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The Impact of Technological Innovations and Food Waste Management on Carbon Emissions: A Time Series Analysis of Indonesia

Safiullah Junejo[1]✉ | Jawad Khan[2] | Mansur Muhammad[1,3] | Fajar B. Hirawan[1]

1. Faculty of Economic and Business, Universitas Islam International Indonesia, Depok, Indonesia
2. School of Economics and Finance, Xi'an Jiatong University, Xian, China
3. Department of Economics, Usmanu Danfodiyo University, Sokoto, Nigeria

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ABSTRACT

Technological innovations have the potential to significantly mitigate the global challenge of food waste and its associated carbon emissions. This study aims to explore the key role of technological innovation as a strategy in reducing carbon emissions from food wastage. Time series annual data from 2000 to 2022, collected from World Developed Indicators (WDI) and Badan Pusat Statistik Indonesia (BPS), was utilized. We applied the Johansen Co-integration test and Autoregressive Distributed Lag (ARDL) model for long-run impact assessment. The findings show that food wastage generation and technological innovation have a statistically positive impact on carbon emissions. In the second model, we predict that food wastage, technological innovations, food production, economic growth, and population density have a positive impact on food waste generation in Indonesia. These findings underscore the significance of incentivizing the adoption of technological innovations in the food supply chain to reduce food waste and carbon emissions. Additionally, sustainable practices through the supply chain, such as food packaging and optimal logistics, should be the trademark of food industries in Indonesia.

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INTRODUCTION

As a country experiencing rapid economic growth, Indonesia faces challenges in managing its solid waste. The country produced approximately 64 million metric tons (Mt) of municipal solid waste (MSW) in 2020 (Brotosusilo et al., 2020). The informal recycling rate stood at a mere 14%, while landfills were responsible for disposing of 45% of the waste, indicating inadequate waste management infrastructure (Malahayati & Masui, 2022). The remaining waste was either burned in the open air or illegally dumped. Alarmingly, 6% of the 361 landfills operated by local governments have implemented landfill gas (LFG) collection of technology (Ministry of Environment and Forestry, 2021). This contains valuable resources ranging from recoverable energy to vital exceptional minerals, and this is despite the UN's Sustainable Development Goal (SDG) 12, which encourages responsible consumption and production. Indonesia was able to meet 46% of waste management and 14% of waste reduction respectively (Budihardjo et al., 2023). SDG 15 recognizes that proper waste management is critical for the land's and its inhabitants' health and vitality. Thus, Indonesia has 70% trash handling and 30% waste reduction targets to enhance waste management (Indrianti, 2016).

Waste management techniques raise the safety hazards connected with COVID-19 and

*Corresponding Author Email: *safiullah.junejo@uiii.ac.id*

unanticipated public health and environmental consequences (Martin et al., 2023). COVID-19 spreads immediately worldwide, which is necessary for physical isolation. Waste recycling activities have been temporarily stopped because of health issues regarding how it spreads using collected waste (Suhartini et al., 2022). While waste management providers must alter their processes considering the epidemic with the border shutdown, because the traditional waste management techniques are inadequate, new waste treatment technologies are necessary to solve its multiple challenges (Kurniawan et al., 2023). Covid-19 reactions may aid in mitigating the effects of climate change. At this point, there is no indication that the epidemic has been exclusively restricted. Innovative technologies are necessary for confronting their consequences, and the world must consider whether innovations might revolutionize society and the economy, along with ways to transform this worldwide recession into an opportunity for economic recovery and growth (Morseletto, 2020).

Indonesia's waste management sector frequently decreased services to the energy sector. The emission of short-lived climatic pollutants (SLCPs) such as black carbon (BC) and methane (CH4), which have a greater GWP than CO2, through combustion or open pit burning procedures, might raise the global warming potential (GWP) (Premakumara et al., 2018). Kaza et al. (2018) found that poor waste management accounts for 5% of worldwide GHG emissions. By 2050, MSW output is predicted to reach 3.4 billion tonnes. Such massive rise then accompanied by MSW neglect, which includes the absence of 3R (reduce, reuse, recycle) activities, inefficient waste transportation and collection services, and ineffective waste closing systems (Ramachandra et al., 2018; Budihardjo et al., 2022b). According to the Paris Agreement, total garbage emissions will be dropped by 45% by 2030. Therefore, comprehensive policies must be developed to attain this goal (Huang et al., 2020). While the globe generates over 1.4 billion tons of waste food each year, the United States discards nearly 40 million tons worth 80 billion pounds of food each year.

Food and Agriculture Organization (FAO) monetary value of agricultural goods waste, excluding seafood and fish, is around 750 billion US dollars. The Environmental Protection Agency (EPA) estimated that 2.6 million tons of food were recycled in 2018, accounting for 4.1% of all food thrown away. Agriculture contributes the highest percentage of overall food waste value, 33% worldwide. These are increasing the production, post-harvest handling, and storage and decreasing the processing, distribution, and consumption waste value by approximately 54% and 46% of total wasted food quantity. This presents a significant social, environmental, and economic issue (Liang, 2021). The temperatures, floods, wildfires, pollution, and drought set records every year. The earth cannot keep up, and feeding a population of over 10 billion

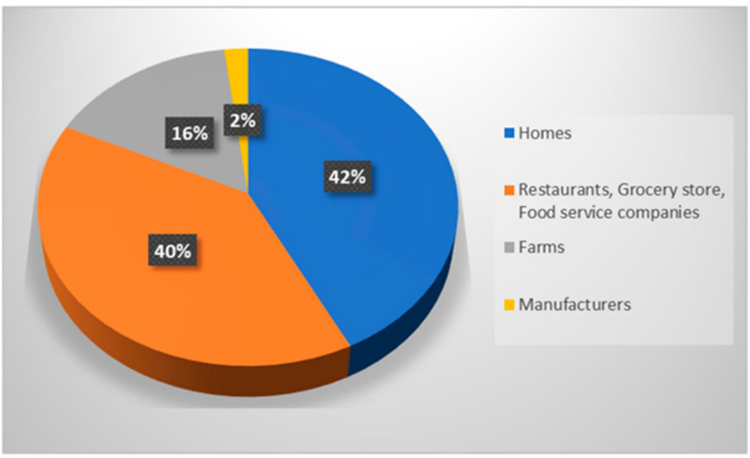

Fig. 1. Food waste shared around the world
Source: FAO

by 2050 would put even more resources. Indonesia is one of the largest food wasters, throwing away 115 kilograms per person annually. Indonesia's food waste management problem and insincerity. Jakarta produces 7500 tons of trash every day (Bisara, 2017; Muliawati, 2021; Cahyani, 2022).

The organic waste disposal solution incorporated the waste composting pre-treatment system and fermenter. The pre-treatment system includes bin lifters, sorting platforms, industrial shredders, dewatering machines, and discharge auger conveyors. Simply put, these waste management techniques apply several technologies and techniques to handle organic waste efficiently. It starts with preparing waste for reuse and recycling, then sorting and breaking it down into several components before forwarding them along a system for further processing. The aim is to manage waste with environmentally conscious ethics, converting it into valuable substances such as composting.

Figure 3 illustrates the food waste generation per capita using a simulation results approach to curve SL = 0.5 Curve; the BPS measures the values above (BPS, 2023) The trend shows a dramatic increase in food waste generation per capita over the years. This could signal changing consumption patterns, economic development, and other factors influencing food waste

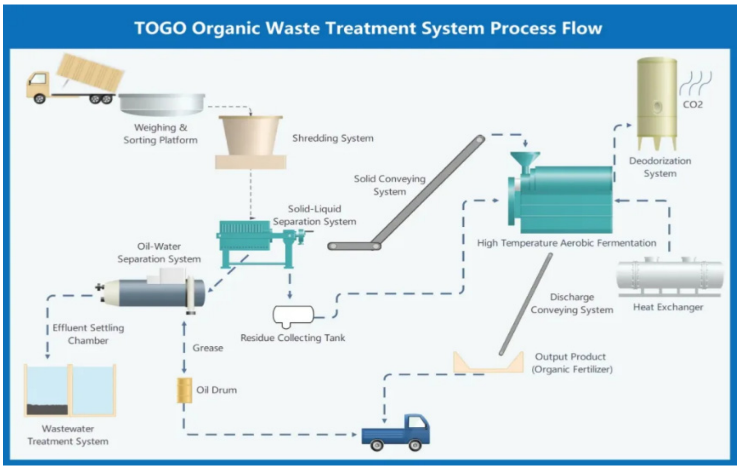

Fig. 2. A waste composting pre-treatment system
Source: Togo

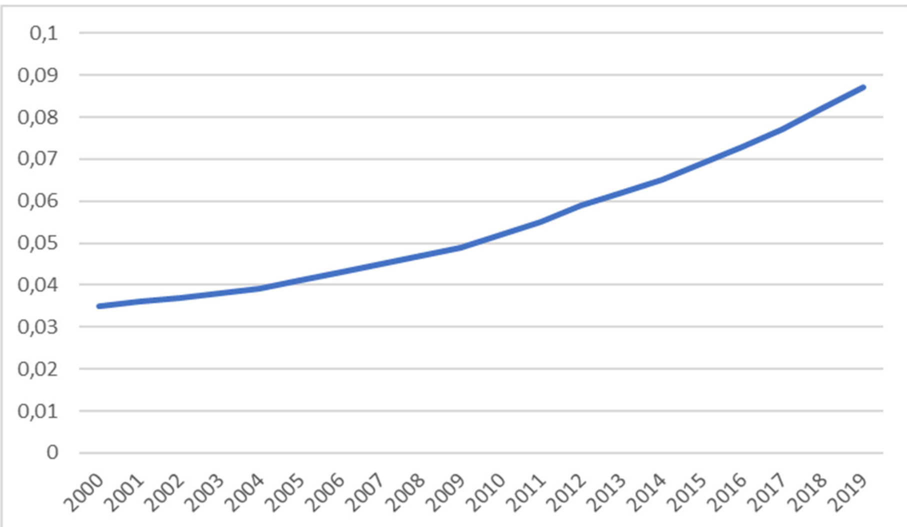

Fig. 3. Food Waste Generation Per capita (simulation approach curve SL = 0.5 Curve)
Source: Author's Computation

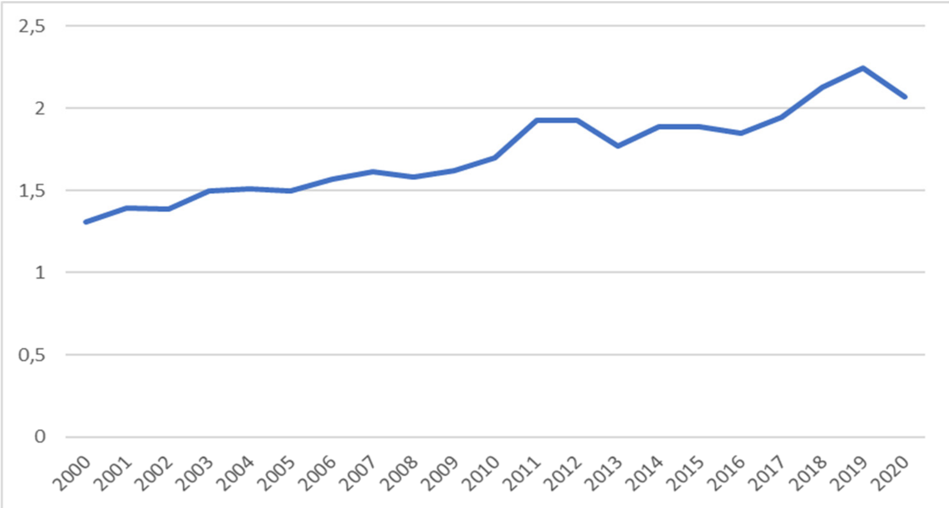

Fig. 4. Demonstrates emissions of carbon dioxide (kg PPP $ of GDP)
Source: Author's Computation

generation in Indonesia. Considering such data trends for study analysis can be helpful for the practical outcomes and understanding of the policymakers and organizations that are working on reducing food waste in different regions of Indonesia and promoting sustainable practices.

Figure 4 demonstrates the trend of increasing carbon emissions over time. It is crucial to consider this because of some reasons that increase the quantity of CO2 in the environment, which include industrial activity, transportation, and energy generation. Therefore, considerations regarding environmental sustainability and ecological impact have been brought to the forefront by the increase in CO2 emissions. It depicts an increase in the carbon footprint, which causes climate change and global warming. Reducing carbon emissions is critical for Indonesia's long-term development and environmental preservation.

The study's objective is to explore the critical role of technological innovation as a primary strategy in reducing carbon emissions from food wastage. Furthermore, technological innovation in food waste management can also help reduce carbon emissions, which are critical to Indonesia's environmental sustainability, economic stability, public health, and international responsibilities. Regarding global environmental standards, a coordinated push toward a low-carbon future may contribute to a more resilient and sustainable Indonesia. This study fills the gap with novel investigation and quantitative analysis, with more potential methodology on the impact of technological innovations and food waste management and how they can be a potential solution for reducing carbon emissions in Indonesia. The following sessions include a literature review to develop hypotheses, research techniques to mitigate study objectives and results, a discussion of findings, and a conclusion and suggestions.

LITERATURE REVIEW

This section highlights the theoretical and empirical underpinnings through which models are formulated. Moreover, it also evaluates theoretically and practically how innovation is conceptualized and classified, with a critical focus on the influence on food waste management and carbon reduction in Indonesia. By examining the nexus between technological innovation, food waste management, and carbon emissions, this review identifies crucial gaps in an existing body of knowledge and emphasizes the essential quantitative analysis to inform policy and practices.

Innovation Theory

This study is grounded in the theoretical premise that innovation and invention serve as a framework for mitigating or addressing challenges. Innovation will be critical to organizational sustainability in a highly dynamic environment. Innovation has the potential to grow and improve organizational performance (Odumeru, 2013; Suhag et al., 2017). According to Said (2007), innovation is a deliberate change that involves using new technology and new tools in a particular company and simplifying processes to increase productivity. Most organizations translate innovation using new technology, and it's known as information system technology. Hamel (1996) suggested an alternative viewpoint on innovation and defined innovation as an exit from conventional management principles, procedures, and methods or abandoning archaic organizational structures that significantly influence management practices (Ancok, 2012; Abuelseoud et al., 2018). In his presentation, he attempted to explain that in this era of globalization, innovation can be interpreted not only as technological progress and change but also as adjustments to management systems and organizational strategies. Nonetheless, both points of view help us understand that innovation is a planned and deliberate effort undertaken by a particular company to bring about improvements.

Halila and Rundquist (2011) provide a more comprehensive picture of innovation, stating that three main categories of innovation are generally associated with innovation: product, process, and organization. Muluk (2008) also outlines five categories of innovation consisting of Product innovation, which refers to services resulting from product changes; Process innovation, which refers to long-term quality improvements that depend on the modification of organizational structures and policies; and procedures; Method innovation, on the other hand, refers to a new approach to providing services; Strategic innovation, on the other hand, refers to changes in strategy, vision, and mission; and Systems innovation, beside that, refers to changes in governance.

Technological innovation and food waste management for conversion into biofuel give several potential development opportunities in Indonesia. Such as fiscal advantages (including foreign investment, revenue generation, and employment growth), social advantages (such as energy security, poverty reduction, and health improvement), and ecological advantages (such as renewable resources preservation and lower GHG emissions) (Gold et al., 2011; Abdelzaher et al., 2021). Sharma et al. (2013) found the factors that contribute to difficulties and unpredictability in the biomass production supply process: biomass supply, weather, biomass properties such as moisture content, biomass cost, technology, expansion plans, demand fluctuations, biofuel price, changes in government incentives, changes in policies and regulations, and natural or human disasters (Hamouda et al., 2023; Junejo et al., 2023; Abbas et al. 2024).

Currently, in Indonesia, food waste is dealt with by waste landfills and garbage-burning processes, which are considered first-generation valorisation processes. Building more sustainable and cost-effective food waste conversion technologies is crucial, particularly for the reduction of carbon emissions and bioenergy provision (Ong et al., 2018; Abdelzaher, 2023). Thus, government incentives in the form of policy and financial instruments (incentives and financing choices) are necessary to encourage the wider adoption and implementation of innovative technologies for food waste management and conversion pathways in Indonesia. Furthermore, logistics and supply chain emancipation increased synergy between waste and energy agencies, consumer attitudes, and behaviour change will all play a role in promoting a shift toward more environmentally friendly waste management throughout Indonesia. Prilliadi (2022a) found that green finance, technological innovation, finance for agriculture, and renewable energy sources are predominant solutions to reduce carbon emissions and build a low-carbon economy-producing country. Taridala et al. (2023) emphasized the essential practices for sustainable-oriented innovation (SOI) for the agriculture sector in Indonesia. Research also explores food waste management and how it influences food waste in big cities in Indonesia like Jakarta; the researcher found that it significantly helps mitigate food waste at the household level (Harsanto, 2021).

There are multiple ways that technological innovations are being utilized in Indonesia to manage and deal with leftover foods and decrease carbon production. One of the significant strategies is to use anaerobic digesters that have a crucial role in converting the waste food into biogas. Biogas can be a notable resource for producing and generating electricity using advanced fuel cell technology (Munir & Fadhilah, 2023). Azzahra et al. (2020) highlight that another method for effectively managing waste food is to develop digital platform-based business models specifically designed to serve as a venue to facilitate the process of efficient usage of waste food. Indonesia has initiated and set up waste banks that encourage individuals to waste management by providing incentives for their activities and efforts (Pramana et al., 2021). The significant problem of food waste in Indonesia, which raises pollution from greenhouse gases and harms the environment significantly at the same time, is what these solutions seek to solve. The Republic of Indonesia may accomplish responsible manufacturing and utilization, climate change mitigation, and ecologically friendly cities and communities by employing these innovative technological ideas into practice. (Cahyani et al. 2022; Maskur, 2018).

Several studies have described emissions reduction strategies implemented by the food waste sector. Lee et al. (2016) claim that increasing recycling frequency and using waste-to-energy (WtE) strategies for converting and utilizing solid waste can contribute to reducing CH4 emissions. Budihardjo et al. (2022) encourage the establishment of material recovery facilities (MRF). Demir et al. (2018) find that waste reduction or minimization at the manufacturing site is the most widely used waste management and emission reduction approach. According to Bian et al. (2020), suitable waste management processes are influenced by waste generation and destruction, the state of the economy, and each community's administrative and operational activities. The significance of developing a strategy for development and determining any dominion's target to decrease the emissions from waste production by 2030.

Literature Gap

The research on the nexus between technological innovation, food waste and carbon emissions in Indonesia underlines the significance of a comprehensive approach to emission reduction following international treaties (Malahayati & Masui, 2018). It entails the management and execution of waste by following the 3R approach and the methods and techniques of using the current waste treatment procedures (Amheka et al., 2015). The regional trend for re-valorising food waste through biological processes has also been identified as significant.

While Abdelzaher and Awad (2022) stressed the importance of agricultural water-saving technology, their study did not delve into food waste management strategy and technology innovations that could contribute to reducing carbon emissions. Similarly, Abdelzaher et al. (2023) emphasized the water-energy-food nexus and sustainable agriculture, but they did not directly discuss the role of technological innovation in food waste management or its critical impact on carbon emissions mitigation.

These investigations highlight the significance of technological advancements and government initiatives in reducing food waste and associated carbon emissions in Indonesia. Nonetheless, there remains a dearth of quantitative analysis based on annual food waste data and advanced econometric tools. This study aims to fill this crucial gap by analyzing the role of technological innovations and food waste management and their potential for mitigating carbon emissions in the country. Furthermore, the study seeks to provide policy suggestions and recommendations grounded in the empirical results derived from the econometric analysis.

By addressing this research gap, the study contributes to a comprehensive understanding of the nexus between technological innovation, food waste management, and carbon emissions mitigation in the Indonesian context. This quantitative approach, coupled with the incorporation

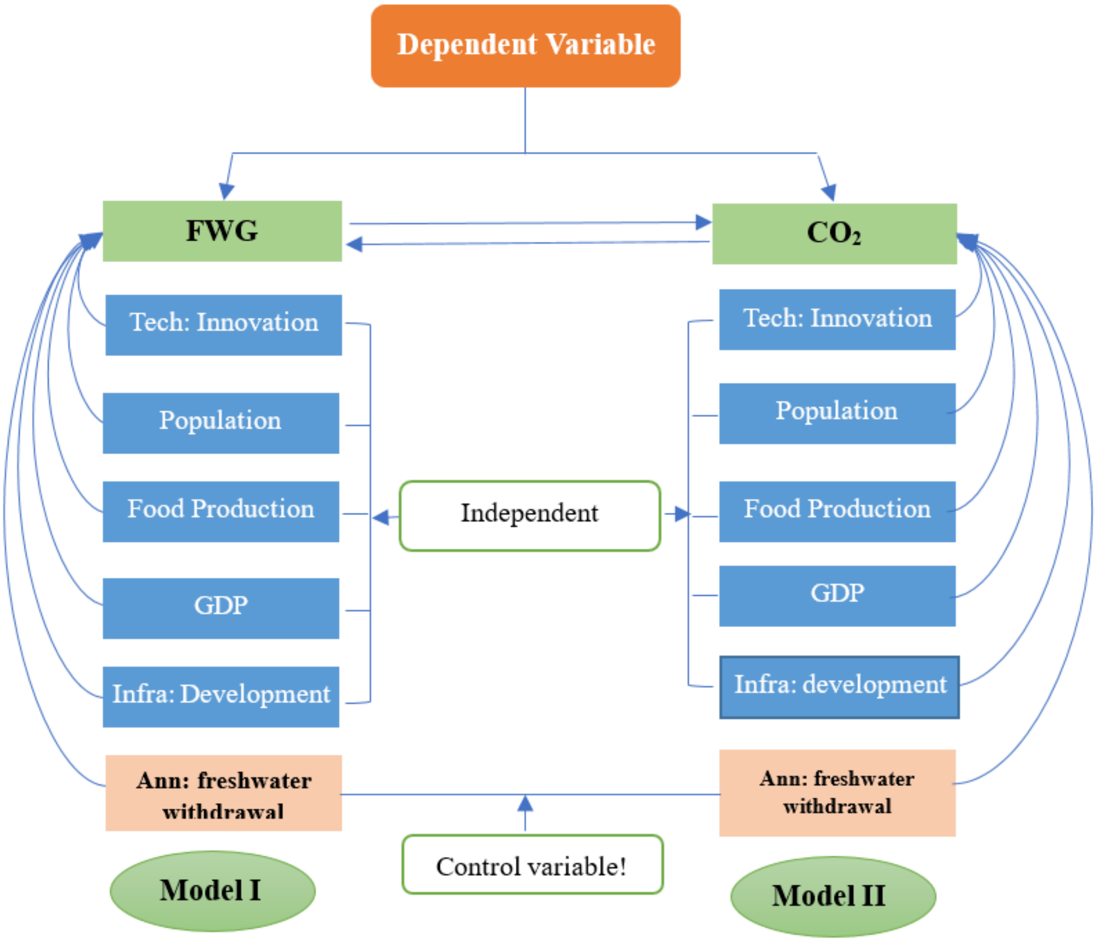

Fig. 5. Conceptual Framework of Food waste generation, CO2, and other variables

of advanced econometric techniques, offers a robust analytical framework to inform evidence-based policymaking and foster sustainable practices in the food industry supply chain.

Figure 5 demonstrates the study's conceptual framework based on previous studies and theory. As it is shown that the study will employ two models to elevate the study objectives, thus we have shown the relationship between dependent and independent variables separately. Moreover, the authors have also included the control variable to make the study more efficient and robust to econometrical assumptions.

MATERIALS AND METHODS

Data Sources

This study employs quantitative research methods to analyse the impact of technological innovation and food waste management on carbon emissions and how these technologies can help reduce carbon emissions. The time series data collected from WDI (World Development Indicators) and BPS (Badan Pusat Statistik Indonesia) from 2000 to 2022. The observed variables of the study are carbon emission (CO2) and food waste generation (FWG). The regressor variables are technological innovation (TI), food production (FP), population density (POLD), and economic growth (GDP), and the control variables are annual freshwater withdrawal (AFW). Table 1 shows variable description and source.

Table 1. Variables Description

No	Variables	Measurement	Unit	Source
	Dependent Variables			
1	Carbon Emission (CO2)	CO2 emissions	metric tons per capita	WDI
2	Food Waste Generation (FWG)	Food Waste Generation Rate	L=0.5 (Kg/p/day)	BPS
	Independent Variable			
3	Technological Innovation (TI)	Patent applications, non-residents	Numeric	WDI
4	Food Production (FP)	Food production index (2014-2016 = 100)	Weighted average (2014-2016 = 100)	FAO
5	Population Density (PD)	Population density	People per sq. km of land area	WDI
6	Economic Growth (GDP)	GDP Per Capita	Current US$	WDI
	Control Variable			
7	Annual Fresh Water Withdrawal (AFW)	Annual freshwater withdrawals, industry	% of total freshwater withdrawal	FAO

Note: WDI (World Data Indicators), BPS (Badan Pusat Statistik Indonesia)

Econometric Methods

The time series variables in most cases display nonstationary behaviour, such as trends and random walks, making them unpredictable. Therefore, it is crucial to apply some preliminary econometric tests to help in selecting the appropriate model for the research. failure to observe these tests in time series analysis can lead to inappropriate regression results and incorrect interpretations (Wooldridge, 2015). Although data with unit roots is considered to be nonstationary, I(1) variables are usually nonstationary, but their first difference is considered to be stationary. On the other hand, I(0) variables are stationary and are usually called integration of order zero, however, we may determine the parameter's integrating sequence and also decide if differencing is required to make variables stationary (Gujarati, 2021).

This is also required to determine the order of integration before estimating the ARDL model since one of the model's assumptions demands that all variables be integrated with either order I(0) or I(1). Thus, the Augmented Dicky-Fuller (1981) and Phillips and Perron (1988) tests are the most frequently employed unit root tests in crucial investigations. These two techniques contribute to the identification of unit roots in time series data. Dickey and Fuller present three types of unit root test equations using a null hypothesis of $\varphi = 0$ versus the alternative hypothesis of $\varphi < 0$, i.e.

$$\Delta y_t = \varphi y_{t-1} + \sum_{i=1}^{p} \beta_i y_{t-1} + \mu_t \tag{1}$$

$$\Delta y_t = \alpha_0 + \varphi y_{t-1} + \sum_{i=1}^{p} \beta_i y_{t-1} + \mu_t \;\_\_\_ \tag{2}$$

$$\Delta y_t = \alpha_0 + p_t + \varphi y_{t-1} + \sum_{i=1}^{p} \beta_i y_{t-1} + \mu_t \tag{3}$$

Model Specification

To investigate the long-run and short-run relationships between green carbon emissions, food waste generation, technological innovation, food production, population density, economic growth, and annual freshwater withdrawal, we used the autoregressive distributed lag (ARDL)

technique. Pesaran and Shin (1995) presented the ARDL technique, which was expanded by Pesaran et al. (2001). We used the Akaike information criterion (AIC) to determine the delays between the first differentiated variables. The ARDL technique offers several advantages for time series analysis. First, this approach is used for variables with various integration orders, such as I(0) or I(1). Finally, the ARDL technique produces unbiased estimators for long-run models while preserving long-run information. Considering the advantages above, we recommended the following ARDL models for this investigation.
Model 1: Dependent variable CO2

$$\begin{aligned}\Delta CO2_t &= \beta_0 + p_1 CO2_{t-1} + p_2 FWG_{t-1} + p_3 TI_{t-1} + p_4 FP_{t-1} + p_5 PD_{t-1} + p_6 GDP_{t-1} \\ &+ p_7 AFW_{t-1} \sum_{i=0}^{q1} \delta_1 CO2_{t-1} \sum_{i=0}^{q2} \delta_2 FWG_{t-1} \sum_{i=0}^{q3} \delta_3 TI_{t-1} \sum_{i=0}^{q4} \delta_4 FP_{t-1} \sum_{i=0}^{q5} \delta_5 PD_{t-1} \\ &+ \sum_{i=0}^{q6} \delta_6 GDP_{t-1} + \sum_{i=0}^{q7} \delta_7 AFW_{t-1} + \mu_t\end{aligned} \tag{4}$$

Model 2: Dependent Variable FWG

$$\begin{aligned}\Delta FWG_t &= \beta_0 + p_1 FWG_{t-1} + p_2 CO2_{t-1} + p_3 TI_{t-1} + p_4 FP_{t-1} + p_5 PD_{t-1} + p_6 GDP_{t-1} \\ &+ p_7 AFW_{t-1} \sum_{i=0}^{q1} \delta_1 FWG_{t-1} \sum_{i=0}^{q2} \delta_2 CO2_{t-1} \sum_{i=0}^{q3} \delta_3 TI_{t-1} \sum_{i=0}^{q4} \delta_4 FP_{t-1} \sum_{i=0}^{q5} \delta_5 PD_{t-1} \\ &+ \sum_{i=0}^{q6} \delta_6 GDP_{t-1} + \sum_{i=0}^{q7} \delta_7 AFW_{t-1} + \mu_t\end{aligned} \tag{5}$$

Where CO_2 and FWG are dependent variables with different models in the study; CO_2 is carbon emission, and FWG is food waste generation. TI represents technological innovation; It is an environmentally friendly technological improvement that is used as an independent variable. Further, FP represents food production, GDP demonstrates the natural Gross Domestic Product (GDP), which is also included as an independent variable. PD represents population density. In the model, AFW represents annual freshwater withdrawal as a control variable. In addition, $\triangle$ is the first difference operator, β_0 is a constant term, p_j denotes the long-run coefficient and δ_j is a short-run coefficient, and μ_t shows error term. While the j shows the lag length. In this work, we employed the general-to-specific strategy to identify ARDL model lags. After determining the significance of each lag, all insignificant lags were eliminated from the regression model employing the test known as Wald.

The first step in ARDL bound testing is to estimate Equation (6) employing the ordinary least squares (OLS) technique. The equations were examined for long-run associations using F-statistics, including the aggregate significance of lagged-level variables. The F-statistic table has two sets of numbers; Pesaran et al. (2001) can compute the upper and lower bound critical values for a particular significance level. Nevertheless, the choice concerning a cointegration is made using the F-statistic values supplied by Pesaran et al. (2001), i.e., if the F-statistic value exceeds the upper critical bound value, we reject the null hypothesis of no cointegration among the series. Similarly, if the F-statistic value falls below the lower bound critical values, we accept the null hypothesis of no cointegration. If the F-statistic value lies between upper and lower bound critical values, we rely on the lagged value to study the long-run relationship among variables.

Cointegration among series indicates a causal relationship but not its direction specification. We employed the technique that Granger (1969) and Engle and Granger (1987) pioneered to analyze causality relationships among conflicting variables. Engle and Granger (1987) used a vector error correction model (VECM) to assess the causal association between a low-carbon economy, green energy, green innovation, GDP per capita, and labour force.

Figure 6 depicts the methodological framework. We first performed a unit root test to ensure that the data none of the series is integrated of the order two i.e. I(2). The Johansen Cointegration test was used to determine cointegration and whether the variables were related in the long term. Further, we employed the autoregressive distributed lag (ARDL) model to examine the long-run and short-run relationship among the dependent and independent variables. The bond test for ARDL was adopted to find the long-run association.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 2 displays the descriptive statistics for the variables in the research. Descriptive statistics

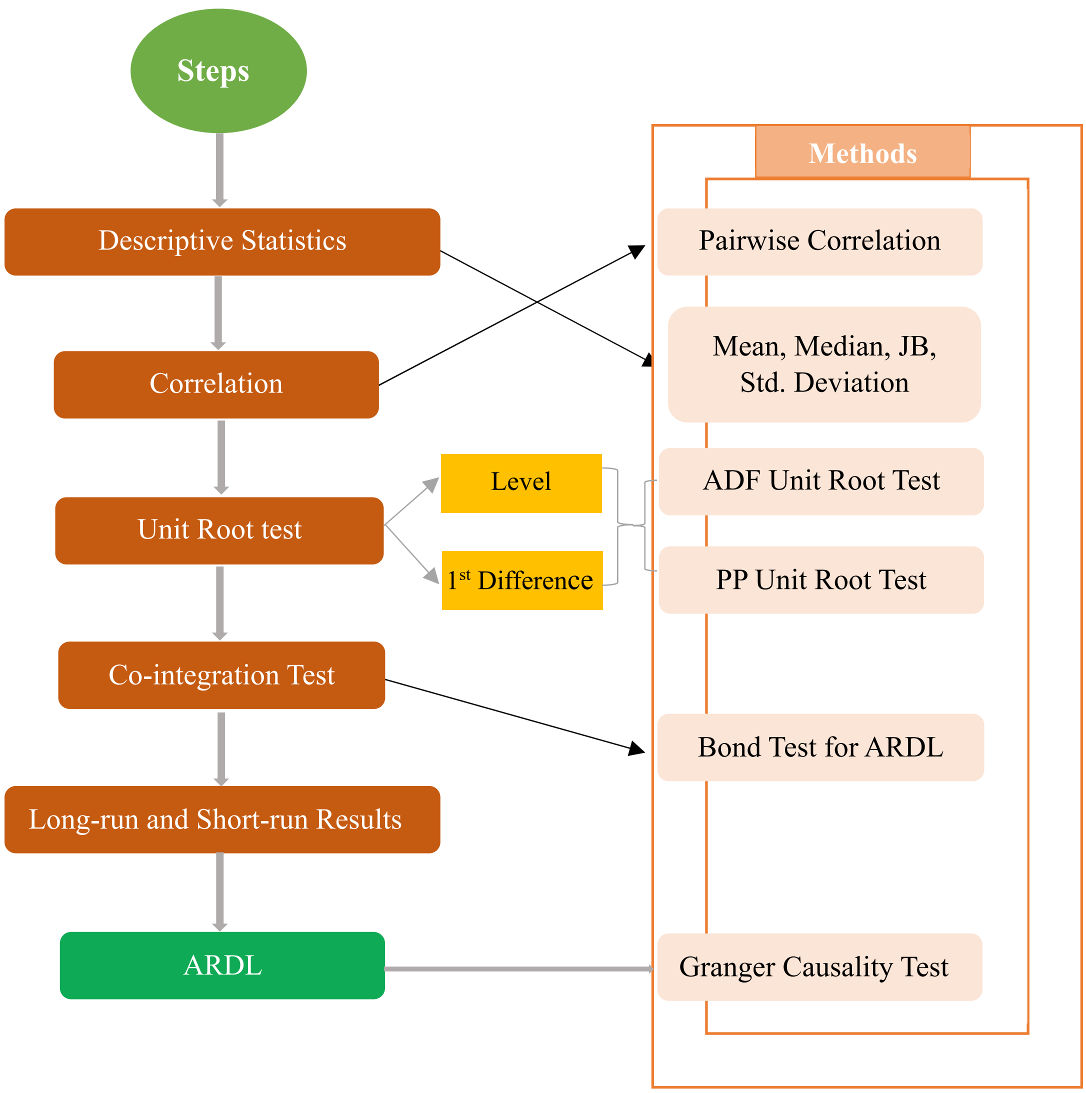

Fig. 6. The methodological foundation of the study

Table 2. Descriptive statistics of utilized variables in the study.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera	Obs
CO2	1.769	1.770	2.245	1.311	0.281	1.325	23
FWG	0.063	0.055	0.152	0.035	0.029	12.961	23
TI	5804.130	5297.000	8583.000	3099.000	1898.503	2.181	23
FP	95.582	95.570	115.840	70.920	13.735	0.980	23
GDP	2734.036	3322.582	4787.999	739.004	1321.102	2.221	23
PD	131.141	131.610	144.867	114.019	10.224	1.702	23
AFW	8.002	7.159	15.015	4.103	3.724	2.107	23

explains how variables are distributed and fluctuate over a dataset by supplying information on their central tendency and dispersion (Gujarati, 2021). From the results, the average CO2 emissions during the period were estimated at 1.769 million metric tons per capita, with a median of 1.770 million metric tons. The data ranges from 1.311 million metric tons to 2.245 million metric tons, with a relatively low standard deviation of 0.281. The Jarque-Bera test suggests the data is close to being normally distributed. The average food waste generation (FWG) rate is approximately 0.063 kg daily per individual, additionally, while minimum and maximum FWG is observed at 0.035 kg and 0.152 kg for the period under investigation with a low standard deviation of 0.029, meaning that it is clustered around the mean.

The mean value for technological innovation stood at 5804.130, with a median of 5297.000. The data ranges from 3099.000 to 8583.000, with a high standard deviation of 1898.503. The Jarque-Bera test suggests that the data is normally distributed. Furthermore, the mean value of food production stood at 95.582 (2014-2016 = 100), while the standard deviation of food production is approximately 13.735 across the observation. The mean value of GDP per person accounted for $2734.036, and the significant standard deviation of $1321.102 shows a wide range of GDP values among the observations in the dataset.

Meanwhile, the mean population density value is approximately 131.141 people per square KM, while the standard deviation of approximately 10.224 indicates people per square km in the country clustered far away from average. Lastly, the average annual freshwater withdrawal for industry accounts for 8% of total freshwater withdrawals with a moderate standard deviation of 3.724. The data ranges from 4.103 to 15.015, and the Jarque-Bera test value is moderate, suggesting some deviation from normality. After providing the overview of the central tendency, variability, and range of each variable in the dataset, further, this study carries out a unit root test in the following section.

Unit Root Test

The unit root test is performed to confirm the data's stationarity level. whether the series are I(0) that is level stationarity, or first difference stationarity I(1) and the combination of I(0) and I(1). We used the Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) unit root tests. Dickey and Fuller first proposed the ADF test in 1979, and the null hypothesis is that the data series have a unit root and are not stationary (Johansen and Juselius 2009). Phillips and Perron's PP established that the series has a unit root (data are not stationary) using the identical null hypothesis as the ADF test. The unit root test's null hypothesis must be rejected to demonstrate that the series is stable.

Table 3 presents the results of Augment Dicky Fuller (ADF) and Phillip-Perron (PP) unit root tests. Most of the variables at the level are not stationary in the ADF and PP tests. We cannot reject the null hypothesis for all variables, which states that unit root exits and data are not stationary. According to both tests, only one variable, AFW, is significant at a 5% significance level. However, most variables became stationary after taking the first difference

Table 3. Results of ADF and PP Tests for the Unit Root

Variables	ADF Unit Root Test		PP Unit Root Test		Decision
	Level	First difference	Level	First difference	
CO2	-0.853	-5.346***	-0.470	-10.757***	I(1)
	(0.783)	(0.000)	(0.879)	(0.000)	
FWG	5.622	1.543***	3.915	1.309***	I(1)
	(1.000)	(0.055)	(0.999)	(0.057)	
TI	-0.639	-4.562***	-0.017	-6.294***	I(1)
	(0.842)	(0.002)	(0.947)	(0.000)	
FP	-0.801	-4.611***	-1.722	-8.414***	I(1)
	(0.794)	(0.002)	(0.406)	(0.000)	
GDP	-0.315	-3.506***	-0.315	-3.517***	I(1)
	(0.907)	(0.018)	(0.907)	(0.017)	
PD	-0.826	2.541***	-2.476	-0.287***	I(1)
	(0.789)	(0.059)	(0.134)	(0.911)	
AFW	-2.090**	-	-0.947**	-	I(0)
	(0.049)	-	(0.050)	-	

H_0: A unit root exists in the series, and data are not stationary.
*** Null Hypothesis Rejection at 1% ($P < 0.01$),
** Null Hypotheses Rejection at 5% ($P < 0.05$),

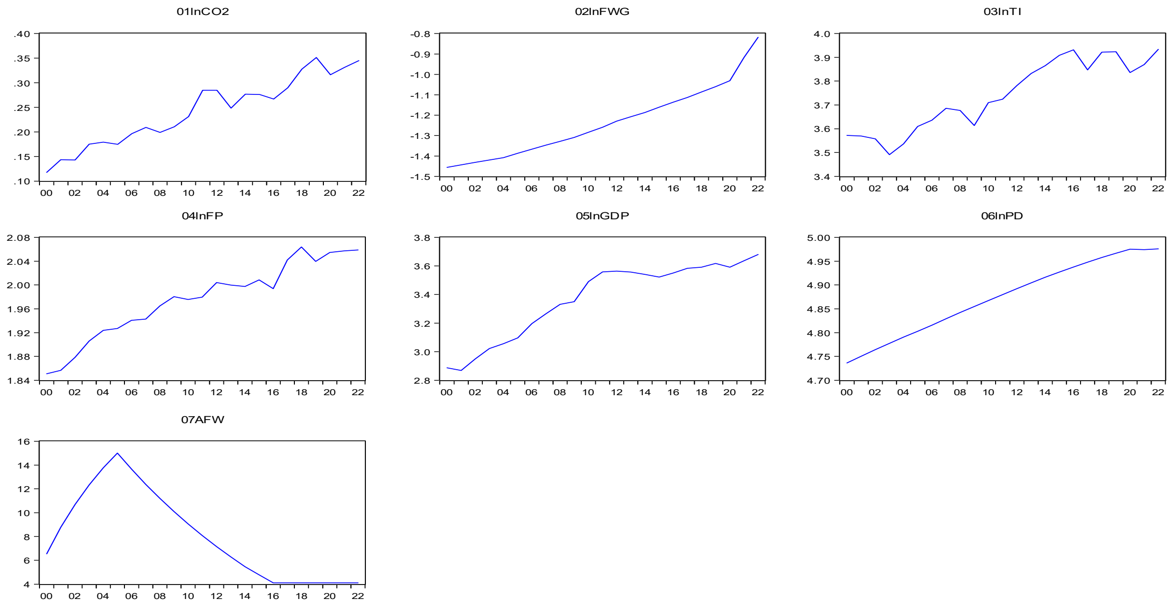

Fig. 7. Graphical trend of all variables

I(1) in both tests, as the p-value is less than the significance level. As a result, we infer that the variable sequence is not steady at level I(0), except for one variable. However, the data became stationary after taking the first I(1) deference for the rest of the variables.

Correlation

The correlation matrix illustrates the existence of a mutually supporting relationship between variables. The correlation coefficient between related variables is displayed in each matrix column. However, there are three correlation coefficients: perfect balance. Correlation is represented by the numbers -1, +1, and 0; 1 indicates a perfect positive correlation.

Table 4 shows an exciting association among the variables, the correlation matrix above

Table 4. Correlation Matrix

	CO2	FWG	TI	FP	GDP	PD	AFW
CO2	1.000	-	-	-	-	-	-
FWG	0.861***	1.000	-	-	-	-	-
TI	0.892***	0.800***	1.000	-	-	-	-
FP	0.955**	0.839**	0.867	1.000	-	-	-
GDP	0.958***	0.832***	0.903	0.947	1.000	-	-
PD	0.964**	0.853***	0.931	0.978	0.967	1.000	-
AFW	-0.758**	-0.714***	-0.849	-0.711	-0.794	-0.790	1.000

demonstrates that carbon emissions (CO2), technological innovations (TI), gross domestic products (GDP), political density (PD), and food production (FP) have an enormously positive correlation with the food waste generation (FWG). We conclude that food waste generation is strongly correlated with all the variables in this study, which suggests their dependency in the context of technological innovation for food waste management and carbon emission reduction in Indonesia. Annual freshwater withdrawal has a robust negative correlation with food waste generation, technological innovation, and carbon emissions. Thus, while one variable tends to increase, the other variables will decrease, which suggests a potential trade-off or complement association.

Cointegration Test

The cointegration test is commonly used to test long-term relationships among variables. This research uses the Johansen cointegration test developed by Johansen and Juselius (2009b). Consequently, we are given different cointegration relationships between variables (Johansen, 1995). The Johansen test works best when the data set is long (Shahbaz et al., 2015). Therefore, it is more suitable for this research investigation. On the other hand, eigenvalues and trace statistics are provided by the Johansen cointegration test.

In the Johansen cointegration test, the null hypothesis is H0: No cointegration exists between variables. Instead, an alternative hypothesis is H1: Cointegration occurs between variables. Table 5 displays the findings of the Johansen cointegration test. The cointegration of all variables indicates that the null hypothesis of no cointegration is rejected, according to the results obtained. Thus, we conclude that there is a long-term relationship and correlation between all the variables in the study.

Regression Estimation

This study's long-term and short-term association among the variables is analysed using the ARDL model. The regression findings for CO2 and FWG, both dependent variables, are shown in Table 8. There are usually a few expectations included in the ARDL results. The study results indicate that technological innovation (TI) has a favourable positive significant impact on CO2 and FWG. In model 1, the coefficient of lnTI is (0.143), which is statistically significant at the 10% level. This indicates that a 1% increase in eco-friendly technological innovation corresponds to a 0.143% drop in CO2 emissions. While in model II, the lnTI coefficient is (0.109), which is statistically significant at 5%, a 1% increase will help reduce FWG by 0.103%. These findings suggest that technological innovation positively impacts CO2 and FWG, considering that eco-friendly or green technological advancement might help mitigate carbon emissions and manage food waste. These results are aligned with the previous studies that mentioned the relevance of technological innovation in reducing food waste and its impact on the environment. For instance, Wang et al. (2021) found that the adoption of eco-friendly and innovative technologies in the food supply chain dramatically reduces food waste.

Moreover, Aramyan et al. (2020) also emphasized that adopting eco-friendly technologies

Table 5. Results of Johansen cointegration test

Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.999	379.980	111.781	0.000
At most 1 *	0.991	234.762	83.937	0.000
At most 2 *	0.905	136.317	60.061	0.000
At most 3 *	0.891	86.787	40.175	0.000
At most 4 *	0.723	40.247	24.276	0.000
At most 5 *	0.444	13.294	12.321	0.034
At most 6	0.046	0.979	4.130	0.374

Trace test indicates 6 cointegrating eqn(s) at the 0.05 level

** denotes rejection of the hypothesis at the 0.05 level*

***MacKinnon-Haug-Michelis (1999) p-values*

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.999	145.218	42.772	0.000
At most 1 *	0.991	98.445	36.630	0.000
At most 2 *	0.905	49.530	30.440	0.000
At most 3 *	0.891	46.540	24.159	0.000
At most 4 *	0.723	26.952	17.797	0.002
At most 5 *	0.444	12.315	11.225	0.032
At most 6	0.046	0.979	4.130	0.374

Max-eigenvalue test indicates 6 cointegrating eqn(s) at the 0.05 level

** denotes rejection of the hypothesis at the 0.05 level*

***MacKinnon-Haug-Michelis (1999) p-values*

H_0: No cointegration exists between the variables.

*Null Hypotheses Rejection at 5% ($P < 0.05$),

Table 6. ARDL estimations for CO_2 and FWG as the dependent Variable

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Model I (CO2)				
Constant	30.275***	17.536	1.726	0.008
lnCO2(-1)	0.125***	0.235	0.532	0.004
lnFWG	-0.977**	0.611	-1.598	0.034
lnTI	0.143*	0.130	1.105	0.089
lnFP	0.413*	0.432	0.957	0.056
lnGDP	0.201*	0.098	2.044	0.062
lnPD	-7.046	4.030	-1.748	0.104
AFW	-0.004*	0.003	-1.374	0.093
@TREND	0.098***	0.056	1.760	0.002
Model II (FWG)				
Constant	25.265***	2.728	9.261	0.000
lnFWG(-1)	0.222*	0.156	1.419	0.080
lnCO2	-0.164**	0.097	-1.695	0.014
lnTI	0.109**	0.043	2.519	0.026
lnFP	0.114**	0.170	0.674	0.012
lnGDP	0.134***	0.025	5.296	0.000
lnPD	-5.768***	0.661	-8.729	0.000
AFW	-0.002**	0.001	-1.625	0.028
@TREND	0.079***	0.010	8.226	0.000

*** Null Hypothesis Rejection at 1% ($P < 0.01$),

** Null Hypotheses Rejection at 5% ($P < 0.05$),

* Null Hypotheses Rejection at 10% ($P < 0.10$),

for food waste in the agricultural food supply chain has a high potential, but it should be economically feasible. Like this, Ikram et al. (2023) emphasized IoT devices' significance in monitoring and decreasing supply chain waste. This study's findings provide weight to the notion that eco-friendly technological innovation can play a significant role in solving the worldwide concern related to food waste and its environmental consequences.

The study also suggests that food production (FP) positively impacted the dependent variables in both models. The LnFP coefficient in model I is (0.413), which is statistically significant at a 10% significance level. This means that a 1% increase in food production will increase carbon emissions by 0.413%. On the other hand, in the second model, the coefficient (0.114) suggests a positive significant impact at a 5% significance level. This means that a 1% increase in food production demonstrates a 0.114% increase in the FWG. These results are more related to Ye et al. (2017); in the context of China which suggests that the agriculture sector (food production) significantly reduces carbon emissions. Our findings further aligned with the study of Scherhaufer et al., (2018) which reveals that 15-16% of food production causes significant increases in food waste in Europe. This also corresponds with the assertion of the Jakarta Environmental Agency that 50% of waste comprises leftover food. Food waste losses occur across all stages of the supply chain and consumption; these include processing, storage, transportation, and consumer wastage, the highest contributor to food waste. Therefore, food banks like "Food Cycle Indonesia" are one way to mitigate the problems. Implementing advanced and innovative technologies is still required to handle food waste nationwide.

The study also investigated how economic growth (GDP) significantly impacted CO2 and FWG. Eventually, in the model, the lnGDP (0.201) is significant at a 10% level, which suggests that a 1% change in GDP results in an increase of CO2 with 0.201%. At the same time, lnGDP in other models suggests a significant solid impact on the FWG at a 1% level. It suggests that a 1% increase in the GDP will cause an increment in the FWG of 0.134%. These findings are aligned with (Adebayo et al., 2021; Bashir et al., 2021).

Moreover, our study supports the findings from Malahayati and Masui (2022); the study shows that food loss may contribute to the Indonesian economy due to increased household

Table 7. ARDL Cointegrating And Long Run Form for CO2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Short-run Coefficients				
Constant	32.655***	7.643	4.273	0.001
Error Correction	-0.940***	0.220	-4.272	0.001
ΔlnFWG	-1.106	0.644	-1.717	0.110
ΔlnTI	0.183*	0.097	1.878	0.083
ΔlnFP	0.393	0.280	1.401	0.185
ΔlnGDP	0.173*	0.094	1.830	0.090
ΔlnPD	-7.782*	4.376	-1.778	0.099
ΔlnAFW	-0.002	0.003	-0.606	0.555
Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
lnFWG	-1.117	0.731	-1.527	0.151
lnTI	0.164	0.152	1.078	0.301
lnFP	0.473	0.514	0.920	0.374
lnGDP	0.230*	0.122	1.882	0.082
lnPD	-8.055	4.955	-1.625	0.128
AFW	-0.005	0.004	-1.253	0.232
@TREND	0.112	0.067	1.672	0.118

*** Null Hypothesis Rejection at 1% ($P < 0.01$),
** Null Hypotheses Rejection at 5% ($P < 0.05$),
* Null Hypotheses Rejection at 10% ($P < 0.10$),

Table 8. Results of ARDL Cointegrating And Long Run Form for Food Waste Generation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Short-run Coefficients				
Constant	16.941***	4.728	3.583	0.003
Error Correction	-0.519***	0.146	-3.563	0.004
ΔlnCO2	-0.087	0.062	-1.408	0.183
ΔlnTI	0.110***	0.028	3.917	0.002
ΔlnFP	0.173*	0.090	1.920	0.077
ΔlnGDP	0.082**	0.030	2.687	0.019
ΔlnPD	-6.182***	0.338	-18.294	0.000
ΔAFW	-0.001	0.001	-1.194	0.254
Long Run Coefficients				
lnCO2	-0.210	0.129	-1.630	0.127
lnTI	0.140**	0.051	2.714	0.018
lnFP	0.147	0.216	0.679	0.509
lnGDP	0.172***	0.044	3.929	0.002
lnPD	-7.412***	0.879	-8.437	0.000
AFW	-0.002*	0.001	-1.791	0.097
@TREND	0.101***	0.009	10.958	0.000

*** Null Hypothesis Rejection at 1% ($P < 0.01$),
** Null Hypotheses Rejection at 5% ($P < 0.05$),
* Null Hypotheses Rejection at 10% ($P < 0.10$),

Table 9. Diagnostics Tests Results

Breusch-Godfrey Serial Correlation	F-statistic	1.824	Prob. F(2,14)	0.097
LM Test:	Obs*R-squared	4.755	Prob. Chi-Square (2)	0.092
Normality test	Jarque-Bera	1.478	Probability	0.077

consumption. The study also suggests that it might reduce 14.19 mt CO2eq of GHG emissions and cropland requirements. Population density (PD) negatively impacts CO2 with (-7.046) but is insignificant. Model II shows that lnPD had a solid negative significant impact on the FWG at 1%. This means that a 1% increase in the population density will decrease the FWG by -5.768%. Similarly, Rahman (2017) highlighted the same relationship in Asian countries from 1970 to 2014. Moreover, annual freshwater withdrawal shows a significant negative impact on both models. We can conclude from the results that a 1% increase in yearly freshwater withdrawal will result in a 0.004% reduction in carbon emissions. Similarly, it will also decrease FWG. This finding supports Slorach et al. (2020).

Tables 7 and 8 show that the ARDL cointegration technique is used to determine the long-run relation between series with different orders of integration. The reparametrized result gives the short-run dynamics and long-run relation of the independent variables with the dependent variable.

Diagnostic Results

This study used several diagnostic tests after the ARDL model's deployment. The results of each of these diagnostic tests are shown in Table 9 below.

The Breusch-Godfrey test has been used to assess the validity of modelling assumptions inherent in applying regression-like models to observe the time series data. The finding shows that all coefficients in our model are stable based on the results.

Figures 8 and 9 show that the blue line is within the red line, and this means that the data is normal and within the 5% significance.

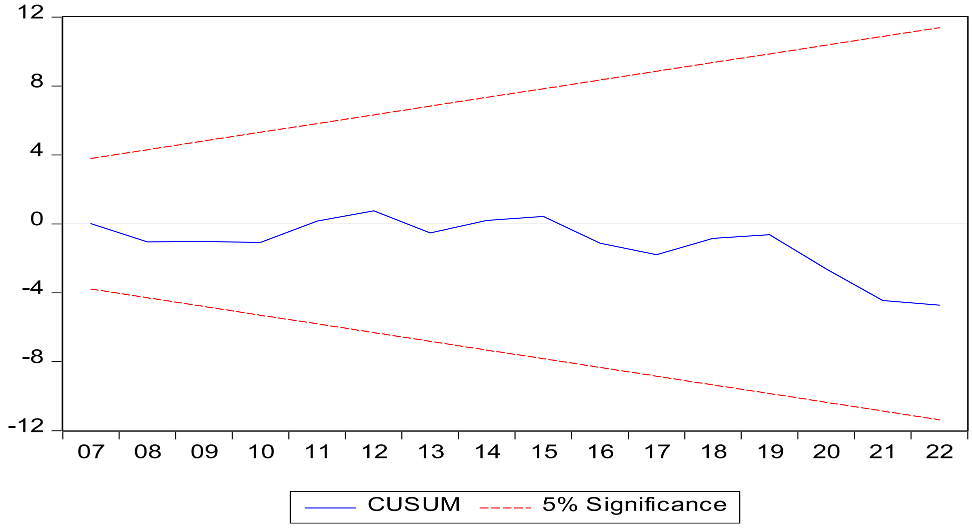

Fig. 8. CUSUM Test for stability

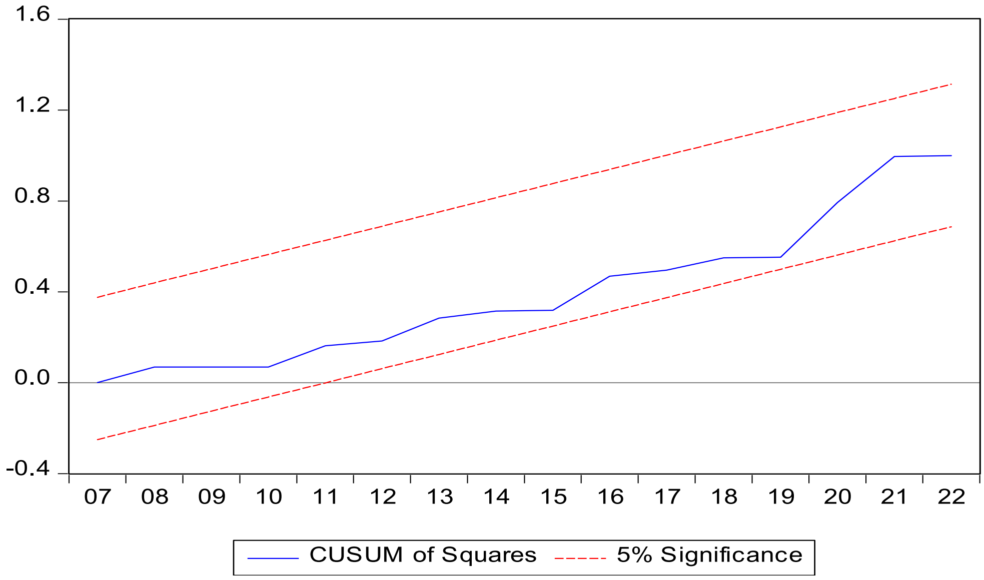

Fig. 9. CUSUM of squares test for stability.

CONCLUSION

Indonesia, experiencing fast economic growth, needs assistance managing its solid waste. The country generated 64 million metric tons (Mt) of municipal solid waste (MSW) in 2020. However, only 14% of garbage was recycled informally, and 45% was disposed of in landfills, demonstrating a lack of infrastructure for effective waste management—the test results for Johansen cointegration. This study employs quantitative research methods to analyse the impact of technological innovation and food waste management on carbon emissions and how these technologies can help reduce carbon emissions. The time series data collected from WDI (World Development Indicators) and BPS (Badan Pusat Statistik Indonesia) from 2000 to 2022. The following variables are used such as dependent variables carbon emission (CO2) and food waste generation (FWG) and independent variables technological innovation (TI), food production (FP), population density (POLD), economic growth (GDP), and the control variables are annual freshwater withdrawal (AFW). We applied the Johansen Co-integration test and Autoregressive Distributed Lag ARDL model for long-run impact. The study findings show that food wastage generation and technological innovation have been a statistically positive impact on carbon emissions.

The findings show that food production (FP) positively affected the dependent variables CO2 and FWG. The research also looked at the significant effects of GDP growth on CO2 and FWG. The long-term relationship between series and various integration orders is ascertained using the ARDL cointegration approach. The re-measured outcome provides the short-term dynamics and long-term relationship between the independent and dependent variables. Technological innovation does not imply that technologies should be layered one on the other. Over-composition of technologies will increase the economic risks associated with technological innovation and impede its spread, ultimately reducing its potential to reduce carbon emissions. Nonetheless, specific prospective policy initiatives can mitigate the financial risks associated with technical innovation (e.g., raising the sales price of carbon emission rights, food sales price, and feed-in tariff for renewable energy). This study can offer fresh viewpoints and policy proposals to carry out technological innovation and sensible management of facility agriculture in the future and to guarantee the scale dissemination of technological innovation solutions.

It is important to acknowledge the limitations of this study. Firstly, the research focuses specifically on the Indonesian context, which may limit the generalizability of the findings to other regions or countries with different carbon emissions levels and waste management systems. Secondly, data availability posed a serious challenge as a reasonably long time data frame yields a better outcome, Additionally, the study's scope and data restrictions didn't allow the researchers to account for factors such as calamity and natural disasters that could potentially impact the relationship between technological innovations, food waste, and carbon emissions.

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The present study did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practised in this research.

JEL

C32, F64, O32

ABBREVIATIONS

MSW (municipal solid waste); LFG (landfill gas); SDG (Sustainable Development Goals), SLCPs (Short-lived climatic pollutants), GWP (Global warming potential), SLCPs (short-lived climatic pollutants), BC (black carbon), CH4 (methane), EPA (Environmental Protection Agency), 3R (Reduce, Reuse, Recycle),

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