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Integrating Life Cycle Assessment and Farmer Surveys to Unlock Sustainability in Rain-Fed Rice Farming of Central Java, Indonesia

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ABSTRACT

This study looks at how environmentally impacts rain-fed rice farming is in Central Java and Yogyakarta. It combines a life cycle assessment (LCA) with an understanding of how aware farmers are about the environment. The LCA was done using SimaPro 9.0, and the Impact 2002+ method was used. The system boundary was defined as cradle-to-farm gate, with a functional unit of 1 ha per cropping season. Information about the main inventory was gathered from 300 farmers, which included the average and the range of how much fertilizer and pesticide they used. The findings show that ecosystem quality and climate change are the main types of environmental harm, mostly because of heavy use of fertilizers and burning fossil fuels. The total weighted environmental impact was 345 Pt for each hectare every season. Even though farmers showed a good understanding, especially when it came to managing water resources, their views didn't match up completely with the actual environmental issues found through the life cycle assessment. The results show a difference between knowing about the environment and actually doing something to protect it, meaning that just being aware isn't enough to make a real change without help from technology and proper systems. Using both environmental data and studies on human behavior gives clear, helpful information to make better plans for managing agriculture that relies on rain.

1. INTRODUCTION

Agriculture plays a central role in Indonesia's food security and rural livelihoods, with rice as the primary staple for over half of the population. However, approximately 36% of the country's rice fields are rainfed, making them particularly vulnerable to erratic rainfall, drought, and flooding [1]. These environmental uncertainties threaten production stability and undermine national food security goals [2]. In Java, especially Central Java and Yogyakarta, rain-fed rice systems remain dominant, yet farmers often rely heavily on synthetic fertilizers, pesticides, and fossil fuels to maintain yields [3]. Such practices, while sustaining short-term productivity, have raised long-term concerns about soil degradation, water contamination, and greenhouse gas emissions.

Previous studies have investigated the biophysical and socio-economic challenges of rain-fed systems, but most have focused narrowly on yield performance or adaptation strategies without quantifying the environmental externalities associated with production [4]. Conversely, life cycle assessment (LCA) provides a standardized and systematic framework to evaluate environmental burdens across the entire production cycle [5]. LCA has been widely applied in irrigated rice systems globally, yet its application in rain-fed smallholder contexts in Southeast Asia remains limited. Moreover, earlier studies have seldom combined LCA outcomes with behavioral or perceptual dimensions, a critical gap considering that environmental sustainability ultimately depends not only on technology and inputs but also on farmers' decisions and awareness.

Recent advances in sustainability research emphasize that farmers' environmental awareness, comprising cognitive, attitudinal, and behavioral dimensions, shapes the adoption of sustainable practices [6]. High awareness may not always translate into lower impacts if behavioral or resource constraints persist [7]. Thus, integrating LCA with awareness analysis enables a dual perspective: LCA quantifies the objective environmental burdens of production, while awareness surveys capture the subjective and behavioral aspects driving those impacts [8]. This integrated approach helps to identify where knowledge or behavioral gaps contribute to unsustainable outcomes, providing a more holistic understanding of sustainability transitions in smallholder systems [9].

Accordingly, this study aims to: (1) assess the magnitude and distribution of environmental impacts of rain-fed rice farming in Central Java and Yogyakarta using LCA with SimaPro 9.0 Impact 2002+, (2) analyze the socio-demographic determinants of farmers' environmental awareness using Spearman Rank Correlation, and (3) integrate both analyses to formulate targeted mitigation strategies linking behavioral change with quantifiable environmental performance. By bridging technical and behavioral domains, this research contributes to filling the empirical gap between awareness and actual environmental outcomes, advancing the methodological scope of sustainability assessment for rain-fed agriculture in developing regions [10].

2. RESEARCH METHOD

2.1 Research location

This study used a purposive sampling method for identifying research sites. Considering the location of the rain-fed rice farmer groups, the area of rain-fed cultivation, and the respective cultivation and harvest calendars, the study identified Central Java districts of Klaten, Karanganyar, Boyolali, and Wonogiri, and Yogyakarta districts of Bantul and Gunung Kidul. These districts were focused on because in the southern parts of Java, rice farming is mainly rain-fed, as there is little to no permanent irrigation support. The initial field visit, review of the agricultural regional data, and discussions with the agricultural experts in the selected regions were used to assess the initial relevance and representativeness of the selected sites.

2.2 Sampling procedure and data collection

This study employed a quantitative descriptive design, with data collection involving structured interviews complemented by standardized questionnaires. A proportional stratified random sampling method was used for the six districts, with 300 respondents allocated based on the number of farming households in the region (Table 1). The dataset included farmers' socio-demographic data, including age, education, household size, and farming experience; data on the agricultural inputs (labor, fertilizers, seeds, and tools); and, in addition, the environmental awareness of rain-fed rice farmers in Central Java and Yogyakarta was measured using six different indicators (Table 2).

Table 1. Number of respondents

Research Location	Number of Respondents
Bantul, Yogyakarta	50
Gunung Kidul, Yogyakarta	50
Klaten, Central Java	50
Karanganyar, Central Java	50
Boyolali, Central Java	50
Wonogiri, Central Java	50
Total	**300**

2.3 Analysis technique

This study employed an LCA approach to quantify the environmental impacts of rain-fed rice farming systems in Central Java and Yogyakarta. The analysis was conducted using SimaPro 9.0 software with the Impact 2002+ method, which integrates midpoint and endpoint indicators to evaluate environmental performance across four damage categories: human health, ecosystem quality, climate change, and resource depletion. The functional unit was defined as one hectare of rain-fed rice cultivation per cropping season, representing the typical production scale of smallholder farmers in the study area. The system boundary followed a cradle-to-farm gate approach, encompassing upstream processes (fertilizer and pesticide production, fuel and electricity generation), transportation, on-farm activities (land preparation, planting, input application, harvesting), and direct field emissions. Post-harvest processing, milling, distribution beyond the farm gate, and infrastructure construction were excluded from the analysis [11].

Table 2. Environmental awareness indicator

No.	Indicator	Explanation
1	Environmental Impact Management	This indicator reflects farmers' awareness of environmental preservation through eco-friendly practices, energy conservation, deforestation prevention, and voluntary actions that support sustainability.
2	Soil Management	This indicator measures the adoption of sustainable soil practices, including fertility monitoring, use of organic inputs, efficient pesticide application, and participation in training to maintain long-term productivity.
3	Water Management	This indicator assesses farmers' capacity for sustainable water use, covering efficient irrigation, monitoring and recycling, scheduled application, and infrastructure maintenance.
4	Fertilizer and Pesticide Use	This indicator evaluates farmers' knowledge of proper fertilizer and pesticide application, emphasizing correct dosage, timing, and the integration of organic alternatives to minimize environmental risks.
5	Education and Environmental Support	This indicator highlights the role of education and institutional support in compliance with regulations, awareness of risks, and recognition of education as a key driver of sustainable farming.
6	Future Goal	This indicator captures farmers' future-oriented commitment to sustainability, including waste management planning, natural pesticide use, energy and water conservation, and alignment with government and community initiatives.

The life cycle inventory (LCI) was derived from structured survey data collected from 300 rain-fed rice farmers. The average urea application rate was 210 kg/ha per cropping season (range: 150–280 kg/ha), while NPK fertilizer averaged 175 kg/ha (range: 120–240 kg/ha). Pesticide use averaged 3.2 L/ha (range: 1.5–5.0 L/ha), reflecting variability in input intensity among farmers across the study regions. These minimum–maximum ranges were incorporated into the LCA model to enhance representativeness and capture heterogeneity in agricultural practices. Background processes were modeled using the Ecoinvent 3.9 database due to its comprehensive and internationally recognized agricultural datasets. As rice grain was considered the only product in the system, no allocation was required [12].

Direct field emissions were estimated using internationally recognized emission factors to ensure methodological transparency and comparability. Nitrous oxide (N_2O) emissions from nitrogen fertilizer application were calculated using the IPCC Tier 1 default emission factor, assuming that 1% of applied nitrogen is emitted as N_2O–N. Ammonia (NH_3) volatilization and related nitrogen losses were modeled using emission fractions embedded within the Ecoinvent 3.9 database. Pesticide emissions to soil and freshwater compartments were estimated based on standard distribution coefficients and runoff fractions ranging from 5–10%, reflecting tropical rain-fed conditions with relatively high precipitation. A ±10% sensitivity analysis was performed on key inputs, including fertilizers, pesticides, and fuel use, to evaluate the robustness of model assumptions. Environmental impacts were expressed per functional unit in standardized units: kg CO_2 eq (climate change), DALY (human health), PDF·m²·yr (ecosystem quality), and MJ primary (resource depletion). Default emission fractions provided within the Ecoinvent agricultural datasets were applied without regional modification due to the limited availability of site-specific emission measurements. This assumption ensures methodological consistency while acknowledging potential uncertainty associated with generalized emission parameters [13].

Farmers' environmental awareness was assessed using a structured questionnaire comprising six indicators measured on a five-point Likert scale. The awareness scores were classified into three levels based on predetermined criteria, namely low (1.00–2.33), moderate (2.34–3.67), and high (3.68–5.00), as presented in Table 3. Descriptive statistics were used to determine average awareness levels across indicators. Normality testing was conducted using a significance threshold of $p = 0.05$, where $p > 0.05$ indicates normal distribution and $p < 0.05$. Given the ordinal nature of several variables and the non-normal distribution identified, Spearman's Rank Correlation was employed to examine relationships between socio-demographic characteristics and environmental awareness indicators. The interpretation of correlation strength followed the classification criteria shown in Table 4, ranging from very weak (0.00–0.19) to very strong (0.80–1.00), with $p < 0.05$ considered statistically significant [14].

Table 3. Environmental awareness score and criteria

Criterion	Value
Low	1.00 – 2.33
Moderate	2.34 – 3.67
High	3.68 – 5.00

Table 4. Spearman correlation (r_s) criteria

Criterion	Value
Very weak (practically negligible)	0.00 - 0.19
Weak	0.20 - 0.39
Moderate	0.40 - 0.59
Strong	0.60 - 0.79
Very strong	0.80 - 1.00

Positive sign = direct/positive relationship; Negative sign = inverse/negative relationship. The strength categories are based on the magnitude $|r_s|$, ranging from 0 to 1, regardless of the direction of the relationship.

3. RESULTS AND DISCUSSION

3.1 Characteristics of a farmer

3.1.1 Age

Age is a key factor that affects both the physical. condition and decision-making behavior of individuals, especially in farming work [15]. As farmers get older, they usually become more careful when taking care of their farms. Resources and avoiding excessive expenditures [16]. The largest age group among respondents falls within the 48 – 60 year range, comprising 116 individuals (38.67%), while the smallest group is 22 – 34 years with only 19 individuals (6.33%). In addition, 20 respondents (6.66%) were aged over 74 years (Table 5). This distribution clearly indicates that the farming population in Indonesia is predominantly composed of older age groups, whereas the participation of younger generations remains limited [17].

Such a demographic structure presents a critical challenge for the sustainability of the agricultural sector, as the involvement of younger farmers is essential to ensure labor force regeneration, adoption of technological innovations, and long-term improvements in productivity [18]. The relatively low proportion of young farmers may hinder the development of sustainable farming systems and, consequently, pose risks to national food security in the future [19]. Therefore, strategic policy interventions are required to attract young people into agriculture, including improved access to capital, technology-oriented training programs, and initiatives to enhance the image of farming as a viable and promising profession [20].

Table 5. Farmers' age

Age	Freq.	Percent
22 – 34	19	6.33
35 – 47	68	22.67
48 – 60	116	38.67
61 – 73	77	25.67
74 - 86	20	6.66
Total	**300**	**100.00**

3.1.2 Education level

Educational attainment, as formally recognized by the Ministry of Education, shapes how individuals grow not just intellectually, but also in terms of character, spirituality, and practical skills [21]. In rural farming communities in Indonesia, however, this growth is often cut short. Most farmers never move beyond basic schooling, and this study reflects the same pattern: (77.33%) of the rain-fed rice farmers surveyed had only completed elementary school, while (16.33%) had received no formal education at all. Junior high graduates made up (5.00%), and senior high and university-educated farmers each accounted for just (0.67%) (Table 6). These numbers are telling when formal education stops early, so does a farmer's exposure to new information, which can quietly limit how they make decisions and whether they feel confident trying new, more sustainable approaches to farming [22].

Table 6. Farmers education level

Education	Freq.	Percent
No School	49	16.33
Elementary School	232	77.33
Junior High School	15	5.00
Senior High School	2	0.67
University	2	0.67
Total	**300**	**100.00**

3.1.3 Land area

The size of land is an important determinant of production capacity, income of the household, and the degree of use of new farming technologies [23]. Generally, farmers with more land are able to achieve greater yields and income, whereas those with less land have greater productivity and innovations [24]. Most of the rain-fed rice farmers (65.00%) have a small land size of between 1,000 and 18,600 m², and only 35.00% have more than 18,601 m² (Table 7). This is a fairly accurate representation of most farmers in Indonesia, who are smallholders. Such a land tenure structure is a constraint to productivity and a barrier to sustainable farming [25].

Table 7. Farmers land area data

Land Area (m^2)	Freq.	Percent
<1,000	24	8.00
1,000 – 9,300	123	41.00
9,301 – 18,600	48	16.00
18,601 – 27,400	92	30.67
>27,400	13	4.33
Total	**300**	**100.00**

3.1.4 Farmers' income

The income from the sale of agricultural products, as well as the farm gate prices and the average yield of farm products, determines the household economic welfare of farmers [26]. In terms of national income, the Indonesian farmers' income is too low, which highly limits their ability to adopt agricultural innovations of a sustainable nature [27]. Most of the farmers, both rain-fed and irrigated, operate in the range of IDR 1,000,000 to 7,399,000 margin in one cropping season (Table 8). Such a distribution highlights the income poverty of farming households, which limits their economic welfare and severely constrains their ability to experiment with and adopt new technologies, modern agricultural inputs, and increase farming per unit area. Therefore, low income is a hindrance to the advancement and adoption of sustainable agricultural practices [28].

Table 8. Farmers' net income per cropping season (IDR)

Income (IDR)	Freq.	Percent
1,000,000 – 7,399,000	261	87.00
7,399,001 – 13,799,000	30	10.00
13,799,001 – 20,199,000	3	1.00
20,199,001 – 26,599,000	4	1.33
26,599,001 – 33,000,000	2	0.67
Total	**300**	**100.00**

Table 9. Household size of farmers

Family Member	Freq.	Percent
1-2	72	24.00
3-4	168	56.00
5-6	56	18.67
7-8	3	1.00
9-10	1	0.33
Total	**300**	**100.00**

3.1.5 Family members

Table 9 shows that most farming households in this study have three to four members (56.00%), followed by those with one to two members (24.00%) and five to six members (18.67%). Households with seven or more members are uncommon, making up just (1.33%) of the sample. Moderately sized households like these can be an advantage in smallholder farming; there are usually enough family members to contribute labor without the household facing excessive pressure to meet daily consumption needs. In smallholder systems, family labor is often the backbone of farm operations, meaning household size can quietly shape how resources are divided, how much work gets done, and ultimately whether a farmer has the capacity to try more sustainable approaches [29].

3.2 Environmental awareness

Environmental awareness is widely seen as a prerequisite for shifting toward more sustainable farming practices [30]. As the primary managers of agricultural land, farmers, particularly those in rain-fed areas where production depends almost entirely on rainfall, also carry responsibility for preserving the ecosystems they work within [31]. Practices such as overusing chemical fertilizers and pesticides, burning land, and managing water poorly can lead to soil degradation, loss of biodiversity, and both freshwater and soil pollution over time. In contrast, environmentally conscious alternatives like organic fertilizer use, crop rotation, and water conservation have shown potential to support ecosystem health while also improving rain-fed rice productivity [32].

3.2.1 Average score of environmental awareness

Table 10 reflects that across all six indicators, farmers' environmental awareness is consistently classified as high. For water management, the highest score was recorded as (4.23), followed by (4.13) and (4.11) for knowledge of environmental impacts and fertilizer–pesticide management, respectively. These outcomes indicate that farmers demonstrate high levels of concern for the conservation of water, as well as understanding the dangers of chemical inputs.

On the contrary, lower scores, but still within the high category, were recorded for soil management (3.84) and education and environmental support (3.78). This indicates that farmers still need a lot more support and technical capacity in soil conservation, as well as more substantial support from institutions, in order to improve their knowledge of the environment. Improved awareness of the environment among farmers is a vital form of social capital that facilitates the sustainable practice of rain-fed rice farming [33].

Table 10. Farmers' average scores of environmental awareness

No.	Indicator	Avg. Farmers Score	Criterion
1	Environmental Impact Knowledge	4.13	High
2	Soil Management Indicators	3.84	High
3	Water Management	4.23	High
4	Use of Pesticides and Fertilizers	4.11	High
5	Education and Environmental Support	3.78	High
6	Future Goal	4.08	High

3.2.2 Correlated factors

The correlation between farmers' characteristics and environmental awareness reveals distinct patterns across the variables [34]. The Spearman Rank Correlation analysis indicates that education emerged as the most consistent and decisive determinant, showing strong and significant positive correlations across all indicators ($r = 0.714$-0.926, $p < 0.01$), underscoring its role in enhancing knowledge of environmental impacts, resource management, and the adoption of sustainable practices. Notably, although the majority of respondents had only completed elementary school (77.33%), even marginal differences in formal educational attainment appear to substantially influence environmental cognition and interpretative capacity. This finding suggests that variations within relatively low educational levels can significantly affect farmers' ability to understand input-related environmental consequences and sustainability concepts.

In contrast, age demonstrated a consistent negative and significant association ($r = -0.222$ to -0.367, $p < 0.01$), indicating that older farmers tend to be less responsive to environmental issues compared to younger cohorts [35]. Income and land size exhibited weaker yet positive associations ($r = 0.099–0.202$), suggesting that greater economic capacity and land ownership may modestly support the adoption of environmentally sound practices, though their influence is less decisive than education. Meanwhile, household size showed no significant relationship ($p > 0.05$), implying that family structure does not directly affect environmental awareness (Table 11). Collectively, these findings position education as the primary lever for strengthening farmers' adaptive capacity, while also emphasizing the need for targeted extension programs that address age-related barriers and resource constraints to foster broader adoption of sustainable practices in rain-fed rice farming systems [36].

Table 11. Spearman's rank correlations between farmers' characteristics and environmental awareness indicators (N = 300)

Environmental Awareness Indicator	Statistic	Age	Education	Income	Land Size	Household Size
Knowledge of Environmental Impact	Correlation Coefficient	-0.343	0.922	0.184	0.129	0.033
	Sig. (2-tailed)	0.000	0.000	0.001	0.025	0.569
	N	300	300	300	300	300
Land Management	Correlation Coefficient	-0.367	0.926	0.143	0.133	0.038
	Sig. (2-tailed)	0.000	0.000	0.013	0.022	0.512
	N	300	300	300	300	300
Water Management	Correlation Coefficient	-0.222	0.714	0.128	0.099	0.020
	Sig. (2-tailed)	0.000	0.000	0.027	0.088	0.729
	N	300	300	300	300	300
Use of Fertilizers and Pesticides	Correlation Coefficient	-0.311	0.713	0.059	0.101	0.055
	Sig. (2-tailed)	0.000	0.000	0.308	0.079	0.340
	N	300	300	300	300	300
Environmental Education and Support	Correlation Coefficient	-0.360	0.843	0.202	0.158	0.041
	Sig. (2-tailed)	0.000	0.000	0.000	0.006	0.484
	N	300	300	300	300	300
Future Goal	Correlation Coefficient	-0.323	0.736	0.087	0.105	0.074
	Sig. (2-tailed)	0.000	0.000	0.132	0.070	0.202
	N	300	300	300	300	300

3.3 Environmental impact assessment

3.3.1 Network

The LCA network analysis of rain-fed rice farming shows that the production and use of fertilizers, pesticides, and fossil fuels are the dominant contributors to total environmental burdens [37]. Figure 1 shows that fertilizer and pesticide production contributed to environmental emissions, followed by diesel combustion, while other supporting activities such as transportation and seed preparation contribute relatively smaller impacts. The main emission nodes were linked to urea and NPK fertilizer production, pesticide formulation, and diesel use for tillage and pumping.

The use of urea fertilizer contributed the highest share of emissions (particularly N_2O and NH_3), followed by NPK fertilizers and pesticides application, which were dominated by chlorpyrifos and carbofuran. These compounds are known for their persistence and toxicity to soil organisms and aquatic biota. The network clearly indicates that upstream input manufacturing and on-farm chemical use remain the critical hotspots in the life cycle of rain-fed rice production systems.

3.3.2 Characterization

The characterization phase quantifies the absolute magnitude of environmental impacts [38]. In the SimaPro model, the process labeled "Harvest" represents the aggregated rice cultivation process, which includes all foreground activities such as fertilizer and pesticide application, fuel use, and field emissions. The characterization results (Table 12) indicate that rain-fed rice cultivation generates considerable environmental pressures across several impact categories, particularly those related to ecosystem quality, human health, climate change, and resource depletion. Among these categories, ecosystem-related impacts appear to dominate, followed by impacts associated with human health and climate change, while resource-related impacts contribute comparatively smaller shares.

The dominance of ecosystem-related impacts is primarily associated with ecotoxic emissions originating from pesticide and fertilizer use. Several pesticide compounds commonly applied in rice cultivation are known for their persistence and toxicity to soil organisms and aquatic biota. Under tropical conditions characterized by high rainfall, runoff and leaching processes can transport agrochemical residues into surrounding water bodies, increasing the risk of aquatic toxicity and nutrient enrichment. Nitrogen losses from fertilizer application also contribute to eutrophication processes that may affect nearby freshwater ecosystems.

This result is significant for Indonesia, a recognized global biodiversity hotspot, where small-scale rice cultivation often borders natural habitats. Continuous input-intensive farming, even on small plots, thus creates localized ecological pressure that aggregates into regional biodiversity risks.

3.3.3 Damage assessment

The damage assessment translates impact categories into aggregated damage scores. The damage assessment phase (Table 13) indicated that the total damage to human health reached 0.412 DALY/ha, mainly from pesticide inhalation and fuel combustion, while ecosystem damage was 2.34E6 PDF·m²·yr, and resource consumption reached 1.03E7 MJ primary. Climate change impacts were also identified, mainly associated with greenhouse gas emissions resulting from nitrogen fertilizer application and diesel combustion during field operations. The high ecosystem damage value reflects the long-term impacts of soil acidification, aquatic toxicity, and nutrient overload caused by fertilizer and pesticide residues.

Field observation revealed that pesticide applications typically occur before heavy rain events, increasing the likelihood of runoff and non-point source pollution. In addition, most farmers lack sediment traps or vegetative buffer strips, which worsens the transfer of agrochemicals to waterways. The damage to human health was also linked to the frequent use of hand sprayers without protective equipment, resulting in chronic exposure. These findings confirm that input handling practices are a key factor influencing damage intensity in rain-fed rice systems [39].

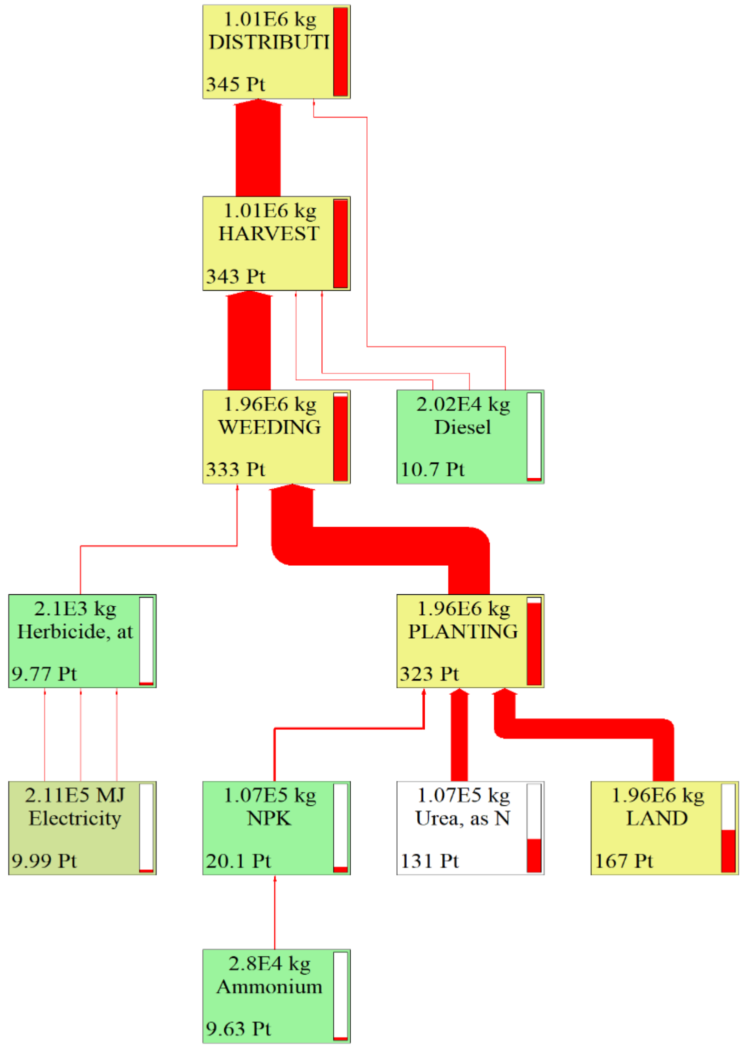

Figure 1. Network analysis of rain-fed rice

Table 12. Output characterization SimaPro 9.0

Impact Category	Unit	Total	Harvest	Diesel {RoW} Market for Diesel	Diesel {GLO} Market for Diesel	Petrol, Unleaded {RoW}
Carcinogens	kg C_2H_3Cl eq	1.35E4	1.35E4	18.3	5.93	35.7
Non-carcinogens	kg C_2H_3Cl eq	6.18E3	6.15E3	22.2	7.23	2.0
Respiratory inorganics	kg $PM_{2.5}$ eq	508	505	1.99	0.641	0.195
Ionizing radiation	Bq C-14 eq	3.54E6	3.46E6	6.09E4	2.06E4	4.89E3
Ozone layer depletion	kg CFC-11eq	0.0772	0.0747	0.00171	0.00057	0.000136
Respiratory organics	kg C_2H_4 eq	129	127	1.7	0.567	0.187
Aquatic ecotoxicity	kg TEG water	3.12E7	3.07E7	3.55E5	1.17E5	2.96E4
Terrestrial ecotoxicity	kg TEG soil	7.6E6	7.49E6	7.83E4	2.58E4	6.51E3
Terrestrial acid/nutri	kg SO_2 eq	1.38E4	1.37E4	34.9	11.5	3.28
Land occupation	m^2org.arable	2.08E6	2.08E6	14.1	4.7	1.2
Aquatic acidification	kg SO_2 eq	2.82E3	2.8E3	13.1	4.33	1.26
Aquatic eutrophication	kg PO_4 P-lim	104	103	0.721	0.239	0.0594
Global warming	kg CO_2 eq	4.83E5	4.81E5	1.28E3	419	143
Non- renewable energy	MJ primary	1.03E7	1.01E7	1.42E5	4.74E4	1.16E4
Mineral extraction	MJ surplus	2.01E4	2.01E4	13	4.31	2.15

Table 13. Output damage assessment SimaPro 9.0

Damage Category	Unit	Total	Harvest	Diesel {RoW} Market for Diesel	Diesel {GLO} Market for Diesel	Petrol, Unleaded {RoW}
Human health	DALY	0.412	0.41	0.00153	0.000492	0.000244
Ecosystem quality	PDF·m²·yr	2.34E6	2.34E6	689	227	57.7
Climate change	kg CO_2 eq	4.83E5	4.81E5	1.28E3	419	143
Resources	MJ primary	1.03E7	1.01E7	1.42E5	4.74E4	1.16E4

Table 14. Output normalization SimaPro 9.0

Damage Category	Unit	Total	Harvest	Diesel {RoW} Market for Diesel	Diesel {GLO} Market for Diesel	Petrol, Unleaded {RoW}
Human health		58.1	57.7	0.215	0.0693	0.0343
Ecosystem quality		171	171	0.0503	0.0166	0.00421
Climate change		48.8	48.6	0.129	0.0423	0.0144
Resources		67.8	66.4	0.936	0.312	0.0765

Table 15. Output weighting SimaPro 9.0

Damage Category	Unit	Total	Harvest	Diesel {RoW} Market for Diesel	Diesel {GLO} Market for Diesel	Petrol, Unleaded {RoW}
Total	Pt	345	343	1.33	0.44	0.129
Human health	Pt	58.1	57.7	0.215	0.0693	0.0343
Ecosystem quality	Pt	171	171	0.0503	0.0166	0.00421
Climate change	Pt	48.8	48.6	0.129	0.0423	0.0144
Resources	Pt	67.8	66.4	0.936	0.312	0.0765

3.3.4 Normalization

Table 14 shows that the ecosystem quality impact accounted for (49.5%), followed by resource depletion (19.6%), human health (16.8%), and climate change (14.1%). Differences between characterization and normalization shares reflect the application of regional normalization factors embedded in the Impact 2002+ method. When compared with Indonesian normalization references, the ecosystem quality impact was approximately 4.2 times higher than the average agricultural baseline.

This suggests that, although rain-fed systems require less irrigation water, their chemical intensity per hectare is relatively high. The results are consistent with regional studies [40], which reported that lowland rice ecosystems in Southeast Asia contribute substantial ecotoxic and eutrophication loads due to excessive agrochemical inputs. Therefore, in the Indonesian context, even "traditional" or "non-irrigated" systems are not inherently sustainable, as input inefficiency outweighs the environmental savings from reduced water use [41].

3.3.5 Weighting

The weighting phase prioritizes impact categories according to their relative importance. In Table 15, ecosystem quality remained the most critical impact category, accounting for (49.6%) of the total weighted score, followed by resource depletion (19.7%), human health (16.8%), and climate change (14.1%). This confirms that biodiversity loss and ecotoxicity are the dominant issues in the rain-fed rice system.

Interestingly, this result contrasts with farmers' perceptions recorded in the awareness survey (Section 3.2). Farmers reported the highest awareness in water management (mean = 4.23), followed by environmental impact knowledge (mean = 4.13), use of pesticides and fertilizers (mean = 4.11), and future goals (mean = 4.08). However, water-related environmental impacts were minimal in the LCA results due to the rain-fed nature of the system, suggesting that water management awareness does not directly translate into environmental improvement. Meanwhile, awareness related to fertilizer and pesticide use, although high, showed only a weak negative correlation ($r_s = -0.28$) with total environmental burden, indicating limited behavioral implementation of sustainable input management practices [42].

3.3.6 Alignment between environmental awareness and LCA damage categories

The comparative assessment between farmers' environmental awareness and the quantified LCA results reveals a structural misalignment between perceived environmental priorities and empirically identified environmental hotspots. Although farmers demonstrated the highest awareness in water resource management, the LCA findings indicate that ecosystem quality and climate change categories constitute the dominant environmental damage. These impacts are primarily driven by intensive fertilizer application, pesticide use, and fossil fuel consumption rather than direct water use. This discrepancy suggests that farmers' environmental perceptions may emphasize visible resource conservation while underestimating less visible but quantitatively dominant impact pathways, particularly nitrogen-related emissions and energy-based greenhouse gas contributions [43].

Furthermore, while higher awareness levels are associated with reduced chemical reliance and improved management practices, the overall environmental burden remains strongly influenced by structural constraints such as input dependency, yield optimization pressures, and limited access to low-emission alternatives. The relatively weak association between awareness indicators and total environmental burden indicates that awareness alone is insufficient to generate measurable reductions in environmental impacts. Bridging this gap, therefore, requires targeted extension strategies, fertilizer efficiency programs, and energy optimization measures to better align behavioral awareness with the environmental priorities identified through life cycle assessment in rain-fed rice farming systems.

4. CONCLUSION

This study integrates life cycle assessment and behavioral awareness analysis to evaluate the environmental performance of rain-fed rice farming systems in Central Java and Yogyakarta. The findings indicate that ecosystem quality and climate change represent the dominant environmental damage categories, primarily driven by intensive fertilizer application and fossil fuel consumption. While farmers exhibit relatively high levels of environmental awareness, particularly in water resource management, these perceptions do not fully correspond to the quantified environmental hotspots identified through LCA modeling.

The observed gap between environmental awareness and measured environmental burden suggests that awareness alone is insufficient to achieve substantial impact reduction. Structural factors, including input dependency, productivity pressures, and limited access to low-emission technologies, continue to shape farming practices. Therefore, improving environmental performance requires not only awareness enhancement but also targeted extension programs, fertilizer efficiency strategies, and energy optimization interventions. By combining environmental quantification with socio-behavioral analysis, this study contributes to a more comprehensive understanding of sustainability challenges in rain-fed agricultural systems and provides evidence-based guidance for policy and extension design.

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