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The Environmental and Economic Dynamics of Food Waste and Greenhouse Gas Emissions: A Causal Time Series Analysis from 2000 to 2022

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Abstract: Food loss and waste pose significant social, economic, and environmental challenges worldwide, threatening food security and hindering sustainable development. While developing countries primarily face losses during production and storage, developed nations struggle with waste driven by consumer habits, spoilage, and overstocking, particularly in markets, restaurants, and homes. This study was aimed to analyze the complex relationships between food loss, waste, and various economic and environmental variables. The study examined the effects of variables such as education expenditures, food security, food prices, greenhouse gas emissions, and carbon emissions per capita on food losses and waste. These analyses shed light on the development of sustainable food policies at both national and global levels. Interventions to reduce food loss and waste will not only optimize food production and consumption processes but will also support a sustainable management of resources. As a result, this study aimed to understand the long-term effects of food loss and waste on economic growth, environmental sustainability, and social welfare. The findings of the study are of great importance in terms of directing future policies and aim to be an important guide in the transition to sustainable food systems.

Keywords: sustainable food systems; greenhouse gas emissions; food loss and waste

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1. Introduction

Food loss and waste stands out as one of the biggest social, economic, and environmental problems considering the increasing population and limited natural resources worldwide. According to the Food and Agriculture Organization of the United Nations (FAO) [1], approximately one-third of the food produced globally is wasted or lost every year. This rate shows a serious problem not only for developing countries but also for developed countries [2]. The high levels of food loss and waste jeopardize food security worldwide and also make it difficult to achieve sustainable development goals [3]. From food production to consumption, there may be many losses. While food losses that occur during the production, harvest, transportation, and storage processes are a fundamental problem in developing countries, consumer habits and waste culture constitute the main causes of food losses in developed countries [4–6]. Waste that occurs during the consumption stage is caused by reasons such as spoilage, damaged packaging, misinterpretation of expiration dates, overproduction, and overstocking especially in markets, restaurants, and homes. These problems reduce food supply efficiency and negatively affect price stability.

The impact of food losses and waste is not limited to the economic issues [7]; it also leads to serious environmental problems [4]. The waste of natural resources such as energy, water, and soil used in food production creates great pressure on ecosystems. In addition, greenhouse gas emissions (GHG) resulting from the sending of discarded food to landfills contribute to climate change and make it difficult to achieve environmental sustainability goals [8]. In this context, reducing food losses and waste provides economic gain and contributes to reduce the carbon footprint and combating climate change [9].

The scope and methodology of the present study have been well-designed to increase the reliability of the results. In this context, long-term and short-term relationships between variables were examined using advanced econometric methods [10–13]. The analyses conducted aimed to reveal guiding information to policy makers on the subject by comprehensively addressing the relationships of food loss and waste with different variables. Additionally, this study offers a unique contribution to the literature by employing a time series approach to explore the long-term and lagged relationships between food loss and waste (FLW) and key economic and environmental factors, including education expenditure, greenhouse gas emissions, food insecurity, GDP per capita, and food prices. Unlike many existing studies that rely on cross-sectional or panel data, our analysis captures temporal dynamics and causal pathways, providing deeper insights into the evolving nature of these interactions. Additionally, the integration of structural break analysis allows us to identify critical shifts in FLW trends, shedding light on the impact of external shocks, such as economic downturns, on sustainability outcomes. These methodological and analytical advancements position the study as a valuable resource for policymakers and researchers working towards sustainable food systems.

2. Materials and Methods

The aim of the study was to analyze the dynamic relationships between food loss and waste and greenhouse gas emission emissions and their effects on the economic, environmental, and social consequences of these factors by analyzing the dynamic relationships between variables that are critical for sustainability and to examine the relationships of food loss and waste with various indicators such as economic growth through gross domestic product per capita, the share of education expenditures in total government expenditures, greenhouse gas emissions, food prices, and food insecurity. Thus, it was aimed to support the road maps for societies to reduce food loss and waste and greenhouse gas emissions and to achieve sustainable development goals by revealing causal relationships. The study elaborates on the dynamic effects of social problems such as the impact of food price fluctuations on GHG emissions and the impact of food insecurity on food loss and waste. Through cointegration analyses including structural breaks, the long-term co-movement tendencies of food loss and waste and greenhouse gas emissions were examined. It was envisaged that changes in consumer behavior due to high food prices may contribute to sustainable food production. In this framework, the relationships between variables such as education expenditures, food insecurity, greenhouse gas emissions, population growth, and economic growth were evaluated with food loss and wastage from both short- and long-term perspectives, causality on each other were investigated, and ways to reduce food loss and wastage were discussed from the outputs obtained. In addition, the study also investigates whether the share of education expenditures has a time-dependent decreasing effect on food loss and food waste and evaluates its long-term effects.

The research was a longitudinal and causality explanatory time series study based on secondary data analysis. Table 1 provides information on the variables used and the sources.

Table 1. The definitions of the variables.

Code	Variable Name	Source	Link	Year Range
FLW	Food Loss and Waste	FAO	https://www.fao.org/platform-food-loss-waste/flw-data/en/, accessed on 30 October 2024	1965–2022
FP	Annual FAO Food Price Indices	FAO	https://www.fao.org/worldfoodsituation/foodpricesindex/en/, accessed on 30 October 2024	1990–2024
GDP	GDP Per Capita	Our World in Data from World Bank (2023)	https://ourworldindata.org/grapher/gdp-per-capita-worldbank?time=latest, accessed on 30 October 2024	1990–2022
POP	Population, total	World Bank (2022)	https://data.worldbank.org/indicator/SP.POP.TOTL, accessed on 30 October 2024	1960–2023
ES	Education spending as a share of total government expenditure	Our World in Data from World Bank World Bank (2024)	https://ourworldindata.org/grapher/share-of-education-in-government-expenditure, accessed on 30 October 2024	2000–2022
GHG	Greenhouse gas emissions (tones)	Jones et al. (2024)—with major processing by Our World in Data.	https://ourworldindata.org/greenhouse-gas-emissions, accessed on 30 October 2024	1850–2022
FI	Prevalence of Severe Food Insecurity (%)	World Bank (2024)	https://microdata.worldbank.org/index.php/catalog/6103/study-description, accessed 30 October 2024	1999–2022

Among the variables obtained in Table 1, data from 2000 to 2022, which was the common year range, were included in the analysis. Since the share of education expenditures in total government expenditures was until 2021, the year 2022 was estimated, and the autoregressive integrated moving average (ARIMA) model was constructed for this. It was stated that the Food Loss and Waste variable includes transportation, storage, shelling, threshing, drying, harvesting, and winnowing activities. The sources from which the other variables were obtained, the coding and explanations of the variables, are presented in Table 1.

Figure 1 shows the level values and changes of the variables used between 2000 and 2022.

Food Insecurity Index, Food Loss and Waste Index, Food Price Per Capita, total GHG, GHG Per Capita (divided by population in the same year), population, and GDP Per Capita variables are given for the period between 2000 and 2022. Educational Spending's total government expenditures are given in Figure 1.

For the variable Educational Spending's share in total government expenditures, data from 2000 to 2021 were obtained from the source. However, since the 2022 data needed to be available as in other variables in order to establish a causal relationship with other variables, the 2022 data were estimated from its own historical data with the ARIMA model. For this, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test was used from the stationarity assumption test, and it was determined that the data were not stationary in the first stage (Lagrange Multiplier [LM] test statistics$_1$ = 0.48616; Truncation lag$_1$ = 2; and p_1 = 0.04478). Thereupon, logarithmic transformation and first-degree difference were taken, and the stationarity problem was eliminated (LM test statistics$_2$ = 0.072683; Truncation lag$_2$ = 2; and p_2 = 0.10000). When the existence of seasonality was examined, it was thought that there may be a repetitive pattern in the function graph, and frequency spectrum analysis was performed (frequency bandwidth = 0.012), and when examined together with the autocorrelation function graph, a weak and insignificant autocorrelation (~0.2 < 0.4[sig.cutoff]) was determined; a pattern that changes in intensity and repeats itself in a variable manner in 2 to 3 years and an insignificant seasonality was observed. Accordingly, instead of a seasonal autoregressive integrated moving average (SARIMA), the autoregressive integrated moving average (ARIMA) model was established on the data from which the logarithmic transformation difference was taken, and the 2022 education expenditures were estimated by applying the inverse logarithmic transformation to the obtained estimation result:

$$y_t = Educational\ Spendingt\ and\ z_t = \log(y_t)\ for\ (2000 \leq t \leq 2021)$$

$$\Delta z_t = z_t - z_{t-1} = \log(y_t) - \log(y_{t-1})\ for\ (2001 \leq t \leq 2021)$$

$$\Delta z_t = c + \varnothing_1 \Delta z_{t-1} + \varnothing_2 \Delta z_{t-2} + \ldots + \epsilon_t\ for\ (2001 \leq t \leq 2021),\ \text{so}$$

$$\Delta \hat{z}_{2022} = c + \varnothing_1 \Delta z_t + \varnothing_2 \Delta z_{t-2} + \ldots + \epsilon_{t+1}\ and$$

$$\hat{y}_{2022} = \exp(z_{2021} + \Delta \hat{z}_{2022})$$

$$\hat{y}_{2022} = \exp\left(\log(y_{2021} + \Delta \hat{z}_{2022}\right) = y_{2021} * \exp(\Delta \hat{z}_{2022})$$

$$\hat{y}_{2022} = \exp(\log(y_{2021}) + 1.4213)$$

$$\hat{y}_{2022} = 4.1424$$

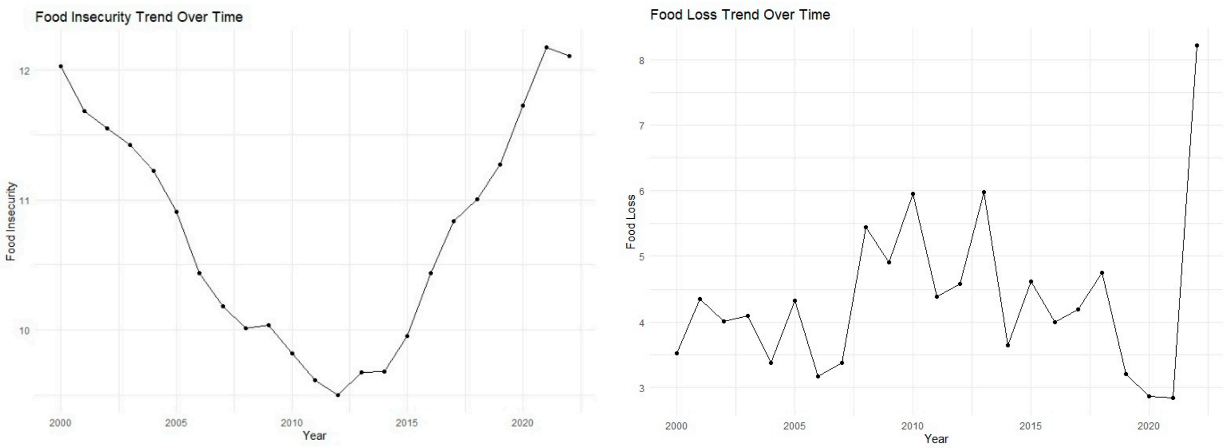

Figure 1. *Cont.*

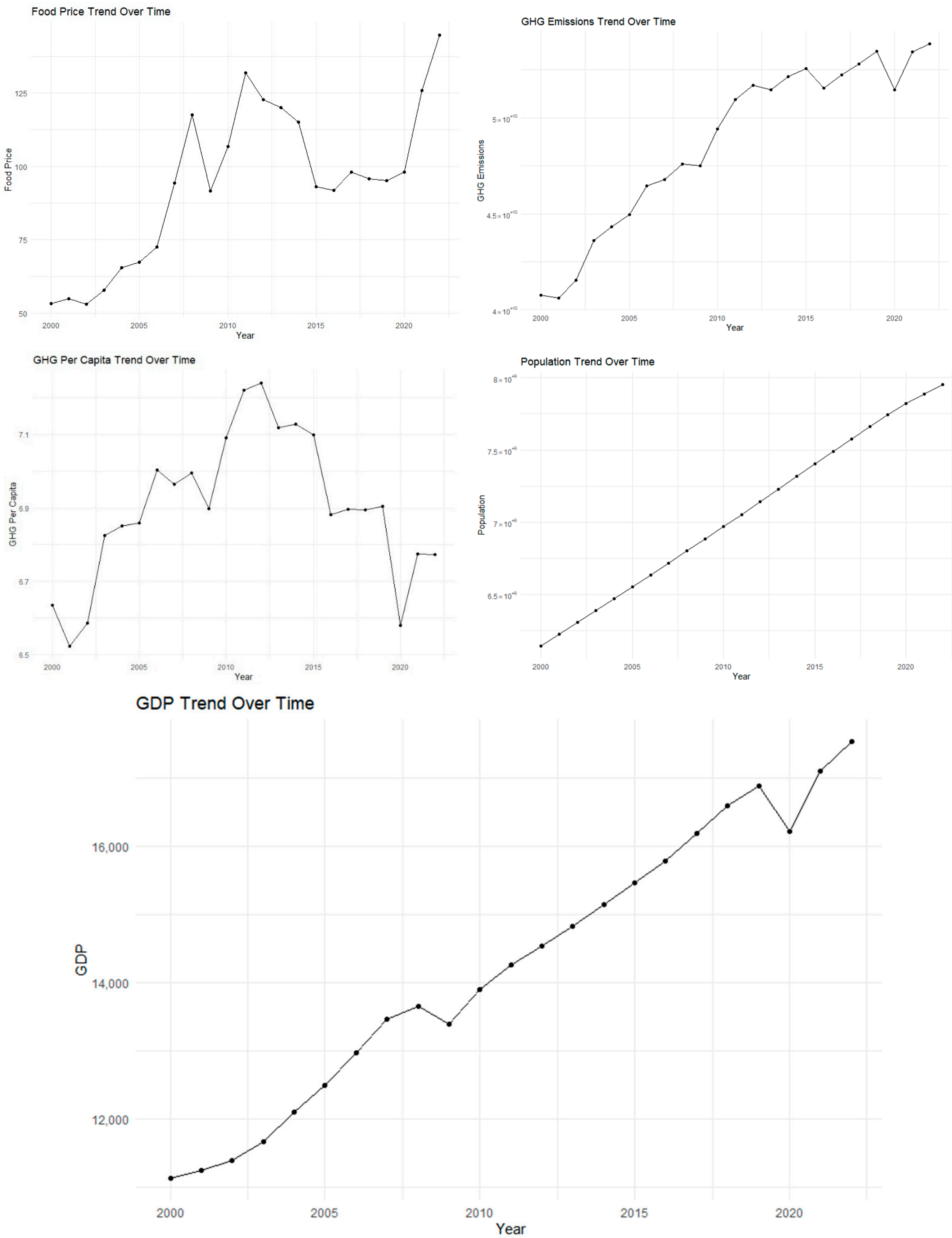

Figure 1. Change of variables between 2000 and 2022.

An ARIMA model was created using the data of Educational Spending's share in total government expenditures for the years 2000–2021, and a forecast was made for the year 2022. In order to evaluate the accuracy of the model, the estimated value was compared with the actual value, and the mean absolute error (MAE) and root mean square error (RMSE) were calculated. The results obtained based on the comparisons of the test and training datasets including the median year, the last two years, and the last year data showed that the MAE and RMSE values varied between 0.0345 and 0.0093 and remained at low levels. Thus, it was determined that the model's predictions had a high accuracy, and the error rates were minimal, and therefore the new data were reliable.

After the prediction, the education expenditure ratio in GDP between 2000 and 2022 is given in Figure 2.

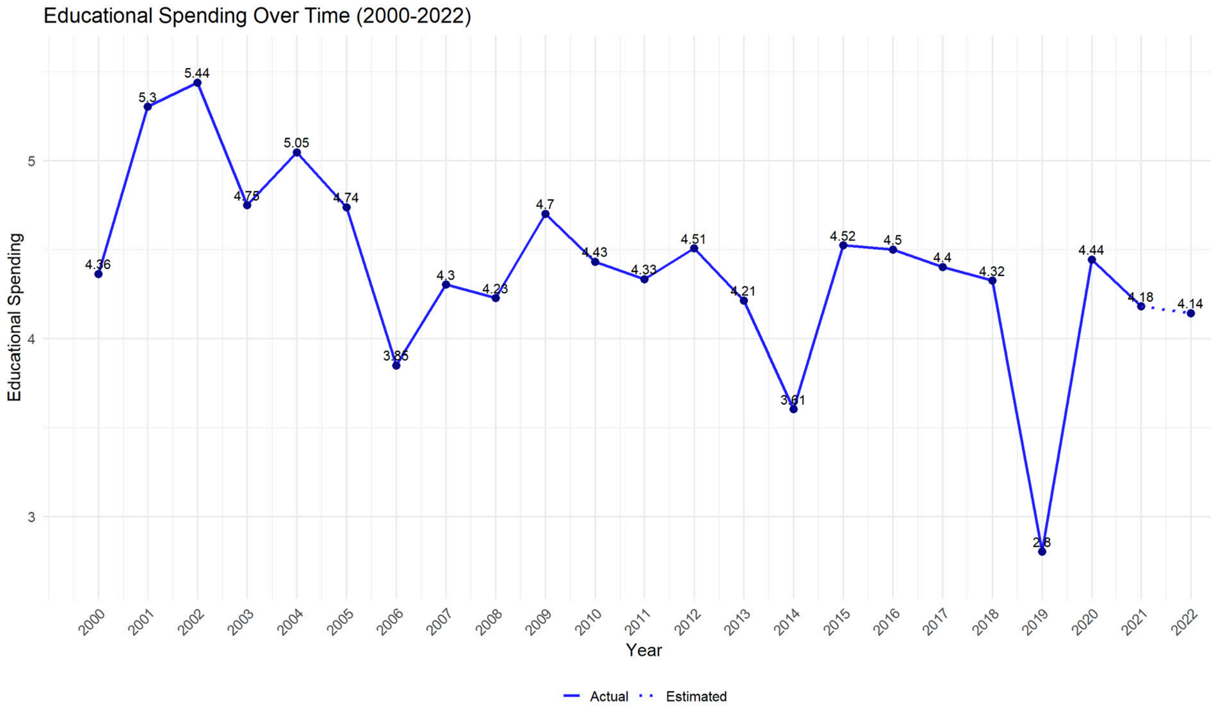

Figure 2. Trend of Educational Spending as a share of total government expenditure (2000–2022) with 2022 estimate.

Figure 2 showed the Educational Spending share of total government expenditures between 2000 and 2022, and 2022 was shown as estimated data with a dashed line. While rapid increases were seen in 2000–2002 and 2004, a sharp decline in 2019, thought to be due to the coronavirus-19 outbreak, was notable.

We used the R 4.4.1 program in the analysis of the data. In the assumption tests, the White test and Breusch–Pagan test were used for homoscedasticity control. Normality control was performed with the Jarque–Bera test. The Breusch–Godfrey test was used for autocorrelation control. The Kwiatkowski–Phillips–Schmidt–Shin test was used in unit root analyses. The Bai–Perron test was used to control multiple structural breaks, and the Chow test was used to control point breaks. The existence of cointegration was checked with the Bound test from the Wald test family. In determining the lag length, the Akaike Information Criterion (AIC) suggestion and the size of the explained variance were evaluated. In addition, the GHG total and Population Wald-Bound test were scaled to correspond to two-digit numbers. Toda–Yamamoto and Granger tests were used in causality tests. The Granger causality test is a widely used test to examine the causality relationship between two variables over time and evaluates the causality relationship by analyzing whether the past values of one series can explain the current values of another series [13]. On the other hand, the Granger test is sensitive to restrictions such as cointegration, different levels of stationarity, and the presence or absence of structural break; therefore the Toda–Yamamoto method was used as a complement when there is cointegration, structural break, or different levels of stationarity [11,13]. The test method developed by Toda and Yamamoto (1995) was an improved version of the traditional Granger causality test and allows causality analyses to be performed regardless of whether there is cointegration between the series [11]. The Toda–Yamamoto approach increases the lag length by considering the maximum degree of integration (dmax) of the model and then tests the causality relationships using the Wald test [10]. In the study, the Toda–Yamamoto method was preferred in some models in order to accurately detect short-term causality relationships between the series by considering cointegration and structural breaks between the variables. Since there was a total of 23 years of observation series, instead of Vector Error Correction Models in short-term series, Autoregressive Distributed Lag (ARDL), Unrestricted Error Correction Model (UECM), and Restricted Error Correction Model (RECM) models, which are effective in the short-term, were used [14]. Error Correction Term (ECT) was used in the RECM model. The ARDL model is a flexible model used to examine short-term and long-term relationships together and was preferred especially in cases where there may be a cointegration relationship between variables [15]. While ARDL allows analysis of series at different stationarity levels (only I(0) and I(1)), it was preferred to examine dynamic relationships in the short- and long-term. Then, the UECM model, which is a derivative of the ARDL model, was used to examine the balance dynamics and especially to observe how the long-term balance is corrected by short-term shocks [16]. The RECM model, as a restricted version of the UECM, was used to examine the dynamics of short-term changes in the long run [12].

The hypotheses determined for the research are as follows:

H1a. *The share of education expenditure in total government expenditure has a significant effect on Food Loss and Waste.*

H1b. *The share of education expenditure in total government expenditure is a causal determinant of Food Loss and Waste.*

H2a. *Food Insecurity has a significant effect on Food Loss and Waste.*

H2b. *Food Insecurity is a causal determinant of Food Loss and Waste.*

H3a. *Food Loss and Waste has a significant effect on Food Insecurity.*

H3b. *Food Loss and Waste is a causal determinant of Food Insecurity.*

H4a. *Food Loss and Waste has a significant effect on Food Price.*

H4b. *Food Loss and Waste is a causal determinant of Food Price.*

H5a. *Food Loss and Waste has a significant effect on greenhouse gas emissions (GHG).*

H5b. *Food Loss and Waste is a causal factor of greenhouse gas emissions (GHG).*

H6a. *Food Loss and Waste has a significant effect on greenhouse gas emissions per capita (GHG Per Capita).*

H6b. *Food Loss and Waste is a causal factor of greenhouse gas emissions per capita (GHG Per Capita).*

H7a. *Food Insecurity has a significant effect on greenhouse gas emissions (GHG).*

H7b. *Food Insecurity is a causal factor of greenhouse gas emissions (GHG).*

H8a. *Food Insecurity has a significant effect on greenhouse gas emissions per capita (GHG Per Capita).*

H8b. *Food Insecurity is a causal factor of greenhouse gas emissions per capita (GHG Per Capita).*

H9a. *Food Price has a significant effect on greenhouse gas emissions (GHG).*

H9b. *Food Price is a causal factor of greenhouse gas emissions (GHG).*

H10a. *Food Price has a significant effect on greenhouse gas emissions per capita (GHG Per Capita).*

H10b. *Food Price is a causal factor of greenhouse gas emissions per capita (GHG Per Capita).*

H11a. *Population has a significant effect on greenhouse gas emissions (GHG).*

H11b. *Population is a causal factor of greenhouse gas emissions (GHG).*

H12a. *GDP Per Capita has a significant effect on Food Loss and Waste.*

H12b. *GDP Per Capita is a causal factor of Food Loss and Waste.*

The equations of the research models are listed according to the models as follows:

Model 1:

$$FLW_t = \alpha_0 + \sum_{i=1}^{2} \beta_i FLW_{t-i} + \sum_{j=1}^{3} \gamma_j ES_{t-j} + \epsilon_t$$

$$FLW_t = \beta_0 + \sum_{i=1}^{2} \alpha_{1i} FLW_{t-i} + \sum_{j=3}^{dmax} \beta_{2j} FLW_{t-j} + \sum_{i=1}^{3} \theta_{1i} ES_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} ES_{t-j} + \epsilon_t$$

Model 2:

$$FLW_t = \alpha_0 + \sum_{i=1}^{4} \beta_i FLW_{t-i} + \sum_{j=1}^{3} \gamma_j ES_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$FLW_t = \beta_0 + \sum_{i=1}^{4} \alpha_{1i} FLW_{t-i} + \sum_{j=4}^{dmax} \beta_{2j} FLW_{t-j} + \sum_{i=1}^{3} \theta_{1i} ES_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} ES_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

Model 3:

$$FI_t = \alpha_0 + \sum_{i=1}^{3} \beta_i FI_{t-i} + \sum_{j=1}^{3} \gamma_j FLW_{t-j} + \delta_1 Dummy_{before2012} + \delta_1 Dummy_{after2012} + \epsilon_t$$

$$FI_t = \beta_0 + \sum_{i=1}^{3} \alpha_{1i} FI_{t-i} + \sum_{j=3}^{dmax} \beta_{2j} FI_{t-j} + \sum_{i=1}^{3} \theta_{1i} FLW_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} FLW_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

Model 4:

$$FP_t = \alpha_0 + \sum_{i=1}^{3} \beta_i FP_{t-i} + \sum_{j=1}^{3} \gamma_j FLW_{t-j} + \epsilon_t$$

$$FP_t = \beta_0 + \sum_{i=1}^{3} \alpha_{1i} FP_{t-i} + \sum_{j=3}^{dmax} \beta_{2j} FP_{t-j} + \sum_{i=1}^{3} \theta_{1i} FLW_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} FLW_{t-j} + \epsilon_t$$

Model 5:

$$GHG_t = \alpha_0 + \sum_{i=1}^{2} \beta_i GHG_{t-i} + \gamma FLW_t + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \gamma \Delta FLW_t + \lambda (GHG_{t-1} - \phi FLW_{t-1}) + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \gamma \Delta FLW_t + \lambda ECT_{t-1} + \epsilon_t$$

$$GHG_t = \beta_0 + \sum_{i=1}^{2} \alpha_i GHG_{t-i} + \sum_{j=0}^{0} \theta_{1j} FLW_{t-j} + \epsilon_t$$

Model 6:

$$GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{3} \beta_i GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j FLW_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{2} \beta_i \Delta GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta FLW_{t-j} + \lambda (GHGPerCapita_{t-1} - \phi FLW_{t-1}) + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{2} \beta_i \Delta GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta FLW_{t-j} + \lambda ECT_{t-1} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$GHGPerCapita_t = \beta_0 + \sum_{i=1}^{3} \alpha_{1i} GHGPerCapita_{t-i} + \sum_{j=3}^{dmax} \beta_{2j} GHGPerCapita_{t-j} + \sum_{i=1}^{3} \theta_{1i} FLW_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} FLW_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

Model 7:

$$GHG_t = \alpha_0 + \sum_{i=1}^{2} \beta_i GHG_{t-i} + \sum_{j=1}^{2} \gamma_j FI_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \sum_{j=1}^{2} \gamma_j \Delta FI_{t-j} + \lambda (GHG_{t-1} - \phi FI_{t-1}) + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \sum_{j=1}^{2} \gamma_j \Delta FI_{t-j} + \lambda ECT_{t-1} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$GHG_t = \beta_0 + \sum_{i=1}^{2} \alpha_{1i} GHG_{t-i} + \sum_{j=2}^{dmax} \beta_{2j} GHG_{t-j} + \sum_{i=1}^{2} \theta_{1i} FI_{t-i} + \sum_{j=2}^{dmax} \gamma_{2j} FI_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

Model 8:

$$GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{2} \beta_i GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j FP_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta FP_{t-j} + \lambda\left(GHGPerCapita_{t-1} - \phi FP_{t-1}\right) + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta FP_{t-j} + \lambda ECT_{t-1} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$GHGPerCapita_t = \beta_0 + \sum_{i=1}^{2} \alpha_{1i} GHGPerCapita_{t-i} + \sum_{j=2}^{dmax} \beta_{2j} GHGPerCapita_{t-j} + \sum_{i=1}^{3} \theta_{1i} FP_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} FP_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

Model 9:

$$GHG_t = \alpha_0 + \sum_{i=1}^{2} \beta_i GHG_{t-i} + \gamma FLW_t + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \gamma \Delta FLW_t + \lambda(GHG_{t-1} - \phi FLW_{t-1}) + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \gamma \Delta FLW_t + \lambda ECT_{t-1} + \epsilon_t$$

$$GHG_t = \beta_0 + \sum_{i=1}^{2} \alpha_{1i} GHG_{t-i} + \sum_{i=0}^{0} \theta_{1i} FLW_{t-j} + \epsilon_t$$

Model 10:

$$GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{2} \beta_i GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j FP_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta FP_{t-j} + \lambda\left(GHGPerCapita_{t-1} - \phi FP_{t-1}\right) + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$\Delta GHGPerCapita_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHGPerCapita_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta FP_{t-j} + \lambda ECT_{t-1} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

$$GHGPerCapita_t = \beta_0 + \sum_{i=1}^{2} \alpha_{1i} GHGPerCapita_{t-i} + \sum_{j=2}^{dmax} \beta_{2j} GHGPerCapita_{t-j} + \sum_{i=1}^{3} \theta_{1i} FP_{t-i} + \sum_{j=3}^{dmax} \gamma_{2j} FP_{t-j} + \delta_1 Dummy_{before2012} + \delta_2 Dummy_{after2012} + \epsilon_t$$

Model 11:

$$GHG_t = \alpha_0 + \sum_{i=1}^{2} \beta_i GHG_{t-i} + \gamma POP_t + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \gamma \Delta POP_t + \lambda(GHG_{t-1} - \phi POP_{t-1}) + \epsilon_t$$

$$\Delta GHG_t = \alpha_0 + \sum_{i=1}^{1} \beta_i \Delta GHG_{t-i} + \gamma \Delta POP_t + \lambda ECT_{t-1} + \epsilon_t$$

$$GHG_t = \beta_0 + \sum_{i=1}^{2} \alpha_i GHG_{t-i} + \sum_{j=0}^{0} \theta_{1j} POP_{t-j} + \epsilon_t$$

Model 12:

$$FLW_t = \alpha_0 + \sum_{i=1}^{2} \beta_i FLW_{t-i} + \sum_{j=1}^{1} \gamma_j GDPPerCapita_{t-j} + \epsilon_t$$

$$FLW_t = \beta_0 + \sum_{i=1}^{2} \alpha_{1i} FLW_{t-i} + \sum_{j=2}^{dmax} \beta_{2j} FLW_{t-j} + \sum_{i=1}^{1} \theta_{1i} GDPPerCapita_{t-i} + \sum_{j=1}^{dmax} \gamma_{2j} GDPPerCapita_{t-j} + \epsilon_t$$

In the present study, it was aimed to observe the trend effects that change depending on the break as well as the long- and short-term relationships between the variables through the relevant models, and the breaks were in 2012 and were the same for both GHG Per Capita and Food Insecurity. We also interpreted the effects of the break points analyzed with trend dummy variables. While a 10% margin of error was accepted in the cointegration and causality tests and long-term balance relationships and causal trends were evaluated, we used a 5% margin of error in order to provide a stronger level of significance in the models in general. While examining the short-term and long-term dynamic relationships with these approaches, we determined the existence or absence of direct causal relationships between the variables. In some models, the lag length could not be included in the independent variable according to the AIC and explained variance, and therefore the short-term could be examined. In addition, in some models, long-term dynamic relationships could not be examined, and cointegration could not be interpreted because H0 hypothesis could not be rejected as a result of the Bound test. The equations given above were created in this direction, and the analysis was performed accordingly.

3. Results

For the selection of causality analysis and suitability for the ARDL model, the stationarity of the variables was tested with unit root analyses (Table 1).

In unit root analyses, the Kwiatkowski–Phillips–Schmidt–Shin test was selected according to trend or fixed existence, and Educational Spending and Greenhouse Gas Emission were made stationary by taking the first difference, and the others were determined to be stationary as a result of the test. Accordingly, the use of variables in the models and the selection of causality analyses were carried out (Table 2).

Cointegration analyses were examined according to models in Table 2, while p is the lag of the dependent variable, q represents the lag of the independent variable, and these were selected by evaluating them together according to the AIC and R2 of the models. In addition, cointegration was examined with the Wald-Bound test, and Bai–Perron's structural breaks were checked with the Chow test, and if there was no break, and if there was cointegration, the Granger causality was selected; if there was no structural break or cointegration, the Toda–Yamamoto causality analysis was selected. If there was cointegration, the ARDL/UECM-RECM models were selected; otherwise, only the ARDL model was used. According to this information, no cointegration was found between the share of Educational Spending in total government expenditures and Food Loss, and accordingly, the ARDL and Toda–Yamamoto methods were selected. A break was detected between Food Insecurity and Food Loss, but no cointegration was found; ARDL and Toda–Yamamoto methods were proposed. There was a break between Food Loss and Food Insecurity, but there was no cointegration; the ARDL and Toda–Yamamoto methods were proposed. No cointegration was found between Food Loss and Food Price; the ARDL and Toda–Yamamoto methods were used. There was cointegration between Food Loss and GHG; the ARDL, UECM, and RECM models were selected, and the Granger causality method was preferred. Break and cointegration were detected between Food Loss and GHG Per Capita, and the ARDL or UECM-RECM and Toda–Yamamoto methods were selected. It was found that there was a break and significant cointegration between Food Insecurity and GHG, and the ARDL, UECM, and RECM methods and the Toda–Yamamoto method were selected. It was seen that there was a break and strong cointegration between Food Insecurity and GHG Per Capita, and accordingly the ARDL or UECM-RECM models and the Toda–Yamamoto causality method were applied. Significant cointegration was detected between Food Price and GHG, and since it was understood that there was no structural break, the ARDL and UECM-RECM models were used, and Granger was selected as the causality analysis method. Since there was a break and cointegration between Food Price and GHG Per Capita, the ARDL and UECM-RECM models were preferred, and the Toda–Yamamoto causality method was preferred. Cointegration was detected between Population and GHG, and since it was determined that there was no structural break, the ARDL and UECM-RECM models were used, and the Granger causality method was preferred. It was seen that there was no cointegration between GDP Per Capita and Food Loss; therefore the ARDL model and the Toda–Yamamoto method were used (Table 3).

Table 2. Unit root tests.

Variable Codes	Result	KPSS Test Result (*p*) for H_A on Non-Stationary	Stationary Hypothesis Result
FLW	Stationary	Level: 0.1379, $p \geq 0.1$	H_0 cannot be rejected.
FP	Stationary	Level: 0.1400, $p = 0.061$	H_0 cannot be rejected.
GDP Per Capita	Stationary	Level: 0.0636, $p \geq 0.1$	H_0 cannot be rejected.
POP	Stationary	Level: 0.1043, $p \geq 0.1$	H_0 cannot be rejected.
ES	First-Degree Differencing than Stationary	Level: 0.0706, $p \geq 0.1$	H_0 cannot be rejected after diff.
GHG	First-Degree Differencing than Stationary	Level: 0.0740, $p \geq 0.1$	H_0 cannot be rejected after diff.
GHG Per Capita	Stationary	Level: 0.2379, $p \geq 0.1$	H_0 cannot be rejected.
FI	Stationary	Level: 0.2230, $p \geq 0.1$	H_0 cannot be rejected.

Kwiatkowski–Phillips–Schmidt–Shin test.

Table 3. Cointegration and breakpoint analysis results.

No.	Models	p	q	Wald-Bound Test		Bai–Perron and Chow Test	Result	Suggested Model	Causality Method
				F Value	*p*-Value				
1	FoodLoss <- EducationalSpending	2	3	2.8281	0.2000	No breakpoint	No cointegration	ARDL	Toda–Yamamoto
2	FoodLoss <- FoodInsecurity	4	3	1.3500	0.7564	Breakpoint	No cointegration	ARDL	Toda–Yamamoto
3	FoodInsecurity <- FoodLoss	3	3	1.5663	0.6508	Breakpoint	No cointegration	ARDL	Toda–Yamamoto
4	FoodPrice <- FoodLoss	3	3	1.3928	0.6674	No breakpoint	No cointegration	ARDL	Toda–Yamamoto
5	GHG <- FoodLoss	2	0	5.9296	0.0062 *	No breakpoint	Cointegration	ARDL/UECM-RECM	Granger

Table 3. *Cont.*

No.	Models	p	q	Wald-Bound Test		Bai–Perron and Chow Test	Result	Suggested Model	Causality Method
				F Value	*p*-Value				
6	GHG Per Capita <- FoodLoss	3	3	3.8785	0.0877 *	Breakpoint	Cointegration	ARDL/UECM-RECM	Toda–Yamamoto
7	GHG <- FoodInsecurity	2	2	8.0017	0.0008 *	Breakpoint	Cointegration	ARDL/UECM-RECM	Toda–Yamamoto
8	GHG Per Capita <- FoodInsecurity	1	3	8.7465	0.0001 *	Breakpoint	Cointegration	ARDL/UECM-RECM	Toda–Yamamoto
9	GHG <- FoodPrice	2	0	9.2837	0.0004 *	No breakpoint	Cointegration	ARDL/UECM-RECM	Granger
10	GHG Per Capita <- FoodPrice	2	3	4.4151	0.0142	Breakpoint	Cointegration	ARDL/UECM-RECM	Toda–Yamamoto
11	GHG <- Population	2	0	5.5857	0.0097	No breakpoint	Cointegration	ARDL/UECM-RECM	Granger
12	FoodLoss <- GDPPerCapita	2	1	2.3421	0.3158	No breakpoint	No cointegration	ARDL	Toda–Yamamoto

p: dependent variable and optimal lag for AIC or R^2 decision; q: independent variable and optimal lag for AIC or R^2 decision; *: significant at 10% margin of error.

Table 4 shows the modeling of temporal dynamics between the share of Educational Spending in total government expenditures and Food Loss and Waste. The 3-year lagged effect of Educational Spending (β = −1.4737) is significant (p = 0.0151) and decreasing on Food Loss and Waste. However, the model can explain 12.22% of the variance and gives insignificant results (p = 0.2723).

Table 4. Model 1: the effect of Educational Spending as a share of total government expenditure on Food Loss and Waste.

	Models	Independent Variable	β	SE	t	*p*
Model 1: Food Loss and Waste <- Educational Spending	**ARDL**	Intercept (Food Loss and Waste)	6.5724	3.9256	1.6740	0.1180
		L (Food Loss$_{(1)}$)	−0.1944	0.3498	−0.5560	0.5879
		L (Food Loss$_{(2)}$)	0.1377	0.3749	0.3670	0.7192
		Educational Spending	0.4043	0.6420	0.6300	0.5398
		L (Educational Spending$_{(1)}$)	0.5243	0.6061	0.8650	0.4027
		L (Educational Spending$_{(2)}$)	0.1204	0.5412	0.2220	0.8275
		L (Educational Spending$_{(3)}$)	**−1.4737**	**0.5271**	**−2.7960**	**0.0151 ***

* significant at 5% margin of error; R^2: 0.3994; Adj R^2: 0.1222; F-statistic = 1.441; p-value = 0.2723.

In Table 5, the modelings of the temporal dynamics between Food Insecurity and Food Loss and Waste were shown. Food Insecurity, which showed a decreasing trend until 2012, resulted in a rapidly increasing trend since 2012, so dummy variables were included in the model due to the structural break and trend cycle of 2012. The instantaneous effect of Food Insecurity on Food Loss and Waste is statistically limited in significance and decreasing (β = −5.4931 and p = 0.0654). The model, which examined long-term relationships and included the trend, was insufficient to explain the variance.

In Table 6, the modeling of the temporal dynamics was established between Food Insecurity and Food Loss and Waste. Food Insecurity, which showed a decreasing trend until 2012, has shown a rapidly increasing trend since 2012, so the structural break and trend cycle of 2012 were included in the model. The 1-year lagged effect of Food Insecurity on itself was found to be increasing (β = 1.3836) and significant (p = 0.0014). The instantaneous effect of Food Loss and Waste tends to decrease Food Insecurity but has limited significance (p = 0.0850).

Table 5. Model 2: the impact of Food Insecurity on Food Loss and Waste.

	Models	Independent Variable	β	SE	t	*p*
Model 2: Food Loss and Waste <- Food Insecurity	**ARDL**	Intercept (Food Loss and Waste)	3.4024	1.6497	2.0620	0.0731
		L (Food $Loss_{(1)}$)	−0.7763	0.6029	−1.2880	0.2339
		L (Food $Loss_{(2)}$)	−0.4976	0.5697	−0.8730	0.4079
		L (Food $Loss_{(3)}$)	−0.0812	0.6288	−0.1290	0.9005
		L (Food $Loss_{(4)}$)	−0.1461	0.7886	−0.1850	0.8576
		Food Insecurity	−5.4931	2.5747	−2.1340	0.0654
		L (Food $Insecurity_{(1)}$)	6.9392	4.3233	1.6050	0.1471
		L (Food $Insecurity_{(2)}$)	−2.7969	4.9105	−0.5700	0.5846
		L (Food $Insecurity_{(3)}$)	−0.9204	3.2458	−0.2840	0.7839
		Trend $Effect_{(before\ 2012)}$	−0.0348	0.2235	−0.1560	0.8800
		Trend $Effect_{(after\ 2012)}$	−0.2097	0.3531	−0.5940	0.5690

R^2: 0.4816; Adj R^2: −0.1665; F-statistic = 0.7431; *p*-value = 0.6763.

Table 6. Model 3: the impact of Food Loss and Waste on Food Insecurity.

	Models	Independent Variable	β	SE	t	*p*
Model 3: Food Insecurity <- Food Loss and Waste	**ARDL**	Intercept (Food Insecurity)	2.0336	1.4054	1.4470	0.1785
		L (Food $Insecurity_{(1)}$)	**1.3836**	**0.3167**	**4.3690**	**0.0014 ***
		L (Food $Insecurity_{(2)}$)	−0.8464	0.4704	−1.8000	0.1021
		L (Food $Insecurity_{(3)}$)	0.2855	0.3225	0.8850	0.3969
		Food Loss	−0.0591	0.0309	−1.9120	0.0850
		L (Food $Loss_{(1)}$)	−0.0476	0.0617	−0.7720	0.4582
		L (Food $Loss_{(2)}$)	0.0066	0.0600	0.1100	0.9148
		L (Food $Loss_{(3)}$)	0.0349	0.0568	0.6140	0.5528
		Trend $Effect_{(before\ 2012)}$	−0.0033	0.0149	−0.2200	0.8304
		Trend $Effect_{(after\ 2012)}$	0.0518	0.0351	1.4790	0.1700

* significant at 5% margin of error; for ARDL Model: R^2: 0.9815; Adj R^2: 0.9648; F-statistic = 58.81; *p*-value = 1.774×10^{-7}.

The temporal dynamics established between Food Price and Food Loss and Waste were shown in Table 7. The 1-year delayed effect of Food Price on itself was found to be increasing (β = 0.8022) and significant (*p* = 0.0143). The instantaneous and delayed effects of Food Loss and Waste were not found to be significant (*p* > 0.05).

In Table 8, the temporal dynamics established between GHG and Food Loss and Waste were evaluated. Although Food Loss and Waste increased GHG instantly, it had no significant effect (*p* = 0.3381). GHG was affected by its previous period and had a positive increasing cumulative effect (β = 0.5591 and *p* = 0.0241). In the long-term, it has been determined that GHG may resist fluctuations in the previous period and has a corrective significant effect on its trend in the current period (β = −0.6261 and *p* = 0.0271). Apart from all these, the cointegration coefficient of Food Loss and Waste and GHG was positive (β = 38.6367) but does not have sufficient statistical significance (*p* = 0.3713).

Table 7. Model 4: effect of Food Loss and Waste on Food Price.

	Models	Independent Variable	β	SE	t	*p*
Model 4: Food Price <- Food Loss and Waste	**ARDL**	Intercept (Food Price)	3.1739	2.97044	1.068	0.3063
		L (Food Price$_{(1)}$)	**0.8022**	**0.2803**	**2.862**	**0.0143 ***
		L (Food Price$_{(2)}$)	−0.3854	0.3662	−1.053	0.3133
		L (Food Price$_{(3)}$)	0.3878	0.2833	1.369	0.1961
		Food Loss	3.1516	3.3118	0.952	0.3601
		L (Food Loss$_{(1)}$)	−3.5135	4.0124	−0.876	0.3984
		L (Food Loss$_{(2)}$)	−3.4758	4.3728	−0.795	0.4421
		L (Food Loss$_{(3)}$)	1.8831	4.7804	0.394	0.7006

* significant at 5% margin of error; for ARDL Model: R^2: 0.7445; Adj R^2: 0.5955; F-statistic = 4.996; *p*-value = 0.007495.

Table 8. Model 5: the impact of Food Loss and Waste on GHG.

	Models	Independent Variable	β	SE	t	*p*
Model 5: GHG <- Food Loss and Waste	**ARDL**	**Intercept (GHG)**	**0.6275**	**0.2388**	**2.6280**	**0.0176 ***
		L (GHG$_{(1)}$)	**0.5591**	**0.2258**	**2.4760**	**0.0241 ***
		L (GHG$_{(2)}$)	0.3148	0.2116	1.4880	0.1551
		Food Loss	0.0162	0.0164	0.9860	0.3381
	UECM	**Intercept (GHG)**	**0.6275**	**0.2388**	**2.6280**	**0.0176 ***
		L (d_GHG$_{(1)}$)	**−0.1261**	**0.0495**	**−2.5470**	**0.0208 ***
		L (FoodLoss$_{(2)}$)	0.0162	0.0164	0.9860	0.3381
		d (L(d_GHG$_{(1)}$)	−0.3148	0.2116	−1.4880	0.1551
	RECM	**Intercept (GHG)**	**0.0599**	**0.0202**	**2.9680**	**0.0086 ***
		L(ECT)	**−0.6261**	**0.2588**	**−2.4190**	**0.0271 ***
		d (Food Loss)	0.0052	0.0130	0.3990	0.6951
	Cointegration Coefficient		38.6367	38.6367	42.3303	0.9127

* significant at 5% margin of error; for ARDL Model: R^2: 0.9535; Adj R^2: 0.9453; F-statistic = 116.3; *p*-value = 1.575×10^{-11}.

The temporal dynamics established between GHG Per Capita and Food Loss and Waste are shown in Table 9. In addition, since GHG Per Capita followed an increasing trend before 2012 and a decreasing trend after 2012, the trend effect was also included in the model. GHG Per Capita's positive significant effect on itself with a 1-year delay was determined in the model (β = 0.8975). In addition, the inverse relationship with the trend before 2012 tended to turn into a positive relationship after 2012. GHG Per Capita tends to correct its instantly changing dynamics in the long-term (β = −1.2616), and this situation is statistically significant (*p* = 0.0006). It was also determined that changes in Food Loss and Waste tend to positively affect GHG Per Capita (β = 0.0281), but this was of limited statistical significance (*p* = 0.0688). It was determined that GHG Per Capita and Food Loss and Waste act together in the long-term (β = 42.9738), but the statistical significance was not sufficient (*p* = 0.2420).

Table 9. Model 6: the impact of Food Loss and Waste on GHG Per Capita.

	Models	Independent Variable	β	SE	t	p
Model 6: GHG Per Capita <- Food Loss and Waste	ARDL	Intercept (GHG Per Capita)	−4.1631	4.1548	−1.0020	0.3457
		L (GHG Per Capita$_{(1)}$)	**0.8975**	**0.2740**	**3.2760**	**0.0113 ***
		L (GHG Per Capita$_{(2)}$)	0.1064	0.3611	0.2950	0.7758
		L (GHG Per Capita$_{(3)}$)	0.2549	0.3637	0.7010	0.5033
		L (GHG Per Capita$_{(4)}$)	0.3189	0.3561	0.8950	0.3967
		Food Loss	−0.0272	0.0458	−0.5930	0.5696
		L (Food Loss$_{(1)}$)	−0.0024	0.0455	−0.0530	0.9587
		L (Food Loss$_{(2)}$)	0.0718	0.0399	1.7980	0.1098
		L (Food Loss$_{(3)}$)	0.0077	0.0390	0.1980	0.8480
		Trend Effect$_{(\text{before 2012})}$	0.0321	0.0157	2.0440	0.0752
		Trend Effect$_{(\text{after 2012})}$	−0.0291	0.0280	−1.0400	0.3288
	UECM	**Intercept (GHG Per Capita)**	**4.6672**	**1.4366**	**3.2490**	**0.0087 ***
		L (GHGPerCapita$_{(1)}$)	**−0.7544**	**0.2379**	**−3.1720**	**0.0100 ***
		L (FoodLoss$_{(1)}$)	0.1469	0.0786	1.8680	0.0913
		Trend Effect$_{(\text{before 2012})}$	−0.0025	0.0100	−0.2550	0.8039
		Trend Effect$_{(\text{after 2012})}$	0.0205	0.0143	1.4330	0.1823
		d (L(GHG Per Capita$_{(1)}$))	−0.2222	0.2303	−0.9650	0.3574
		d (L(GHG Per Capita$_{(2)}$))	−0.1413	0.2995	−0.4720	0.6471
		d (Food Loss)	0.0294	0.0235	1.2500	0.2399
		d (L(Food Loss$_{(1)}$))	−0.0865	0.0590	−1.4670	0.1731
		d (L(Food Loss$_{(2)}$))	−0.0379	0.0403	−0.9420	0.3683
	RECM	Intercept (GHG Per Capita)	−0.0065	0.0461	−0.1410	0.8898
		L (ECT)	**−1.2616**	**0.2855**	**−4.4180**	**0.0006 ***
		d (Food Loss)	0.0281	0.0142	1.9710	0.0689
		Trend Effect$_{(\text{before 2012})}$	−0.0060	0.0069	−0.8620	0.4030
		Trend Effect$_{(\text{after 2012})}$	0.0086	0.0085	1.0100	0.3297
	Cointegration Coefficient		42.97382	42.9738	35.7407	1.2024

* significant at 5% margin of error; for ARDL Model: R^2: 0.762; Adj R^2: 0.5477; F-statistic = 3.556; p-value = 0.03037.

The temporal dynamics established between GHG and Food Insecurity are shown in Table 10. The instantaneous effect of Food Insecurity on GHG was significant and decreasing (β = −0.3815 and p = 0.0244). Short-term changes in Food Insecurity were also negatively related to GHG. In the long-term model, the trend after the 2012 break created a positive relationship between GHG and Food Insecurity, but this effect was determined to be of limited significance (p = 0.0815). In addition, GHG and Food Insecurity tend to move together in the long-term (β = 1.0237), but this relationship was not statistically significant enough.

In Table 11, the temporal dynamics were established between GHG Per Capita and Food Insecurity. The instantaneous decreasing effect of Food Insecurity on GHG Per Capita was determined (β = −0.4918 and p = 0.0009). The structural break in 2012 revealed a negative significant relationship between them (β = −0.0151 and p = 0.0332). In addition, dynamic changes in Food Insecurity tend to decrease GHG Per Capita (β = −0.3815 and p = 0.0244). This situation was also valid in the long-term, and Food Insecurity creates a decreasing effect on GHG Per Capita (β = −0.3450 and p = 0.0338). In addition, GHG Per Capita and Food Insecurity have a tendency to move negatively in the long run (β = −2.0822), but its statistical significance was not sufficient (p = 0.1320).

Table 10. Model 7: Food Insecurity's Effect on GHG.

	Models	Independent Variable	β	SE	t	p
Model 7: GHG <- Food Insecurity	**ARDL**	Intercept (GHG)	3.8839	3.7308	1.0410	0.3168
		L ($GHG_{(1)}$)	0.3202	0.2937	1.0900	0.2954
		L ($GHG_{(2)}$)	0.2388	0.3146	0.7590	0.4614
		Food Insecurity	**−0.3815**	**0.1499**	**−2.5450**	**0.0244 ***
		L (Food $Insecurity_{(1)}$)	0.3803	0.2079	1.8290	0.0904
		L (Food $Insecurity_{(2)}$)	−0.1663	0.1403	−1.1850	0.2572
		Trend $Effect_{(before\ 2012)}$	−0.0009	0.0068	−0.1280	0.9004
		Trend $Effect_{(after\ 2012)}$	0.0529	0.0579	0.9140	0.3771
	UECM	Intercept (GHG)	3.8839	3.7308	1.0410	0.3168
		L ($d\_GHG_{(1)}$)	−0.4410	0.4226	−1.0430	0.3158
		L (Food $Insecurity_{(1)}$)	−0.1675	0.1725	−0.9710	0.3492
		Trend $Effect_{(before\ 2012)}$	−0.0009	0.0068	−0.1280	0.9004
		Trend $Effect_{(after\ 2012)}$	0.0529	0.0579	0.9140	0.3771
		d (L($d\_GHG_{(1)}$)	−0.2388	0.3146	−0.7590	0.4614
		d (Food Insecurity)	**−0.3815**	**0.1499**	**−2.5450**	**0.0244 ***
		d (L(Food $Insecurity_{(1)}$))	0.1663	0.1403	1.1850	0.2572
	RECM	**Intercept (GHG)**	**4.8631**	**0.1222**	**39.7820**	**$<2 \times 10^{-16}$ ***
		L (ECT)	0.3905	0.9692	0.4030	0.6927
		d (Food Insecurity)	0.4008	0.3115	1.2870	0.2177
		Trend $Effect_{(before\ 2012)}$	−0.0010	0.0222	−0.0460	0.9637
		Trend $Effect_{(after\ 2012)}$	0.0436	0.0233	1.8680	0.0815
	Cointegration Coefficient		1.023663	1.0237	2.5722	0.3980

* significant at 5% margin of error; for ARDL Model: R^2: 0.9711; Adj R^2: 0.9555; F-statistic = 62.33; p-value = 5.464×10^{-9}.

In Table 12, the temporal dynamics were established between GHG and Food Price. Food Price had an increasing effect on GHG in the short-term (β = 0.4681 and p = 0.0304). It also had an increasing effect momentarily (β = 0.0025 and p = 0.0237). In this model, GHG has been found to return to its own trend in the long-term and to be less affected and corrected by changing dynamics in the long-term (β = −0.7300 and p = 0.0092). In the long-term, Food Price and GHG tend to move together (β = 294.8786), and this is of limited significance (p = 0.0711).

In Table 13, the temporal dynamics were established between Food Price and GHG Per Capita. Structurally, the 2012 break has created a significant effect on the relationship between Food Price and GHG Per Capita, turning it negative (β = −0.0498 and p = 0.0033). While short-term changes in Food Price have created a significant effect that makes it difficult for GHG Per Capita to return to its trend (β = 0.0060 and p = 0.0157), GHG Per Capita has a corrective effect that quickly returns to its trend after short-term changing dynamics in the system (β = −1.0554 and p = 0.0025). In the long-term, the changing dynamics of Food Price have created a significant effect that reduces GHG Per Capita (β = −1.1380 and p = 0.0008). On the other hand, in the long run, GHG Per Capita and Food

Price move together (β = 378.9154), but this does not have a sufficient statistical significance (p = 0.1557).

Table 11. Model 8: Food Insecurity's impact on GHG Per Capita.

	Models	Independent Variable	β	SE	t	p
Model 8: GHG Per Capita <- Food Insecurity	ARDL	**Intercept (GHG)**	**1.4228**	**2.4004**	**5.9280**	**0.0001 ***
		L ($GHG_{(1)}$)	−0.5426	0.2509	−2.1620	0.0515
		Food Insecurity	**−0.4918**	**0.1122**	**−4.3820**	**0.0009 ***
		L (Food $Insecurity_{(1)}$)	0.0168	0.2019	0.0830	0.9351
		L (Food $Insecurity_{(2)}$)	0.3737	0.2174	1.7190	0.1113
		L (Food $Insecurity_{(3)}$)	−0.2278	0.1187	−1.9200	0.0789
		Trend $Effect_{(before\ 2012)}$	**−0.0151**	**0.0063**	**−2.4060**	**0.0332 ***
		Trend $Effect_{(after\ 2012)}$	0.0127	0.0149	0.8540	0.4098
	UECM	Intercept (GHG)	3.8839	3.7308	1.0410	0.3168
		L ($GHG_{(1)}$)	−0.4410	0.4226	−1.0430	0.3158
		L (Food $Insecurity_{(1)}$)	−0.1675	0.1725	−0.9710	0.3492
		Trend $Effect_{(before\ 2012)}$	−0.0009	0.0068	−0.1280	0.9004
		Trend $Effect_{(after\ 2012)}$	0.0529	0.0579	0.9140	0.3771
		d (L($GHG_{(1)}$))	−0.2388	0.3146	−0.7590	0.4614
		d (L(Food Insecurity))	**−0.3815**	**0.1499**	**−2.5450**	**0.0244 ***
		d (L(Food $Insecurity_{(1)}$))	0.1663	0.1403	1.1850	0.2572
	RECM	Intercept (GHG)	−0.0049	0.0633	−0.0770	0.9399
		L (ECT)	−1.0240	0.6114	−1.6750	0.1162
		d (Food Insecurity)	**−0.3450**	**0.1467**	**−2.3520**	**0.0338 ***
		Trend $Effect_{(before\ 2012)}$	−0.0037	0.0113	−0.3290	0.7471
		Trend $Effect_{(after\ 2012)}$	0.0086	0.0112	0.7660	0.4564
	Cointegration Coefficient		−2.082163	−2.0822	1.3310	−1.5644

* significant at 5% margin of error; for ARDL Model: R^2: 0.9026; Adj R^2: 0.8458; F-statistic = 15.89, p-value = 3.417 × 10^{-5}.

Table 12. Model 9: Food Price Impact on GHG.

	Models	Independent Variable	β	SE	t	p
Model 9: GHG<- Food Price	ARDL	**Intercept (GHG)**	**0.9464**	**0.2432**	**3.8910**	**0.0012 ***
		L ($GHG_{(1)}$)	**0.4681**	**0.1982**	**2.3620**	**0.0304 ***
		L ($GHG_{(2)}$)	0.3053	0.1778	1.7180	0.1040
		Food Price	**0.0025**	**0.0010**	**2.4840**	**0.0237 ***
	UECM	**Intercept (GHG)**	**0.9464**	**0.2432**	**3.8910**	**0.0012 ***
		L ($GHG_{(1)}$)	**−0.2266**	**0.0618**	**−3.6680**	**0.0019 ***
		Food Price	**0.0025**	**0.0010**	**2.4840**	**0.0237 ***
		d (L($GHG_{(3)}$))	−0.3053	0.1778	−1.7180	0.1040
	RECM	**Intercept (GHG)**	**0.0501**	**0.0183**	**2.7360**	**0.0141 ***
		L (ECT)	−0.7300	0.2486	−2.9360	0.0092 *
		d (FoodPrice)	0.0024	0.0012	1.9660	0.0659
	Cointegration Coefficient		294.8786	294.8786	155.5032	1.8963

* significant at 5% margin of error; for ARDL Model: R^2: 0.964; Adj R^2: 0.9576; F-statistic = 151.6, p-value = 1.826 × 10^{-12}.

Table 13. Model 10: Food Price's impact on GHG Per Capita.

	Models	Independent Variable	β	SE	t	*p*
Model 10: GHG Per Capita <- Food Price	**ARDL**	**Intercept (GHG Per Capita)**	**6.9200**	**1.7464**	**3.9620**	**0.0022 ***
		L (GHG Per Capita$_{(1)}$)	−0.0109	0.2535	−0.0430	0.9665
		L (GHG Per Capita $_{(2)}$)	−0.0445	0.2089	−0.2130	0.8352
		Food Price	0.0030	0.0019	1.5650	0.1458
		L (Food Price$_{(1)}$)	0.0004	0.0026	0.1420	0.8896
		L (Food Price$_{(2)}$)	0.0003	0.0025	0.1000	0.9218
		L (Food Price$_{(3)}$)	0.0024	0.0019	1.2500	0.2371
		Trend Effect$_{(before\ 2012)}$	0.0083	0.0087	0.9490	0.3630
		Trend Effect$_{(after\ 2012)}$	**−0.0498**	**0.0133**	**−3.7350**	**0.0033 ***
	UECM	**Intercept (GHG Per Capita)**	**6.9200**	**1.7464**	**3.9620**	**0.0022 ***
		L (GHG Per Capita$_{(1)}$)	**−1.0554**	**0.2705**	**−3.9010**	**0.0025 ***
		L (Food Price$_{(1)}$)	**0.0060**	**0.0021**	**2.8530**	**0.0157 ***
		Trend Effect$_{(before\ 2012)}$	0.0083	0.0087	0.9490	0.3630
		Trend Effect$_{(after\ 2012)}$	**−0.0498**	**0.0133**	**−3.7350**	**0.0033 ***
		d (L(GHG Per Capita$_{(1)}$)	0.0445	0.2089	0.2130	0.8352
		d (Food Price)	0.0030	0.0019	1.5650	0.1458
		d (L(Food Price$_{(1)}$))	−0.0027	0.0022	−1.2290	0.2448
		d (L(Food Price$_{(2)}$))	−0.0024	0.0019	−1.2500	0.2371
	RECM	**Intercept (GHG Per Capita)**	**−0.6904**	**0.1965**	**−3.5140**	**0.0031 ***
		L (ECT)	−0.0065	0.0450	−0.1450	0.8865
		d (Food Price)	**−1.1380**	**0.2659**	**−4.2790**	**0.0008 ***
		Trend Effect$_{(before\ 2012)}$	**0.0035**	**0.0015**	**2.2890**	**0.0381 ***
		Trend Effect$_{(after\ 2012)}$	−0.0025	0.0074	−0.3390	0.7399
	Cointegration Coefficient		378.9154	378.9154	257.7324	1.4702

* significant at 5% margin of error; for ARDL Model: R^2: 0.7306; Adj R^2: 0.5347; F-statistic = 3.73, *p*-value = 0.02354.

The temporal dynamics were established between Population and GHG in Table 14. It was found that GHG has a significant cumulative increasing effect on itself (β = 0.6059 and *p* = 0.0135). In addition, GHG tends to correct itself by quickly returning to its trend in short-term changes with limited statistical significance (β = −0.5375 and *p* = 0.0559). In the long-term, it was found that there is a tendency for Population and GHG to move together (β = 6.3145), but this situation was not statistically significant (*p* = 0.5351).

In Table 15, the temporal dynamics established between GDP Per Capita and Food Loss and Waste. No statistically significant relationship was found in the two-year lagged model (*p* > 0.05). The instantaneous effect of GDP on Food Loss and Waste was found to be increasing (β = 0.3114) but was not found to have a sufficient statistical significance (*p* = 0.770). In addition, the model is far from being significant in explaining the variance (*p* = 0.9624).

Table 14. Model 11: Population impact on GHG.

	Models	Independent Variable	β	SE	t	*p*
Model 11: GHG <- Population	**ARDL**	Intercept (GHG)	0.5268	0.2974	1.7710	0.0945
		L ($GHG_{(1)}$)	**0.6059**	**0.2198**	**2.7570**	**0.0135** *
		L ($GHG_{(2)}$)	0.1770	0.2289	0.7730	0.4500
		Population	0.0851	0.1285	0.6620	0.5167
	UECM	Intercept (GHG)	0.5268	0.2974	1.7710	0.0945
		L ($d\_GHG_{(1)}$)	−0.2171	0.1614	−1.3450	0.1963
		Population	0.0851	0.1285	0.6620	0.5167
		d (L($GHG_{(1)}$)	−0.1770	0.2289	−0.7730	0.4500
	RECM	Intercept (GHG)	0.1026	0.2789	0.3680	0.7175
		L (ECT)	−0.5375	0.2619	−2.0520	0.0559
		d (Population)	−0.5106	3.3843	−0.1510	0.8818
	Cointegration Coefficient		6.314508	6.3145	10.0202	0.6302

* significant at 5% margin of error; for ARDL Model: R^2: 0.9521; Adj R^2: 0.9437; F-statistic = 112.7; *p*-value = 2.032×10^{-11}.

Table 15. Model 12: GDP Per Capita's impact on Food Loss and Waste.

	Models	Independent Variable	β	SE	t	*p*
Model 12: Food Loss and Waste <- GDP Per Capita	**ARDL**	Intercept (FoodLoss)	3.2608	3.2967	0.9890	0.3370
		L($FoodLoss_{(1)}$)	−0.0014	0.3612	−0.0040	0.9970
		L($FoodLoss_{(2)}$)	−0.1181	0.3711	−0.3180	0.7540
		GDP	0.3114	1.0483	0.2970	0.7700
		L($GDP_{(1)}$)	−0.2042	1.0442	−0.1960	0.8470

R^2: 0.03508; Adj R^2: −0.2062; F-statistic = 0.1454; *p*-value = 0.9624.

When the causality analysis results were examined, it was found that Educational Spending, the share of total government expenditure, has no significant causality on Food Loss and Waste ($p = 0.1598$). Food Insecurity was a significant cause of Food Loss and Waste ($p < 0.001$). Food Loss and Waste had no causal effect on Food Insecurity ($p = 0.5134$). Again, Food Loss and Waste had no significant causality on Food Price ($p = 0.5652$). Also, Food Loss and Waste did not have a direct causal effect on GHG ($p = 0.8496$). On the other hand, Food Loss and Waste had a significant causality on GHG Per Capita ($p = 0.0219$). Food Insecurity had no causal effect on GHG ($p = 0.5805$). But Food Insecurity was a significant cause of GHG Per Capita ($p < 0.001$). Food Price did not have a direct causal effect on GHG ($p = 0.3193$). Also, Food Price had no causal effect on GHG Per Capita ($p = 0.9115$). Population was a significant cause of GHG ($p = 0.0171$). GDP Per Capita was a significant cause of Food Loss and Waste ($p = 0.0939$) (Table 16).

Table 16. Causality analysis results.

No.	Model	χ^2/F	df	*p*	Result
1	Food Loss and Waste <- Educational Spending	$7.9363_{\chi 2}$	5	0.1598	H_0 could not be rejected.
2	Food Loss and Waste <- Food Insecurity	$76.3294_{\chi 2}$	7	<0.001 ***	H_0 was rejected.
3	Food Insecurity <- Food Loss and Waste	$5.2403_{\chi 2}$	7	0.5134	H_0 could not be rejected.
4	Food Price <- Food Loss and Waste	$4.8349_{\chi 2}$	6	0.5652	H_0 could not be rejected.

Table 16. *Cont.*

No.	Model	χ^2/F	df	*p*	Result
5	GHG <- Food Loss and Waste	0.1639_{F}	df_1:2; df_2:30	0.8496	H_0 could not be rejected.
6	GHG Per Capita <- Food Loss and Waste	$14.7953_{\chi2}$	6	0.0219 **	H_0 was rejected.
7	GHG <- Food Insecurity	$2.8660_{\chi2}$	4	0.5805	H_0 could not be rejected.
8	GHG Per Capita <- Food Insecurity	$41.2964_{\chi2}$	7	<0.001 ***	H_0 was rejected.
9	GHG <- Food Price	1.1863_{F}	df_1:2; df_2: 30	0.3193	H_0 could not be rejected.
10	GHG Per Capita <- Food Price	$2.0872_{\chi2}$	6	0.9116	H_0 could not be rejected.
11	GHG <- Population	4.6773_{F}	df_1:2; df_2:30	0.0171 **	H_0 was rejected.
12	Food Loss and Waste <- GDP Per Capita	$6.3950_{\chi2}$	3	0.0939 *	H_0 was rejected.

χ^2:Toda–Yamamoto technique; F: Granger causality; *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

4. Discussion

This study explores the complex relationships between food loss and waste (FLW), greenhouse gas (GHG) emissions, and economic indicators such as education spending, food insecurity, GDP per capita, and food prices across short- and long-term frameworks. The analysis identifies several critical insights into how these variables interact, underscoring both direct and indirect impacts on sustainability efforts.

This study identifies a significant three-year lagged effect of education spending on reducing FLW, although evidence for a direct causal relationship remains insufficient. This finding suggests that sustainability issues, particularly food waste reduction, may not yet be a key focus within the educational sector. However, the delayed impact underscores the potential for long-term benefits from strengthened education-based sustainability programs. Greater emphasis on sustainability principles in education, particularly regarding food resource management, could lead to more immediate and potentially causal reductions in FLW. Previous research supports the role of education in food loss reduction [17,18] and facilitating food waste reduction [19]. Future studies using longer datasets could clarify whether the observed lagged relationship evolves into a definitive causal link, reinforcing the importance of education as a strategic driver in promoting sustainable food systems.

The relationship between food insecurity and FLW reveals complex dynamics. While no significant direct impact of food insecurity on FLW was found, evidence suggests a minor immediate reduction in FLW during heightened food insecurity, likely due to precautionary behaviors to conserve resources. Diana et al. [20] also observed reduced household food waste with increased food insecurity, though income significantly influenced this relationship.

A seven-year lagged model suggests that FLW may contribute to worsening food insecurity over time by reducing resource availability. Studies in Iran and China support this, showing that FLW reduction enhances food security by increasing resource access [21,22]. Extended datasets are needed to fully capture these long-term interactions.

Food insecurity exhibits a self-reinforcing trend, where higher levels persist and worsen over time. Wang et al. [23] highlighted this path dependency, noting transitions to high insecurity are more likely than reversals. These findings underscore the vicious cycle of food insecurity.

A structural break in 2012, marking a shift from declining to rising food insecurity, coincided with a stronger alignment between food insecurity and FLW trends. While FLW does not directly cause food insecurity, the causative link from food insecurity to FLW and the post-2012 trends emphasize the need for interventions to reduce FLW. Targeted efforts could mitigate food insecurity's impact and improve resource stability [4].

In line with prior studies [5,6], our findings suggest that FLW has a minimal impact on food prices with no clear causal relationship, though there is a slight, positive lagged effect after one year, which might reflect cumulative impacts. This observation aligns with Aschemann-Witzel et al. [24], who noted that food waste reduction does not directly lower food prices due to the indirect nature of these economic effects. However, the lagged effect suggests a potential cumulative impact, aligning with arguments by Buzby and Hyman [25] that FLW influences food supply dynamics, which might impact prices over the long-term. These cumulative effects likely emerge from broader economic fluctuations and input costs (e.g., fuel and labor), supporting the complex relationship between FLW and market stability [1].

Regarding GDP per capita, while no direct dynamic relationship with FLW was observed, a limited level of causality was detected based on prior FLW levels and a two-year lagged effect from GDP per capita. This indicates that GDP per capita may, to a limited extent, act as a contributing factor to FLW. Moreover, although not statistically significant, higher GDP per capita values show an immediate reactive association with increased FLW, suggesting that economic growth could indirectly lead to higher waste through increased production and consumption patterns [26].

Our findings indicate a positive cointegration between FLW and GHG emissions without a statistically significant causal relationship in the temporal analysis. However, a positive cointegration coefficient suggests a long-term tendency for them to move together, warranting further research with longer datasets. This may relate to food production's resource-intensive nature, as Scherhaufer et al. [7] noted. FLW shows a short-term tendency to increase GHG emissions, though this is not statistically significant, indicating stronger influences from other factors [27]. On the other hand, a significant causal relationship was found between FLW and GHG emissions per capita in a six-year lagged model. The results also showed that FLW and GHG per capita tend to move together in the long-term. Additionally, while the long-term effects were limited in significance, FLW was found to have an increasing effect on GHG per capita as it grows [2].

An important observation from the findings is that the GHG system demonstrates resilience to fluctuations in prior periods, indicating a tendency to maintain long-term stability. Moreover, GHG emissions per capita demonstrated a lagged self-reinforcing effect, with a corrective role in maintaining its overall trend. This underscores the necessity of swift and decisive measures to slow the upward trend in GHG emissions [28].

The study's identification of a structural break in 2012 corresponds with a decoupling between GHG emissions and population growth aligning with the literature suggesting that advancements in low-emission agricultural technologies and energy efficiency may help mitigate per capita emissions [29]. However, the resilience of GHG levels and their tendency to stabilize despite fluctuations imply that, without stringent policy efforts, natural reductions in emissions may be insufficient to achieve environmental targets [8]. Thus, the findings underscore the need for systematic reduction efforts in FLW and GHG emissions to ensure environmental sustainability and resource adequacy amidst growing populations. Our findings suggest a complex and dynamic relationship between food insecurity and total GHG emissions. Short-term reductions associated with rising food insecurity, contrast with a weak positive correlation in the long-term without statistical significance. This aligns with research by Vermeulen et al. [30], who found that food scarcity often coincides with reduced food production and emissions due to lower economic activity and consumption. Conversely, as food insecurity becomes more persistent, increasing demand for affordable food production might drive higher GHG emissions, reflecting similar findings by

Niles et al. [31]. The co-movement post-2012 suggests that socioeconomic and environmental stressors may exacerbate one another [32], highlighting the need for integrated responses to food insecurity and emissions.

In contrast, food insecurity emerges as a causal factor for per capita GHG emissions, displaying a significant negative association in the short- and long-term. The 2012 structural break amplifies this dynamic, with food insecurity continuing to rise while per capita GHG emissions decline. This inverse relationship likely reflects the compounded effects of economic hardship caused by food insecurity. Reduced access to food may lower per capita consumption and waste, thereby decreasing emissions. Additionally, rapid population growth relative to production capacity may exacerbate food scarcity, further suppressing per capita consumption and emissions [33].

The analysis reveals a long-term co-movement between GHG emissions and food prices, though food prices are not a direct cause of GHG emissions. In the short-term, rising food prices are positively associated with GHG emissions, which aligns with theories in environmental economics, particularly concerning the impact of fossil fuel prices on food production costs and related emissions [9]. Over time, higher food prices may incentivize energy-intensive production expansions and indirectly raise GHG emissions due to the carbon intensity of production processes [34].

A positive long-term association between food prices and per capita GHG emissions is also observed, without food prices being the direct cause. Interestingly, the study finds that long-term fluctuations in food prices tend to decrease per capita GHG emissions. This inverse effect may be attributed to reduced consumer access to food as prices rise, leading to decreased per capita consumption. Additionally, elevated food prices may encourage a shift toward lower-cost and possibly lower-emission production and consumption practices, like less animal-based and more plant-based foods, indirectly contributing to reduced emissions on a per capita basis [35].

The analysis reveals a long-term co-movement between GHG emissions and population growth, with the latter emerging as a significant driver in a two-year lagged model. Population growth amplifies GHG emissions cumulatively, reinforced by the self-perpetuating nature of emissions. These findings underscore the environmental impact of demographic pressure and highlight the need for strategies to reduce emissions in high-growth regions [36]. Population increases generally lead to greater resource consumption and waste production, amplifying GHG levels [37].

The complex dynamics between food loss and waste (FLW) and environmental and economic factors require a detailed understanding. While this study addresses many critical variables, there are potential effects of hidden or unobserved factors, such as economic growth and economic downturns during and prior to the pandemic. Economic growth, as a general driver of increased production capacity, consumption, and waste generation, may indirectly influence FLW. Furthermore, economic contraction periods, such as the global economic slowdown experienced during the COVID-19 pandemic, could have impacted food production, distribution, and consumer behavior, thereby altering FLW dynamics. Disruptions in supply chains and reduced purchasing power during economic recessions may have led to changes in food consumption patterns and waste generation.

Although the present study does not directly model economic growth or downturns, the inclusion of GDP per capita partially accounts for broader economic trends. However, we acknowledge that GDP alone may not fully capture the multifaceted impacts of economic fluctuations on FLW. Future research could integrate additional economic indicators, such as unemployment rates, inflation, or trade disruptions, to provide a more comprehensive perspective on these dynamics.

5. Limitations

The study faced several limitations primarily due to the restricted period of the dataset and the relatively small sample size of 23 observations. These constraints hindered the use of more robust models that could provide stronger results over the longer time series. The limited dataset also restricted the comprehensive modeling of lag lengths and impeded a deeper exploration of the dynamic relationships within the time series. Additionally, the use of estimated data for Educational Spending in 2022 introduced a minor degree of uncertainty that could slightly affect the accuracy of the findings. Another limitation was the focus on examining the temporal effects of a single independent variable at a time. This approach restricted the inclusion of external factors and other determinants in the models, limiting the ability to evaluate relationships between variables more holistically.

Nevertheless, the study hypotheses and analytical methods were appropriately designed to align with the dataset's structure, ensuring the findings were as reliable as possible despite the limited observations. Expanding the time series and increasing the number of observations in future research would enhance the robustness of the modeling and improve the generalizability of the results.

6. Conclusions

This study highlights the complex relationships between food loss and waste, greenhouse gas emissions, and economic indicators such as education expenditure, food insecurity, GDP per capita, and food prices. By emphasizing their direct and indirect impacts on sustainability, the findings underscore the necessity of targeted efforts to reduce FLW and GHG emissions. Long-term datasets and interdisciplinary approaches prove invaluable for understanding these dynamics, supporting resource security, and ensuring environmental sustainability.

The analysis reveals significant delayed effects of education expenditure and GDP per capita on FLW, highlighting the importance of long-term policy planning. The identification of a six-year lagged causal relationship between FLW and per capita GHG emissions provides new insights into the environmental impacts of food waste. Additionally, the incorporation of structural break analysis offers critical insights into temporal shifts, such as the post-2012 alignment of food insecurity and FLW trends, reflecting broader economic and social disruptions.

In light of these findings, the study presents actionable policy recommendations. Sustainability must be integrated into education programs without exception, as education-based interventions have the potential to yield long-term reductions in FLW. Furthermore, addressing per capita food waste requires not only fostering economic growth but also balancing social inequalities. Policies such as increasing incentives for sustainable agricultural technologies and implementing subsidy programs can enhance food security. Finally, the delayed effects of food waste on per capita GHG emissions emphasize the need for robust waste management strategies. Practices such as recycling food waste, utilizing it for energy production (e.g., biogas), and converting it into organic fertilizers are effective approaches to reduce these emissions.

While the study adopts a global perspective using time series analysis, future research could explore country-specific dynamics to provide more localized insights. Country-specific datasets and methods would better capture the unique cultural, economic, and political factors influencing FLW. However, modeling multiple countries simultaneously would require panel data analysis, a method distinct from the time series approach used here. Such complementary frameworks could further enrich the policy implications of these findings and support the development of sustainable food systems at both national and global levels.

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References

1. Food and Agriculture Organization of the United Nations. *The State of Food and Agriculture 2019: Moving Forward on Food Loss and Waste Reduction*; FAO: Rome, Italy, 2019.
2. Zhu, J.; Luo, Z.; Sun, T.; Li, W.; Zhou, W.; Wang, X.; Fei, X.; Tong, H.; Yin, K. Cradle-to-grave emissions from food loss and waste represent half of total greenhouse gas emissions from food systems. *Nat. Food* **2023**, *4*, 247–256. [CrossRef] [PubMed]
3. Tchonkouang, R.D.; Onyeaka, H.; Miri, T. From waste to plate: Exploring the impact of food waste valorisation on achieving zero hunger. *Sustainability* **2023**, *15*, 10571. [CrossRef]
4. Wani, N.R.; Rather, R.A.; Farooq, A.; Padder, S.A.; Baba, T.R.; Sharma, S.; Mubarak, N.M.; Khan, A.H.; Singh, P.; Ara, S. New insights in food security and environmental sustainability through waste food management. *Environ. Sci. Pollut. Res.* **2024**, *31*, 17835–17857. [CrossRef] [PubMed]
5. Bellemare, M.F.; Çakir, M.; Peterson, H.H.; Novak, L.; Rudi, J. On the measurement of food waste. *Am. J. Agric. Econ.* **2017**, *99*, 1148–1158. [CrossRef]
6. Sheahan, M.; Barrett, C.B. Food loss and waste in Sub-Saharan Africa. *Food Policy* **2017**, *70*, 1–12. [CrossRef]
7. Scherhaufer, S.; Moates, G.; Hartikainen, H.; Waldron, K.; Obersteiner, G. Environmental impacts of food waste in Europe. *Waste Manag.* **2018**, *77*, 98–113. [CrossRef]
8. Höhne, N.; Den Elzen, M.; Escalante, D. Regional GHG reduction targets based on effort sharing: A comparison of studies. *Clim. Policy* **2014**, *14*, 122–147. [CrossRef]
9. Tariq, G.; Sun, H.; Ali, I.; Ali, S.; Shah, Q. Influence of access to clean fuels and technology, food production index, consumer price index, and income on greenhouse gas emissions from food system: Evidence from developed countries. *Environ. Sci. Pollut. Res.* **2023**, *30*, 59528–59539. [CrossRef]
10. Toda, H.Y.; Yamamoto, T. Statistical inference in vector autoregressions with possibly integrated processes. *J. Econom.* **1995**, *66*, 225–250. [CrossRef]
11. Zapata, H.O.; Rambaldi, A.N. Monte Carlo evidence on cointegration and causation. *Oxf. Bull. Econ. Stat.* **1997**, *59*, 285–298. [CrossRef]
12. Engle, R.F.; Granger, C.W. Co-integration and error correction: Representation, estimation, and testing. *Econom. J. Econom. Soc.* **1987**, *55*, 251–276. [CrossRef]
13. Granger, C.W. Investigating causal relations by econometric models and cross-spectral methods. *Econom. J. Econom. Soc.* **1969**, *37*, 424–438. [CrossRef]
14. Narayan, P.K. The saving and investment nexus for China: Evidence from cointegration tests. *Appl. Econ.* **2005**, *37*, 1979–1990. [CrossRef]
15. Pesaran, M.H.; Shin, Y.; Smith, R.J. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econom.* **2001**, *16*, 289–326. [CrossRef]
16. Banerjee, A.; Dolado, J.; Mestre, R. Error-correction mechanism tests for cointegration in a single-equation framework. *J. Time Ser. Anal.* **1998**, *19*, 267–283. [CrossRef]
17. Chrisendo, D.; Piipponen, J.; Heino, M.; Kummu, M. Socioeconomic factors of global food loss. *Agric. Food Secur.* **2023**, *12*, 23. [CrossRef]

18. Delgado, L.; Schuster, M.; Torero, M. On the origins of food loss. *Appl. Econ. Perspect. Policy* **2021**, *43*, 750–780. [CrossRef]
19. Mariam, N.; Nina, L.; Fabian, B.; Florence, Z.; Simone, A.; Ulf, S.; Daniel, F. The Food Waste Lab: Improving food waste reduction behavior through education. *J. Clean. Prod.* **2022**, *370*, 133447. [CrossRef]
20. Diana, R.; Martianto, D.; Baliwati, Y.F.; Sukandar, D.; Hendriadi, A. Prevalence of household food insecurity and its association with food waste. *J. Egypt. Public Health Assoc.* **2024**, *99*, 21. [CrossRef] [PubMed]
21. Fami, H.S.; Aramyan, L.H.; Sijtsema, S.J.; Alambaigi, A. The relationship between household food waste and food security in Tehran city: The role of urban women in household management. *Ind. Mark. Manag.* **2021**, *97*, 71–83. [CrossRef]
22. Durán-Sandoval, D.; Durán-Romero, G.; López, A.M. Achieving the food security strategy by quantifying food loss and waste. A case study of the chinese economy. *Sustainability* **2021**, *13*, 12259. [CrossRef]
23. Wang, D.; Andrée, B.P.J.; Chamorro, A.F.; Spencer, P.G. Transitions into and out of food insecurity: A probabilistic approach with panel data evidence from 15 countries. *World Dev.* **2022**, *159*, 106035. [CrossRef]
24. Aschemann-Witzel, J.; De Hooge, I.; Amani, P.; Bech-Larsen, T.; Oostindjer, M. Consumer-related food waste: Causes and potential for action. *Sustainability* **2015**, *7*, 6457–6477. [CrossRef]
25. Buzby, J.C.; Hyman, J. Total and per capita value of food loss in the United States. *Food Policy* **2012**, *37*, 561–570. [CrossRef]
26. Blagoeva, N.; Georgieva, V.; Dimova, D. Relationship between GDP and Municipal Waste: Regional Disparities and Implication for Waste Management Policies. *Sustainability* **2023**, *15*, 15193. [CrossRef]
27. Poore, J.; Nemecek, T. Reducing food's environmental impacts through producers and consumers. *Science* **2018**, *360*, 987–992. [CrossRef]
28. Van Boven, L.; Burgess, M.G. Introduction to topical collection: Social science and sustainability technology. *Clim. Change* **2024**, *177*, 69. [CrossRef]
29. Clark, M.A.; Domingo, N.G.; Colgan, K.; Thakrar, S.K.; Tilman, D.; Lynch, J.; Azevedo, I.L.; Hill, J.D. Global food system emissions could preclude achieving the 1.5 and 2 C climate change targets. *Science* **2020**, *370*, 705–708. [CrossRef] [PubMed]
30. Vermeulen, S.J.; Campbell, B.M.; Ingram, J.S. Climate change and food systems. *Annu. Rev. Environ. Resour.* **2012**, *37*, 195–222. [CrossRef]
31. Niles, M.T.; Ahuja, R.; Barker, T.; Esquivel, J.; Gutterman, S.; Heller, M.C.; Mango, N.; Portner, D.; Raimond, R.; Tirado, C. Climate change mitigation beyond agriculture: A review of food system opportunities and implications. *Renew. Agric. Food Syst.* **2018**, *33*, 297–308. [CrossRef]
32. Cottrell, R.S.; Nash, K.L.; Halpern, B.S.; Remenyi, T.A.; Corney, S.P.; Fleming, A.; Fulton, E.A.; Hornborg, S.; Johne, A.; Watson, R.A. Food production shocks across land and sea. *Nat. Sustain.* **2019**, *2*, 130–137. [CrossRef]
33. Springmann, M.; Clark, M.; Mason-D'Croz, D.; Wiebe, K.; Bodirsky, B.L.; Lassaletta, L.; De Vries, W.; Vermeulen, S.J.; Herrero, M.; Carlson, K.M. Options for keeping the food system within environmental limits. *Nature* **2018**, *562*, 519–525. [CrossRef] [PubMed]
34. Khan, A.A.; Cui, F.-J.; Ullah, S.; Ali, K. Food production and food-related CO_2 emissions in China: An examination of the role of economic governance; insights from innovative fourier approach. *Environ. Dev. Sustain.* **2024**, 1–24. [CrossRef]
35. Chen, J.; Zhong, F. The Role of Income and Food Prices in Diet-Related Greenhouse Gas Emissions in China: A Path towards a Sustainable Diet. *Foods* **2022**, *11*, 4051. [CrossRef]
36. Purohit, S. Demographic Transition Model and Population Growth of India-Implications and Assessments. *J. Environ. Sci. Public Health* **2023**, *7*, 176–184. [CrossRef]
37. Jie, H.; Khan, I.; Alharthi, M.; Zafar, M.W.; Saeed, A. Sustainable energy policy, socio-economic development, and ecological footprint: The economic significance of natural resources, population growth, and industrial development. *Util. Policy* **2023**, *81*, 101490. [CrossRef]