emissions. We used the ReCiPe 2016 midpoint method for impact assessment using the OpenLCA 1.11 software. Figure 1 represents the LCA goal and system boundary. All the processes, starting from land preparation to harvesting, were included in the LCA. We then performed a sensitivity analysis using a Monte Carlo simulation of 1,000 iterations to obtain the most reliable result.

3.2.2 Data envelopment analysis

Due to the limitation of using single-time-frame crop data, we employed DEA for efficiency measurement. Additionally, we also used DEA–DDF, as it allows for the incorporation of undesirable outputs, such as emissions, and provides a more comprehensive assessment of eco-efficiency. The analysis was conducted using RStudio, leveraging relevant statistical and econometric packages for DEA–DDF. The methods also required a weighting process. Since the process entailed some subjectivity, the weights assigned do not match stakeholders' values.

We measured the EE ratio using a single emission index comprising various categories of impacts on the environment. The numerator was the contribution of crops to the economy and the environment, and the denominator was the inputs required to produce crops. To assign weights to environmental impacts, we adopted the AHP method (discussed further), following Zhu's (1996) approach for textile manufacturing. The weighting process for various impact categories is described below.

This study adopted a general approach to calculating eco-efficiency coined by Färe and Grosskopf (2004), wherein the production output set can be written as:

$$P(I) = \left\{(I^w, O^d, ED) \sum_{j=1}^{n} \alpha_j I_j^w \le I^w, \sum_{j=1}^{n} \alpha_j O_j^d \ge 0^d, \sum_{j=1}^{n} \alpha_j ED_j = ED, \alpha_j \ge 0,\ j = 1,2,3 \ldots n\right\}$$

here, *P(I)* represents the production possibility, α is the slack weights of input, desirable output, and undesirable output. Null jointness is imposed via the following restriction on the undesirable outputs: $ED_j > 0$, $(j = 1, 2\ldots, n)$.

EE is written as follows:

$$\frac{\sum\alpha_j O_j^d + \sum\alpha_j ED_j}{\sum I_j^w}$$

where $ED = \sum_{j=1}^{n} w_{ij} m_{ij}$. Here, m_{ij} is the midpoint impact, and w_{ij} is the subjective weight for the respective impact of the j^{th} DMU (j^{th} crop). O^d

consists of two desirable outputs: O_j^1 and O_j^2 are output 1 (crop yield) and output 2 (crop residue) of the j^{th} DMU, respectively. $\sum I_j^w$ is the weighted input of the j^{th} DMU, typically denoted as $\sum_{j=1}^{n} w_k I_{kj}$. Further, I_{kj} represents the k^{th} input of the j^{th} DMU. Similarly, w_k represents the weights for the k^{th} input. The detailed process for selecting the subjective weightage for the input and ED calculation is described further.

A directional growth was introduced to the model:

$$g = \begin{vmatrix} gO_{11} & gO_{21} & -gED_1 \\ gO_{12} & gO_{22} & -gED_2 \\ gO_{1j} & gO_{2j} & -gED_j \end{vmatrix}$$

where the direction vector g represents the desired direction in which we want to improve efficiency or move in the output space. Each component of the vector represents the weight or importance assigned to a specific output. We assumed an increase of 20% and 10% in crop yield and residue, respectively, and a 20% decrease in ED, forming a direction $\{g$ = (20%, 10%, −20%)} for each DMU, respectively. In this way, we assigned directions to the desirable outputs while imposing restrictions on the undesirable outputs.

The objective function of the model is:

$$\vec{D}\left(I_0^w, O_0^d, ED_0; g\right) = Max\,\beta$$

This objective function can be easily understood as:

$$\frac{max\ \left(\sum \alpha_J O_j^d\right) min\ \left(\sum \alpha_j ED_j\right)}{min\left(\sum I_j^w\right)}$$

Subject to:

$$\sum_{j=1}^{n} \alpha_j I_j^w \leq I_{j0}^w$$

$$\sum_{j=1}^{n} \alpha_j O_j^d \geq O_{j0}^d + \beta g_{O^d}$$

$$\sum_{j=1}^{n} \alpha_j ED_j = ED_{j0} - \beta g_{ED}$$

$$\sum_{j=1}^{n} \alpha_j \geq 0 \leq 1;\ \sum_{j=1}^{n} w_{ij} \geq 0 \leq 1;\ \sum_{j=1}^{n} w_k \geq 0 \leq 1;\ j = 1,2 \ldots n$$

As discussed earlier, due to the subjectivity of environmental damage, subjective weights were assigned to emissions. The method for assigning weight is described in the following section. The various impact categories have been aggregated to a single weighted emission (ED), which is considered an undesirable output in the study.

3.2.3 Subjective weights for impacts and inputs

To create a composite measure of environmental impact, we assigned subjective weights to individual emission categories and inputs, which are further discussed below.

a. Single emission index

In this study, we assigned weights using the AHP developed by Saaty (1980), where the emissions hierarchy is constructed based on the relative damage potential of the impacts, as adopted from Huijbregts *et al.* (2016), similar to Khangar and Mohanasundari (2023). We performed the AHP using a 15×15 matrix, where "*m*" depicts the row and "*n*" column, as shown here:

$$\begin{vmatrix} a_{11} & a_{12} & a_{13} \ldots\ldots a_{1n} \\ q_{21} & a_{22} & a_{23} \ldots\ldots a_{2n} \\ a_{31} & a_{32} & a_{33} \ldots\ldots a_{3n} \\ a_{m1} & a_{m2} & a_{m3} \ldots\ldots a_{mn} \end{vmatrix}$$ where the sum of each column "n" is

depicted as $$\begin{vmatrix} x_1 \\ x_2 \\ x_3 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{vmatrix}$$

The relative value matrix (RVM) is obtained by dividing the individual variable by the sum of columns (i.e., $X_1, X_2 \ldots X_n$). Then, the priority vectors are obtained by averaging the RVM row-wise (1):

$$RVM = \begin{bmatrix} \frac{a_{11}}{x_1} & \frac{a_{12}}{x_2} & \frac{a_{13}}{x_3} & \dots\dots & \frac{a_{1n}}{x_n} \\ \frac{a_{21}}{x_1} & \frac{a_{22}}{x_2} & \frac{a_{23}}{x_3} & \dots\dots & \frac{a_{2n}}{x_n} \\ \frac{a_{31}}{x_1} & \frac{a_{32}}{x_2} & \frac{a_{33}}{x_3} & \dots\dots & \frac{a_{3n}}{x_n} \\ \frac{a_{m1}}{x_1} & \frac{a_{m_2}}{x_2} & \frac{a_{m_3}}{x_3} & \dots\dots & \frac{a_{m_n}}{x_n} \end{bmatrix}$$

Row average of "m" $PV = \begin{vmatrix} P_1 \\ P_2 \\ P_3 \\ . \\ . \\ . \\ . \\ P_m \end{vmatrix}$ .... (1)

The priority vectors function as ambivalent weightage for the respective impact categories. To confirm the weightage, we checked the consistency of the weights. The weighted sum matrix (WSM) was calculated based on the matrix provided in equation (2) to proceed further:

WSM = $P_1 \begin{vmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{1n} \end{vmatrix} + P_2 \begin{vmatrix} a_{21} \\ a_{22} \\ a_{23} \\ a_{2n} \end{vmatrix} + P_3 \begin{vmatrix} a_{31} \\ a_{32} \\ a_{33} \\ a_{3n} \end{vmatrix} + \dots\dots\dots P_m \begin{vmatrix} a_{m_1} \\ a_{m_2} \\ a_{m_3} \\ a_{m_n} \end{vmatrix}$ ...... (2)

Thereafter, we divided all the elements of the WSMs by their respective priority vector element (i.e., $P_1, P_2 \dots. P_m$). Then, λ_{max} was obtained by estimating the average of the values derived when WSMs were divided by the respective priority vector elements. Next, we calculated the consistency index (CI) as follows:

$$CI = \lambda_{max} - n / n-1$$

The consistency ratio (CR) is calculated by dividing the CI by the average random consistency. On the condition that CI < 0.1, the calculation is deemed acceptable (Golden and Wang 1989); the priority vector elements (i.e., $P_1, P_2 \dots. P_m$) were considered as the weightage for the respective impact categories.

b. Weights used for agri-inputs

The agro-production scenario has various inputs such as seeds, soil nutrients, crop protection chemicals, fuel, and water. However, considering Golany and Roll's (1989) rule of thumb for dataset size, the inputs were aggregated into a single-weighted input. As this study involved seven DMUs, we limited it to three outputs (including one undesirable output) and one input to achieve good discriminatory power from the CCR and BCC models. The uniform weighting method was adopted to assign weights to the inputs manually. We assigned a conditional equal weight to each input ($w_i = \frac{1}{n}$ or $\sum_{i=1}^{n} w_i = \frac{1}{n} + \frac{1}{n} + \frac{1}{n} \cdots \frac{1}{n} = 1$; where "$w_i$" represents the assigned weight for the respective input, and "n" represents the number of inputs), assuming that each input is equally important for the production process. Another reason for using this weighting approach was to ensure the balanced treatment of each input, making it a practical scheme in agricultural production scenarios.

4. RESULTS

The results revealed significant environmental impacts associated with the crops, demonstrating their efficiency and performance. Detailed findings are presented below in the respective subsections.

4.1. Environmental Impacts of Crops

The LCA results revealed distinct environmental impacts across the studied crops, highlighting differences in resource use and emissions. Key impact categories included global warming potential, land use, and eutrophication. These variations underscore the importance of crop selection in sustainable agricultural practices. The detailed results are further discussed in the subsequent subsections.

4.1.1 Descriptive statistics of environmental impacts

Table 2. Descriptive Statistics of the Environmental Impacts of Crops

Impact	Reference/ measurement unit	Mean	Standard deviation	Min	Max-	Range (max–min)
PMF	kg PM2.5 eq	1.42	0.27	0.88	2.9	2.02
FRS	kg oil eq	227.4	41.92	72.55	429.2	356.65
FWET	kg 1,4-DCB	72.32	27.85	4.5	191.67	187.17
FEUT	kg P eq	0.28	0.07	0.16	0.7	0.54
GWP	kg CO_2 eq	862.67	120.24	459.49	1387.45	927.96
HCT	kg 1,4-DCB	1438.11	786.12	4.7	5514.36	5509.66
HNCT	kg 1,4-DCB	104662.2	52556.72	567.47	346564	345996.6
ALU	m2a crop eq	293.66	95.07	16.5	597.2	580.7
MET	kg 1,4-DCB	114979.93	59004.6	6.48	389969.4	389962.9
MEUT	kg N eq	1.12	0.86	0.05	6.24	6.19
MRS	kg Cu eq	23.43	6.92	0.9	40.84	39.94
OF	kg NOx eq	6.74	1.39	3.58	14.35	10.77

OD	kg CFC11 eq	0.01	0	0.01	0.03	0.02
TEAF	kg SO_2 eq	3.79	0.5	2.71	6.56	3.85
TETO	kg 1,4-DCB	24522.12	9037.7	641.86	69653.1	69011.2

Note: ALU: agricultural land use, DSR: direct-seeded rice, GWP: global warming potential, FWET: freshwater ecotoxicity, FEUT: freshwater eutrophication, MET: marine ecotoxicity, MEUT: marine eutrophication, TEAF: terrestrial acidification, TETO: terrestrial ecotoxicity, OF: ozone formation emission, FRS: fossil resource scarcity, MRS: mineral resource scarcity, HCT: human carcinogenic toxicity, HNCT: human non-carcinogenic toxicity, OD: stratospheric ozone depletion.
Source: Authors' analysis

The average environmental impact of particulate matter formation (PMF) from all the crops ranged between 1.42 ± 0.27 (mean ± standard deviation). The average global warming potential (GWP) was found to be 862.67 ± 120.24. The land-use emissions arising from the cultivation of the selected crops were found to be 293.66 ± 95.07 per hectare of production. The descriptive statistics are presented in Table 2.

4.1.2 Crop- and category-wise environmental impacts

Table 3 presents a comprehensive environmental impact assessment for various crops, elucidating their ecological footprint across diverse categories. The study shows that direct-seeded rice (DSR) production has the highest emissions among crops. Most of the fossil fuel (diesel) induced emissions were found to be higher in DSR production. Bajra (a millet) was observed to be the most environmentally sustainable crop. In terms of PMF, DSR has the highest impact, at 2.90 kg PM2.5 eq, while bajra and soybeans exhibit comparatively lower values at 0.88 and 0.90 kg PM2.5 eq, respectively. This can primarily be attributed to field preparation and harvesting processes.

Further, DSR was found to have the highest GWP, with a value of 1,387.45 kg CO_2 eq, while bajra has the least GWP of 459.49 kg CO_2 eq. DSR and sorghum have the highest freshwater eutrophication potential, with values of 191.67 and 158.86 kg 1,4-DCB, respectively, owing to the runoff of nutrients to water bodies. Fossil resource scarcity (FRS) potential indicates that rainfed wheat has the lowest impact at 188.50 kg oil eq, while DSR records the highest impact at 429.20 kg oil eq.

The production of crops also releases certain carcinogenic and non-carcinogenic pollutants. DSR was found to have the highest potential to cause cancerous and non-cancerous diseases (Khangar and Mohanasundari 2024; Khangar *et al.* 2025); conversely, bajra has the least potential. This can be attributed to the use of agrochemicals and anaerobic conditions in DSR production, which contribute to the release of pollutants.

Freshwater ecotoxicity (FWET) values indicate that millet is the least impactful at 4.50 kg 1,4-DCB, in contrast to DSR. Terrestrial acidification (TEAF) and terrestrial ecotoxicity (TETO) similarly reveal the varying environmental impacts of different crops across multiple dimensions. Table 3 presents all other impact categories of the crops. The values contribute to a comprehensive understanding of the environmental consequences of agricultural practices, aiding in the identification of areas for improvement and promoting sustainable cultivation methods.

Table 3. Crop-wise Environmental Impacts

Impact category	**Reference unit**	**Irrigated wheat**	**Rainfed wheat**	**DSR**	**Maize**	**Sorghum**	**Millet**	**Soybean**
PMF	kg PM2.5 eq	1.3	1.4	2.9	1.0	1.6	0.9	0.9
FRS	kg oil eq	266.0	188.5	429.2	205.8	266.5	72.6	163.3
FWET	kg 1,4-DCB	36.4	36.2	191.7	66.4	158.9	4.5	12.2
FEUT	kg P eq	0.2	0.2	0.3	0.2	0.2	0.7	0.2
GWP	kg CO_2 eq	854	613	1388	931	1121	460	674
HCT	kg 1,4-DCB	2041	2420	5515	23	45	4.7	19
HNCT	kg 1,4-DCB	208033	171149	346564	1770	3310	568	1244
ALU	m2a crop eq	524.4	553.8	110.2	140.1	113.4	16.5	597.2
MET	kg 1,4-DCB	227976	186329	389970	200	244	7	135
MEUT	kg N eq	0.5	0.4	0.1	0.1	0.1	6.2	0.4
MRS	kg Cu eq	35.9	5.0	38.6	40.8	6.1	0.9	36.6
OF	kg NOx eq	5.6	6.8	14.4	3.9	7.8	5.3	3.6
OD	kg CFC11 eq	0.0	0.0	0.0	0.0	0.0	0.0	0.0
TEAF	kg SO_2 eq	4.0	3.3	6.6	2.9	4.0	3.0	2.7
TETO	kg 1,4-DCB	12658	12720	40475	69653	27687	642	7821

Note: ALU: agricultural land use, DSR: direct-seeded rice, GWP: global warming potential, FWET: freshwater ecotoxicity, FEUT: freshwater eutrophication, MET: marine ecotoxicity, MEUT: marine eutrophication, TEAF: terrestrial acidification, TETO: terrestrial ecotoxicity, OF: ozone formation emission, FRS: fossil resource scarcity, MRS: mineral resource scarcity, HCT: human carcinogenic toxicity, HNCT: human non-carcinogenic toxicity, OD: stratospheric ozone depletion.
Source: Authors' analysis using the ReCiPe 2016 midpoint impact assessment method

4.2. Eco-efficiency of Crops

In a classical DEA model, where only desirable outputs are considered, efficiency scores range from 0 to 1. A score of 1 implies full efficiency, meaning a DMU operates on the efficiency frontier. In contrast, scores less than 1 indicate relative inefficiency. The classical model prefers higher values for desirable outputs, and efficiency is maximized when a DMU achieves the highest output levels given its inputs. However, when undesirable outputs are incorporated into the analysis, the interpretation of efficiency scores can change. In the presence of undesirable outputs, lower values for these outputs are preferred. The directional distance DEA model with undesirable outputs aims to assess efficiency while minimizing undesirable outputs. In this model, the efficiency score is formulated to reflect both the maximization of desirable outputs and the minimization of undesirable outputs. As a result, an efficiency score of 0 represents a DMU that fully achieves the desirable output while minimizing the undesirable output. Scores greater than 0 indicate inefficiency, with higher values representing larger deviations from the efficiency frontier in both directions (for desirable and undesirable outputs).

This study, when conducted per the CCR model, identified three efficient decision-making units (EDMUs). Conversely, when employing the BCC model—which assumes variable returns to scale (either increasing or decreasing)—the study identified five EDMUs. The BCC model offers a more flexible approach to efficiency assessment compared to the CCR model. This discrepancy in the number of identified EDMUs underscores the influence of assumptions, specifically constant or variable returns to scale, on the outcomes of DEA studies. The efficiency ratios of the various crop productions in Madhya Pradesh are depicted in Table 4.

Table 4. Eco-efficiency of Crops under the CCR and BCC Assumptions

	Eco-efficiency	
DMU	**Constant return to scale (CCR)**	**Variable return to scale (BCC)**
IW	0.0000	0.0000
RF	0.2686	0.0000
DSR	0.0000	0.0000
Maize	0.1131	0.0000
Sorghum	0.2888	0.1981
Millet	0.0000	0.0000
Soybean	0.8975	0.8466
EDMU	3	5
AIn	0.224	0.149
AAIn	0.39	0.52

Note: IW: irrigated wheat, RF: rainfed wheat, DSR: direct-seeded rice, EDMU: number of eco-efficient crops, AAIn: aggregated average inefficiency of inefficient crops, AIn: average inefficiency of all crops.
Source*:* Authors' analysis

Under the CCR assumption, the study found that IW, DSR, and bajra (millet) can be produced efficiently in Madhya Pradesh. However, the production of RF, sorghum, soybean, and maize is relatively inefficient.

Thus, their production can be improved, and the environmental damage (ED) caused by them can be reduced. With the BCC assumption, the study observed that IW, RF, DSR, maize, and millet perform efficiently; meanwhile, sorghum and soybean are less efficient. The primary cause of this might be the crops' relatively higher input requirements and lower yield levels. These DMUs can be made efficient by achieving the target amount of output while reducing input consumption and ED.

Aggregate mean crop inefficiency was found to be 0.22 and 0.149 under the CCR and BCC assumptions, respectively, indicating that there is a 22% and 14.9% directional potential for effective resource utilization under both assumptions. Inconsistency in maize and RF efficiency, as well as inefficiency under different assumptions, suggests that these crops operate at a scale where they could potentially adjust their input usage to achieve higher efficiency levels. In the CCR model, they may appear inefficient because they are not adjusting their scale of operations optimally, whereas in the BCC model, they can adjust their scale, thus appearing efficient.

4.2.1 Targets under the CCR and BCC assumptions

This study aimed to identify and analyse the key targets for achieving efficiency among DMUs. Efficiency is a paramount consideration for organizations seeking optimal performance, effective resource utilization, and enhanced productivity. DEA was used as a robust framework for evaluating and benchmarking the performance of DMUs. As we delve into the results, it becomes evident that understanding the specific targets contributing to efficiency is essential when trying to enhance the overall efficiency and effectiveness of crops. This study sheds light on the critical factors and benchmarks that propel DMU efficiency, providing valuable insights for strategic decision-making and performance improvement.

Under the CCR and BCC assumptions, we find that inefficient DMUs can be converted into efficient ones by reducing input and ED while simultaneously increasing the desirable output (crop and residue) based on the functional direction given to them. Under the CCR assumption, the inputs of RF, maize, sorghum, and soybean can be reduced by 26.86%, 11.31%, 28.88%, and 89.75%, respectively. Meanwhile, the undesirable output (environmental damage) can be reduced by 0.01%, 0.004%, 0.03%, and 0.29%, respectively, with a significant increase in desirable outputs. Table 4 presents the results for the BCC assumption. However, assuming nonlinearity between input and output, the BCC model disseminates the best results in this situation. Under this assumption, sorghum and soybean have the potential to reduce input by 19.81% and 84.66% and ED by 0.02% and 0.27%, respectively, with a significant increase in crop residue and crop grain to become efficient DMUs. The input can be decreased by sharing it with their peer crops.

The eco-efficiency ratio and associated targets are influenced by the chosen direction vector, denoted as "*g*". For instance, when prioritizing a 10% reduction in inputs and a 40% decrease in ED—while concurrently aiming for a 20% increase in yield and a 10% increase in residue—the efficiency ratios and requisite targets for achieving crop efficiency change (Table 5).

Table 4. Targets to Achieve Eco-efficient Production (G = 0%, 20%, 10%, −20%)

	Increase and decrease under CCR (%)				**Increase and decrease under BCC (%)**			
DMU	**I**	**CY**	**CR**	**ED**	**I**	**CY**	**CR**	**ED**
IW	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RF	−26.86	0.16	7.25	-0.01	0.00	0.00	0.00	0.00
DSR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maize	−11.31	0.02	39.03	-0.004	0.00	0.00	0.00	0.00
Sorghum	−28.88	1.28	0.08	−0.03	−19.81	2.27	2.48	−0.02
Millet	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Soybean	−89.75	53.45	0.34	−0.29	−84.66	123.12	46.79	−0.27

Note: Negative values indicate a decrease. IW: irrigated wheat, RF: rainfed wheat, DSR: direct-seeded rice, I: aggregated input, CY: crop yield, CR: crop residue, ED: environmental degradation.
Source: Authors' analysis

The findings indicate that to enhance the eco-efficiency of soybean cultivation under the BCC assumption, a reduction of 25.86% in ED and 84.64% in inputs is necessary, alongside increases of 125.27% and 48.30% in yield and residue, respectively. Similarly, assuming CCR, a reduction of 26.47% in ED and 86.61% in inputs is warranted, along with increases of 100.28% and 31.47% in soybean yield and residue, respectively, to ensure sustainable crop production.

Table 5. Targets to Achieve Eco-efficient Production (G = −10%, 20%, 10%, −40%)

DMU	**CCR**					**BCC**				
	EE	**I**	**CY**	**CR**	**ED**	**EE**	**I**	**CY**	**CR**	**ED**
IW	0	0	0	0	0	0	0	0	0	0
RF	3.08	−26.24	2.16	9.15	−0.07	0	0	0	0	0
DSR	0	0	0	0	0	0	0	0	0	0
Maize	1.95	−10.89	0.5	39.72	−0.08	0	0	0	0	0
Sorghum	4.45	−27.92	2.64	1.48	−0.47	3.16	−19.81	2.31	2.53	−0.33
Millet	0	0	0	0	0	0	0	0	0	0
Soybean	73.52	−86.61	100.3	31.47	−26.47	71.84	−84.64	125.3	48.3	−25.86

Note: Negative values indicate a decrease. IW: irrigated wheat, RF: rainfed wheat, DSR: direct-seeded rice, I: aggregated input, CY: crop yield, CR: crop residue, ED: environmental degradation.
Source: Authors' analysis

It is noteworthy that efficiency ratios are contingent upon the chosen direction of inputs and outputs; however, the categorization of crops into efficient and inefficient remains consistent across both directional choices. Hence, it can be inferred that these crops demonstrate inefficiency in their production processes, underscoring the need for sustainable practices to enhance efficiency.

5. DISCUSSION

This study represents a pioneering effort in evaluating the eco-efficiency of agricultural produce in the central region of India, specifically, in the state of Madhya Pradesh. In the field of agricultural eco-efficiency, determining the returns to scale holds significant importance. Given the absence of precise information on the correlation between input and output, and the increased proportion of input to output, this study, following the approach of Fusco *et al.* (2023), adopted the constant returns to scale (CCR model) assumption. Additionally, the study employed the variable returns to scale model (BCC model) to address uncertainties and identify the sensitivity of crops to changes in scale. The DEA results reveal that when the scale of production is assumed to have no impact on efficiency, four crops—rainfed wheat, maize, sorghum, and soybean—are found to be inefficient. Conversely, when the scale of production is assumed to be disproportionate to output, inefficiency is observed only in the production of sorghum and soybeans. It is noteworthy that, despite exhibiting higher environmental emissions in major impact categories, DSR proves to be an efficient crop in both scenarios. Its efficiency score remains unaffected by the scale of production and input–output ratio.

It is crucial to recognize that the outcomes derived from DEA serve as a relative efficiency measure and vary based on the specific crop or farm. In this study, the aggregated eco-efficiency results for the selected crops reveal an aggregated average inefficiency of 0.39 at CRS and 0.52 at VRS. While these figures align closely with findings by Ding *et al.* (2024) and Fusco *et al.* (2023), they deviate slightly, reinforcing the notion that India exhibits greater ecological efficiency than China, as argued by Aslam *et al.* (2021). Zyłowski and Kozyra's (2023) investigation underscores the multifaceted nature of these results. They highlight that factors such as geographical area, cultivation season, crops included, soil condition, temperature, the use of soil nutrients, and the type of DEA model employed can influence crop efficiency. Consequently, variations in outcomes compared to other studies are to be expected. Furthermore, this study identified DSR as an efficient cultivation method, characterized by a reduced environmental impact and higher yield potential compared to traditional flooded paddy cultivation practices. This conclusion diverges from the findings of Huang *et al.* (2022) and Chaloob *et al.* (2018).

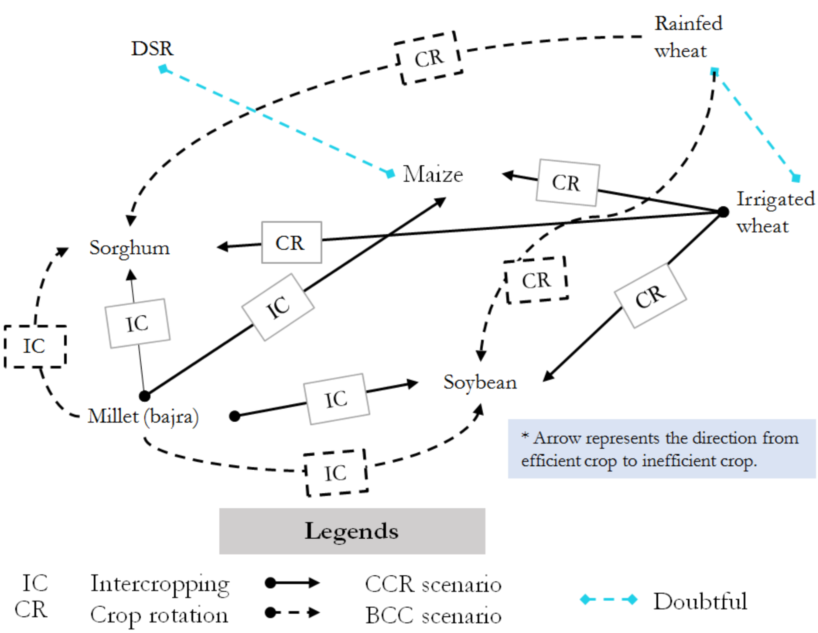
Additionally, the DEA results facilitate the identification of benchmark units from which inefficient units can seek guidance. Under the BCC assumption, to enhance the efficiency of soybean and sorghum production, rainfed wheat and millet stand out as notable reference crops, exhibiting potential avenues for improving resource utilization and productivity. In the context of CRS, irrigated wheat, DSR, and millet emerge as potential benchmarking crops, providing insights into best practices and efficient resource allocation. In the pursuit of improving the efficiency of rainfed wheat, soybean, and maize, DSR and irrigated wheat emerge as possible peer crops.

Identifying these peer crops creates opportunities for the exchange of farm inputs, including fertilizers, pesticides, and herbicides. By adopting best practices from these efficient peer crops, rainfed wheat cultivation can optimize resource use, potentially reducing its overall reliance on inputs. Furthermore, for enhancing the efficiency of soybean and sorghum production, irrigated wheat serves as a pertinent peer crop. This opens avenues for the exchange and adoption of farming techniques and inputs to elevate the efficiency of soybean and sorghum cultivation, potentially reducing the use of fertilizers, pesticides, and herbicides while promoting sustainable and resource-efficient farming practices.

The identification of peer crops for inefficient crops also provides an opportunity to exchange inputs to optimize output while minimizing both input usage and ED. This collaborative approach can be implemented through techniques such as intercropping or crop rotation, tailored to the specific season. Intercropping involves sowing crops in the same season, whereas crop rotation involves planting crops in different or successive seasons. In intercropping, two crops share nutrients concurrently, enhancing overall resource efficiency. Similarly, the immediate sowing of a different crop in crop rotation allows the utilization of existing nutrients and inputs left by the previous crop, leading to a simultaneous reduction in inputs and environmental impact. For instance, implementing a crop rotation strategy that involves planting sorghum following irrigated wheat can enhance nitrogen use efficiency and decrease reliance on synthetic fertilizers.

Figure 2 illustrates various cropping patterns and the interconnectedness of crops in both scenarios, providing a visual representation of the identified peer connections among crops and potential cropping patterns to increase eco-efficiency. The findings of this study support those of Paroda (2022) for better, sustainable, and eco-efficient agriculture. The findings from various global studies on crop rotation and intercropping, such as millet with soybean in Chapagain *et al.* (2018), wheat with soybean and maize in Janovicek *et al.* (2020), wheat with sorghum in Holman *et al.* (2023), millet with sorghum in Stoop (1987), and rice with maize in Erythrina *et al.* (2022), suggest potential benefits for these crop combinations. However, in the specific climatic conditions of Madhya Pradesh, further primary experimental investigation is necessary.

Figure 2. Peer Crops and Crop Eco-efficiency Optimization Pattern



Source: Authors' compilation

6. CONCLUSION

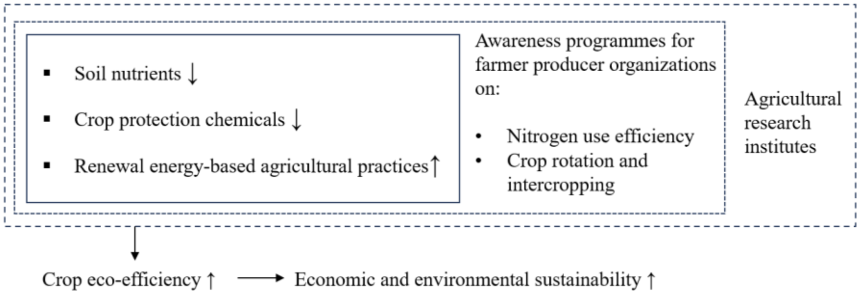
This study makes a fundamental contribution to achieving the SDGs, particularly goals 2 (zero hunger), 12 (sustainable production and consumption), and 13 (climate action). The findings highlight that eco-efficient agricultural production plays a crucial role in promoting sustainability and mitigating environmental degradation, thereby ensuring food security. Food security and environmental preservation are inherently interconnected, as efforts to enhance one invariably influence the other. In agricultural production, there is often a trade-off between increased yields and environmental depletion. This study emphasises the importance of striking a balance between productivity and sustainability, as increased crop production often leads to greater environmental degradation.

The DEA–DDF framework adopted in this study focuses on reducing input use and emissions while increasing crop production, thereby providing a valuable tool for optimizing eco-efficiency. The results demonstrate that inefficient production systems can improve their performance through peer benchmarking, wherein input usage and the environmental impact levels of inefficient crops can be adjusted to match efficiency benchmarks. The study also emphasizes that crops such as rainfed wheat and maize operate at a scale where optimizing resource use can significantly improve efficiency. Additionally, intercropping and crop rotation patterns have the potential to enhance resource efficiency.

To render these findings into action, we offer targeted policy recommendations (Figure 4). First, reducing input use and improving efficiency should be prioritized through precision agriculture, optimal soil nutrient management, and renewable energy–based mechanization to sustain yields while minimizing environmental impacts. Second, given the prevalence of intercropping in Madhya Pradesh, academia and policymaking should focus on identifying the most efficient crop rotation and intercropping patterns to enhance resource-use efficiency. Third, block- and panchayat-level farmer awareness programmes, facilitated by farmer producer organizations, can play a key role in promoting efficient input use, crop succession planning, and intercropping systems. Moreover, agricultural research institutions and extension services should strengthen their efforts to disseminate knowledge on sustainable and climate-resilient farming practices.

Finally, demonstration farms should be established to showcase successful eco-efficient farming models and provide hands-on learning opportunities for farmers. Encouraging a collaborative farming environment can promote knowledge sharing and the adoption of diversified agricultural systems, thereby maximizing productivity while minimizing environmental trade-offs. By implementing these policies, Madhya Pradesh can transition towards a more sustainable agricultural system, ensuring efficient resource utilization and reduced environmental impacts.

Figure 4. Policy Framework for Agricultural Economic and Environmental Sustainability



Source: Authors' compilation

7. LIMITATION AND FUTURE RESEARCH DIRECTION

This study relied on secondary data to estimate the environmental impacts of crop production in Madhya Pradesh, using average input use per hectare as the functional unit. While this approach allows for broad comparisons across cropping systems, it may obscure significant farm-level variations. Collecting primary data would allow for the measurement of actual on-farm input usage, leading to more accurate estimates of emissions and efficiency. This would improve the precision of LCAs by capturing the heterogeneity in farming practices that aggregated state-level data cannot reveal.

Another key limitation is the unavailability of cost data in the secondary sources used. As a result, the study could only estimate environmental and technical efficiency, but not economic efficiency. If primary data collection includes cost-related variables such as input prices, revenues, or profit margins, it would be possible to conduct a comprehensive economic–environmental efficiency analysis, going beyond technical efficiency for a more comprehensive assessment of how effectively resources are being used. This would be particularly valuable for researchers and policymakers seeking to design strategies that balance sustainability with the livelihoods of farmers.

Additionally, while crop peer benchmarking was conducted in this study, it is essential to acknowledge that some of the identified peer crops may not be agronomically or economically feasible for intercropping or crop rotation, given the regional conditions of Madhya Pradesh. For example, crops requiring high soil moisture or cooler temperatures may not perform well in areas with coarse-textured soils and semi-arid climatic conditions that are prevalent in parts of the region. Implementing such changes without context-specific validation could lead to unintended negative consequences. This warrants further exploration through localized studies that incorporate both environmental and economic criteria.

Ethics Statement: This study is based on publicly available secondary data and therefore does not require ethical approval from an institutional ethics committee.

Data Availability statement: The input data used for the Life Cycle Analysis (LCA) in this study was derived from multiple publicly available government sources, including official agricultural package of practices. Due to the fragmented nature of these sources and the integration of data across several platforms that are not centrally archived, the complete dataset is not hosted in a single repository. However, to promote transparency and facilitate further research, the processed LCA results and the subsequent Data Envelopment Analysis (DEA) outputs will be made available by the authors upon reasonable request.

Conflict of Interest Statement: No potential conflict of interest was reported by the authors.

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