Vol. 1,No. 1, June 2025 ISSN (Print): 3088-5426 | ISSN (Online): 2953-2728

Eastern Africa Journal of Official Statistics

Journal Homepage: https://journal.eastc.ac.tz/index.php/eajos/index

DOI: https://doi.org/10.63933/eajos.1.1.2025.8%20

The Contribution of Conservation Agriculture on Food Security in Mainland Tanzania

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KEYWORDS

Conservation Agriculture, Food Security, Minimal Soil Tillage, Crop, Diversification, Agroforestry.

ABSTRACT

Introduction: Conservation agriculture (CA) is increasingly recognized as one of the most practical and promising strategies for achieving sustainable agricultural practices. This study aimed to explore the impact of CA on food security in Mainland Tanzania, using time series data from 1988 to 2023. The primary focus was to evaluate both the short-term and long-term effects of key CA practices such as minimal soil tillage, water management, crop diversification, and agroforestry on food security, while also investigating causal relationships and forecasting future trends. Methodology: To estimate the effects of CA on food security, the study utilized the Vector Error Correction Model (VECM), which allows for the analysis of both short-term and long-term relationships between variables. The Granger Causality test was applied to determine the direction of causality between CA adoption and food security. Furthermore, food security was forecasted for the years 2024 to 2028 using the ARIMA (2, 1, 1) model, providing predictions based on historical trends. Results: The study's findings revealed that CA has a positive long-term impact on food security, though its effects in the short term were negative. A unidirectional causality was identified, with food security driving the adoption of CA practices. The ARIMA model projections indicated steady increases in food *security from 2024 to 2028, with forecasted values of 3532.187, 3682.171, 3837.568, 3996.199, and 4158.478 metric tons. Conclusion: The study concludes that CA practices are vital for improving food security in Tanzania. It recommends prioritizing practices such as minimal soil tillage, water management, crop diversification, and agroforestry to enhance the impact of CA. By focusing on these practices, the adoption of CA can be promoted as a key strategy for improving food security in the country.*

1.0 Introduction

Conservation agriculture is a sustainable farming approach that minimizes soil disturbance, maintains continuous soil cover, and promotes crop diversification to improve soil health, water efficiency, and long-term productivity (FAO, 2022). In recent decades, the global adoption of Conservation Agriculture (CA) has grown, encouraging sustainable agricultural practices such as minimal tillage and crop diversification (FAO, 2022). In Phase I (1988-2008), the adoption of Conservation Agriculture (CA) expanded gradually, starting with research-driven initiatives in South America, particularly in Brazil and Argentina. By 2008, Conservation Agriculture (CA) had been implemented on 100 million hectares globally, fueled by notable yield improvements (FAO, 2021). In the second phase (2009-2023), this growth continued, with CA adoption exceeding 200 million hectares worldwide by 2023. Countries like Brazil, Argentina, Zambia, and Tanzania reported enhanced food security and yield increases through CA. For example, Brazil's soybean yields rose from 2.4 to 3.1 tons per hectare between 2000 and 2020 (FAO, 2021). Likewise, Tanzania experienced rapid CA adoption, with 50,000 farmers practicing it by 2023, raising yields from 1.0 to 3.5 tons per hectare (World Bank, 2021). These developments highlight CA's potential to support long- term sustainability and food security in the face of climate change.

Despite the progress made in Conservation Agriculture (CA), significant gaps remain in localized research that tracks adoption trends and evaluates its impact on agricultural productivity across different regions of Tanzania (Waaswa, 2022). While CA is widely recognized for its benefits in improving yields and soil health, its long-term effects on crop nutritional quality and broader livelihoods have not been sufficiently explored. Additionally, limited research exists on how CA practices can adapt to climate change, extreme weather events, and other future challenges (FAO, 2021). Understanding these factors is critical for effectively leveraging CA to enhance food security in Tanzania and inform future agricultural policies.

The study by Li et al. (2022) analyzed the impact of CA on wheat and maize yields in the North China Plain over a ten-year period using the Autoregressive Distributed Lag (ARDL) model, with significant results, as also highlighted by Wang et al. (2020). Similarly, FAO (2021) compared yields from CA and conventional agriculture in Tanzania from 1988 to 2023. From 1988 to 1993, conservation agriculture yielded 1.1 tons per hectare, slightly surpassing conventional agriculture's 0.9 tons. By the 1994-1998 period, conservation agriculture’s yield increased to 1.3 tons per hectare, while conventional agriculture rose to 1.0 tons, maintaining a consistent yield advantage for CA.

This study seeks to fill these research gaps by investigating CA adoption trends and its impacts on agricultural productivity in Tanzania. The study’s objectives include: Analyzing adoption trends of CA in Tanzania, assessing both the short-term and long-term effects of CA on agricultural productivity and livelihoods, and forecasting food security trends in mainland Tanzania over the next five years. By addressing these objectives, the study aims to provide valuable insights that will help improve food security and guide future agricultural policy development. Furthermore, it will offer crucial information for policy formulation, identify barriers to CA adoption within agricultural extension services, and assist development organizations in making informed decisions regarding infrastructure investments and services that promote sustainability and resilience.

1.1 Study Area

The study was conducted in Mainland Tanzania, a region where a significant portion of the land is well- suited for agricultural activities. Tanzania country follows a bimodal rainfall pattern, with the long rains typically occurring from March to May, and the short rains from October to December. However, the timing and intensity of these rainfall periods can vary across different regions (Smith, 2023).

1.2 Research Design

The study employed a quantitative time series data analysis because they consist of continuous, numerical measurements for variables such as FS, MT, WM, CD, and AG, recorded at uniform annual intervals from 1988 to 2023. This regular spacing of data points enables the identification of trends, fluctuations, and dynamic relationships over time, which is critical for applying predictive models and understanding temporal patterns (Creswell, J. W. 2014).

1.3 Data type and collection methods

Secondary data spanning from 1988 to 2023 was collected, focusing on key metrics such as crop yields (tons per hectare), adoption rates of conservation agriculture practices, and food security indicators. Quantitative data on conservation agriculture variables and food security indicators were sourced from the National Bureau of Statistics (NBS). Information on minimal soil tillage and agroforestry practices was obtained from the Ministry of Agriculture (MoA), while data on water management and crop diversification were provided by Sustainable Agriculture Tanzania (SAT).

1.4 Data analysis

Data analysis was conducted using Stata MP 17 software, which supported both descriptive and inferential analyses based on the indicators outlined in the Conceptual Framework (Fig. 1). Descriptive statistics were presented through tables and figures to provide a summary of the data, while inferential analysis was employed to draw conclusions and explore the relationships between variables. The study utilized three models: The Vector Error Correction Model (VECM) to evaluate both short-term and long-term effects of conservation agriculture on food security, the Granger causality test to assess the relationship between CA adoption and food security, and the Autoregressive Integrated Moving Average (ARIMA) model to forecast food security trends for 2024 to 2028.

1.5 Ethical Considerations

Ethical considerations were strictly adhered to throughout the study. The research received approval from the Eastern Africa Statistical Centre (EASTC) and Sokoine University of Agriculture (SUA) as part of the Master of Science in Agricultural Statistics program. Efforts were made to ensure confidentiality, anonymity, and privacy was maintained at all stages of the research process.

1.6 Study limitations

The study's limitations stem from its focus on specific variables, potentially neglecting key elements of conservation agriculture, such as integrated pest management, organic soil amendments, and sustainable livestock integration. These factors are vital for soil health, crop yields, and ecosystem resilience, all of which influence food security. Excluding them may result in an incomplete understanding of conservation agriculture's impact, limiting the study's overall conclusions.

INDEPENDENT VARIABLE **DEPENDENT VARIABLE**

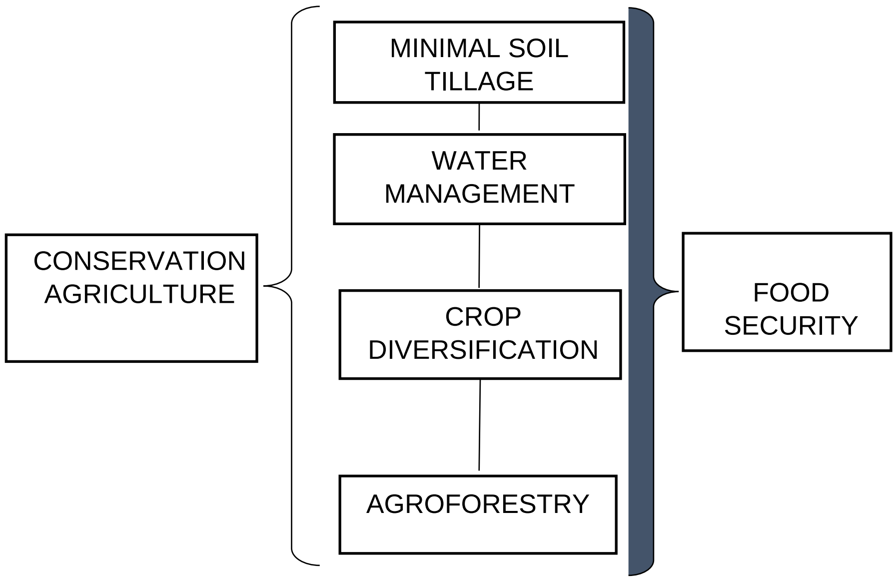


Fig. 1: Contribution of Conservation Agriculture on Food Security

Source: Adapted from FAO, (2022)

1.7 Data Analysis Techniques

1.7.1 Descriptive Analysis

The Stata MP 17 software facilitated the estimated output in clearly tabulated forms of the result in summary where Food Security, Minimal Soil Tillage, Water Management, Crop Diversification and Agroforestry were the relevant variables. The tables and figures presented a descriptive analysis of the half-yearly data series.

1.7.2 Inferential Analysis

The estimated models in this work were based on three types: The vector error correction model (VECM) which determined the effects of conservation agriculture on food security in the long term and short term, the Granger causality test used to test the trend of adoption of Conservation Agriculture on Food Security and Autoregressive Integrated Moving Average (ARIMA) model which used to forecast food security for five years (2024 to 2028).

1.7.3 *Model Specification*

The vector error correction model (VECM) which determined the effects of conservation agriculture on food security in the long term and short term, the Granger causality test which was used to test the trend of adoption of Conservation Agriculture on Food Security and Autoregressive Integrated Moving Average (ARIMA) model which was used to forecast food security for five years (2024 to 2028). The model took the following functional form:

FS = f (MT, WM, CD, AG)

Where:

FS: Food Security,

MT: Minimum Soil Tillage, WM: Water Management, CD: Crop Diversification, AG: Agroforestry

The linear regression model of this study was constructed as follows:

$$FS = \beta_0 + \beta_1 CA + \beta_2 WMT + \beta_3 CD + \beta_4 AT + \varepsilon \ldots\ldots\ldots\ldots(01)$$

Where: β_0: Is an intercept

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$: Are coefficients of MT, WM, CD and AG variables respectively.

ε : An error term.

The model is a multiple linear regression where all variables are quantitative and continuous. Here, FS (Metric T) is the dependent variable measured on a continuous scale, while the independent variables CA, WMT, CD, and AT also represent continuous measurements (often corresponding to variables like MT, WM, CD, and AG in your dataset). The model assumes linear relationships among these variables, and the residual term accounts for variability not explained by the predictors.

The Augmented Dickey-Fuller (ADF) used to test for a unit root. The Akaike's Information Criteria (AIC), was attempted to balance the information gained by adding additional lags against the increase in the complexity of lags and it estimated the lowest lag length in the model.

(Burnham & Anderson, 2004). and contributing to the advancement of knowledge in the field. The Vector

Error Correction Model (VECM) and the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots was applied to respectively allows for the inclusion of an error correction term, measures the correlation between the current value of the series and its lagged values, and visually depicted the long-term relationships between Conservation Agriculture and Food Security in Mainland Tanzania. To forecast the food security trend in mainland Tanzania for five years ARIMA model was used to fit the model to historical data and then using the fitted model to predict future value (Box et al., 2008).

The ARIMA model:

$FS_t = c + \varphi_1 FS_{t-1} + \ldots + \varphi_p FS_{t-p} + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} + e_t$ ...(02).

Where:

FS_t: Represents the economic growth rate at time t.

c: Is a constant

φ-1 to φ-p are Auto-regressive Coefficients

FS_{t-1} to FS_{t-p} are the past values of economic growth $t-1$ to θ_q are the moving average coefficients

e_{t-1} to e_{t-q} are the past error terms in the forecast.

Testing for Stationarity ***w***as done by employing the ADF test which calculated a test statistic that measures the significance of the trend in the series. The decision of whether to reject the null hypothesis or not the p-value is compared with a 0.05 significance level. The null hypothesis of the ADF test was that "A unit root is present in a time series, indicating non-stationarity". If the p-value obtained from the test was less than a chosen significance level, the null hypothesis was rejected and the conclusion was that "the time series is stationary (there is no unit root)".

The unit root test was estimated using the following equation:

$\Delta FS_t = \alpha_0 + \rho_i FS_{t-1} + \sum_{i=1}^{k} \alpha_i \; FS_{t-1} + \mu_t$ ……..(03)

Where:

α_0: The constant term or intercept μ_t: Pure white noise

ρ_i, α_i: Coefficients

ΔFS_t : Is the lagged dependent variable at time (��−1)

FS_t: Is the dependent variable at time t, k is the lagged value of ΔFS.

1.7.4 Lag Order Selection Criteria.

The optimal lag was essential to strike a balance between capturing relevant patterns and avoiding over-drafting to build a robust and accurate time series model.

This study applied the information criteria to determine the maximum number of lags in the model. The criteria used are Akaike's Information Criteria (AIC), Schwarz Bayesian Information Criteria (BIC), Hannan-Quinn Information Criteria (HQIC), sequential Likelihood –Ratio (LR) test and Final Prediction Error (FPE). The Akaike's information criteria (AIC) attempted to balance the information gained by adding additional lags against the increase in the complexity of lags and it estimated the lowest lag length in the model (Burnham & Anderson, 2004). This study applied AIC because it was a consistent estimator of the true lag order and yields so few lags (Gonzalo, 2000), the selected lag order length was used in the Vector Error Correction Model (VECM) for identifying the cointegration test.

AIC was calculated as follows:

AIC = 2k – 2/ln(L) ……………………(04)

Where:

K: Is the number of estimated parameters in the model.

L: Is the maximum likelihood of the model.

1.7.5 Visual Inspection

Correlogram (ACF and PACF) which means, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots visually depicted the correlation between observations at different lags. The plots used to identify the significant lag values where correlations deviate from zero.

For more convenient results, the lag order selection of the Akaike Information Criterion (AIC) was pivotal for deriving accurate insights and contributing to the advancement of knowledge in the field when used in the Vector Error Correction Model (VECM) for identifying the cointegration test. So, this study applied AIC because it is a consistent estimator of true lag order and yields so few lags (Gonzalo, 2000).

AIC = 2k – 2/ln(L) ……………………… (04)

Where:

K: Is the number of estimated parameters in the model.

L: Is the maximum likelihood of the model.

Cointegration test for time series analysis, was done to investigate the long-term relationships between variables," The contribution of Conservation Agriculture on Food Security in Mainland Tanzania. It assessed whether there was a stable or long-term relationship between conservation agriculture practices and food security indicators as it is useful when dealing with non-stationary time series that may have common trends (Granger, 1987). The model equations for the Johansen cointegration test can be expressed as follows:

$$FS_t = \alpha + \beta_{1t}CA + \beta_{2t}WMT + \beta_{3t}CD + \beta_{4t}AT + \varepsilon_t \dots\dots\dots\dots\dots (05).$$

Where:

α:This is a matrix coefficient.

$\beta_{1,}\beta_{2}, \beta_{3}, \beta_{4}$: These are matrices coefficients of MT, WM, CD and AG variables respectively.

ε: Is a vector of error terms

1.7.6 *Vector Error Correction Model (VECM)*

The Vector Error Correction Model (VECM) is an extension of the Vector Autoregressive (VAR) model that is commonly used in time series analysis especially when dealing with non- stationary variables that may exhibit cointegration (Wei, 2006). Model specification for the VECM involved defining the key components of the model, including the lag order, the number of cointegrating relationships and the dynamic structure of the system. Number of Lags (p), Cointegrating Relationships (r) error correction term (εt), Model Testing and Diagnostics, Cointegration Existence and correction for short-term dynamics are the key elements of model specification for a VECM which were set by (Hamilton, 1994).

Model Testing and Diagnosis was done to diagnose tests and ensure the model's validity such as tests for serial correlation, heteroscedasticity and normality of residuals. The general formula specified by Hamilton, (1994) was as follows:

$$lnFS_t = a + \sum_{i=1}^{k}\beta_i lnGDP_{\ t-i} + \sum_{j=1}^{k}\theta_j lnCA_{t-j} + \sum_{m=1}^{k}\varphi_m lnWMT_{\ t-m} + \sum_{n=1}^{k}\omega_n lnCD_{t-n} + \sum_{d=1}^{k}\delta_d ln\ AT_{t-d} + \varepsilon t \dots\dots\dots\dots\dots\dots\dots\dots.. (06)$$

(Hauser, 2010) explained the reasons why the transformation of a Vector Autoregressive (VAR) model to a Vector Error Correction Model (VECM) was often motivated as follows:

Correction for Short-Term Dynamics

VAR models do not explicitly capture the long-term relationships among variables. Transforming to a VECM allows for the inclusion of an error correction term, which represents the adjustment of variables toward their cointegrating relationships in the short term. This improves the modeling of short-term dynamics while preserving the long-term equilibrium (Johansen, 1995).

The Granger causality test, was used to determine if past values of one variable can help predict future values of another. In this study, it was applied to examine whether Conservation Agriculture (X) influences Food Security (Y).

The test compares two models: one includes past values of X and one excluding them, using the F-test to assess which model better predicts future values of Y (Granger, 1969)

.

The following equations represent the Granger causality model:

$FS_t = \alpha_1 + \sum(\beta_i * FS_i, t - i) + \sum(\gamma_i * CA_i, t - i) + \varepsilon t \ldots\ldots..(07).$

$CA_t = \alpha_2 + \sum(\theta_i * FS_i, t - i) + \sum(\delta_i * CA_i, t - i) + \varepsilon_t \ldots..\ldots(08).$

Here FS_t and CA_t are two-time series variables to investigate for causality. The ������and�� parameters are coefficients that represent the strength of the causal relationships between the variables and �� was an error term. The lagged values of FS and CA (��������������and ��������) were included in the model to capture the temporal dependence between the variables.

The Granger causality model determined whether Food Security (FS) Granger causes Conservation Agriculture (CA) or CA causes FS. If FS Granger causes CA, then the lagged values of FS significantly improve the prediction of CA beyond what was predicted from past values of CA alone. Conversely, if CA Granger causes FS, then the lagged values of CA significantly improve the prediction of FS beyond what was predicted from past values of FS
alone. The test statistics for Granger causality is:

$CapF = \frac{(RSS_R - RSS_{UR})/m}{(RSS_{UR})(n-k)}$. Where:

RSS_R: This is the restricted residual sum of squares.

RSS_{UR}:This is the unrestricted residual sum of the squares.

m: Is the number of lagged CA terms

k: Is the number of parameters

n: Is the total number of observations

Model Diagnosis, the rigorous diagnostic tests were conducted in this study to confirm the validity of the econometric model's key criteria such as multicollinearity, autocorrelation, heteroscedasticity and model specification. Collectively, these diagnostics confirmed that the models met all the critical econometric criteria, ensuring robust and reliable results (Gujarati, & Porter, 2009).

After checking for stationarity using Augmented Dickey-Fuller (ADF) tests, my variables were mostly I,1 and cointegrated therefore, VECM was preferable compared to other models such as ARDL.

$$Increment\Delta lnFS_t = b + \sum_{i-1}^{k-1} \beta_i \Delta lnFS\, FS_{t-1} + \sum_{j=1}^{k-1} \theta_j \Delta lnCA_{t-j} + \sum_{m=1}^{k-1} \varphi_m \Delta lnWMTWMT_{t-m} + \sum_{n=1}^{k-1} \omega_n \Delta lnCD_{t-n} + \sum_{d=1}^{k-1} \delta_d \Delta lnAT_{t-d} + \lambda ECT_{t-1} + \mathcal{U}_t \ldots \ldots \ldots (09)$$

Where:

$\kappa - 1$: Means that optimal lag length is reduced by 1

a, b: Are intercepts

$\beta_i, \theta_j, \varphi_m, \omega_n, \delta_d$: These are short-term dynamic coefficients of the model's adjustment long-term equilibrium.

λ: Speed of adjustment

ECT_t: The error correction term

u_t: Residual error

The equation for error estimation is:

$$ECT_{t-1} = FS_{t-1} + \eta_j CA_{t-1} + \xi_m WMT_{t-1} + \partial_n CD_{t-1} + \delta_d lnAT_{t-d} + c \ldots \ldots (10)$$

According to (Razali & Wah, 2011), a normality test was used to assess whether a given sample or dataset follows a normal distribution. The normal distribution, also known as the Gaussian distribution or bell curve, is a symmetric probability distribution characterized by a bell-shaped curve.

The recommended test that was used in normality tests was the Jarque-Bera test because it is sensitive to small, moderate to large sample sizes and it has a good power in detecting even minor departures from normality compared to the other normality tests (Seth, 2007). The general equation for the test statistic in the Jarque-Bera test was as follows:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right),$$

JB: Jarque-Bera test.

n: Is the sample size.

S: Is the Sample Skewness

K: Is the sample Kurtosis

1.7.7 Forecasting by Auto-regressive Integrated Moving Average Model (ARIMA).

Before implementing an ARIMA model for forecasting, a preliminary analysis of the time series data was conducted to identify patterns, determine transformations, and select appropriate model parameters. This included assessing the stationarity of the data using graphical methods and the Augmented Dickey-

Fuller (ADF) test. The ADF test tested the null hypothesis that the data was non-stationary, with the null rejected if the test statistic was less than the critical value at a 5% significance level. The differentiating technique was applied to transform a non-stationary series into a stationary one, which is crucial for ARIMA modeling. The ARIMA model was used to forecast time series data by fitting the model to historical data and then using the fitted model to predict future values. The preliminary analysis of checking variable stationary, identifying the order of the ARIMA model, estimating the parameters of the model, and a diagnostic test of residuals were used to ensure the model was appropriate for forecasting (Box *et al.*, 2008).

The following equation was used to forecast food security using an ARIMA model:

$$FS_t = c + \varphi_1 FS_{t-1} + \cdots + \varphi_p FS_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t \ldots (11)$$

Where:

FS_t: Represents the economic growth rate at time

t. c: Is a constant

φ_1 to φ_p are Auto-regressive Coefficients

FS_{t-1} to FS_{t-p} are the past values of economic

growth θ_1 to θ_q are the moving average coefficients

e_{t-1} to e_{t-q} are the past error terms in the forecast

1.7.8 Model Identification

Identifying the order of the ARIMA model was done by looking at the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the data. The ACF measures the correlation between the current value of the series and its lagged values. The PACF measures the correlation between the current value of the series and its lagged values after removing the effect of the intervening lags. Autoregressive term (p): These terms capture the connection between the current data point and its previous values. Differentiating Term (d): Differentiating was employed to render the time series stationary. A stationary series exhibits consistent mean and variance over time. Moving Average Term (q): MA terms model the links between the current data point and its lagged errors.

When pinpointing the ARIMA model's order, attention was given to the ACF and PACF patterns. Typically, the ACF displayed a diminishing autocorrelation at the AR order, while the PACF revealed a decline in autocorrelation at the MA order. These patterns in the ACF and PACF plots aid in selecting the appropriate p, d, and q orders for the ARIMA model.

1.7.9 Selecting and estimating the parameters of the model

After identifying the ARIMA model, the parameters of the model were estimated. The process of estimating the model was done by using techniques including Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), volatility, significant coefficient, and log- likelihood to evaluate the performance and validation of the forecasting model. The best model selected was the one with the most significant coefficient, lowest volatility, highest log- likelihood statistic, lowest AIC and lowestBIC.

A preliminary analysis of the time series data was performed before applying the ARIMA model. This involved checking for stationarity using graphical methods and the Augmented Dickey- Fuller (ADF) test. The data was made stationary using the differentiating technique, which is essential for ARIMA modeling. The ADF test assessed whether the data had a unit root, with stationarity confirmed if the test statistic was below the critical value at a 5% significance level.

1.7.10 Research Limitations

This study's limitations stem from its focus on specific independent variables potentially overlooking other critical elements of conservation agriculture such as integrated pest management, organic soil amendments, and sustainable livestock integration. These omitted practices can significantly impact soil health, crop yields, and overall ecosystem resilience, thereby influencing food security (Mabagala *et al.*, 2017). The exclusion of these elements might result in an incomplete understanding of the full impact of conservation agriculture practices on food security, potentially leading to less comprehensive and applicable conclusions.

2.0 Results and Discussion.

2.1 Descriptive Statistics.

The descriptive statistics from 1988 to 2023 years show that the average area practicing Minimal Soil Tillage (MT) was 486.37 Ha, with a range from 1.41 Ha in 1988 to 3159.99 Ha in 2023. Food security averaged 1531.14 metric tons, peaking at 3319.70 metric tons in 2023 and reaching a low of 459.00 metric tons in 1988. Water management areas averaged 9.75 Ha, with a maximum of 29.40 Ha in 2023 and a minimum of 0.70 Ha in 1988. Crop diversification areas averaged 42.13 Ha, fluctuating between 23.98 Ha in 1988 and 65.69 Ha in 2023. Agroforestry averaged 1157 Ha, ranging from 64.26 Ha in 1988 to 2325.94 Ha in 2023.

Table 1: Descriptive statistics of study variables

Variable	Observations	Mean	Std. Dev.	Min	Max
FS	36	1531.14	894.36	459.00	3319.70
CA	36	486.37	840.02	1.41	3160

WM	36	9.75	7.06	0.70	29.40
CD	36	42.13	11.64	23.98	65.69
AG	36	1157.08	731.51	64.26	2325.94

Source: Author's computation from data (2024)

2.2 Relationship between the variables

The analysis showed a significant positive correlation between food security and minimal soil tillage (0.5334) at a p-value of 0.0008, indicating strong association. There was also a positive correlation between food security and crop diversification (0.3865) at a p-value of 0.0199, both significant at the 5% level. Agroforestry had the strongest positive correlation with food security (0.9826) at a p-value of 0.0000. However, water management had an insignificant negative correlation with food security (-0.2907) at a p-value of 0.0854. Overall, all variables except water management were significantly correlated with food security at the 5% level. These findings suggest that conservation agriculture techniques, particularly minimal soil tillage, crop diversification, and agroforestry, were positively associated with improved food security.

Table 2: Relationship between the variables

	FS	**MT**	**WM**	**CD**	**AG**
FS	1				
MT	0.5334*	1			
	0.0008				
WM	-0.2907	-0.0516	1		
	0.0854	0.7652			
CD	0.3865*	0.08	0.085	1	
	0.0199	0.6427	0.622		
AG	0.9826*	0.4752*	-0.2256	0.4060*	1
	0.0000	0.0034	0.1858	0.014	

Source: Author's computation from data (2024)

2.3 Unit root test

Table 3 reveals that the test statistics were less than their corresponding critical value for all variables. Therefore, all variables were non-stationary at a 5% level. However, after the first difference, all variables became stationary because all test statistics were greater than corresponding critical values at the 5% level, as shown in Table 3.

Table 3: Summary Unit Root Tests

Variables	Test statistics at the level	5% Critical Value	ADF result	Test statistic at *I* (I)	5% Critical Value	ADF result
FS	-0.861	-2.975	Not stationary	-4.956	-2.978	stationary
MT	-2.166	-2.975	Not stationary	-6.481	-2.978	stationary
CD	-2.787	-2.975	Not stationary	-3.462	-2.978	stationary
AG	-2.716	-2.975	Not stationary	5.221	-2.978	stationary

Source: Author's computation from data (2024)

2.4 Optimal Lag Order Selection Criteria

The results indicated that the fourth lag out of five pieces of information was an ideal optimal lag length having lag order selected by the criterion as shown in Table 4 below. The value of the log- likelihood function was relatively large and the AIC value was small, which indicated that the explanatory ability of the model was very strong.

Table 4: Optimal lag selection

Lag	L L	LR	Df	FPE	AIC	HQIC	SBIC
0	-	102.447		0.0006	6.71546	6.7914	6.9445
1	75.521	355.94	25	4.10e-08	-2.8451	-2.3896	-1.4709*
2	103.961	56.88	25	3.70e-08	-3.0601	-2.225	-0.5408
3	142.79	77.657	25	2.20e-08	-3.9244	-2.7097	-0.2601
4	199.066	112.55*	25	7.1e-09*	-5.8791*	-4.2849*	-1.0697

*** Indicates lag order selected by the criterion Source: Author's computation from data (2024)**

2.5 Cointegration Test

Table 5 reveals that there were cointegrating equations where by the null hypothesis presented by ranks 0, 1, 2, 3, and 4 gave trace statistics greater than their corresponding critical values causing the null hypothesis to be rejected for the respective ranks. Consequently, it provided strong evidence that the data are cointegrated implying that, food security and conservation agriculture had a long-term relationship in mainland Tanzania.

Table 5: Johansen tests for cointegration results

maximum rank	LL	Eigenvalue	Trace statistics	Critical value at 5%
0	122.717	.	152.699	68.52
1	154.481	0.8627	89.1709	47.21
2	175.047	0.7235	48.0394	29.68
3	187.12	0.5298	23.8915	15.41
4	194.791	0.3809	8.5505	3.76
5	199.066	0.2345		

Source: Author's computation from data (2024)

2.6 Vector Error Correction Model (VECM)

The Vector Error Correction Model (VECM) was used to analyze both long-term and short-term relationships between conservation agriculture variables and food security. All variables became stationary at their first difference and were cointegrated, indicating a long-term equilibrium relationship. The model, based on Hamilton (1994), was suitable for determining the effects of conservation agriculture on food security over time. Results showed that food security was positively influenced by conservation agriculture techniques in the long term, as all variables had Chi^2 values greater than the p-values at the 0.05 significance level. This means that conservation agriculture techniques significantly contributed to food security improvements. Table 6 demonstrated that the regression model had a good fit, with all variables being significant. The R^2 value was above 68%, suggesting that the model captured most of the variation in the data. Therefore, conservation agriculture was shown to have a strong and direct positive impact on food security in Mainland Tanzania in both the short and long term

Table 6: Vector Error Correction model

Equation	R-square	Chi^2	p-value
lnFSt-1	0.9364	257.94	0.000
lnMTt-1	0.7969	42.5598	0.0006
lnWMt-1	0.6845	25.1171	0.0921
lnCDt-1	0.8847	71.4083	0.000
lnAGt-1	0.7441	33.1421	0.0108

Source: Author's computation from data (2024)

2.7 Relationship of Conservation Agriculture and Food Security in Short Term.

The Vector Error Correction Model (VECM) revealed that while conservation agriculture had a significant positive impact on food security in the long term, its short-term effects were limited, with only agroforestry showing positive contributions. The error correction term indicated a correction speed of 8.91%, and minimal soil tillage, water management, and crop diversification had insignificant short-term contributions but became significant in the long term as shown in Table 7. Agroforestry contributed positively in both short and long terms. These findings align with other studies, such as those by Joshi *et al.* (2021) in Nepal, Mango *et al.* (2017) in Southern Africa, and Chan *et al.* (2017) in India, all of which demonstrated that the adoption of conservation agriculture techniques led to improved food security and agricultural resilience.

The number of Error Correction Terms (ECTs) in an econometric model should align with the number of variables involved in a cointegration relationship. In my dataset, the five variables (FS, MT, WM, CD, AG) should have one ECT because they have formed a cointegrated system even though in my research I was interested only in the first equation and the other equations are not useful.

Table 7: Short-term relationship.

Variables	Coef.	Std. Err.	Z	Prob	[95% Conf. Interval]	
ECT_{t-1}	-0.0891	0.0301	-2.96	0.004	-0.1783	-0.0301
$\Delta \ln FS_{t-1}$	-0.4375	0.2091	-2.09	0.036	-0.8751	-0.0278
$\Delta \ln FS_{t-2}$	-0.3611	0.2292	-1.58	0.115	-0.8102	0.0881
$\Delta \ln FS_{t-3}$	-0.1954	0.2411	-0.81	0.418	-0.6678	0.2771
	-0.0179	0.0053	-3.37	0.001	-0.0358	-0.0075
$\Delta \ln FS_{t-1}$	-0.0099	0.0042	-2.37	0.018	-0.0199	-0.0017

$\Delta\ln FS_{t-2}$	-0.0049	0.0033	-1.5	0.134	-0.0113	0.0015
$\Delta\ln FS_{t-3}$	0.0037	0.0089	0.42	0.673	-0.0136	0.0211
$\Delta\ln FS_{t-1}$	-0.0048	0.0066	-0.73	0.465	-0.0177	0.0081
$\Delta\ln FS_{t-2}$	0.0069	0.0074	0.93	0.353	-0.0077	0.0215
$\Delta\ln FS_{t-3}$	-0.0014	0.0438	-0.03	0.974	-0.0874	0.0845
$\Delta\ln FS_{t-1}$	-0.0644	0.3821	-1.69	0.092	-0.1393	0.0105
$\Delta\ln FS_{t-2}$	-0.0256	0.0434	-0.59	0.555	-0.1106	0.0595
$\Delta\ln FS_{t-3}$	0.0978	0.0816	-1.2	0.231	-0.2578	0.6215
$\Delta\ln FS_{t-1}$	0.0415	0.0826	0.5	0.615	-0.1204	0.2034
$\Delta\ln FS_{t-2}$	0.2347	0.0851	2.76	0.006	0.0679	0.4015
$\Delta\ln FS_{t-3}$	0.0763	0.0358	2.13	0.033	0.0061	0.1465

Source: Author's computation from data (2024)

28 Relationship of Conservation Agriculture and Food Security in the Long Term

Table 8 represents a regression analysis that revealed significant insights into the long-term effects of independent variables (conservation agriculture) on food security $\Delta\ln FS_{t-1}$. The coefficient for $\Delta\ln MT_{t-1}$ (minimal soil tillage) was 0.1234 with a z-value of 4.34 and a p-value of 0.000, indicating a strong positive and significant impact. This suggested that advancements in minimal soil disturbance techniques positively influenced food security over time.

Similarly, $\Delta\ln CD_{t-1}$ (crop diversity) and $\Delta\ln AG_{t-1}$(agroforestry) also showed significant positive effects with coefficients of 0.1153 and 0.4116 respectively and p-values below 0.05. These findings underscored the importance of promoting diverse crops and agroforestry to enhance food security in the long term.

Conversely, the coefficient for $\Delta\ln WM_{t-1}$(water management) was -0.8295 with a p-value of 0.073, indicating a negative but not statistically significant relationship. This suggested that while changes in water management practices may negatively impact food security, the evidence was not strong enough to draw definitive conclusions. Overall, the results advocated for the implementation of conservation agriculture practices, such as increased crop diversity, minimal soil tillage and agroforestry which revealed significant positive impacts on food security.

Table 8 Long-term relationship.

Variables	Coef.	Std. Err.	Z	Prob	[95% Conf. Interval]	
$\Delta\ln FS_{t-1}$	1					
$\Delta\ln MT_{t-1}$	0.1234	0.2847	4.34	0	0.1793	0.0676
$\Delta\ln WM_{t-1}$	-0.8295	0.0618	-13.42	0.073	-0.9506	0.7083
$\Delta\ln CD_{t-1}$	0.1153	0.0386	2.98	0.003	0.1911	0.0395
$\Delta\ln AG_{t-1}$	0.4116	0.1205	3.41	0.001	0.1753	0.6478
Constant	2.3949					

Source: Author's computation from data (2024)

2.8 Forecasting

Forecasting of food security was done by using the Autoregressive Integrated Moving Average (ARIMA) model. Before making predictions, the first step was to ensure that the food security data was stable (not changing over time). Then, identify the appropriate model choose the best one and perform diagnostic checks on the chosen model.

2.9 Stationarity Test

Figure 1 below shows the yearly Food security growth from 1988 to 2023. The pattern of the graph was an upward trend. The food security was recorded at 3319.7 in 2023 which was the highest, followed by 3275 in 2021. The time plot in Figure 4.1 shows that the data were not completely stationary since the series did not fluctuate around the mean. An upward trend in the table showed that the Augmented Dickey-Fuller (ADF) test of stationarity, which was used to supplement the graphical method, had a p-value of 0.9675 which was larger than the significance level of 0.05 indicating that, the series was non-stationary and after the first difference, the ADF test had a p-value of 0.0000 less than the significance level indicating a stationary series.

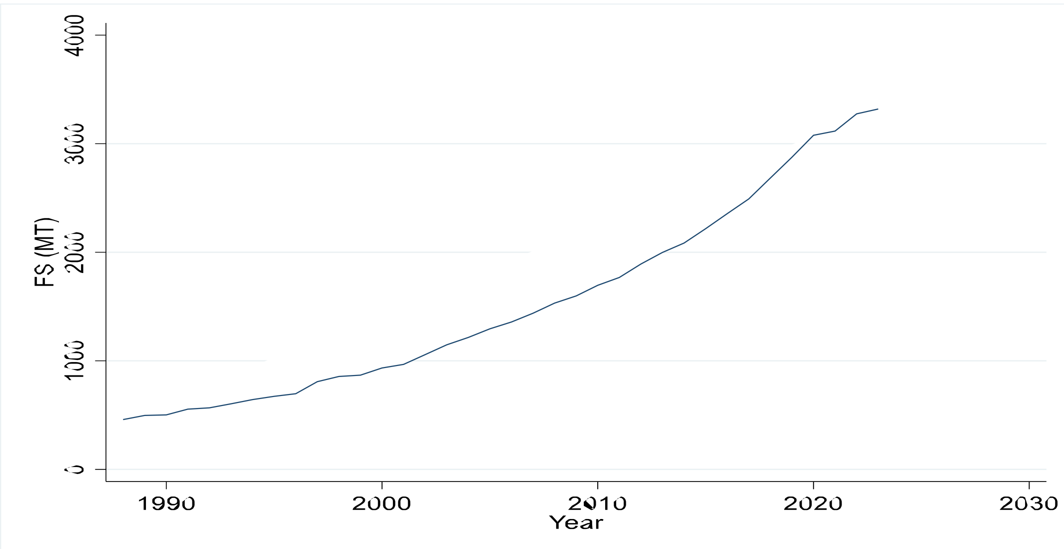


Figure 1 Shows that the time series is non-stationary. Source: Author's computation from data (2024)

2.10 Model Identification

The figures below show the plots of ACF and PACF of the stationary time series examined to identify the values of the auto-regressive (p) and moving average (q) components, respectively. The value of d, which is the number of seasons equal to one, that is, d = 1, transformed the time series from non-stationary to stationary.

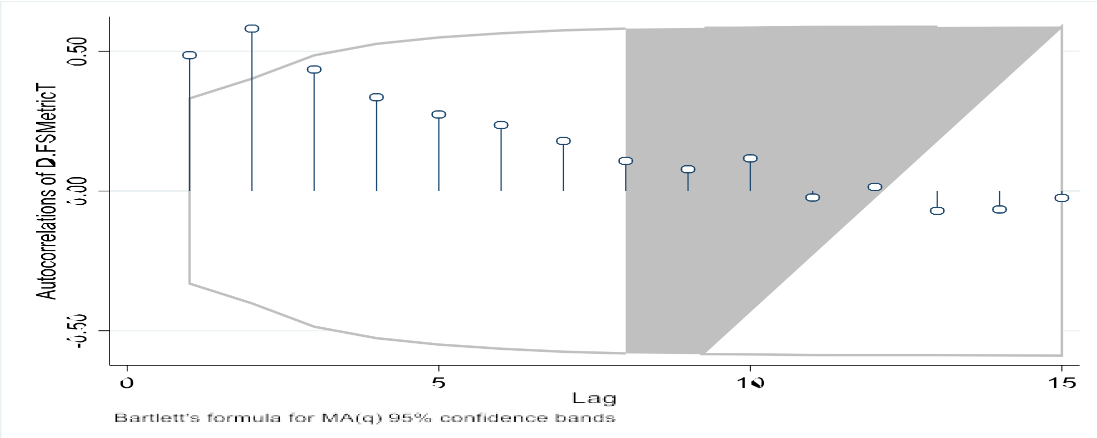


Figure 2: ACF for adjusted FS

Source: Author's computation from data (2024)

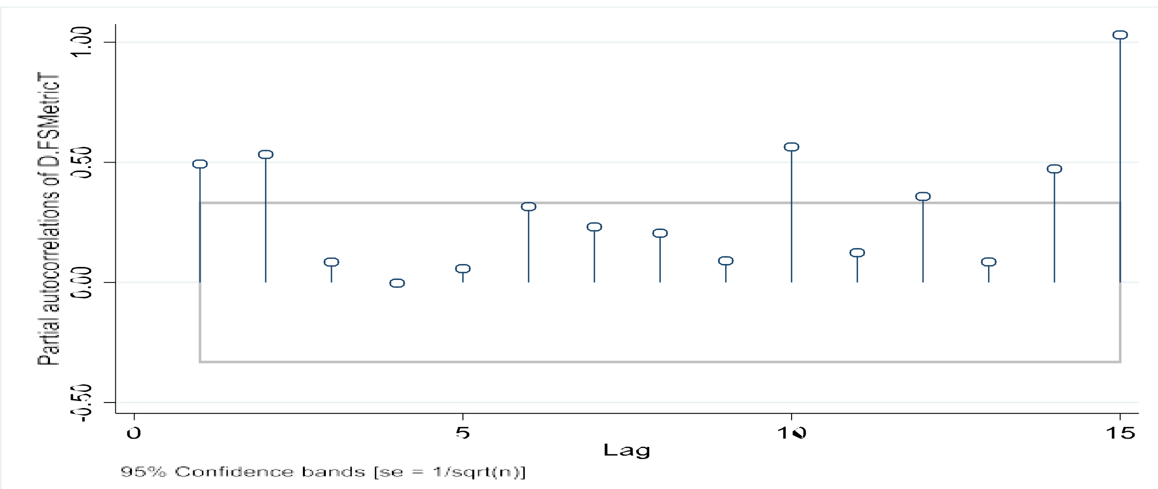


Figure 3: PACF for adjusted FS

Source: Author's computation from data (2024)

2.11 Model Selection and Estimation.

The best model was selected based on the five criteria namely, most significant coefficient, lowest volatility, highest log-likelihood statistic, lowest Akaike Information Criterion (AIC), and lowest Bayesian Information Criterion (BIC).

According to the result of Table 9**, ARIMA (2, 1, 1)** qualified as the ideal model because three of the five criteria have been chosen for it to be an appropriate model. Generally, the most appropriate ARIMA model in forecasting was essential because it enabled the capture of time series patterns, seasonal fluctuations, policy formulation and risk management, and all these contributed to overall food security growth and stability.

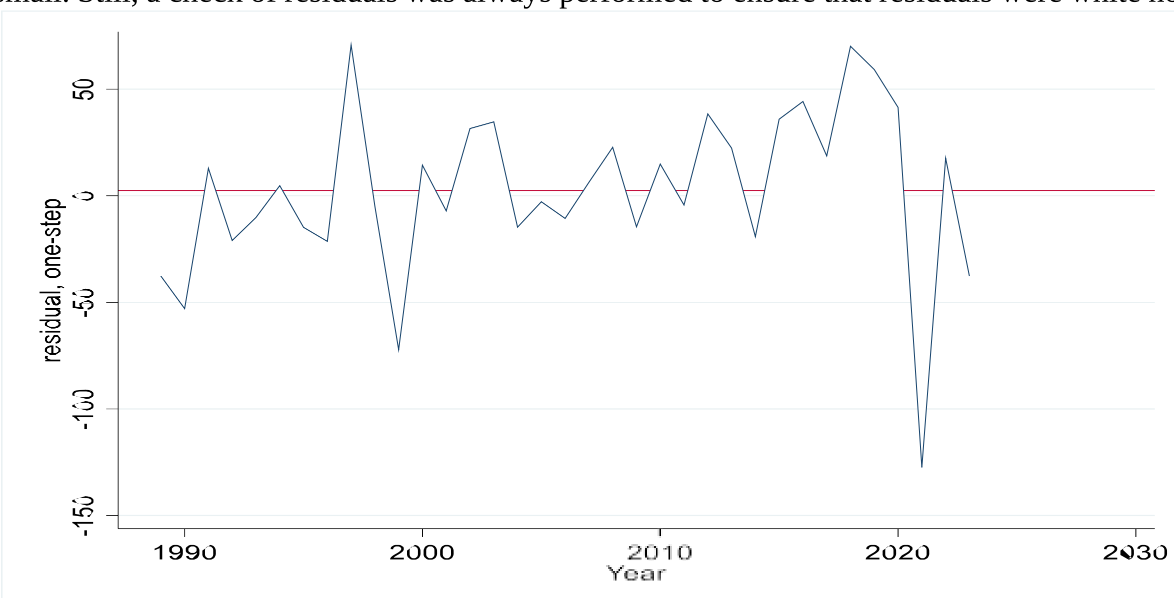
Table 9: Accuracy measures for Food Security (FS)

Model	**Significant coefficient**	**Volatility**	**Log-likelihood**	**AIC**	**BIC**
ARIMA (1, 1, 1)	0	39.702	-173.735	355.469	361.575
ARIMA (2, 1, 1)	**2**	**35.795**	**-171.502**	**351.003***	**357.109***
ARIMA (1, 1, 3)	0	35.245	-171.058	354.116	363.274

Source: Author's computation from data (2024)

2.12 Diagnostic Checking

However, most of the results from the error measures of the best model showed that errors were relatively small. Still, a check of residuals was always performed to ensure that residuals were white noise without



any remaining patterns. The usual checking was done by computing the Auto-Correlation Function (ACF) and Auto-regressive Integrated Moving Average (ARIMA) residual series. The process involved checking whether the fitted model has adequately captured the information in the data. The residual from the fitted model as shown in Figure 4 has a constant variance and a zero mean, indicating that the fitted model is adequate.

Figure 4: Mean Residual Diagnostic of Food Security (FS) Source: Author's computation from data (2024)

2.13 Forecast Food Security (FS)

The forecast yield of all crops in metric tons harvested is 3532.187, 3682.171, 3837.568, 3996.199, and 4158.478 for the years 2024, 2025, 2026, 2027 and 2028, respectively as shown in Table 4.12 below, consistently showed positive Food Security (FS) growth across all years and a gradual increase from year to year due to positive adoption of Conservation agriculture. This implied that the economy of mainland Tanzania is expected to expand steadily in the coming years and food security is expected to be relatively stable and sustainable. The findings from Conservation Agriculture resembled the results done by Farhad Zuliqar & Abid Hussain (2014) in the journal entitled "Forecasting Wheat Production Gaps to Assess the State of Future Food Security in Pakistan". The methodology used in forecasting comprised the data from the national wheat production and the country's population for the period 2013-2025 and the ARIMA model was used. Forecasted statistics under Conservation agriculture showed that wheat production is continuously increasing in the absence of random shocks, changes in price and policies and any change in consumers' food patterns. The net domestic availability (NDA) of wheat will rise nearly by 20% in 2020 comparing the year 2013. Likewise, the estimated NDA showed a 30% rise in 2025 over the available quantities in 2013. Forecasted wheat production and its NDA have shown an overwhelming rise over the statistics of 2013 however forecasted population.

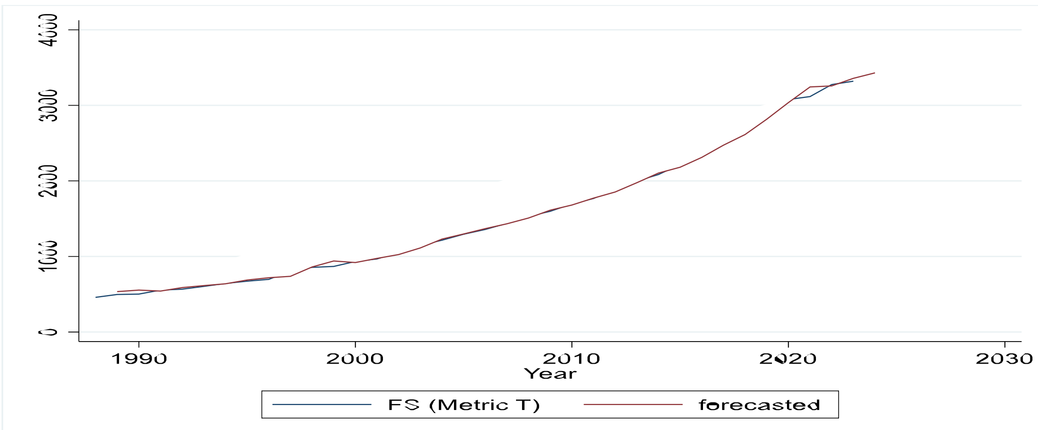
Also, these findings resembled the findings of a research study done by (Marques & Rodrigues, 2022). Their research study used an ARIMA model to forecast the food security of Portugal and Germany until 2031. The results showed that both countries were expected to experience an increase in food security, with Portugal's food security increasing at an average annual rate of 1.5% and Germany's food security increasing at an average annual rate of 1.8%.

Table 10: Forecast Food Security (FS)

Year	Forecast amount (Metric tons)
2024	3532.187
2025	3682.171
2026	3837.568
2027	3996.199
2028	4158.478

Source: Author's computation from data (2024)

Figure 5: Forecast Food Security (FS)



Source: Author's computation from data (2024)

3.0 Conclusion and Recommendations

3.1 Summary

The study used secondary-time series data on conservation agriculture and food security variables from 1988 to 2023. Specifically, the study aimed to assess the contribution of conservation agriculture on food security in mainland Tanzania and forecast the food security trend for the next five years using the **ARIMA (2,1,1)** model and the results from forecasting showed a gradual increase in food security in the next five years. Descriptive statistics, unit root tests (all variables were stationary at first difference), lag length selection, and cointegration tests were used to assess the contribution of conservation agriculture on food security. The result shows that there was a significant positive relationship between conservation agriculture and food security in the long term and a significant negative relationship in the short term. The causal effect of conservation agriculture on food security was that conservation agriculture contributes to food security.

3.2 Conclusion

This study concluded that the adoption of conservation agriculture practices, including minimal soil tillage, water management, crop diversification, and agroforestry, has a significant positive impact on food security. Analysis showed that minimal soil tillage, Agroforestry and crop diversification positively influenced food security in the long term as evidenced by statistically significant coefficients. However, water management practices showed a negative but not statistically significant relationship, indicating a need for further optimization. The trend towards adopting these conservation methods was favorable from 1988 to 2023 and forecasting food security for the next five years suggested that continued emphasis on minimal soil tillage, crop diversification and agroforestry alongside improved water management strategies, will likely enhance food security outcomes in Mainland Tanzania.

3.3 Recommendations

To evaluate the adoption of conservation agriculture and its impact on food security, it is recommended that longitudinal studies track practices such as soil tillage, water management, crop diversification, and agroforestry. These studies should use systematic data collection methods, including surveys, field observations, and remote sensing. Engaging farmers is crucial to understanding the challenges and motivations behind adoption, which will help shape targeted policies.

The effects of conservation agriculture should be assessed both in the short term, by monitoring changes in crop yields and soil health, and in the long term, by focusing on sustained yields and economic benefits. A combination of controlled experimental plots and real-world farm studies will provide a comprehensive evaluation.

To forecast food security over the next five years, dynamic models should incorporate adoption trends, climate change, and economic variables. Collaborating with experts and integrating farmer perspectives will ensure the models' relevance, while regular updates will keep them accurate and reliable.

Conflict of interest

The authors declare that there is no conflict of interest related to this study.

Acknowledgement

To all institutions and individuals contributed to this study

References

Box, G. E., Jenkings, G.M., Reinsel, G. C., & Ljung, G.M. (2015). Time series Analysis: *Forecasting and control (5Th ed.). John Wiley & Sons.*

Burnham, K.P, & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods & Research, 33(2), 261-304.*

Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for Testing the Constancy of Regression Relationships Over Time. Journal of the Royal Statistical Society: *Series B (Methodological), 37(2), 149-192. https://doi.org/10.1111/j.2517-6161.1975.tb01532.x*

Creswell, J. W. (2014). Research Design*: Qualitative, Quantitative, and Mixed Methods Approaches (4th ed.). SAGE Publications, Inc.*

Durbin, J &Watson, G.S. (1950). Testing for serial Correlation in the least squares regression. *Biometrika, 37(¾), 409-428.*

Food and Agriculture Organization of the United Nations. (2006). *Food security (Policy Brief, Issue 2). Rome: FAO.*

FAO, (2021). Climate-smart agriculture case studies 2021. In Climate-smart agriculture case studies 2021. *https://doi.org/10.4060/cb5359en*

FAO, (2022). Conservation Agriculture: *A Manual for Farmers and Extension Workers in Africa (pp. 24, 45, 67, 89). FAO.*

Gonzalo, J. ((2000). Estimating the order of an autoregressive process. *Econometric Theory, 16(3), 560-599*

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics (5th ed.). McGraw-Hill/Irwin*

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross- spectral Methods. *Econometrica, 37(3), 424-438. https://doi.org/10.2307/1912791*

Hamilton, J.D. (1994). *Time Series Analysis. Princeton University Press.*

Hauser, R. (2010). *Vector Error Collection Models: An introduction. Stata Journal, 109(1), 53- 82.*

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice (2nd ed.), OTexts.*

Johansen, S. (1995). Likelihood-Based Inference in Cointegrated Vector Autoregressive Models. *Oxford University Press*

, *105(3), 217–228. https://doi.org/10.1007/s10705-015-9711-8*

Seth, A. K. (2007). Granger causality Analysis in neuroscience and neuroimaging. *Journal of Neuroscience*, *27(41), 8819-8822*.

Smith, R., Mdee, A., & Sallu, S. (2023). How gender mainstreaming plays out in Tanzania's climate-smart agricultural policy: Isomorphic mimicry of international discourse. Development Policy Review, 41(6). *https://doi.org/10.1111/dpr.12718*

URT. (2015)._Agricultural Sector Development Programme Phase II. *United Republic of Tanzania.*

Waaswa, A., Oywaya Nkurumwa, A., Mwangi Kibe, A., & Ngeno Kipkemoi, J. (2022). Climate- Smart agriculture and potato production in Kenya: *a review of the determinants of practice*.

Wang, L., Chen, Y. J., & Wang, Q. (2005). Robust estimating functions and bias correction for longitudinal data Analysis. *Biometrics, 71(3), 1040-1042.*

Wei, S. J. (2006). Stock market volatility and Economic fluctuations: *A vector autoregressive approach. The Quarterly Journal of Economics, 121(4), 1593-1633.*

World Bank. *(2021).* Conservation agriculture. *Retrieved from https://www.worldbank.org/en/topic/climate-smart-agriculture*

Joshi, D. R., Ghimire, R., Kharel, T., Mishra, U., & Clay, S. A. (2021). Conservation agriculture for food security and climate resilience in Nepal. *Agronomy Journal, 113(6), 4484–4493.*

https://doi.org/10.1002/agj2.20830 Gonzalo, J. ((2000). Estimating the order of an autoregressive process. *Econometric Theory, 16(3), 560-599*

Razali, N. M., & Wah, Y.B. (2011). Power comparisons of Shapiro-Wilk, Kolmogorov-Sminov, Lillefors, and Anderson-Darling tests. *Journal of Statistical Modeling and Analytics, 2(1), 21-33.*

Mabagala, R. B, Massawe, B. H. J., & Mwatawala, M. W., (2017). Impact of conservation agriculture on crop yields in Dodoma, Tanzania: *An empirical analysis using VECM. Tanzania Journal of Agricultural Sciences, 18(2), 102-110.*

https://doi.org/10.4314/tjas.v18i2.1

Mango, N., Siziba, S., & Makate, C. (2017). The impact of adoption of conservation agriculture on smallholder farmers' food security in semi-arid zones of southern Africa. *Agriculture and Food Security, 6(1), 1–8. https://doi.org/10.1186/s40066-017-0109-5*

Wooldridge, J. M. (2016). Introductory Econometrics: *A Modern Approach (6th ed.). Cengage Learning.*

World Bank. *(2021).* Conservation agriculture. *Retrieved from https://www.worldbank.org/en/topic/climate-smart-agriculture*