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Measuring Circular Economy Index in Agriculture at the Farm Level by using the Fuzzy Analytical Hierarchy Process

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Abstract

Purpose: The Circular economy has emerged as a vital framework for achieving sustainable agriculture in the face of global climate change, environmental degradation, and rising food demand. However, most existing indicators measure circularity from isolated aspects, resulting in biased or incomplete assessments. To get a solution to the issue, this study develops a comprehensive Circular Economy Index (CEI) for agriculture at the farm level by using the Fuzzy Analytical Hierarchy Process (FAHP), and by providing a multidimensional and consistent approach to evaluate circular performance.

Design/methodology/approach: The study integrates expert judgments and farm-level data to assess circularity across the technical and impact dimensions—covering environmental, economic, and social aspects. The FAHP method enables systematic weighting of multiple indicators under uncertainty, offering a robust framework for both empirical analysis and policy evaluation.

Findings: The results demonstrate that impact-related criteria account for 61% of the total CEI weight, underscoring the dominance of environmental and social factors in assessing circularity. Among six agricultural models examined, the integrated VAC (Vuon-Ao-Chuong) system achieved the highest CEI score (42.2), highlighting its superior performance in nutrient recycling, biodiversity conservation, and overall sustainability.

Originality/value: This study is the first to design and implement a comprehensive, multi-dimensional CEI tailored to farm-level agriculture in Vietnam, overcoming the limitations of conventional single-aspect measures. It contributes to the literature of decision sciences by demonstrating how FAHP can operationalize complex and multi-criteria evaluations in uncertain contexts. For academics, the study offers a replicable model for quantitative CE assessment; and for policymakers and practitioners, it provides an evidence-based tool to identify, benchmark, and scale up circular agricultural systems that promote both economic efficiency and environmental stewardship.

Keywords: Circular economy index, agriculture, farm level, fuzzy analytic hierarchy process (FAHP), sustainability assessment

JEL Classifications: O13, Q00, Q15, R11

1. Introduction

Global climate change, environmental degradation, water scarcity, and growing demand for food have placed unprecedented pressure on agriculture, calling for a transition toward sustainable production models. The circular economy (CE) has emerged as a transformative approach to achieve sustainability by reducing resource use and waste generation, diminishing negative impacts on agroecosystems, and improving economic performance (Velasco-Muñoz, et al., 2021). CE in agriculture lessens input slack and pesticide residues, minimizing negative environmental impacts and increasing production efficiency. In this context, measuring and understanding the degree of circularity in agricultural systems becomes crucial for ensuring sustainability at the farm level and for guiding both theoretical advancement and practical decision-making in agricultural policy and management.

However, existing studies often assess circularity using fragmented or single-aspect indicators—such as recycling rates or waste reduction—without integrating social, environmental, and economic dimensions into a unified analytical structure (Kristensen & Mosgaard, 2020; Velasco-Muñoz, et al., 2021). Such partial approaches risk producing biased assessments of circular performance, limiting the capacity of policymakers and practitioners to design effective interventions. This gap underscores the need for a comprehensive, multidimensional indicator system capable of capturing the complexity of circular processes at the micro (farm) level.

Vietnam provides a compelling context for this investigation. The country's agricultural sector is both a cornerstone of national development and a major source of resource consumption and environmental stress. Over recent decades, the Government of Vietnam has incorporated CE principles into key policy frameworks, including the Law on Environmental Protection (2020), the Green Growth Strategy (2021–2030), and the Circular Economy Development Scheme (2022). These initiatives highlight agriculture as a priority sector for transitioning to zero-emission, resource-efficient, and climate-resilient systems. In this setting, the Red River Delta—Vietnam's second-largest agricultural region—faces pressing challenges such as land conversion, pollution, and declining soil fertility, while retaining great potential for innovation through integrated circular farming models such as VAC (Vuon–Ao–Chuong: garden–pond–livestock).

The motivation for this study stems from the urgent need to evaluate and guide the implementation of CE practices in such high-pressure contexts. Measuring circularity at the farm level not only helps identify high-performing models but also provides empirical evidence to support local and national policy design. Despite the growing attention to CE in Vietnam, there remains a lack of quantitative frameworks that integrate environmental, economic, technical, and social factors in a consistent and replicable manner.

To address this research gap, this study develops a Circular Economy Index (CEI) specifically tailored to agriculture at the farm level, applying the Fuzzy Analytic Hierarchy Process (FAHP) to assign relative weights to sub-indicators under uncertainty. This approach enhances the robustness of the evaluation by systematically incorporating expert judgment and multidimensional data. The research makes two principal contributions. First, it proposes a holistic CEI framework that captures the interlinked technical

and impact dimensions of circular agriculture, overcoming the limitations of conventional, single-aspect indicators. Second, it advances methodological innovation in decision sciences by demonstrating how FAHP can effectively manage subjectivity and imprecision in multi-criteria assessments, thereby offering a replicable decision-support tool for both researchers and policymakers.

By focusing on the Red River Delta as a representative case, this study provides actionable insights into how integrated farming systems—particularly the VAC model—can enhance circularity performance, strengthen environmental stewardship, and improve rural livelihoods. Ultimately, the findings aim to inform the development of evidence-based strategies and performance-driven incentives to accelerate the transition toward a circular and sustainable agricultural economy in Vietnam and comparable developing contexts.

2. Literature Review

The notion of circular economy (CE) was mentioned in the 1960s and 1970s (Stahel & Reday-Mulvey, 1976) and has gradually developed. The United Nations Environment Program defines a circular economy as keeping the value of products, materials, and resources in the economy as long as possible and minimizing waste (Hertwich, et al., 2020). CE focuses on the optimal use and reuse of resources in restorative and regenerative ways to close the loop (Rood & Hanemaaijer, 2017).

Recently, Kirchherr, et al. (2023) analyzed 221 different definitions to identify the circular economy as "a generative economic system which necessitates a paradigm shift to replace the "end of life" concept with reducing, alternatively reusing, recycling, and recovering materials throughout the supply chain, with the aim to promote value maintenance and sustainable development, creating environmental quality, economic development, and social equity, to the benefit of current and future generations. It is enabled by an alliance of stakeholders (industry, consumers, policymakers, academia) and their technological innovations and capabilities." This concept describes the "R" strategies to implement CE, the goals of CE as prolonging value and sustainable development, and the stakeholders in CE.

Within the agricultural realm, Velasco-Muñoz, et al. (2021) have defined CE in agriculture as a set of activities designed to ensure economic, environmental, and social sustainability in agriculture through activities that pursue the efficient use of resources in all stages of the value chain, as well as ensure regeneration and biodiversity in agroecosystems and surrounding ecosystems. CE in agriculture has been put into action in many countries. According to the Circular Economy Action Plan and Eco-Design Plan 2016-2019 of the European Commission (2019), the priority areas of CE in agricultural production include (1) Biomass and biological products, as some greenhouse gases commonly found in agriculture are causing a strong greenhouse effect. (2) Organic fertilizers, especially those processed from organic waste in agriculture; (3) Circulation of water, aiming at reducing the pressure of water shortage for agriculture; and (4) Prevention of food waste, optimizing food supply chains and developing the system of food waste monitoring to minimize excess local food supply at a point in time.

Another circular agriculture has been developed from the recycling model, aiming at pollution-free agricultural products and green food (Jun & Xiang, 2011). Chinese ecological agriculture has gained several achievements from a combination of advanced science and technology, traditional farming techniques, ecological principles, and a system of engineering methods to achieve high-quality, efficient, and sustainable development of agriculture and healthy cycles of both ecological and economic systems. Waste in agricultural production can go through physical, chemical, and biological transformation processes to create agricultural products and increase economic value for producers (Toop, et al., 2017).

Studies measuring CE proximity have increased in the last few years (Kristensen & Mosgaard, 2020). Several of them focus on CE in agriculture. Velasco-Muñoz, et al. (2021) classify 41 agriculture CE indicators in the literature based on CE strategies – including narrowing, closing, and generating – and sustainability dimensions comprising technical, environmental, economic, and social aspects.

The CE strategies rely on the CE principles. According to the Ellen MacArthur Foundation (EMF, 2023), a circular economy is based on three principles: (1) Elimination of waste and pollution; (2) Circulation of products and materials at their highest value; and (3) Regeneration of nature. The various Rs (such as Refuse, Rethink, Reduce, Reuse, Repair, Refurbish, Remanufacture, Repurpose, Recycle, and Recover) have been employed in many countries to turn the vision of CE into practice (Kirchherr, et al., 2023; Potting, et al., 2017; Zero Waste International Alliance, 2022).

Regarding the recovery of materials and energy from waste, the CE indicators often focus on the input-output relationship. Moreno, et al. (2020) employ the input-output conversion ratio to analyze the performance of a promising technology that recovers energy from biomass waste in the European agricultural landscape. The nutrient circularity indicators are calculated as the amount of nutrient (nitrogen, carbon, phosphorus) that is recycled, applied to land, and uptaken by crops with respect to the amount of nutrients present in the collected organic waste (Cobo, Dominguez-Ramos, & Irabien, 2018), or nutrient losses from agricultural lands to the environment (Fernandez-Mena, Nesme, & Pellerin, 2016). Molina-Moreno, et al. (2017) evaluate the CE performance of a manure treatment process, and the CE indicators are calculated based on the three resources recovered from pig manure in the process, including water, biofertilizer, and biogas. Another indicator that can represent the circularity for biofertilizers is the nitrogen balance index, which includes inflows (N from chemical fertilizers, compost, decomposers, and sludge) and outflows (N in harvested crops, leaching, as well as loss of N_2O , $-NH_3$, and $+NO_x$) (Valkama, et al., 2016). The partial nitrogen balance index, which comprises partial nitrogen balance and nitrogen recycling rate, is intended to evaluate the performance of mixed crop and animal husbandry using nutrient management indicators (Tadesse, et al., 2019).

To measure the degree of material circulation, Cobo, Dominguez-Ramos, and Irabien (2018) propose a circularity indicator of components, which is the amount of the element with an extended lifetime due to technological progress compared to the amount of that component present in the collected waste. This index aims to study the recycling of components in an organic waste treatment system. The Waste-output

index (WOI) is calculated based on the amount of waste per output unit (de Kraker, et al., 2019); $WOI = 0$ if there is no waste, reflecting an entire circular system.

Laso, et al. (2016) evaluate different scenarios related to the waste management of canned anchovies by comparing energy consumption. Recovering energy and biofuel generation are also employed to measure CE in agriculture (Martin, et al., 2017; Moreno, et al., 2020).

In terms of environmental impact, carbon emission attracts the most attention from academia (Fernandez-Mena, et al., 2020; Iacovidou, et al., 2017; Lim, et al., 2019; McBride, et al., 2011; Moreno, et al., 2020; Repo, Tuomi, & Liski, 2011). Reducing environmental burdens on air and water is also considered (Laso, et al., 2016; Zabaniotou, 2018). Zoboli, Zessner, and Rechberger (2016) measure the phosphorus released into the water since phosphorus in water limits plant growth and eutrophication of water resources. Phosphorus can also have adverse effects on human health. Zabaniotou (2018) measures water quality through the contaminants released into the water bodies. The author also evaluates soil quality as the percentage of land area that is maintained or improved in quality in the total land area.

Economic impacts in CE models are measured using standard economic indicators such as Net Present Value (de Kraker, et al., 2019; Moreno, et al., 2020), Internal Rate of Return (Moreno, et al., 2020), Return on Investment (Matrapazi & Zabaniotou, 2020), Payback Period (de Kraker, et al., 2019; Matrapazi & Zabaniotou, 2020), Gross Margin (Tadesse, et al., 2019), and Net Income (Tadesse, et al., 2019).

Although social impacts are mentioned in various CE definitions (Kirchherr, et al., 2023), few studies use social indicators to measure CE proximity. In bioenergy production, Zabaniotou (2018) considers the change in unpaid time spent by women and children collecting biomass and allocation and tenure of land for new bioenergy production. Zhijun and Nailing (2007) suggest the unemployment rate and social security coverage for CE in China. Golinska, et al. (2015) consider the harmfulness of the production process in the classification of the sustainability level of remanufacturing companies. Still, this indicator applies to the agricultural sector.

Table 1 lists the CE indicators in the literature taken from Kristensen and Mosgaard (2020); Sassanelli, et al. (2019); Velasco-Muñoz, et al. (2021), and others. These indicators are selected as they are applicable at the farm level.

Table 1. Indicators to measure the circular economy in agriculture

Aspect	Indicators	Sources	Description	Notes
Technical aspect	Indicator of CE efficiency for biofertilizer	Molina-Moreno, et al. (2017)	The mass flow of biofertilizer obtained during the pig manure treatment process is divided by the mass flow of digestion generated during the anaerobic digestion stage	Biofertilizer products often include other organic materials, such as leaves, straw, etc.
	Nitrogen balance	Fernandez-Mena, et al. (2020); Valkama, et al. (2016)	Nitrogen input from fertilizers and output in crops	Measuring nitrogen output in crops becomes more complicated when there are many different crops.

Aspect	Indicators	Sources	Description	Notes
	Partial nitrogen balance	Tadesse, et al. (2019)	The difference between farmer-managed N inputs and N outputs	
	N use efficiency	Tadesse, et al. (2019); Wang, et al. (2008)	The ratio between the harvested N output and the managed N inputs	
	N recycling index	Banerjee, et al. (2017); Rufino, Hengsdijk and Verhagen (2009); Tadesse, et al. (2019)	The proportion of total N that is recycled. Total N is the sum of N recycled in the farm and N input imported from external sources.	N in biofertilizers varies significantly depending on species and the ingredients of biofertilizers. Measuring N is not an easy task.
	Indicator of CE efficiency for water	Molina-Moreno, et al. (2017).	The rate of water recovered is in total water use.	The water recovery rate in total water use makes sense for the manure treatment process, but it is not a correct indicator for planting.
	Indicator of CE efficiency for biogas	Molina-Moreno, et al. (2017).	The rate of biogas obtained in total natural gas use	Total natural gas should be replaced with total energy use for a more general indicator.
	Circularity indicator of component <i>i</i>	Cobo, Dominguez-Ramos and Irabien (2018)	The amount of component <i>i</i> with extended lifetime owing to service in the upstream processes with respect to the amount of that component present in the collected waste.	The components from the collected waste need to be measurable.
	Nutrient circularity indicator	Cobo, Dominguez-Ramos and Irabien (2018)	The amount of nutrient <i>i</i> that is recycled and applied to land and taken up by corn with respect to the amount of nutrient <i>i</i> present in the collected organic waste.	Measuring nutrients becomes more complicated when there are many different crops simultaneously.
	Food circularity Papangelou, Achten and Mathijs (2020)	Papangelou, Achten and Mathijs (2020)	Phosphorus reused or reusable in total phosphorus input	Measuring phosphorus in food becomes more complicated when there are many different ingredients.
	Thermal efficiency	Moreno, et al. (2020)	The ratio between the energy recoverable from the combustion of the product and the potential energy of the product	This indicator does not measure the energy recovered from biogas and other thermal collection methods.
	Emergy investment ratio Liu, et al. (2018)	Liu, et al. (2018)	Ratio of purchased emergy resources to free local emergy resources	Emergy refers to the amount of available emergy used directly and indirectly to make products or services expressed as solar emjoules per joule (seJ) Liu, et al. (2018).
	Emergy Yield Ratio	Liu, et al. (2018); Santagata, et al. (2020)	The ability of a system to provide a yield by investing energy resources from outside. The lowest value is when a process provides the same amount of emergy invested, equal to 1.	

Aspect	Indicators	Sources	Description	Notes
	Emergy loading ratio	Liu, et al. (2018); Santagata, et al. (2020)	Ratio of emergy from nonrenewable resources to renewable resources	AFEF = 1 indicates technically efficient production, and AFEF = 0 shows technically inefficient production. Nutrients disposed of on land are considered recycled, not waste. Although this indicator was initially applied to canned anchovy production, it is applicable to agriculture. Although these indicators are suggested for assessment at a national level, they are appropriate when we would like to compare the different production activities at the farm level.
	Emergy ratio of wasteful to renewable resources	Liu, et al. (2018)	Ratio of emergy in waste to emergy in renewable resources	
	Renewable fraction of emergy used	Santagata, et al. (2020)	Percentage of emergy from local renewable resources	
	Agricultural Foods Economic Efficiency	Guo (2015).	Technical efficiency of producing agro-food outputs from inputs	
	Waste-output index	Cobo, Dominguez-Ramos and Irabien (2018); de Kraker, et al. (2019)	Nutrients go to landfills or are lost during treatment out of the total nutrient inputs.	
	Natural resources index Laso, et al. (2016)	Laso, et al. (2016)	Consumption of energy, materials, and water for the considered process/product	
	Reduction indicators	Zhijun and Nailing (2007)	For example, land-output ratio, annual reduction ratio of material consumption per output value, energy consumption per output value, water consumption per output value, and waste discharge per output value	
	Reuse indicators Zhijun and Nailing (2007)	Zhijun and Nailing (2007)	For example, reuse ratios of water, products, or energy.	
	Resource indices	Zhijun and Nailing (2007)	For example, utilization ratios of industrial waste gases, solid wastes, and urban domestic wastes	
	Consumption of fossil-P fertilizers	Zoboli, Zessner and Rechberger (2016)	Consumption of fossil-P fertilizers	
Environmental impact	Overall greenhouse gas balance	Moreno, et al. (2020)	Total of CO ₂ emissions per unit of output in all production processes	Calculating CO ₂ emissions at the farm level is quite complicated, especially when we try to estimate the CO ₂ emissions from different types of farm waste.
	Circular carbon elements within the system	Lim, et al. (2019)	Carbon emissions and carbon fixation per unit of land use	
	Carbon balance	Fernandez-Mena, et al. (2020).	The difference between CO ₂ emission and avoided CO ₂ emission.	
	Net carbon equivalent emissions	McBride, et al. (2011).	Contribution of bioenergy systems to greenhouse gases	

Aspect	Indicators	Sources	Description	Notes
	Avoided carbon emissions	Iacovidou, et al. (2017).	Savings from energy substitution by renewable energy, measured in tCO ₂ e	Although this indicator was initially applied to canned anchovy production, it is applicable to agriculture. The calculation of indicators is complicated.
	Indirect carbon dioxide (CO ₂) emissions	Repo, Tuomi and Liski (2011).	Carbon emissions into the atmosphere	
	Environmental burdens on air	Laso, et al. (2016).	Complex indicator of atmospheric acidification, global warming, human health (carcinogenic) effects, stratospheric ozone depletion, photochemical ozone (smog) formation	
	Environmental burdens on water	Laso, et al. (2016).	Complex indicator of aquatic acidification, aquatic oxygen demand, ecotoxicity to aquatic life (metals to seawater), ecotoxicity to aquatic life (other substances), and eutrophication	
	Emissions to water bodies	Zoboli, Zessner and Rechberger (2016).	The amount of phosphorus emitted to water bodies	Phosphorus is considered harmful to the water environment
	Net present value	de Kraker, et al. (2019); Moreno, et al. (2020).	The difference between the present value of cash inflows and the present value of cash outflows over a period of time	These indicators are often used to evaluate economic performance at a firm level. In agriculture, the value of agricultural land as an investment should be paid attention to.
	Internal rate of return	Moreno, et al. (2020).	The discount rate that makes the net present value (NPV) of all cash flows equal to zero	
	Return on Investment	Matrapazi and Zabaniotou (2020)	The ratio between net income (over a period) and investment	
	Payback period	de Kraker, et al. (2019); Matrapazi and Zabaniotou (2020).	The amount of time it takes to recover the cost of an investment	
	Pay-out time	Matrapazi and Zabaniotou (2020).	Time required to recover the initial investment	
	Gross Margin	Tadesse, et al. (2019).	Gross value minus variable costs	
	Net farm income	Tadesse, et al. (2019).	Gross margin minus total fixed costs	
Social Impact	Change in the unpaid time spent by women and children collecting biomass	Zabaniotou (2018).	The average number of unpaid hours women and children spend collecting biomass	Although these indicators are initially suggested for the national level, they apply to the farm level.
	Allocation and tenure of land for new bioenergy production	Zabaniotou (2018).	Percentage of land used for new bioenergy production	

Aspect	Indicators	Sources	Description	Notes
	Harmfulness of the production process	Golinska, et al. (2015).	The consequences associated with the threat to the safety and health of workers in the production process	

Note: This table summarizes key indicators for assessing circular economy practices at the farm level, compiled from a comprehensive review of existing literature. Indicators are organized into four main dimensions: technical, environmental, economic, and social, providing a foundation for developing a multi-dimensional CE assessment framework.

Using a multidimensional approach, Shen, et al. (2013) employ a set of indicators of both performances, such as eco-design, resource consumption, environmental certifications, green commitment from managers, use of environmentally friendly materials, staff environmental training, and sustainable aspects, including pollution production, the ratio of green customers to total customers. Wibowo and Grandhi (2017) also consider the technical, commercial, environmental, and societal aspects of CE to evaluate the performance of recoverable end-of-life products. Petit, Sablayrolles, and Yannou-Le Bris (2018) relate eco-social and ecological indicators for assessing the sustainability of a food value chain. The indicators include carcass pH, maximum transport without pause, localness, farmer welfare, employee welfare, biodiversity, GMO feed ratio, water losses after cooking, additional cost paid to the farmer, and production valorization loss rate.

3. Methods and Data

3.1 Research Approaches

This study applies different approaches to selecting indicators to develop a broad CE index at the micro level.

Material and energy balance: This approach is widely used in studies using Material Flow Analysis (MFA) or Material Flow Cost Accounting (MFCA) (Cobo, Dominguez-Ramos, & Irabien, 2018; Fernandez-Mena, et al., 2020; Franklin-Johnson, Figge, & Canning, 2016; Grimaud, Perry, & Laratte, 2017; Pagotto & Halog, 2016; Pauliuk, 2018; Santagata, et al., 2020). This approach applies the first law of thermodynamics, i.e., the total energy in a system remains constant, although it may be converted from one form to another. The total amount of material and energy input into the production process will equal the total amount of material and energy output, which are favorable products or waste. This approach identifies the material loss during production and hints at minimizing waste.

Circular value chain approach: This approach is found in studies using Life Cycle Assessment (LCA) and its related methods such as Life Cycle Inventory (LCI), Life Cycle Impact Assessment (LCIA), Life Cycle Sustainability Assessment (LCSA) (Angelis-Dimakis, Alexandratou, & Balzarini, 2016; Biganzoli, Rigamonti, & Grosso, 2018; Fregonara, et al., 2017; Gbededo, Liyanage, & Garza-Reyes, 2018; Hadzic, Voca, & Golubic, 2018; Huysman, et al., 2017; Laso, et al., 2016; Martin, et al., 2017; Molina-Moreno, et al., 2017; Park & Chertow, 2014; Petit, Sablayrolles, & Yannou-Le Bris, 2018). The value chain approach is commonly used in analyzing an organization's or industry's production and business activities to understand the actors participating in the chain and their linkages, thereby improving the value chain. The

classical linear value chain approach concerns useful products that pass through the chain of activities in order, and at each activity, the product acquires some added value. The circular value chain is a closed-loop system that focuses on reusing, repairing, refurbishing, remanufacturing, repurposing, recycling, and recovering products and materials (Eisenreich, et al., 2022). The circular value chain is interested in valuable products and waste, and finding solutions to recycle and recover waste.

Efficiency approach: The implementation of the circular economy in agricultural production relates to the efficiency of each activity and the overall production cycle. Indicators of economic efficiency, technical efficiency, social efficiency, ecological efficiency, and environmental efficiency are considered. Data Envelopment Analysis (DEA) and Input-Output (I-O) analysis are the two prominent methods to estimate CE indicators based on the efficiency approach (Guo, 2015; Liu, et al., 2018; Matrapazi & Zabaniotou, 2020; Molina-Moreno, et al., 2017; Moreno, et al., 2020; Pagotto & Halog, 2016; Tadesse, et al., 2019; Vasa, Angeloska, & Trendov, 2017; Zabaniotou, 2018).

Sustainable development approach: Concerns the agricultural system's economic, social, and environmental sustainability (Sachs, 2015). The sustainable development approach is applied in multi-criteria analysis, such as Multi-Criteria Decision Methods (MCDM), Multiple-Attribute Decision-Making (MADM), and fuzzy logics to determine the importance of economic, social, and environmental factors and their sub-criteria (Cobo, Dominguez-Ramos, & Irabien, 2018; Iakovou, et al., 2009; Ng & Hernandez, 2016; Olugu & Wong, 2012; Petit, Sablayrolles, & Yannou-Le Bris, 2018; Shen, et al., 2013; Wibowo & Grandhi, 2017; Xia & Ruan, 2020; Xu, et al., 2018).

The review of studies shows that assessing the approximation of CE involves many different technical aspects (the Rs) in production cycles and sustainable elements (economy, society, environment) when considering CE outcomes. The most popular methods in literature are Multi-Criteria Decision Making (MCDM) and its related models. MCDM can deal with many aspects of both quantitative and qualitative measurements at different scales. Among the systems of MCDM methods, the Analytical Hierarchy Process (AHP), introduced by Thomas Saaty in 1980, is one of the widely used methods to solve multi-criteria decision problems because of its simplicity and ease of use. AHP assigns higher weights to the more critical criteria based on pairwise comparison (Saaty, 2008). Fuzzy AHP merges the strength of Fuzzy methods with AHP to allow uncertain, imprecise, subjective judgment and vague contexts (Liu, Eckert, & Earl, 2020). The following section describes how the fuzzy AHP is applied in developing the CE index for agriculture in the Red River Delta of Vietnam.

3.2 Fuzzy Analytic Hierarchy Process (FAHP)

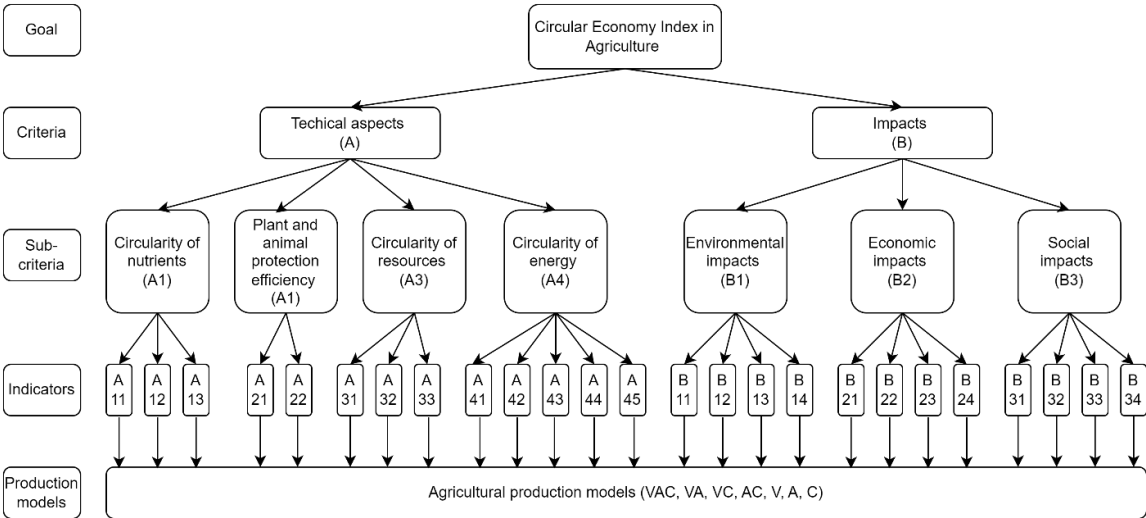
3.2.1 Hierarchical Structure Development

The Analytic Hierarchy Process (AHP) is a flexible tool for decision support analysis, providing a quantitative evaluation technique for mixed quantitative and qualitative data. AHP builds a hierarchy that breaks down decisions from top to bottom, with goals at the top, criteria and sub-criteria in the middle, and choices at the bottom. The opinions of experts and decision-makers on the importance of the criteria

are compared in pairs, and the option with the highest ranking will be considered the best option. AHP procedures are relatively simple, so AHP and FAHP have been widely applied to many fields in natural, economic, and social sciences (Liu, Eckert, & Earl, 2020). Several studies have found AHP and FAHP in the agricultural sector (Kumar, et al., 2022; Ngo, et al., 2021; Peng, et al., 2015; Wang, et al., 2019).

The first stage in applying FAHP is to develop a hierarchical structure for evaluating the CEI. This study proposes a broad CE measure to be applied at the farm level, including two groups of sub-indicators reflecting technical and impact aspects. Each group has sub-criteria; each sub-criterion is measured by a specific set of indicators (Figure 1). This hierarchy is appropriate for classifying CE indicators by Velasco-Muñoz, et al. (2021).

Figure 1. Proposed hierarchy for a circular economy index in agriculture



Note: This figure illustrates the hierarchical structure used to construct the Circular Economy Index (CEI) at the farm level. The model comprises two primary dimensions—technical aspects and impact aspects—each containing sub-criteria and associated indicators. This hierarchy guides the application of the FAHP methodology for weight assignments.

The selection of indicators follows the hierarchical structure illustrated in Figure 1. To provide a comprehensive overview, the complete hierarchy of criteria, sub-criteria, and indicators, along with their measurement details, is presented in Appendix Table A1. While Figure 1 outlines the two main aspects (technical and impact) and their sub-dimensions, Table A1 elaborates on each sub-criterion by listing specific measurable indicators. For example, under the technical aspect (A), indicators such as resource efficiency, recycling ratio, and input substitution are specified. Under the impact aspect (B), environmental and socio-economic indicators are included. In this way, Figure 1 conveys the conceptual framework, while Appendix Table A1 provides the operational details necessary for constructing the CEI.

The first group relates to circularity’s technical aspects in agriculture based on the CE principles (Ellen MacArthur Foundation, 2023). The indicators focus on the circularity of nutrients, energy, and other materials related to the first and second principles. They include designing the production system for local circulation, eliminating external inputs by reusing and recycling materials and waste (Fernandez-Mena, et al., 2020), and using renewable energy and recovering energy within the system (Liu, et al., 2018).

Indexes on rates of organic and recycled nutrients, including nitrogen and phosphorus, are employed to measure the circularity of nutrients, following several authors (Molina-Moreno, et al., 2017; Papangelou, Achten, & Mathijs, 2020; Tadesse, et al., 2019; Valkama, et al., 2016; Zoboli, Zessner, & Rechberger, 2016). The nutrient circularity indexes are intended to maximize the local circulation of the fertilization process. They can explain the level of nutrients (nitrogen, phosphorus) circulating on a farm and account for the effort to recycle these nutrients by exchanging materials between farms (Fernandez-Mena, et al., 2020).

The indicators on the circularity of energy and materials are developed similarly. The rates of biogas/other renewable energy used on farms and the rate of recycled energy reflect the conditions for maximum use of natural capital [41], recovering energy from organic waste, and reducing fossil fuel consumption (Liu, et al., 2018). The rate of recycled organic waste, the rate of recycled inorganic waste, the rate of recycled water, and the rate of recycled materials measure the circularity of materials, as suggested by Fernandez-Mena, et al. (2020) and Cobo, Dominguez-Ramos, and Irabien (2018).

The third principle considers the regenerating of nature by improving the nutrient loop and ecological balance on farms and improving efficiency in plants and animal production by enhancing their ecological balance and reducing the use of pesticides, insecticides, and other medical treatment substances that pollute the environment and human health (Tadesse, et al., 2019). So, the number of species, including plants and animals, to be protected from symbiosis and the rate of bioproducts in total plant and animal protection drugs used on farms are considered components of CE indicators (Molina-Moreno, et al., 2017).

The second group relates to the impacts of CE in terms of environmental, economic, and social aspects.

The environmental criteria reflect the level of environmental pollution or pollution minimization effort of production activities (Fernandez-Mena, Nesme, & Pellerin, 2016) as measured by the amount of phosphorus and other contaminants released into the water source (Zoboli, Zessner, & Rechberger, 2016), the quality of wastewater (Zabaniotou, 2018), the waste-output ratio (de Kraker, et al., 2019), and the soil quality maintenance (Zabaniotou, 2018). Except for the latter, the other indicators reflect the negative side, so we will subtract those indicators from one to come up with a positive indication of environmental impacts.

The economic indicators reflecting economic efficiency include (1) Internal Rate of Return, (2) Value Added Index, (3) Return on Investment, and (4) Payback Period.

Internal Rate of Return (IRR) is the discount rate that sets the net present value of all cash flows to zero, as determined by the formula:

$$NPV = \sum_{t=0}^T \frac{C_t}{(1 + IRR)^t} = 0, \quad (1)$$

where NPV is the net present value with a discount rate at IRR , and C_t is the net cash inflow during period t , IRR is the internal rate of return, and T is the total number of periods. If $IRR > r$, where r is the real interest rate, the production plan is profitable and should be invested. If $IRR < r$, the project is unprofitable by the end of the investment period T and should not be financed. The Internal Rate of Return assesses the efficiency or profitability of a CE investment.

The value-added index (VAI) is the ratio between the added value divided by the value of the resources used in production or process (Di Maio, et al., 2017). This index aims to assess the economic performance of supply chain actors in terms of resource efficiency and circularity. It also measures resource efficiency based on the resource's environmental burden relative to output and measures its value creation.

Return on Investment (ROI) is calculated by net return divided by the cost of the investment (Matrapazi & Zabaniotou, 2020; Tadesse, et al., 2019). In agriculture, the net return is often measured as net income, calculated from the total revenue minus the farm's total costs (Tadesse, et al., 2019). For ease of assessment, costs on agricultural land are not counted in investment or expenditure. ROI is an indicator of farm profitability.

$$ROI = \frac{\text{Net income}}{\text{Cost of investment}} \quad (2)$$

ROI is a measure of profitability. It is also used as an effective economic management solution, providing businesses with socio-ecological innovation to find the returns of effective investments. However, ROI does not consider the length of time an investment is held.

The payback period is the time it takes for the project to generate net cash flows equal to the initial investment cost (Matrapazi & Zabaniotou, 2020). The period is measured in the number of years out of 10, assuming that most investments can be paid back within ten years.

ROI and payback period help investors manage their investments. They help compare alternatives for eco-innovative solutions in the circular economy, identifying opportunities for an efficient circular economy.

The social impacts are measured regarding work safety, health effects from agricultural chemical use on farmers and communities, and job creation (Golinska, et al., 2015; Zabaniotou, 2018; Zhijun & Nailing, 2007).

A survey of household farms in the Red River Delta in 2023 was conducted to collect data on the CE indicators. Six types of farms were chosen to represent different agricultural production models, including (1) gardening only (V), (2) fish farming only (A), (3) animal husbandry only (C), (4) integrated planting and fish farming (VA), (5) gardening and animal husbandry (VC), and (6) integrated planting, fish farming, and animal husbandry (VAC) (Paramesh, et al., 2022; Thanh, 2010).

3.2.2. Weight Elicitation using FAHP

To determine the relative importance of criteria and sub-criteria, expert judgments are elicited using pairwise comparisons on a fuzzy nine-point scale. Triangular fuzzy numbers $A_i = (l_i, m_i, u_i)$ are assigned to assess relative importance as described in Table 2.

Table 2. The scale of relative importance and equivalent fuzzy numbers

Relative importance		Assigned a fuzzy number
Equal		(1,1,1)
	Intermediate	(1,2,3)
Moderate		(2,3,4)
	Intermediate	(3,4,5)
Strong		(4,5,6)
	Intermediate	(5,6,7)
Very strong		(6,7,8)
	Intermediate	(7,8,9)
Extremely strong		(9,9,9)

Note: This table presents the linguistic scale and corresponding triangular fuzzy numbers used in pairwise comparisons under the FAHP method. The scale captures varying degrees of relative importance, enabling experts to express uncertainty and subjectivity in their judgments.

The criteria weights are calculated using the geometric mean FAHP method (Buckley, 1985).

Assume that we have t judges with n criteria, the fuzzy triangular pairwise comparison matrix of $(n \times n)$ for expert k ($k = 1$ to t) is given as:

$$\tilde{A}_k = [\tilde{a}_{ij}^k] = [l_{ij}^k, m_{ij}^k, u_{ij}^k], \quad (3)$$

where $\tilde{A}_k$ is a fuzzy matrix and $\tilde{a}_{ij}^k$ is a fuzzy number with the lower bound l_{ij}^k , middle number m_{ij}^k and upper bound u_{ij}^k , $l_{ij}^k \leq m_{ij}^k \leq u_{ij}^k$, $i = 1, \dots, n$, and $j = 1, \dots, n$.

The joint matrix from all t experts is derived by taking the geomean of the individual fuzzy matrices:

$$\tilde{A} = [l_{ij}, m_{ij}, u_{ij}] = (\tilde{A}_1 \otimes \tilde{A}_2 \otimes \dots \otimes \tilde{A}_t)^{\frac{1}{t}}, \quad (4)$$

$$\tilde{A} = \left[(\tilde{a}_1 \otimes \tilde{a}_2 \otimes \dots \otimes \tilde{a}_t)^{\frac{1}{t}} \right] = \left[\prod_{k=1}^t (l_{ij}^k)^{\frac{1}{t}}, \prod_{k=1}^t (m_{ij}^k)^{\frac{1}{t}}, \prod_{k=1}^t (u_{ij}^k)^{\frac{1}{t}} \right], \quad (5)$$

where $\otimes$ denotes fuzzy matrix multiplication, l_{ij} , m_{ij} , and u_{ij} are the lower bound, middle number and upper bound of the joint matrix $\tilde{A}$, $l_{ij} \leq m_{ij} \leq u_{ij}$, $i = 1, \dots, n$, and $j = 1, \dots, n$.

The fuzzy geometric mean matrix of criterion i is defined as:

$$\tilde{R}_i = [l_i, m_i, u_i] = [\tilde{r}_i] = \left[\prod_{j=1}^n (l_{ij})^{\frac{1}{t}}, \prod_{k=1}^t (m_{ik})^{\frac{1}{t}}, \prod_{k=1}^t (u_{ik})^{\frac{1}{t}} \right], \quad (6)$$

where l_i, m_i , and u_i are the lower bound, middle number and upper bound of the geomean matrix $\tilde{R}_i$, $l_i \leq m_i \leq u_i$ with $i = 1, \dots, n$.

We derive the fuzzy weights:

$$\tilde{W} = [l_i^w, m_i^w, u_i^w] = [\tilde{w}_i] = [\tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1}] = \left[\frac{l_i}{\sum_{j=1}^n u_j}, \frac{m_i}{\sum_{j=1}^n m_j}, \frac{u_i}{\sum_{j=1}^n l_j} \right], \quad (7)$$

where $\oplus$ denotes fuzzy matrix addition, l_i^w, m_i^w , and u_i^w are the lower bound, middle number and upper bound of the fuzzy weights, $l_i^w \leq m_i^w \leq u_i^w$ with $i = 1, \dots, n$.

Taking the center of area of the fuzzy weights, we get the non-fuzzy weights:

$$W = [w_i] = \left[\frac{1}{3} (l_i^w + m_i^w + u_i^w) \right]. \quad (8)$$

Since the sum of total weights might not equal 1, the normalized weights should be used as the final ones.

$$W_{normalized} = [w_{i_{normalized}}] = \left[\frac{w_i}{\sum_{j=1}^n w_j} \right]. \quad (9)$$

3.2.3. Consistency Verification

Since the experts' judgments are highly subjective, the evaluation results are only reliable when the subjective appraisals of each expert are consistent. Gogus and Boucher (1997) propose a consistency test for fuzzy pairwise comparisons as described as follows:

- (1) Transform a fuzzy triangular matrix into two independent non-fuzzy matrices. The first one includes the middle numbers of the triangular matrix, that is $A_m = [m_{ij}]$. The second matrix is created by the geometric mean of the lower and upper bounds of the triangular fuzzy numbers, that is $A_g = [\sqrt{l_{ij} * u_{ij}}]$.
- (2) Calculate the largest eigenvalue of the A_m and A_g matrices; we get λ_{max}^m and λ_{max}^g , respectively.
- (3) Compute the consistency index (CI) for each matrix based on the following formulas:

$$CI_m = \frac{\lambda_{max}^m - n}{n-1} \quad \text{and} \quad CI_g = \frac{\lambda_{max}^g - n}{n-1}. \quad (10)$$

- (4) Calculate the consistency ratio (CR) of the matrices using the below formulas:

$$CR_m = \frac{CI_m}{RI_m} \quad \text{and} \quad CR_g = \frac{CI_g}{RI_g}. \quad (11)$$

If CR_m and CR_g are less than 0.1, the matrices are consistent. Gogus and Boucher (1997) define RI_m and RI_g as random indices depending on n and calculate their values from 400 random matrices, as shown in Table 4.

3.2.4. CEI Calculation and Ranking

In the final stage, the validated weights are applied to the survey data collected from household farms. For each farm, indicator values are normalized and multiplied by their respective weights to generate scores for each sub-criterion. These scores are then aggregated into technical and impact scores, which together yield the overall CEI for each farm model.

The CEI results are subsequently compared across the six production systems (V, A, C, VA, VC, VAC). This allows for the ranking of farm models based on their degree of circularity. The integration of expert-derived weights with farm-level data provides a robust, multi-dimensional assessment of circular economy performance in the Red River Delta.

3.3 Data Collection

Data for this study were obtained from two complementary sources.

First, expert judgments were collected to derive FAHP weights. A group of six experts in agriculture and circular economy in Vietnam joined the judgment panel. Three of them came from universities in Vietnam, two from research institutions, and one from a governmental agency at the ministerial level. They evaluated the importance of the criteria using pairwise comparisons for each group of indicators. Four experts worked independently, and two experts worked in pairs during the interviews, so five individual sets of pairwise comparison matrices were collected.

Second, a household farm survey was conducted in April and May 2023 across the Red River Delta region. A total of 69 farms were surveyed, representing six agricultural production models as described in Table 3. Farms were selected on purpose to capture the diversity of production systems in the region.

Table 3. Data sample

Farm model	Number of farms
Gardening only	14
Fish farming only	12
Animal husbandry only	10
Integrated planting– fish farming	12
Integrated gardening–animal husbandry	10
Integrated gardening, fish farming, and animal husbandry	11
Total	69

Data was collected through a structured questionnaire and supplemented by direct observation and measurement of inputs, outputs, and circularity practices.

This dual-source dataset allows the FAHP-derived weights to be combined with empirical observations, ensuring both methodological rigor and contextual accuracy in calculating the CEI.

4. Results and Discussion

4.1 The CE Indicators

Table 4: Tests of consistency

Criteria	n	RI _m	RI _g	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5	
				CR _m	CR _g	CR _m	CR _g	CR _m	CR _g	CR _m	CR _g	CR _m	CR _g
CE	2	0		0.000		0.000		0.000		0.000		0.000	
A	4	0.7937	0.2627	0.031	0.068	0.025	0.054	0.021	0.042	0.022	0.047	0.036	0.084
A1	3	0.489	0.1796	0.019	0.075	0.055	0.094	0.019	0.017	0.055	0.094	0.019	0.075
A2	2	0		0.000		0.000		0.000		0.000		0.000	
A3	3	0.489	0.1796	0.019	0.017	0.055	0.094	0.009	0.001	0.055	0.094	0.019	0.075
A4	4	0.7937	0.2627	0.016	0.040	0.025	0.047	0.038	0.088	0.022	0.042	0.013	0.024
B	3	0.489	0.1796	0.009	0.001	0.055	0.094	0.055	0.094	0.055	0.094	0.009	0.001
B1	4	0.7937	0.2627	0.016	0.040	0.028	0.051	0.051	0.096	0.022	0.090	0.008	0.037
B2	4	0.7937	0.2627	0.021	0.064	0.008	0.037	0.023	0.045	0.051	0.096	0.021	0.042
B3	4	0.7937	0.2627	0.033	0.054	0.026	0.058	0.021	0.042	0.051	0.096	0.017	0.070

Note: This table reports the consistency ratios (CR_m and CR_g) of fuzzy pairwise comparison matrices across all expert evaluations. Values below 0.1 indicate acceptable consistency levels, ensuring the reliability of the derived weights for CE criteria and sub-criteria. Source: *RI_m* and *RI_g* taken from Gogus and Boucher (1997); *CR_m* and *CR_g* calculated in MS Excel.

As shown in Table 4, all pairwise comparison matrices satisfy CR_m and $CR_g < 0.10$ (for the corresponding matrix sizes), indicating that expert judgments are logically coherent. Consistency in the judgments of the experts is crucial as it demonstrates the reliability of the derived weights used in the FAHP (Fuzzy Analytic Hierarchy Process) model. This consistency ensures that the subjective evaluations made by each expert reflect a stable and trustworthy decision-making process, minimizing any bias or error that could affect the overall results. Consequently, the derived weights for the criteria and sub-criteria can be considered robust, and the FAHP model is more reliable for subsequent analysis and decision-making in the circular economy assessment.

According to the judges, the impact plays a more critical role than the technical aspect in evaluating CE proximity. The total weight of impacts is 0.61, in which environmental, social, and economic impacts are assigned the top three weights in the CE index, which are 0.260, 0.186, and 0.165, respectively. The technical aspect bears a total weight of 0.390, comprising circularity of energy (weight = 0.112, rank #4), plant-animal protection efficiency (weight = 0.105, rank #5), circularity of materials (weight = 0.098, rank #6), and circularity of nutrients (weight = 0.075, rank #7).

To complement the results presented in this section, the full hierarchy of criteria, sub-criteria, and their associated measurement indicators is provided in Appendix Table A1. While Figure 1 illustrates the overall conceptual structure of the CEI, Table A1 details the operationalization of each sub-criterion by specifying measurable indicators, their definitions, and their detailed weights. This table ensures transparency in how the CEI was constructed and enables replication of the methodology in future applications.

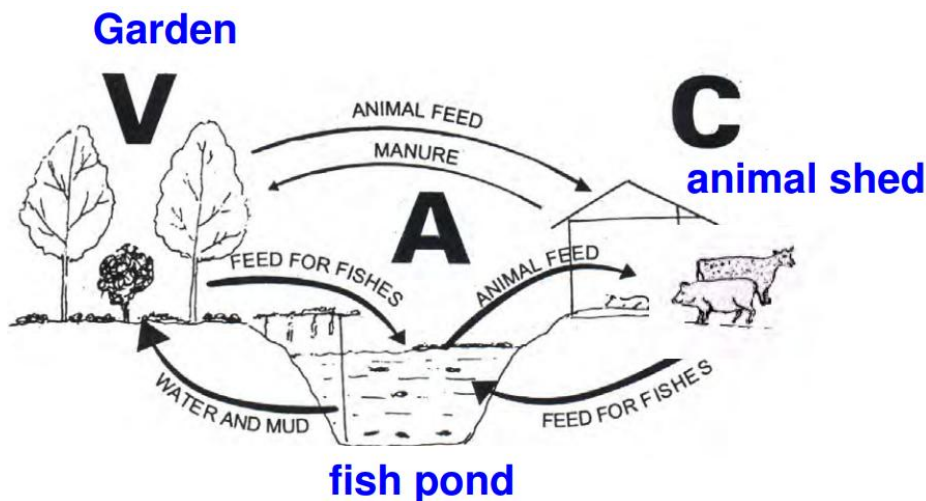
4.2 Application in Agriculture at the Farm Level

VAC-integrated farming systems are considered a good practice of circularity in agriculture (Thanh, 2010). The relationships among planting, fish farming, and animal husbandry are described in Figure 2.

Some gardening products (V) are used to feed the fish (A), and the fishpond provides water and mud to irrigate and fertilize the garden (V). Some fish can be used for animal feed (C), and manure (C) is used for plant (V) and fish food (A). In addition, animal husbandry waste (C) and planting (V) can be used to generate biogas for household use and biofertilizers for gardening (V) (Paramesh, et al., 2022).

The interdependence did not stop there; some fish reared (A) could be repurposed as animal feed (C), creating a cyclical and sustainable loop within the farming ecosystem. Moreover, the waste generated from animal husbandry (C) proved valuable, as it contributed to both plant nutrition in gardening (V) and served as nourishment for the aquatic life in fish farming (A).

Figure 2. VAC system



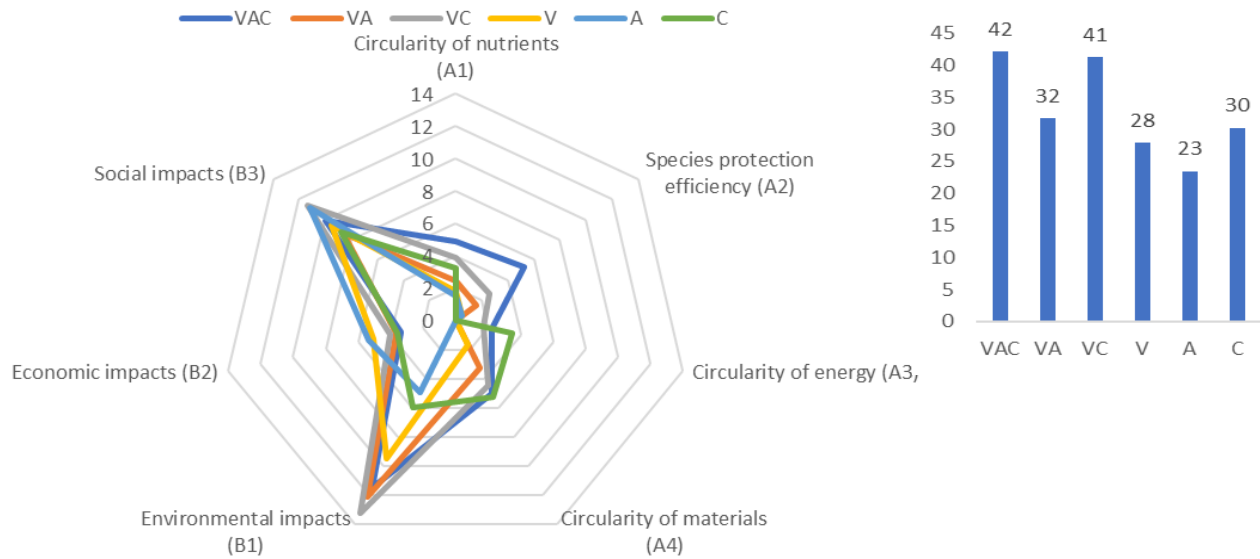
Note: This diagram depicts the interactions among the three components of the VAC model: gardening (V), aquaculture (A), and animal husbandry (C). It illustrates the material and energy flows that enable internal nutrient recycling, energy recovery, and symbiotic production relationships within the system.

Source: Thanh (2010)

Further emphasizing sustainability, the survey uncovered practices where animal husbandry waste (C) and certain planting materials (V) played pivotal roles in generating biogas for household energy needs. Simultaneously, these same waste products contributed to the production of biofertilizers, enriching the soil for gardening (V). This multifaceted approach highlighted the intricate synergy between different agricultural components, showcasing the diversity of farming models and the potential for resource optimization and environmental stewardship within the Red River Delta's agricultural landscape.

The results in Figure 3 and Table 5 illustrate the CE indices for the six types of household farming models. They show that different farming integrations have different levels of CE implementation.

Figure 3: Circular Economy Indices of Farms



Note: This radar chart compares the weighted scores of the seven main sub-criteria across six different farming models. The axes represent the final normalized scores for each sub-criterion. The accompanying bar chart shows the total Circular Economy Index (CEI) calculated as the sum of technical and impact scores for each model.

Table 5: CEIs of farms

Criteria	VAC	VA	VC	V	A	C
Technical aspect (A)	17.4	7.3	12.6	4.0	2.0	11.9
Circularity of nutrients (A1)	4.9	2.5	3.9	1.8	1.5	3.3
Species protection efficiency (A2)	5.3	1.6	2.6	0.5	0.5	0.0
Circularity of energy (A3)	2.3	0.0	1.7	0.0	0.0	3.5
Circularity of materials (A4)	5.0	3.3	4.5	1.7	0.0	5.2
Impacts (B)	24.8	24.4	28.7	24.0	21.5	18.3
Environmental impacts (B1)	11.5	12.1	13.2	9.5	5.0	5.9
Economic impacts (B2)	3.3	3.7	4.0	5.0	5.4	3.6
Social impacts (B3)	9.9	8.6	11.4	9.5	11.2	8.8
CEI	42.2	31.7	41.3	28.0	23.5	30.3

Note: This table presents the calculated scores for the technical dimension (A), the impact dimension (B), and the final Circular Economy Index (CEI) for six farm models. The CEI is computed as the sum of scores from both A and B dimensions, providing a comprehensive measure of circularity performance.

VAC, i.e., a combination of planting (V), fish farming (A), and husbandry (C), is an agricultural practice to implement the circular economy effectively in both technical and impact aspects ($A = 17.4$ and $B = 24.8$). It brings the highest benefits in nutritional circulation ($A1 = 4.9$) and is most effective in creating a symbiotic habitat for plants and animals ($A2 = 5.3$). However, in terms of energy and material circulation, VAC is less efficient than specialized livestock activities (with livestock, $A3 = 3.5$, $A4 = 5.2$, while with VAC, $A3 = 2.3$ and $A4 = 5.0$). In Vietnam, livestock farms have widely used biogas digesters and bio-mats to convert manure and leftover food into energy and fertilizer. Specialized production activities in aquaculture or animal husbandry bring smaller technical efficiency in the circular economy, and therefore, the CE indices are also lower. Households specializing in aquaculture hardly realize the circulation of

energy and materials. The ability to create a symbiotic environment is poorer, and nutrient circulation is also worse compared to other agricultural production models. Specializing in growing crops has virtually no benefit in energy circulation. Organic waste from agriculture is rarely used as cooking fuel, as it was before. In terms of impact, planting-husbandry integration is more effective than other combinations ($B = 28.7$ for VC), ranked second by VA and third by VAC. The VC combination brings good economic, social, and environmental impacts.

Meanwhile, the impact factor of the circular economy in livestock farming is lower than that of other models, especially in terms of the environment and society. Specializing in livestock production creates high levels of CO₂ emissions and a high risk of environmental pollution, thus potentially having a negative impact on society. This argument explains why the VAC model has a lower impact index than the VC model.

CEIs rank the proximity of CE at the farm level and indicate how farms can improve their CE performance. VAC is the best practice for CE among the six models, followed by VC and VA. Specialization is not an excellent approach to achieving farm-level circularity, as aquaculture is the weakest CE actor, followed by planting and husbandry farming.

5. Conclusion

The accelerating challenges of environmental degradation, resource depletion, and unsustainable agricultural practices underscore the need for robust tools to guide the transition toward a circular agricultural economy. To get a solution to the issue, this study has developed and applied a comprehensive Circular Economy Index (CEI) tailored to the farm level, with a focus on the Red River Delta of Vietnam. By integrating expert judgment and farm-level data through the Fuzzy Analytic Hierarchy Process (FAHP), the study provides a robust and context-sensitive framework for measuring circularity in agriculture.

The empirical results demonstrate that the impact-related criteria—particularly environmental impacts—carry greater weight than the purely technical dimensions in assessing circularity performance. Impact aspects accounted for 61% of the total CEI, underscoring that the benefits of circular farming extend beyond resource reuse to broader sustainability outcomes. Among the six farming models analyzed, the integrated VAC system exhibited the highest CEI score (42.2), excelling in nutrient recycling, biodiversity conservation, and overall sustainability. This finding infers that integration and symbiosis among production activities are the key mechanisms driving circular performance at the farm level. In contrast, specialized production systems such as monoculture or stand-alone aquaculture show limited capacity for internal resource circulation, suggesting the need for integrated production structures to achieve sustainable efficiency.

These results indicate that advancing circular agriculture requires a shift from isolated technical interventions to systemic, multi-actor solutions that align ecological regeneration, economic efficiency, and social well-being. The CEI framework, thus, provides a diagnostic tool to quantify and compare

circularity performance across diverse farm types, enabling stakeholders to identify best practices and improvement priorities.

The study offers several important implications. For academics, the CEI provides an operational, multidimensional measurement framework that bridges the gap between conceptual models of circular economy and empirical assessment at the micro level. It captures both technical and outcome-based aspects of circular agriculture, overcoming the narrow scope of existing single-dimension indicators. The study advances literature by integrating Decision Sciences with Sustainability Assessment, demonstrating how FAHP can be used to handle subjectivity and uncertainty in expert-based evaluations. The methodological innovation contributes to ongoing debates on how to measure circularity in complex agroecosystems, offering a replicable model adaptable to other contexts or sectors.

For practitioners and policymakers, the findings provide concrete evidence to guide decision-making and policy design. The CEI can be applied as a benchmarking and monitoring tool to assess the effectiveness of circular agriculture initiatives, track progress toward national sustainability goals, and inform the allocation of support programs. Local authorities can use the CEI results to prioritize investment in high-performing integrated models such as VAC, while extension agencies and cooperatives can employ it to design training programs promoting resource efficiency, waste reduction, and nutrient recycling. For farmers, the framework translates the abstract concept of circular economy into measurable actions that improve productivity, profitability, and environmental outcomes simultaneously.

This study makes three main contributions to the literature. First, it is the first to develop and empirically apply a comprehensive, multi-dimensional CEI specifically tailored to farm-level agriculture in Vietnam, moving beyond single-aspect or qualitative assessments commonly found in previous studies. Second, it introduces the FAHP as an analytical tool to integrate expert judgments under uncertainty, thereby enhancing methodological rigor and transparency in circular economy evaluation. Third, it provides empirical evidence linking circular practices to sustainability outcomes in a developing-country context, filling an important gap in the global CE literature that remains dominated by industrialized economies. Together, these contributions advance both theoretical and applied understanding of circularity measurement in agriculture.

Nevertheless, several limitations should be acknowledged. The analysis is confined to one geographical region—the Red River Delta—and thus may not fully capture the diversity of Vietnam's agroecological systems. The reliance on expert-based weighting introduces an element of subjectivity, even though the FAHP method mitigates inconsistency. Additionally, the cross-sectional nature of the data limits insights into how circularity evolves over time or responds to policy interventions.

Future research should therefore extend the CEI framework to other regions and farming systems across Vietnam and internationally, allowing for comparative and longitudinal analyses. Additionally, longitudinal studies could explore how circularity evolves over time, while integrating feedback loops and behavioral dimensions would enhance the model's dynamism and predictive capacity. Furthermore, expanding the indicator system to include institutional and behavioral dimensions—such as farmer

cooperation, market incentives, and governance mechanisms—would enrich understanding of how circular practices are adopted and sustained. Collaboration between researchers, policymakers, and local communities will be essential to refine and scale the CEI as both a scientific and a practical tool for sustainable agricultural transformation.

By quantifying circularity through a multidimensional lens, this study bridges the gap between theory and practice in sustainable agriculture. It provides academics with a replicable methodological framework and offers policymakers and practitioners an actionable tool for evidence-based planning. Ultimately, the CEI developed here supports a broader vision of resource-efficient, low-emission, and inclusive agricultural systems, aligning with Vietnam's national strategies for green growth and circular economy development.

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Appendix.

Table A1: Circular economy criteria and indicators

Criteria	Sub-criteria	Index	Measurement	Weights of criteria	Weights of sub-criteria	Weights of indicators	Final weights	Sub-criteria ranking
Technical aspect (A)	Circularity of nutrients (A1)	Organic nitrogen rate (Fernandez-Mena, et al., 2020; Valkama, et al., 2016) (A11)	Percentage of organic N in total N used on the farm. Organic N can be imported from outside of farm.	0.192	0.262	0.020	0.030	7
		Recycled nitrogen rate (Fernandez-Mena, et al., 2020; Valkama, et al., 2016) (A12)	Percentage of recycled N in total N used on the farm. Only counted the N recycled within the farm.					
		Recycled phosphorus rate (Papangelou, Achten, & Mathijs, 2020; Zoboli, Zessner, & Rechberger, 2016) (A13)	Percentage of recycled P in total P used on the farm. Only counted the N recycled within the farm.					
	Species protection efficiency (A2)	Symbiosis efficiency (A21)	The rate of plants and animals to be protected from symbiosis in the habitat at the farm level.	0.390	0.477	0.050	0.055	5
		Rate of species protection bioproducts (Molina-Moreno, et al., 2017; Tadesse, et al., 2019) (A22)	Percentage of bioproducts in total plant and animal protection drugs used on farms. Bioproducts can be imported from outside the farm.					
	Circularity of energy (A3)	Renewable energy rate (Liu, et al., 2018; Santagata, et al., 2020) (A31)	Percentage of renewable energy in total energy used on the farm.	0.288	0.356	0.040	0.040	4
		Biogas rate (Liu, et al., 2018; Santagata, et al., 2020) (A32)	Percentage of biogas energy in total energy used on the farm.					

Criteria	Sub-criteria	Index	Measurement	Weights of criteria	Weights of sub-criteria	Weights of indicators	Final weights	Sub-criteria ranking
	Circularity of materials (A4)	Recycled energy rate (Liu, et al., 2018; Santagata, et al., 2020) (A33)	Percentage of recycled energy in total energy used on the farm. Only counted the energy recycled within the farm.	0.610	0.252	0.291	0.033	6
		Recycled waste rate (Cobo, Dominguez-Ramos, & Irabien, 2018; Fernandez-Mena, et al., 2020) (A41)	Percentage of recycled waste in total waste. Only counted the waste recycled within the farm.			0.330	0.032	
		Recycled inorganic waste rate (Cobo, Dominguez-Ramos, & Irabien, 2018; Fernandez-Mena, et al., 2020) (A42)	Percentage of recycled inorganic waste in total inorganic waste. Only counted the inorganic waste recycled within the farm.			0.194	0.019	
		Recycled water rate (Cobo, Dominguez-Ramos, & Irabien, 2018; Fernandez-Mena, et al., 2020) (A43)	Percentage of recycled water in total water consumption on the farm. Only counted the water recycled within the farm.			0.213	0.021	
		Recycled rate of raw materials (Cobo, Dominguez-Ramos, & Irabien, 2018; Fernandez-Mena, et al., 2020) (A44)	Percentage of recycled raw materials in the total use of raw materials on the farm. Only counted the raw materials recycled within the farm.			0.262	0.026	
Impact (B)	Environmental impacts (B1)	Phosphorus not releasing into water bodies (Zoboli, Zessner, & Rechberger, 2016) (B11)	Subtracting the percentage of phosphorus released into waterbodies from one.	0.610	0.426	0.213	0.055	1
		Quality of wastewater (Zabaniotou, 2018) (B12)	Subtracting the percentage of contaminant amount released into waterbodies from one.			0.337	0.088	

Criteria	Sub-criteria	Index	Measurement	Weights of criteria	Weights of sub-criteria	Weights of indicators	Final weights	Sub-criteria ranking
		Soil quality maintenance (Zabaniotou, 2018) (B13)	Percentage of soil with maintained or improved quality in the total farmland area.			0.240	0.062	3
		Waste output ratio (de Kraker, et al., 2019) (B14)	Output per unit of waste.			0.210	0.055	
	Economic impacts (B2)	Internal Rate of Return (Moreno, et al., 2020) (B21)	The discount rate that sets the net present value of all cash flows to zero.			0.171	0.028	
		Value-added index (Di Maio, et al., 2017) (B22)	Added value divided by the value of resources used in production or process.			0.260	0.043	
		Return on Investment (Matrapazi & Zabaniotou, 2020) (B23)	Net return divided by the cost of the investment.			0.235	0.039	
		Payback period (Matrapazi & Zabaniotou, 2020) (B24)	The reciprocal of the years it takes for the project to generate net cash flows equal to the initial investment cost.			0.334	0.055	
		Work safety (Golinska, et al., 2015; Zabaniotou, 2018; Zhijun & Nailing, 2007) (B31)	Level of work safety perceived by farmers (0.2: highly unsafe; 0.4: unsafe; 0.6: neutral; 0.8: safe; 1: highly safe)			0.177	0.033	
	Social impacts (B3)	Health effects from chemical use in agriculture on farmers (Golinska, et al., 2015; Zabaniotou, 2018) (B32)	0.2: highly negatively affected; 0.4: negatively affected; 0.6: moderately affected; 0.8: lightly not affected; 1: totally not affected			0.294	0.055	
		Health effects on community (Golinska, et al.,	0.2: highly negatively affected; 0.4: negatively			0.344	0.064	

Criteria	Sub-criteria	Index	Measurement	Weights of criteria	Weights of sub-criteria	Weights of indicators	Final weights	Sub-criteria ranking
		2015; Zabaniotou, 2018) (B33)	affected; 0.6: moderately affected; 0.8: lightly not affected; 1: totally not affected					
		Female job creation (Zhijun & Nailing, 2007) (B34)	Percentage of female workers with jobs			0.184	0.034	
Total				1.000	2.000	7.000	1.000	