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The Effects of Fiscal Policy on Forest Cover Conditions and Dynamics: Empirical Findings from Tanzania.

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DECLARATION OF ORIGINALITY

"I declare that this thesis has never been submitted, in whole or in part, for the purpose of obtaining any degree, in this or any other institution, and that it is the result of my own individual work. This thesis is submitted in partial fulfilment of the requirements for the degree of Master in Agricultural Economics, in the Department of Agricultural Economics and Rural Development, Faculty of Agronomy and Forest Engineering, Eduardo Mondlane University.

…….. Date……

I confirm that the work reported in this thesis was carried out under my supervision.

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…….. Date……

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Resumo

As condições da cobertura florestal na Tanzânia permanecem predominantemente negativas, com implicações significativas para a biodiversidade, os meios de subsistência rurais e a estabilidade climática. Apesar das políticas nacionais de gestão florestal, dos sistemas de rastreabilidade, dos programas de florestação, das iniciativas REDD+ e do Centro Nacional de Monitorização de Carbono, as condições florestais continuam a deteriorar-se, as florestas de regeneração natural diminuíram para 42,8 milhões de hectares em 2025, a desflorestação anual aumentou para aproximadamente 469 mil hectares após 2015, os incêndios florestais consumiram cerca de 4.014 hectares em 2025, e o stock de crescimento florestal caiu para 3.143 milhões de m³. Os estudos existentes atribuem estas tendências à expansão agrícola, à pressão demográfica e à dependência do carvão vegetal, permanecendo o papel da política fiscal ainda pouco explorado. Este estudo aborda esta lacuna recorrendo a um modelo VAR, complementado pela análise da função impulso-resposta e pela decomposição da variância do erro de previsão, para examinar a relação entre a política fiscal e a cobertura florestal na Tanzânia, no período de 2001 a 2024. Os resultados mostram que os instrumentos fiscais exercem efeitos heterogéneos sobre a cobertura florestal, consoante o tipo de despesa, a estrutura de financiamento e o horizonte temporal. Tanto a despesa de desenvolvimento como a mobilização da receita fiscal estão associadas a melhorias de curto prazo, sugerindo que o investimento público e a mobilização de recursos internos reforçam a capacidade do governo para financiar a protecção ambiental. Contudo, a eficácia fiscal depende da estrutura de financiamento, as condições de orçamento equilibrado geram melhorias mais estáveis do que as expansões financiadas por défice. Ao nível sectoral, a despesa em energia apresenta uma resposta inicial positiva que se inverte, tornando-se um efeito negativo significativo, reflectindo uma desarticulação entre o investimento em energia e a transição para o abandono dos combustíveis de biomassa. Estes resultados apontam para o reforço dos sistemas de receita interna, a disciplina fiscal e uma maior articulação entre a despesa pública e os objectivos ambientais como prioridades de política.

Abstract

Forest cover conditions in Tanzania remain predominantly negative, with significant implications for biodiversity, rural livelihoods, and climate stability. Despite national forest management policies, traceability systems, afforestation programs, REDD+ initiatives, and the National Carbon Monitoring Centre, forest conditions continue to deteriorate, naturally regenerating forests declined to 42.8 million hectares in 2025, annual deforestation rose to approximately 469 thousand hectares post-2015, fire disturbances burned around 4,014 hectares in 2025, and forest growing stock fell to 3,143 million m^3. Existing studies attribute these trends to agricultural expansion, population pressure, and charcoal dependence, while fiscal policy's role remains underexplored. This study addresses this gap using a VAR framework, complemented by impulse response analysis and forecast error variance decomposition, to examine the relationship between fiscal policy and forest cover in Tanzania from 2001 to 2024. Results show fiscal instruments exert heterogeneous effects on forest cover across expenditure types, financing structures, and time horizons. Development expenditure and tax revenue mobilization are both associated with short-run improvements, suggesting public investment and domestic resource mobilization enhance government capacity to finance environmental protection. Fiscal effectiveness, however, depends on financing structure, balanced-budget conditions generate more stable improvements than deficit-financed expansions. At the sectoral level, energy expenditure shows an initial positive response that reverses into a significant negative effect, reflecting a disconnect between energy investment and the transition away from biomass fuels. These findings point to strengthened domestic revenue systems, fiscal discipline, and closer alignment of public expenditure with environmental objectives as policy priorities.

Key words: EVI, Development Government Expenditure, Fiscal Policy, Forest Cover Conditions and Dynamics, Tanzania, VAR.

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List of Abbreviations

ADF – Augmented Dickey-Fuller

EKC – Environmental Kuznets Curve

EVI – Enhanced Vegetation Index

FAO – Food and Agriculture Organization of the United Nations

FEVD – Forecast Error Variance Decomposition

GDP – Gross Domestic Product

GHG – Greenhouse Gases

IRFs – Impulse Response Functions

IUCN – International Union for Conservation of Nature

LPG – Liquefied Petroleum Gas

MNRT – Ministry of Natural Resources and Tourism (Tanzania)

NASA – National Aeronautics and Space Administration

NDVI – Normalized Difference Vegetation Index

PP – Phillips Perron

REDD+ – Reducing Emissions from Deforestation and Forest Degradation

TCOSTECH – Tanzania Commission for Science and Technology

UNEP – United Nations Environment Programme

URT – United Republic of Tanzania

VAR – Vector Autoregressive

1. INTRODUCTION

1.1. Background of the Study

Forests cover approximately 30.8% of the global land surface (4.06 billion hectares), over half concentrated in five countries, Russia, Brazil, Canada, the United States, and China (Food and Agricultural Organization of United Nations (FAO) and United Nations Environment Program (UNEP), 2020). They provide ecosystem services of universal importance, including biodiversity conservation, carbon sequestration, water regulation, and climate stabilisation (Costanza *et al*., 2014; Pan *et al*., 2011), sheltering roughly 80% of amphibian, 75% of bird, and 68% of mammal species (Hassan, 2005; Vié *et al*., 2009). An estimated 880 million people depend on forests for fuel wood or charcoal, and forest-linked pollination underpins about 75% of global food crops (FAO and UNEP, 2020; Klein *et al*., 2007).

Globally, naturally regenerating forest area fell from 4,132.6 million hectares in 1990 to 3,808.2 million hectares in 2025, only partly offset by planted-forest growth from 183.6 to 303.6 million hectares (FAO, 2025). Forest loss is linked to increased flood risk, soil erosion, freshwater decline, and elevated zoonotic spillover risk, including for Ebola, malaria, and COVID-19 (Bonan, 2008; Ellison *et al*., 2017; Keesing *et al*., 2010). Global forest cover fell from 32.5% in 1990 to 30.8% in 2020, a net loss of about 178 million hectares, driven primarily by agricultural expansion, demographic growth, infrastructure development, and weak land governance (Curtis *et al*., 2018; Geist & Lambin, 2002).

Africa has recorded the highest regional deforestation rate of any continent, rising from 3.9 to 4.41 million hectares per year between 2010 and 2025, with naturally regenerating forest area falling from 770.6 to 648.5 million hectares (FAO, 2020, 2025). Forest condition has deteriorated alongside area loss, growing stock fell from 99.22 to 85.13 billion m^3, and biomass carbon stock from 65.45 to 56.64 Gt (FAO, 2025), reflecting sustained pressure from agricultural expansion and fuel wood demand.

Tanzania illustrates these dynamics acutely. Forests cover about 48.1 million hectares (50.6% of national land area) and support roughly 63.5% of households with food, medicine, materials, and energy, contributing 3.3% of GDP (NAFORMA, 2015; URT MNRT, 2021a, 2021b). Yet naturally regenerating forest area fell from 57.6 to 42.8 million hectares between 1990 and 2025, with annual loss accelerating from about 403,000 to 469,000 hectares per year (FAO, 2025; URT TCOSTECH, 2022). Growing stock declined from 4,215 to 3,143 million m^3 despite existing management policies (FAO, 2025), and Tanzania now ranks among the world's top five countries for annual forest loss (Hansen *et al*., 2013), driven by agricultural

expansion, charcoal production, population growth, and timber extraction. These trends undermine biodiversity, water cycles, and the rural livelihoods and energy systems dependent on forests (Barbier & Burgess, 2001). Understanding the fiscal determinants of forest cover conditions, rather than deforestation alone, is essential for conservation strategies balancing ecological protection with socio-economic needs (Barbier & Hochard, 2018).

1.2. Problem Statement

Despite the Government of Tanzania's extensive conservation efforts, afforestation programmes, REDD+ strategies, traceability systems, and international partnerships, forest deterioration remains severe; even temporary bans on charcoal businesses failed to curb deforestation (Mabele, 2020). Tanzania ranks fifth globally in average annual net forest area loss (FAO, 2020), with naturally regenerating forest area falling from 57.6 to 42.8 million hectares between 1990 and 2025 and annual loss rising from about 403,000 to 469,420 hectares per year (FAO, 2025; URT TCOSTECH, 2022). Growing stock fell from 4,215 to 3,143 million m^3 over the same period (FAO, 2025), indicating the problem extends beyond area loss to declines in forest structure and quality. Consequences are far-reaching, over 8,000 of more than 20,000 Red-Listed tree species globally are at risk (*The IUCN*, 2024), over 252 million forest-dependent Africans live on less than USD 1.25 per day (FAO and UNEP, 2020), and in Tanzania forest to non-forest conversion accounts for two-thirds of national CO2 emissions (URT, 2019).

Existing Tanzanian literature has largely examined deforestation through biophysical and socio-economic drivers, land use change, agricultural expansion, charcoal production, population growth, and energy demand (Doggart, Morgan-Brown, *et al*., 2020; Kessy *et al*., 2016; Kilawe *et al*., 2018), with limited attention to broader economic growth linkages (Gweba *et al*., 2023). Largely overlooked is the fiscal environment shaping conservation efforts, revenue generation, expenditure allocation, and budget position, which structurally determine how programmes are designed, funded, and enforced. Evaluating why specific programmes failed would require implementation data that remain fragmented in Tanzania, whereas fiscal variables are systematically recorded and offer a tractable entry point for examining these structural conditions. This study addresses that gap by analysing the impact of tax revenue, government expenditure, and budget position on forest cover conditions and dynamics in Tanzania.

1.3. Research Objectives

General Objective

To empirically evaluate the effects of fiscal policy instruments on forest cover conditions and dynamics in Tanzania.

Specific Objectives

Specifically, this study seeks to;

a) Examine the effects of development government expenditure on forest cover conditions over time,
b) Assess the effects of tax revenue on forest cover conditions over time,

1.4. Research Questions

a) What are the effects of development government expenditure on forest cover conditions over time?,
b) What are the effects of tax revenue on forest cover conditions over time?,

1.5. Research Hypothesis

a) H_o: "Development government expenditure has no significant effect on forest cover conditions over time."
   H_1: "Development government expenditure has significant effect on forest cover conditions over time."
b) H_o: "Tax revenue has no significant effect on forest cover conditions over time."
   H_1: "Tax revenue has significant effect on forest cover conditions over time."

1.6. Significance of the Study

By empirically linking fiscal policy instruments to forest cover conditions and dynamics, this study fills a knowledge gap with direct implications for conservation planning and fiscal governance in Tanzania, across Africa, and in other resource-dependent economies. The findings offer evidence-based guidance for government authorities, conservation practitioners, environmental organisations, and rural communities in designing fiscally grounded conservation approaches that reconcile economic development with long-term forest protection. For the academic community, the study advances empirical knowledge on the macroeconomic determinants of environmental outcomes, addressing a gap in the literature on resource-dependent developing economies, and informs strategies that balance conservation with economic need.

1.7. Scope and Limitations

The study examines the relationship between fiscal policy instruments and forest cover conditions and dynamics in Tanzania from 2001 to 2024, using available secondary data. Reliance on aggregate data means localised and community-level dynamics may not be fully captured, and the model focuses on fiscal variables, excluding other structural drivers such as land tenure, governance, and population growth. Data availability constraints also limited the fiscal variables included, offering directions for future, more comprehensive research.

2. LITERATURE REVIEW

2.1. Definition of Key Terms

This section defines the key variables used throughout the study, drawing on their standard definitions from national and international institutions, with additional context on their relevance to the study's objectives.

Development Government Expenditure refers to government spending directed toward capital investment and development projects, including infrastructure, energy, agriculture, environmental protection, education, and other public services aimed at promoting economic growth, living standards, and environmental quality. In this study, development expenditure captures the fiscal channel through which government investment in forest-relevant sectors is examined, addressing the study's first objective.

Agriculture Sector Expenditure is government spending allocated to Tanzania's agricultural sector, covering public investment in crop production, irrigation, agricultural research and extension services, and rural support programmes aimed at improving food security and farmer productivity. Because agricultural expansion is the leading proximate driver of deforestation in Tanzania, this component of development expenditure bears directly on forest cover outcomes.

Energy Sector Expenditure is government spending allocated to Tanzania's energy sector, encompassing public investment in electricity generation and transmission, rural electrification, renewable energy development, and energy infrastructure projects intended to expand access to affordable and reliable energy. Since biomass fuels supply nearly half of Tanzania's national energy needs, expenditure that expands access to alternative energy sources may relieve pressure on forest resources.

Forestry and Environmental Protection Expenditure is government spending allocated to the management, conservation, and protection of Tanzania's forest and environmental resources, including expenditure on afforestation, reforestation, anti-deforestation programmes, wildlife conservation, and institutional capacity for natural resource governance. This represents the most direct fiscal channel linking development expenditure to forest cover conditions.

Total Tax Revenue is the total amount of compulsory financial charges collected by the government from individuals and businesses, including income tax, value-added tax (VAT), corporate tax, and other levies. Total tax revenue represents the fiscal instrument examined

under the study's second objective, capturing government capacity to finance conservation and development programmes.

Forest Cover Conditions, measured through the Enhanced Vegetation Index (EVI), refer to a satellite-derived measure that quantifies vegetation density and health, used to assess forest cover extent and condition over time (Huete *et al*., 2002), and sourced from NASA's Terra satellite, Google Earth Engine, and the Hansen Global Forest Change dataset. EVI capturing both the extent and the conditions of forest cover rather than deforestation alone.

The Consumer Price Index (CPI) is a measure of the average change over time in the prices paid by consumers for representative baskets of goods and services, used to track inflation (*CPI Home*, n.d.), as compiled by the Food and Agriculture Organization. CPI is included as a control variable to account for the influence of inflation on the real value of fiscal expenditure and revenue.

Exchange Rates refer to the price at which one country's currency can be exchanged for another, reflecting the relative value of currencies in international markets. Exchange rate movements are included as a control variable given their influence on trade-related and agricultural incentives that affect land-use decisions.

Trade and Export Performance is a measure of a country's ability to sell goods and services to foreign markets, capturing the volume, value, and growth of exports relative to imports and overall trade activity. It is included to control for external demand pressures, particularly on agricultural commodities, that may influence forest cover change.

2.2. Forest Cover Conditions and Dynamics in Tanzania: Drivers and Empirical Evidence

The literature on forest cover conditions and dynamics in Tanzania consistently identifies agricultural expansion as the dominant driver of deforestation (Curtis *et al*., 2018; Doggart, Morgan-Brown, *et al*., 2020; Doggart, Ruhinduka, *et al*., 2020; Nzunda & Midtgaard, 2019; Willcock *et al*., 2016), accounting for an estimated 110,000 - 150,000 hectares annually between 2011 and 2015 (Pendrill *et al*., 2022). Debate persists over other drivers, charcoal production alone is estimated to account for about 33.16% of Tanzania's deforestation, among the highest rates globally (Chidumayo & Gumbo, 2013), while shifting cultivation shows strong regional heterogeneity, acting as a regeneration driver in central and southern Tanzania but declining around Lake Victoria and in the eastern-central region (Heinimann *et al*., 2017; Kilawe *et al*., 2018). Kessy *et al*. (2016), investigating the Masito forests, identify both direct drivers (agriculture, illegal settlements, grazing, charcoal production) and indirect drivers

(population growth, weak law enforcement, limited alternatives) that jointly sustain forest loss despite initiatives such as REDD+, though the qualitative design limits broader applicability.

Forest condition studies show that biomass and carbon stocks vary with management and disturbance levels, aboveground biomass in miombo woodlands ranges from about 37.9 tonnes per hectare in degraded forests to over 48 tonnes per hectare under participatory forest management (Lusambo *et al*., 2016), dry miombo ecosystems store about 68.64 megagrams of carbon per hectare (Mwakalukwa *et al*., 2024), and forest land holds substantially higher carbon than non-forest land uses, reinforcing the link between stable forest cover and carbon retention (Manyanda *et al*., 2021; Mauya *et al*., 2015). Remote sensing evidence corroborates this picture of persistent decline with limited recovery. (Hamunyela *et al*., 2020) found that 27% of Eastern Arc montane forests (20,487 ha) were disturbed between 2001 and 2017, with only 9% regeneration, and that global datasets underestimated deforestation there by over 10,000 ha.

Overall, while the literature converges on agricultural expansion as the dominant driver, disagreement persists on the relative contribution of charcoal production and shifting cultivation, pointing to a need for integrated approaches. Because these activities pressure both forest area and forest condition, fiscal instruments that subsidise or control them may strongly affect forest outcomes, yet this channel, government expenditure and tax revenue, is rarely modelled in the Tanzanian context, motivating this study's objectives.

2.3. Theoretical Perspectives on Fiscal Policy, Economic Growth, and the Environment

The fiscal policy-environment literature originates in work exploring the intersection of government expenditure, taxation, and environmental outcomes, with early research focused on how environmental taxes, subsidies, and public investment in green infrastructure could align economic growth with sustainable practice (Lans Bovenberg & Goulder, 2002). Subsequent studies integrated fiscal policy with general equilibrium models to assess environmental taxes, carbon pricing, and fiscal transfers (Heutel, 2012), and more recent work has used DSGE and CGE frameworks to design fiscal policies that reduce environmental degradation while fostering growth (Lans Bovenberg & Goulder, 2002; Xepapadeas, 2005). Effectiveness, however, remains contested. Lans Bovenberg & Goulder (2002) find environmental taxes effective in reducing pollution, Heutel (2012) argues the impact depends on broader economic conditions and market distortions, and Xepapadeas (2005) notes implementation challenges in developing economies with weak governance.

This body of work draws heavily on the Environmental Kuznets Curve (EKC), which proposes that economic growth and environmental degradation follow an inverted U-shaped pattern, with deforestation rising in early development and declining once income reaches a sufficiently high level. Empirical studies including Caravaggio (2022), Grossman & Krueger, (1995), and Koop & Tole (1999) support this relationship, though Harbaugh *et al*. (2002) argue that data limitations and methodological inconsistencies weaken its applicability. Related work links deforestation directly to macroeconomic conditions. Berman *et al*. (2023) found that crop price movements meaningfully influenced tropical deforestation, with effects varying by trade openness and development level, though without adequately accounting for governance quality or land tenure, Ayad *et al*. (2024) similarly found that income and forest degradation in Brazil follow a non-linear (U-shaped) path over 49 years, though without sufficiently isolating fiscal policy from other macroeconomic factors. Together, this foundation establishes economic growth as the backdrop against which the more specific fiscal instruments examined below, government expenditure and tax revenue, operate.

2.4. Government Expenditure and Forest Cover Conditions

A distinct strand of the fiscal-environment literature isolates public expenditure as the policy instrument of interest. Using a Vector Autoregressive (VAR) framework, Halkos & Paizanos (2016) assessed the environmental effects of fiscal policy in the United States and found that deficit-financed public spending lowered pollution from both production and consumption, supporting the argument that government expenditure can be a useful tool for environmental protection.

Attílio *et al*. (2024) extended this line of inquiry directly to deforestation, examining the fiscal policy-deforestation nexus in the Brazilian Amazon and Atlantic forests. Drawing on a theoretical dynamic model and a VAR framework spanning around 24 years, they found that higher public spending is associated with reduced forest loss across both forest types, and that a balanced-budget fiscal expansion produces a stronger dampening effect on deforestation than a deficit-financed one. For developing economies, this finding is especially meaningful, as it demonstrates that deforestation reduction is achievable through budget-neutral public investment, thereby preserving fiscal stability, the results also held when the analysis was restricted to expenditure on public goods. Nevertheless, the study carries several limitations, it does not disaggregate government expenditure by sector, data on public good expenditures are only available from January 2008, shortening the usable time series, and the applicability of

the findings may be constrained in contexts where institutional capacity and policy enforcement are weaker, such as Tanzania.

Taken together, Attílio *et al*. (2024) and Halkos & Paizanos (2016) point to a broad consensus that public expenditure can help reduce environmental degradation and deforestation by shaping economic incentives and directing investment toward conservation-compatible activities, and underscore the comparative advantage of balanced fiscal frameworks relative to deficit-financed approaches in generating durable improvements in environmental outcomes. This evidence directly motivates the study's first objective, examining the effects of development government expenditure on forest cover conditions in Tanzania.

2.5. Tax Revenue and Forest Cover Conditions

A second strand of the literature isolates taxation as the relevant fiscal instrument. Lans Bovenberg & Goulder (2002) find that environmental taxes can be effective in reducing pollution, though Heutel (2012) cautions that this effectiveness depends on broader economic conditions and market distortions. Using their VAR framework for the United States, Halkos & Paizanos (2016) further found that tax reductions financed through borrowing raised consumption-related CO2 emissions without affecting production-side pollution, highlighting the risks associated with tax cuts as a fiscal policy measure and, by extension, the potential of tax revenue mobilisation to support environmental outcomes.

Despite this evidence from the broader fiscal-environment literature, empirical studies linking tax revenue specifically to forest cover conditions and dynamics remain scarce, particularly in developing and resource-dependent economies such as Tanzania. This gap directly motivates the study's second objective, assessing the effects of tax revenue on forest cover conditions in Tanzania.

2.6. Literature Gap and Study Contribution

While extensive research on forest cover conditions and dynamics in Tanzania exists, most studies focus on environmental and socio-economic drivers such as agricultural expansion, population growth, charcoal production, and land-use changes (Curtis *et al*., 2018; Doggart, Morgan-Brown, *et al*., 2020; Doggart, Ruhinduka, *et al*., 2020; Nzunda & Midtgaard, 2019). Economic influences, including trade openness, income levels, and agricultural commodity prices, have also been explored (Ayad *et al*., 2024; Berman *et al*., 2023). However, studies on fiscal policy's role in environmental sustainability have primarily focused on

taxation, carbon pricing, and green investments in developed economies (Heutel, 2012; Lans Bovenberg & Goulder, 2002; Xepapadeas, 2005).

More recent studies, such as Halkos & Paizanos (2013, 2016), have analysed the impact of government expenditure on air pollution, focused on Sulphur Dioxide (SO_2) and Carbon Dioxide (CO_2) emissions, while Attílio *et al*. (2024) provided empirical evidence on fiscal expenditure and deforestation in Brazil. This study aligns with such research by examining macroeconomic linkages to forest cover conditions and dynamics, and contributes to the EKC literature (Grossman & Krueger, 1995; Koop & Tole, 1999), which suggests an inverted U-shaped relationship between economic growth and forest cover loss.

Building on Attílio *et al*. (2024), this study assesses fiscal policy, specifically development government expenditure and tax revenue, as tools for shaping forest cover conditions and dynamics, with a specific focus on Tanzania. While Halkos & Paizanos (2013, 2016) examined fiscal policy's impact on pollution, this research expands the scope to forest cover conditions and dynamics. It adopts a VAR modelling approach, similar to Halkos & Paizanos (2016) and Attílio *et al*. (2024), and draws from Gweba *et al*. (2023), who used a VAR with exogenous variables model to analyse economic drivers of deforestation in Tanzania.

This study makes three key contributions. First, it uniquely focuses on Tanzania, where forest cover continues to decline in both extent and condition despite the country having the third largest forest cover in Africa after Angola and the Democratic Republic of Congo. Unlike most studies that emphasize agricultural expansion (Pendrill *et al*., 2022), charcoal production (Chidumayo & Gumbo, 2013), or shifting cultivation (Heinimann *et al*., 2017), this research examines the direct role of government expenditure and taxation. Second, it offers a comprehensive empirical analysis of fiscal policy's effects on forest cover conditions and dynamics, distinguishing itself from previous studies that focused on air pollution (Halkos & Paizanos, 2013, 2016). Lastly, while Attílio *et al*. (2024) analysed total government expenditure and public goods expenditure in Brazil, this study steps ahead into separate and specific fiscal expenditure and revenue measures relevant to Tanzania's forest cover drivers. Given the differences in deforestation drivers between the two countries, shifting agriculture and charcoal production in Tanzania versus cattle ranching and soy production in Brazil, the effects of fiscal policy are likely to vary, necessitating context-specific policy recommendations.

By addressing this gap in the literature on fiscal policy and forest cover conditions and dynamics in Tanzania, this study, structured around its two specific objectives, government

expenditure and tax revenue, provides valuable insights for policymakers. Its findings contribute to the design of fiscal policies that balance economic development with sustainable forest management, supporting long-term environmental and economic stability. While the empirical analysis focuses specifically on Tanzania, the results offer relevant implications for other Sub-Saharan African countries facing similar forest cover and fiscal policy challenges.

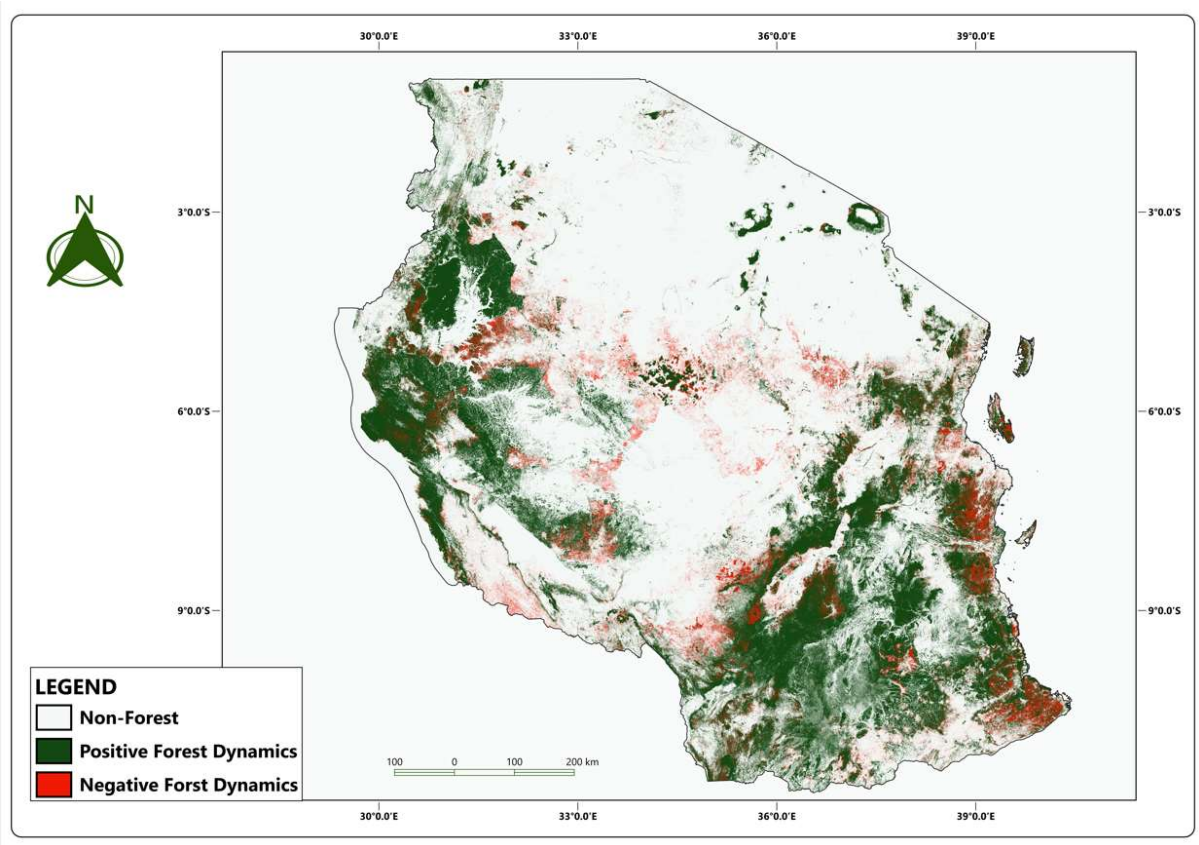
3. RESEARCH METHODOLOGY

3.1. Study Area and Spatial Representation

The study area encompasses Tanzania, whose national boundaries define the spatial extent of the analysis and from which all geospatial datasets were derived. Forest cover data were obtained from the Hansen Global Forest Change dataset and processed within Google Earth Engine. A tree cover threshold of 30% for the year 2000 was applied to delineate the baseline forest extent.

For visualization purposes, three primary spatial layers were generated, baseline forest cover for 2000, remaining forest canopy coverage for 2024, and comprehensive spatial transition map, distinguishing stable forest, forest loss, and non-forest areas. All outputs were produced at a spatial resolution of 30m and subsequently exported for further processing and cartographic visualization in QGIS. For cartographic representation, a consistent classification and symbology scheme was applied, with forest areas depicted using a green colour gradient and forest loss indicated in red, as presented in **Figure 1.** This comprehensive spatial overview of forest distribution and transformation across Tanzania form the basis for subsequent analyses of forest cover dynamics.

Figure 1: Map of Forest cover distribution and change in Tanzania based on Hansen Global Forest Change data (2000 - 2024).



3.2. Theoretical Model

This study adopts, the theoretical model developed by Attílio *et al*. (2024), which represents utility as a function of consumption and forest cover trade-offs. The structure and variables used in this model are retained as originally specified, due to their direct relevance and applicability to the objectives of this study.

Here, Zt represent the forest cover at time t, and let the dynamics of forest cover be formulated as:

$$\dot{Z}t = R(Zt) - \beta(Gt)Ct$$

Where, $\dot{Z}t$ is the rate of change of forest cover over time (deforestation or reforestation rate). R(Zt) is the rate of renewal of forest cover, which is constrained by the forest's capacity for regeneration. This function depends on the existing forest cover and captures natural growth processes like regeneration, afforestation, or reforestation programs. β(Gt): A function that captures the impact of government expenditures (Gt) on deforestation. This function allows the government to influence deforestation through policies, infrastructure expenditure (for example roads, agricultural development), regulation enforcement, and conservation initiatives. While Ct representing the demand for land and resources, which leads to deforestation. This consumption includes land demand for agriculture, settlements, and timber extraction.

Production in the economy is described by a neoclassical production function, which is dependent on the stock of produced capital K. The production function reflects how capital contributes to the economy's output. $Yt = F(Kt)$

The capital accumulation equation governs how capital evolves over time. The change in capital stock Kt, depends on output, consumption Ct, and lump-sum taxes Tt, as given by the equation: $\dot{K}t = F(Kt) - Ct - Tt$

Where, $\dot{K}t$ is the rate of change of the capital stock at time t (the accumulation of capital).

In this context the government aims to maximize the present value of the representative agent's utility, where the utility depends on both the consumption Ct and the environmental asset (forest cover) Zt. The objective is to determine the optimal level of consumption over time to maximize this while obeying to the constraints related to capital accumulation and forest dynamics.

The objective function is; $\mathbf{Max} \int_0^\infty \mathbf{U(Ct, Zt)}\ \mathbf{e}^{-\rho t}\mathbf{dt}$ **(1)**

Where, U(Ct, Zt): The instantaneous utility function at time t, which depends on consumption Ct and the forest cover Zt. And ρt is the rate of time preference (discount rate), which reflects the social government's preference for present consumption over future consumption. A higher ρ places less value on future outcomes. The integral represents the sum of discounted utility over an infinite time horizon.

The utility function U(Ct, Zt) is strictly concave and continuously differentiable. The marginal utility of consumption is positive, $UC > 0$, which means that higher consumption increases utility. The marginal utility of the forest cover can be either positive or negative, $UZ \geq 0$ or $UZ \leq 0$, because; Positive marginal utility ($UZ > 0$) suggests that the forest cover contributes positively to utility (preserving forest cover increases well-being). While negative marginal utility ($UZ<0$) suggests that beyond a certain point, additional forest cover may not increase utility or could even decrease it (for example over regulation or over protection might reduce utility by limiting land available for productive uses like agriculture).

The optimization problem is subject to the constraints defined by the dynamics of forest cover Żt and capital accumulation Ḱt, as shown below:

$$\dot{Z}t = R(Zt) - \beta(Gt)Ct \quad (2)$$

$$\dot{K}t = F(Kt) - Ct - Tt \quad (3)$$

The social planner must choose Ct, the level of consumption, while respecting the dynamics of forest cover (the renewal and depletion of the forest) and capital accumulation.

To derive analytically tractable solutions, we adopt the following assumptions relevant to socio-economic and environmental realities:

$$U(C, Z) = \ln C + \phi \ln Z \quad (4)$$

$$R(Z) = rZ\left(1 - \frac{Z}{Zmax}\right) \quad (5)$$

$$G = T \quad (6)$$

From (4), the utility depends on the natural logarithm of consumption C and forest cover A, with ϕ capturing the relative importance or weight that Tanzanians place on forests. The log Cobb-Douglas utility form is appropriate in this context as it ensures diminishing marginal utility and reflects both subsistence needs and ecological preferences. Equation (5) models the regeneration of forests using a logistic growth function. This reflects the reality that forest regrowth is constrained by ecological and spatial limits. Efforts from institutions like the Tanzania Forest Services (TFS) and Community Based Forest Management (CBFM) programs contribute positively to the natural regeneration rate r. Moreover, in reality Tanzania finances its public expenditure through a combination of tax revenue (T), non-tax revenue (N), and debt

financing (D), but from (6) we assume a balanced budget condition. This simplifying assumption serves several purposes including Theoretical Clarity, as it allows us to analyse the effects of fiscal policy on deforestation, abstracting from the more complex dynamics introduced by debt accumulation or donors contributions. In the context of fiscal policy, taxation is one of the most direct instruments under national control. Non-tax revenues and external aid are often volatile and conditional. By focusing on T, we explore how domestically raised funds, through fiscal decisions, affect long-term environmental sustainability. Additionally, balanced-budget rules are commonly used in environmental and macro-fiscal models to avoid dynamic complications from debt and allow clearer derivation of comparative statics.

Hamiltonian framework and corresponding first-order conditions.

In this framework and the corresponding first-order conditions are modified to reflect balanced budget condition. Where T is treated as an exogenous policy variable.

Hamiltonian framework is represent as:

$$\mathbf{H = lnC + \phi lnZ + q[F(K) - C - T] + \theta\ [rZ(1- \frac{Z}{Zmax}) - \beta\ (T)C]} \quad \mathbf{(7)}$$

First-Order Conditions;

(i) With respect to consumption C:

$$\mathbf{\frac{1}{C} - q = \beta(T)\ \theta} \quad \mathbf{(8)}$$

(ii) Using costate equation With respect to capital accumulation K;

$$\mathbf{\dot{q} - \rho q = - \frac{dH}{dK} = - qF'(K)} \quad \mathbf{(9)}$$

(iii)Using costate equation with respect to forest cover Z;

$$\mathbf{\dot{\theta} - \rho\theta = - \frac{dH}{dZ} = - \frac{\phi}{Z}\ - \theta[r\ (1- \frac{2Z}{Zmax})\ ]} \quad \mathbf{(10)}$$

(iv)Transversality Conditions for capital K;

$$\mathbf{\lim_{t\to\infty}(e)^{-\rho t} qK = 0} \quad \mathbf{(11)}$$

(v) Transversality Conditions for forest cover Z;

$$\mathbf{\lim_{t\to\infty}(e)^{-\rho t}\theta Z = 0} \quad \mathbf{(12)}$$

At steady state, the following conditions must be satisfied:

(i) $\mathbf{F'(K) = F_d(K) = \rho}$ **(13)**

(ii) $\mathbf{F(K) = C + T}$ **(14)**

(iii) $\mathbf{rZ(1- \frac{Z}{Zmax}) = \beta(T)C}$ **(15)**

(iv) $\mathbf{\rho\theta = \frac{\phi}{Z} + \theta[r\ (1- \frac{2Z}{Zmax})\ ]}$ **(16)**

(v) $\frac{1}{C} - q = \beta(T)\,\theta$ **(17)**

Equation (13) can be used to determine optimal capital accumulation at a given discount rate. While equation (14) can be used to determine Optimal consumption C, equation (15) shows the Steady-state forest stock, Z as function of T. Moreover, equations (16) and (17) will give the value of q and θ.

By substituting equations (13) and (14) into (15) we can assess the impact of government expenditure (taxes) on forest cover under the stated assumptions, such that;

$$rZs\left(1 - \frac{Zs}{Zmax}\right) = \beta(T)\,[F(\,F_d^{-1}(\rho) - T] \quad \textbf{(18)}$$

By using the implicit function theorem we obtain;

$$Zs'(T) = \frac{-\beta(T) + \beta'(T)[F(Fd^{-1}(\rho)) - T]}{r\left(1 - \frac{2Zs}{Zmax}\right)} \quad \textbf{(19)}$$

To determine the sign of the derivative Zs'(T) in Equation (19), we consider two primary situations based on the sign of β'(T), the marginal effect of taxation on the environmental (forest) degradation rate:

(i) Situation (1): $\beta'(T) < 0$

The numerator of Zs'(T) is negative, so:

Zs'(T) < 0 when Zs < Zmax/2,

Zs'(T) > 0 when Zs > Zmax/2.

This implies that increasing taxes can lead to a decrease in steady-state forest stock when forest cover is already low [Zs < Zmax/2] and a rise in steady-state forest cover when it is relatively abundant [Zs > Zmax/2]. To understand this, we return to the steady-state conditions equation (14), an increase in taxes T leads to a decrease in consumption C, since output is fixed. This change has two effects. First, it reduces the level of consumption. And second, it reduces the impact of consumption on environmental degradation.

From Equation (15), where consumption is proportional to the environmental regeneration function R(Z), a decrease in C implies a decrease in R(Z). Because R(Z) follows a logistic function, this implies:

If Zs < Zmax/2 (logistic is convex), a decrease in R(Z) leads to a decrease in Zs,

If Zs > Zmax/2 (logistic is concave), a decrease in R(Z) leads to an increase in Zs.

(ii) Situation (2): $\beta'(T) > 0$

Here, Three scenarios emerge:

a) Neutral Effect: $\beta'(T)[F(F_d^{-1}(\rho) - T] = \beta(T)$, then changes in T have no effect on the steady-state forest cover Z

b) Same as Case (i): If $\beta'(T)[F(F_d^{-1}(\rho) - T] < \beta(T)$, then the effects follow situation (1), a decrease in steady-state forest stock when forest cover is already low [Zs < Zmax/2] and a rise in steady-state forest cover when it is relatively abundant [Zs > Zmax/2].

c) Reverse of Case (i): $\beta'(T)[F(F_d^{-1}(\rho) - T] > \beta(T)$, then the effects reverse: An increase in steady-state forest stock when forest cover is already low [Zs < Zmax/2] and a decrease in steady-state forest cover when it is relatively abundant [Zs > Zmax/2].

Moreover, mathematically this ambiguity arises because changes in taxes affect both β(T) and C, and the sign of the derivative;

$\frac{d[\beta(T)Cs]}{dT} = \beta'(T)Cs + \beta(T)Cs'(T)$ is decisive. Using $Cs = F(F_d^{-1}(\rho) - T$ and $Cs'(T) = -1$, this becomes: $\frac{d[\beta(T)Cs]}{dT} = \beta'(T)[F(F_d^{-1}(\rho) - T] - \beta(T)$

When the derivative is zero, the R(Z) does not change, so the Zs also remains unchanged. If this derivative is negative, the R(Z) falls, which takes us back to the outcome described in case (i). If the derivative is positive, the R(Z) rises, reversing the logic of case (i).

Taxes affect the steady-state forest stock via two channels. First the level of consumption C and second the rate at which consumption depletes the environment [β(T)]. Hence, the net effect of taxation depends on the sign and strength of the two effects and the initial state of the forest cover.

In conclusion, the theoretical framework suggests that fiscal policy specifically taxation and government expenditure under a balanced-budget setting has an ambiguous impact on deforestation. The model establishes a direct link between fiscal policy and forest cover by showing how government expenditure or taxation influences the dynamics of deforestation and reforestation. Specifically, changes in tax revenue or government expenditure affect the consumption of natural resources and the rate of environmental degradation, which in turn determine the steady-state forest stock. This mechanism aligns with the study's hypotheses by providing a formal framework to assess how government expenditure or tax revenue effects forest cover depending on the initial state of forests. The effect can be positive, negative, or neutral, depending on specific structural parameters and forest conditions. Overall, this

underscores the critical role of fiscal policy in shaping environmental outcomes, highlighting it as an empirical question that warrants careful investigation.

Given the analytical ambiguity of the theoretical model, the sign and magnitude of fiscal policy effects on forest cover become an empirical question. To address this, the present study estimates a reduced-form VAR model with Tanzanian data (2001 - 2024), allowing fiscal shocks to propagate through the system and their dynamic effects on forest cover to be traced via IRFs and FEVD.

Table 1: Variables from section 3.2.

C = Consumption	Zs = sustainable forest cover
Cs = Sustainable consumption	$\beta(G)$ = Rate of forest degradation
K = Capital	q = Shadow price of capital
T = Lump-sum taxes	ρ = Discount rate
R(Z) = regeneration of forests	θ = Shadow price of forest cover
Y = Total output	r = natural rate of forest growth
Z = Forest cover at time	ϕ = forest semi-elasticity of utility
Zmax = the maximum sustainable forest cover	

3.3. Time-Series Design for Fiscal-Forest Cover Conditions Analysis

This study employs a quantitative longitudinal research design, leveraging time-series analysis to establish how fiscal policy interventions dynamically shape forest cover conditions and dynamics in Tanzania. Monthly data spanning January 2001 to December 2024 provide sufficient temporal depth to capture the evolution of fiscal-forest linkages across varying budgetary conditions, including deficit and balanced-budget scenarios.

The empirical framework is based on a VAR model, which is well suited to systems in which all variables are jointly determined. The VAR specification allows each variable to be modelled as a function of its own past values and those of all other variables within the system, enabling the identification of how fiscal policy shocks propagate and influence forest cover over time. The framework further facilitates the derivation of Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD), which together reveal the direction,

magnitude, and persistence of the dynamic effects of fiscal shocks on forest cover conditions across both short and long run horizons.

3.4. Econometric Approach

Pre-Estimation Condition for Stationarity

Before specifying the multivariate model, each series must be checked for stationarity, as most time series techniques assume the underlying variables do not exhibit systematic trends or changing variance over time. A preliminary indication of stationarity can be obtained by visually inspecting the plotted series, a stationary series tends to fluctuate around a constant mean, whereas a non-stationary series typically displays a clear upward or downward trend. To confirm this more rigorously, two formal statistical tests are employed:

The Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Where a series is found to be non-stationary, it is differenced repeatedly until stationarity is achieved. For a unit root test with lag length p, the ADF model including a constant term C is specified as:

$$\Delta X_t = C + AX_{t-1} + \sum_{i=1}^{p-1} A_t X_{t-1} + U_t \quad \textbf{(20)}$$

Where; $\Delta X_t = X_t - X_{t-1}$ represents the first difference of the series and U_t denotes the white noise error term. The null hypothesis, H_0: A = 0, indicates the presence of a unit root (i.e., the series is non-stationary), while the alternative hypothesis, H_a: A < 0, indicates stationarity. The test statistic, denoted τ (tau), follows an approximate t-distribution. At the 5% significance level ($\alpha = 0.05$), the null hypothesis of non-stationarity is rejected if:

τ < -2.57, or if the corresponding p-value < 0.05(Gweba *et al*., 2023; Jebb *et al*., 2015).

$$\text{The test statistic is computed as: ADF, } \tau = \frac{\hat{A}}{Se(\hat{A})} \quad \textbf{(21)}$$

Where; $\hat{A}$ is the estimated coefficient of from equation (5), and $Se(\hat{A})$ is its standard error.

As a complement to the ADF test, the Phillips-Perron (PP) test is also applied. Both tests share the same null and alternative hypotheses, but the PP test corrects for serial correlation and heteroskedasticity in the error term through a non-parametric adjustment to the test statistic, rather than by adding lagged difference terms as in the ADF test. The PP test is based on the regression (Phillips & Perron, 1988):

$$\Delta X_t = C + AX_{t-1} + U_t$$

Where, as before, H_0: A = 0 indicates a unit root and H_a: A < 0 indicates stationarity. The null hypothesis is rejected at the 5% level if the PP test statistic is less than the critical value, or if the associated p-value is less than 0.05.

Each variable is tested individually using both procedures at level and after differencing then proceed to model specification. Applying both tests together strengthens confidence in the stationarity conclusions for each variable.

Model Specification

Following Mountford & Uhlig (2009), Halkos & Paizanos (2016), Gweba *et al*. (2023) and Attílio *et al*. (2024) our study employs a VAR model to analyse the dynamic interrelationships between fiscal policy variables and forest cover conditions and dynamics in Tanzania from January 2001 to December 2024. The VAR framework is appropriate as it captures feedback effects and temporal dynamics among macroeconomic and environmental variables without imposing strong a priori theoretical restrictions.

Unlike Mountford & Uhlig (2009) and Halkos & Paizanos (2016) who estimated their VAR models in demeaned form, this study retains a constant term in the specification. By incorporating a constant, the model captures the underlying average magnitude of the variables over time and ensures unbiased estimation, given that the variables are not mean zero processes.

The general reduced form VAR model is expressed as follow:

$$\mathbf{Q_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{Q_{t-1}} + \boldsymbol{\beta_2}\mathbf{Q_{t-2}} \dots \boldsymbol{\beta_p}\mathbf{Q_{t-p}} + \mathbf{e_t} \quad \textbf{(22)}$$

Where;

$\mathbf{Q_t}$, denotes the vector of endogenous variables observed at time t;

$\boldsymbol{\beta_0}$, represents the vector of intercept (constant) terms;

$\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$ up to $\boldsymbol{\beta_p}$ are coefficient matrices that measure the effects of past values of the variables and capture their dynamic interactions across p lags; and

$\mathbf{e_t}$ is the vector of error terms (white-noise disturbances).

The vector Q_t in the VAR specification contains macroeconomic and forest cover dynamics variables relevant to Tanzania.

In the first model, Q_t includes development government expenditure, total tax revenue, trade and export performance, and the forest cover dynamics. This specification focuses on aggregate fiscal policy variables and their interaction with overall economic activity in influencing forest cover conditions and dynamics.

In the final part, the joint effects of government expenditure and taxation on forest cover conditions are examined under two alternative fiscal policy scenarios. The first scenario reflects

an expansionary fiscal position characterized by higher government expenditure alongside lower tax revenues, resulting in a fiscal deficit. In contrast, the second scenario reflects a balanced budget approach, in which higher government expenditure is offset by an equivalent rise in tax revenue, maintaining fiscal neutrality. Within the VAR framework, these scenarios are implemented through simultaneous shocks to expenditure and tax variables, with the direction of the shocks distinguishing the two regimes. This approach allows the analysis to isolate how different fiscal policy combinations influence forest cover conditions and dynamics.

In the second model, Q_t is expanded to include sector specific fiscal variables, namely agriculture sector expenditure, energy sector expenditure, and forestry and environmental protection expenditure, alongside trade and export performance and the forest cover dynamics. This specification enables a disaggregated assessment of how various categories of government expenditure affect forest cover dynamics.

These two model specifications enable the study to distinguish between the aggregate effects of fiscal policy and the sectoral channels through which government expenditure influences deforestation and forest conservation outcomes in Tanzania.

To identify structural shocks, particularly unanticipated fiscal policy innovations, the study applies a recursive ordering approach using the Cholesky decomposition technique (Lütkepohl, 2005; Sims, 1980). This approach orthogonalizes the residuals, allowing the model to isolate the dynamic effects of distinct shocks on forest cover dynamics. Incorporating trade and export performance helps distinguish the environmental effects of fiscal policy from those driven by economic expansion, consistent with literature examining the link between economic development and environmental performance, including studies focused on the EKC hypothesis.

Variable Definitions (natural-log-transformed fiscal variables)

All fiscal (and trade) variables are transformed using natural logarithms (ln), while forest cover is retained in its original units:

LnDVPt = ln(Development Government Expenditure)

LnTAXt = ln(Total Tax Revenue)

LnTEPt = ln(Trade and Export performance)

LnAGRIt = ln(Agriculture Sector Expenditure)

LnENERt = ln(Energy Sector Expenditure)

LnFORESt = ln(Forestry & Environmental Protection Expenditure)

Forest Cover Conditions (EVIt) remains untransformed.

Model 1: Aggregate Fiscal Policy Model

Vector of endogenous variables:

$$Qt = [LnDVPt, LnTEPt, LnTAXt, EVIt\ ]^T$$

The reduced-form equations of the model (single-equation form, extending to p lags) are specified as follows:

$$LnDVP_t = b_{10} + \sum_{i=1}^{p} \left[b_{11}^{i} LnDVP_{t-i} + b_{12}^{i} LnTEP_{t-i} + b_{13}^{i} LnTAX_{t-i} + b_{14}^{i} EVI_{t-i}\right] + e_{1t} \quad \textbf{(23)}$$

$$LnTEP_t = b_{20} + \sum_{i=1}^{p} \left[b_{21}^{i} LnDVP_{t-i} + b_{22}^{i} LnTEP_{t-i} + b_{23}^{i} LnTAX_{t-i} + b_{24}^{i} EVI_{t-i}\right] + e_{2t} \quad \textbf{(24)}$$

$$LnTAX_t = b_{30} + \sum_{i=1}^{p} \left[b_{31}^{i} LnDVP_{t-i} + b_{32}^{i} LnTEP_{t-i} + b_{33}^{i} LnTAX_{t-i} + b_{34}^{i} EVI_{t-i}\right] + e_{3t} \quad \textbf{(25)}$$

$$EVI_t = b_{40} + \sum_{i=1}^{p} \left[b_{41}^{i} LnDVP_{t-i} + b_{42}^{i} LnTEP_{t-i} + b_{43}^{i} LnTAX_{t-i} + b_{44}^{i} EVI_{t-i}\right] + e_{4t} \quad \textbf{(26)}$$

The forest cover equation **(26)** is the equation of primary interest, as it expresses forest cover dynamics as a function of its own past values and the lagged fiscal and trade variables.

Impulse Response Function

While the reduced-form VAR coefficients in equation (26) describe the statistical association between variables, they do not by themselves reveal how a shock to one variable propagates through the system over time. To trace these dynamic effects, the study relies on the Impulse Response Function, which simulates the response of forest cover to a one-time shock in a given fiscal or trade variable, holding all other shocks at zero, and traces this response over successive future periods (Enders, 2015; Lütkepohl, 2005; Sims, 1980).

Because the reduced-form residuals e_t are generally contemporaneously correlated across equations, a shock cannot be attributed to a single variable without first orthogonalizing the residuals. The study therefore applies the Cholesky decomposition described above, which decomposes the residual covariance matrix Σ such that $\Sigma = PP^T$, with P lower triangular.

This yields the structural, mutually uncorrelated shocks:

$$\varepsilon_t = P^{-1} e_t \quad \textbf{(27)}$$

Re-expressing the VAR in its moving-average (Wold) form and shifting the time index forward by h periods allows each variable in Q_{t+h} to be written as the cumulative sum of the shock occurring at time t and all shocks preceding it:

$$Q_{t+h} = \mu + \sum_{k=0}^{\infty} \Psi_k \varepsilon_{t+h-k}\,, \qquad \Psi_o = I \tag{28}$$

The matrices Ψ_k trace the marginal effect of a unit structural shock at time t on the vector Q_{t+h} observed h periods later, the sequence of these matrices, plotted against the horizon h, constitutes the impulse response function. For the forest cover equation specifically, the response to a shock in variable j at horizon h is given by the (4,j) element of $\Psi^{(h)}$:

$$EVI_{t+h} = \Psi_{4,j}^{h}\, \varepsilon_{jt} \tag{29}$$

In practice, the IRFs are generated directly from the estimated VAR using EViews, which computes the full sequence of Ψ_k matrices from the estimated coefficient matrices b_1, b_2, up to b_p, and reports the horizon by horizon response of forest cover to a one standard deviation shock in each fiscal and trade variable, together with the associated confidence bands. These single variable IRFs form the building blocks for the combined, joint-shock scenario analysis presented next, in which the individually estimated responses to the expenditure and tax shocks are algebraically combined consistent with the linearity of the moving average representation to trace the effect of simultaneous fiscal policy shocks on forest cover conditions.

Joint Effects of Government Expenditure and Taxation (Scenario Analysis)

This part traces the response of forest cover dynamics **(29)** to the structural shocks ε_{1t}^{LnDVP} and ε_{3t}^{LnTAX}, orthogonalized innovations to development expenditure and tax revenue, obtained via Cholesky decomposition of the system's residual covariance matrix Σ. Only the forest cover conditions responses row 4 of Ψ(h), namely $\Psi_{4,1}(h)$ and $\Psi_{4,3}(h)$ are reported.

Orthogonalized shocks, obtained from the Cholesky decomposition of the residual covariance matrix Σ, where $\Sigma = PP^T$ and P is lower triangular:

$$\varepsilon_t = P^{-1}\, e_t, \quad \varepsilon_t = [\varepsilon_{1t}^{LnDVP}, \varepsilon_{2t}^{LnTEP}, \varepsilon_{3t}^{LnTAX}, \varepsilon_{4t}^{EVI}]^T \tag{30}$$

Joint fiscal shock vector, combining the two structural fiscal innovations:

$$\delta_t = [\varepsilon_{1t}^{LnDVP}, \varepsilon_{3t}^{LnTAX}]^T \tag{31}$$

Scenario 1: Expansionary fiscal position (deficit-financed), development expenditure rises while tax revenue falls, generating a fiscal deficit shock.

$$\varepsilon_{1t}^{LnDVP} = +\delta, \quad \varepsilon_{3t}^{LnTAX} = -\delta, \qquad \delta > 0 \tag{32}$$

Scenario 2: Balanced-budget position (fiscal neutrality), development expenditure and tax revenue rise by an equivalent proportional magnitude, leaving the net fiscal balance unchanged.

$$\varepsilon_{1t}^{LnDVP} = +\delta, \quad \varepsilon_{3t}^{LnTAX} = +\delta, \qquad \delta > 0 \tag{33}$$

Cumulative impulse response of forest cover conditions to the joint shock, at horizon h:

$$EVI_{t+h}^{scenario} = \Psi_{4,1}^{h}\varepsilon_{1t}^{LnDVP} + \Psi_{4,3}^{h}\varepsilon_{3t}^{LnTAX} \tag{34}$$

where Ψ4,1(h) and Ψ4,3(h) are the (4,1) and (4,3) elements of the impulse response matrix at horizon h, capturing the response of forest cover to a one-unit ln shock in development expenditure and tax revenue, respectively. Comparing $EVI^{expansionary}$ against $EVI^{balanced}$ isolates the differential forest cover impact of the two fiscal stances.

Model 2: Specific Sector Fiscal Policy Model

Vector of endogenous variables:

$Q_t = [LnENER_t, LnAGRI_t, LnFORES_t\ LnTEP_t, EVI_t\ ]^T$

The reduced-form equations of the model are specified as follows:

$$LnENER_t = c_{10} + \sum_{i=1}^{p}\left[c_{11}^{i}LnENER_{t-i} + c_{12}^{i}LnAGRI_{t-i} + c_{13}^{i}LnFORES_{t-i} + c_{14}^{i}LnTEP_{t-i} + c_{15}^{i}EVI_{t-i}\right] + e_{1t} \tag{35}$$

$$LnAGRI_t = c_{20} + \sum_{i=1}^{p}\left[c_{21}^{i}LnENER_{t-i} + c_{22}^{i}LnAGRI_{t-i} + c_{23}^{i}LnFORES_{t-i} + c_{24}^{i}LnTEP_{t-i} + c_{25}^{i}EVI_{t-i}\right] + e_{2t} \tag{36}$$

$$LnFORES_t = c_{30} + \sum_{i=1}^{p}\left[c_{31}^{i}LnENER_{t-i} + c_{32}^{i}LnAGRI_{t-i} + c_{33}^{i}LnFORES_{t-i} + c_{34}^{i}LnTEP_{t-i} + c_{35}^{i}EVI_{t-i}\right] + e_{3t} \tag{37}$$

$$LnTEP_t = c_{40} + \sum_{i=1}^{p}\left[c_{41}^{i}LnENER_{t-i} + c_{42}^{i}LnAGRI_{t-i} + c_{43}^{i}LnFORES_{t-i} + c_{44}^{i}LnTEP_{t-i} + c_{45}^{i}EVI_{t-i}\right] + e_{4t} \tag{38}$$

$$EVI_t = c_{50} + \sum_{i=1}^{p}\left[c_{51}^{i}LnENER_{t-i} + c_{52}^{i}LnAGRI_{t-i} + c_{53}^{i}LnFORES_{t-i} + c_{54}^{i}LnTEP_{t-i} + c_{55}^{i}EVI_{t-i}\right] + e_{5t} \tag{39}$$

As in Model 1, the forest cover equation **(39)** is the equation of primary interest, as it expresses forest cover dynamics as a function of its own past values and the lagged specific sectors and trade variables.

Forecast Error Variance Decomposition

While the impulse response function traces the direction and magnitude of forest cover's response to a shock over time, it does not indicate how much of the overall unpredictability in forest cover is attributable to each source of shock. To address this, the study complements the IRF analysis with the FEVD, which apportions the h-step-ahead forecast error variance of forest cover among the structural shocks in the system which quantifies the relative importance of each fiscal, trade, and own-shock in explaining fluctuations in forest cover conditions over the forecast horizon (Hamilton, 1994; Lütkepohl, 2005).

Using the moving-average (Wold) representation of the VAR, the h-step-ahead forecast error for the j variable in Q_{t+h} can be written as a weighted sum of current and past structural shocks:

$$Q_{t+h} - \widehat{Q}_{t+h|t} = \sum_{k=0}^{h-1} \Psi_k \varepsilon_{t+h-k} \quad \textbf{(40)}$$

For variable j (e.g., forest cover), the total h-step-ahead forecast error variance is the sum, across all N structural shocks in the system, of the squared cumulative impulse responses:

$$\mathrm{Var}(Q_{j,t+h} - \widehat{Q}_{j,t+h|t}) = \sum_{n=1}^{N} \sum_{k=0}^{h-1} \left(\Psi_{j,n}(k)\right)^2 \quad \textbf{(41)}$$

The proportion of variable j's h-step-ahead forecast error variance attributable specifically to shock m (e.g., the LnDVP shock, the LnTAX shock, or, in Model 2, the sectoral expenditure shocks) is then given by:

$$\mathrm{FEVD}_{j,m}(h) = \frac{a \sum_{k=0}^{h-1} \left(\Psi_{j,m}(k)\right)^2}{\sum_{n=1}^{N} \sum_{k=0}^{h-1} \left(\Psi_{j,n}(k)\right)^2} \quad \textbf{(42)}$$

By construction, $\mathrm{FEVD}_{j,m}(h)$ lies between 0 and 1 for each shock m, and the shares across all N shocks sum to unity at every horizon h. Applied to the forest cover dynamics equations indicate what percentage of the forecast error variance in forest cover at horizon h is explained by innovations in development expenditure, tax revenue, trade performance, sectors expenditures and forest cover's own past shocks, respectively. A large and rising share attributable to a fiscal variable over the forecast horizon provides evidence that fiscal policy is a meaningful driver of forest cover dynamics in Tanzania, complementing the directional evidence already provided by the impulse response functions.

3.5. Sources of Data and Key Variables

Drawing on secondary time-series data, this study examines more than two decades of fiscal and environmental dynamics in Tanzania, encompassing the period 2001 to 2024. All data were

sourced from credible national and institutional repositories, namely the Bank of Tanzania, Ministry of Finance, National Aeronautics and Space Administration (NASA), the Hansen global Forest Change, Google Earth Engine, and the FAO, as detailed in **Table 2**. The analysis includes the following variables, forest cover condition, development government expenditure, agricultural sector expenditure, energy sector expenditure, forestry and environmental protection sector, total tax revenue and trade and export performance.

Total government expenditure is disaggregated into recurrent and development components. This study focuses on development government expenditure, as it better captures public investment in infrastructure and productive sectors, which are more likely to influence land use change and forest cover dynamics compared to recurrent expenditure.

Trade and export performance is incorporated as an indicator (proxy) of overall economic activity and business cycle fluctuations. Changes in trade and export performance reflect variations in production and trade dynamics, which may exert pressure on forest resources through demand for land, energy, and raw materials.

All fiscal variables were transformed into natural logarithms to stabilize variance and reduce skewness. To ensure comparability over time and control for inflationary effects, all monetary series were deflated using the national Consumer Price Index, with 2015 as the reference year, yielding real values expressed in constant Tanzanian Shillings. Trade and export values, originally reported in US dollars, were converted into Tanzanian Shillings using official exchange rates prior to deflation and transformation.

Table 2: Data sources.

Data	**Source**
Agriculture Sector Expenditure	Ministry of Finance
Consumer Price Index	Food and Agriculture Organization
Development Government Expenditure	Bank of Tanzania
Energy Sector Expenditure	Ministry of Finance
Exchange Rates	International Monetary Fund
Forest Cover Conditions (EVI)	NASA (Terra satellite), Google Earth Engine and Hansen Global Forest Change
Forestry & Environmental Protection Expenditure	Ministry of Finance
Total Tax Revenue	Bank of Tanzania
Trade and Export performance	Bank of Tanzania

Vegetation indices are mathematical transformations of satellite spectral bands designed to enhance vegetation signals and enable consistent spatial and temporal comparison of photosynthetic activity and canopy characteristics (Huete *et al*., 2002). Vegetation indices are widely used to monitor short, medium, and long-term changes in vegetation condition, phenology, and biophysical properties (Huete *et al*., 2002; Justice *et al*., 1998; Running *et al*., 1994).

The Moderate Resolution Imaging Spectroradiometer (MODIS) provides standardized global vegetation index products that support continuous monitoring of terrestrial vegetation dynamics. Among these, EVI and NDVI are generated at spatial resolutions of 1 km and 500 m with 16 days compositing intervals (Fusami *et al*., 2020; Gao, 2000; Huete *et al*., 2002; Tucker, 1979). NDVI is primarily sensitive to chlorophyll content and vegetation greenness, whereas EVI provides greater sensitivity to canopy structural characteristics, including leaf area, vegetation type, and canopy architecture (Fusami *et al*., 2020; Gao, 2000; Huete *et al*., 2002; Tucker, 1979). Together, these indices provide complementary information for assessing vegetation status and change.

NDVI is defined as:

$$\mathbf{NDVI} = \frac{\mathbf{NIR} - \mathbf{R}}{\mathbf{NIR} + \mathbf{R}} \tag{43}$$

Where; NIR and R represent reflectance in the near-infrared and red spectral bands, respectively. NDVI values range from −1 to +1, with higher values indicating dense and healthy vegetation, while values near zero or negative typically represent sparse vegetation, bare soil, or water (Blanco *et al*., 2020; Fusami *et al*., 2020; Ratnayake, 2002; Rouse *et al*., 1974; Tucker, 1979).

Although NDVI is widely applied in vegetation monitoring, it tends to saturate in high biomass regions, limiting its sensitivity in dense forest environments. To overcome this limitation, EVI was developed to improve sensitivity to canopy structural variation while reducing atmospheric and background effects in complex vegetation systems (Huete *et al*., 2002).

EVI is expressed as:

$$\mathbf{EVI} = \mathbf{G}.\frac{(\boldsymbol{\rho}\mathbf{NIR} - \boldsymbol{\rho}\mathbf{R})}{(\boldsymbol{\rho}\mathbf{NIR} - \mathbf{C_1}\boldsymbol{\rho}\mathbf{R} - \mathbf{C_2}\boldsymbol{\rho}\mathbf{B} + \mathbf{L})} \tag{44}$$

Where; ρNIR, ρR, and ρB are surface reflectance in the near-infrared, red and blue bands respectively, L is the canopy background adjustment factor, C_1 and C_2 are aerosol resistance coefficients, and G is a gain factor (Huete, 1997; Huete *et al*., 2002).

The aerosol resistance term uses the blue band to correct for atmospheric scattering effects in the red band, improving performance under conditions such as haze and biomass burning (Kaufman & Tanre, 1992). Additionally, the canopy background adjustment reduces the influence of soil, litter, and other non-vegetation components, particularly in open and heterogeneous landscapes. These improvements enable EVI to better isolate vegetation signals and capture spatial and temporal vegetation dynamics.

Overall, EVI and NDVI provide complementary perspectives on vegetation conditions, with NDVI representing general greenness and EVI offering improved sensitivity to structural variation and dense canopy environments.

Therefore, in this study, EVI was used as the primary indicator for forest cover conditions and dynamics analysis due to its improved performance in high biomass and structurally complex forest ecosystems. Compared to other vegetation indices, EVI is less sensitive to saturation effects and atmospheric influences, making it better suited for assessing within forest vegetation dynamics.

EVI was derived from MODIS Terra vegetation indices 16-days L3 global 250m (MOD13Q1) products processed using Google Earth Engine. EVI calculation incorporated the near-infrared, red and blue bands, following the standard formulation. The MODIS image collection was filtered for the study period, and appropriate radiometric conversion coefficients applied to transform digital number values into surface reflectance data. Each image was assigned temporal attributes (year and month) based on acquisition metadata, enabling the construction of a structured time series. Monthly composites were generated by grouping observations by year and month and computing mean values, reducing noise from cloud contamination and atmospheric variability. This resulted in a continuous monthly EVI time series. Forest specific vegetation dynamics were extracted by applying a forest mask derived from the Hansen Global Forest Change dataset, applying a 30% tree cover threshold for the year 2000. This ensured that only forested pixels were included, while non-forest areas were excluded through spatial masking. Finally, mean EVI values were computed for forested areas within the national boundary of Tanzania for each monthly composite, producing a consistent time series for analysing forest dynamics over time.

To address seasonal variation driven by rainfall and phenological cycles unrelated to forest cover change, the raw monthly EVI series is deseasonalised prior to analysis equivalent

to computing EVI anomalies (Appelhans *et al*., 2015; Detsch *et al*., 2016; Fusami *et al*., 2020). This procedure eliminates recurring seasonal fluctuations, accounts for inherent differences in baseline greenness across vegetation types, and allows the analysis to focus on inter-annual variability and structural changes in forest cover rather than predictable seasonal cycles. The deseasonalised EVI series used in the VAR model therefore reflects genuine deviations from expected seasonal vegetation patterns, attributable to underlying changes in forest conditions rather than normal seasonal variation in greenness.

4. RESULTS AND DISCUSSION

4.1. Estimation using Development Government Expenditure and Tax Revenue

In the government budget framework, total government expenditure consists of two main components, recurrent expenditure, which covers wages, salaries, and other operational expenses, and development expenditure, which is allocated to investment and capital formation activities. For the purposes of this model, only development expenditure is included in the estimation. This decision reflects the view that development expenditure more directly captures the resources allocated to productive and investment activities, which are expected to exert a stronger impact on forest cover than routine operational spending.

Given that the government may operate under a balanced, surplus, or deficit budget, government expenditure and tax revenue are included separately in the model. This specification allows a more comprehensive assessment of the fiscal-forest cover nexus by distinguishing between the spending and revenue sides of the fiscal position, rather than treating them as a single aggregate measure.

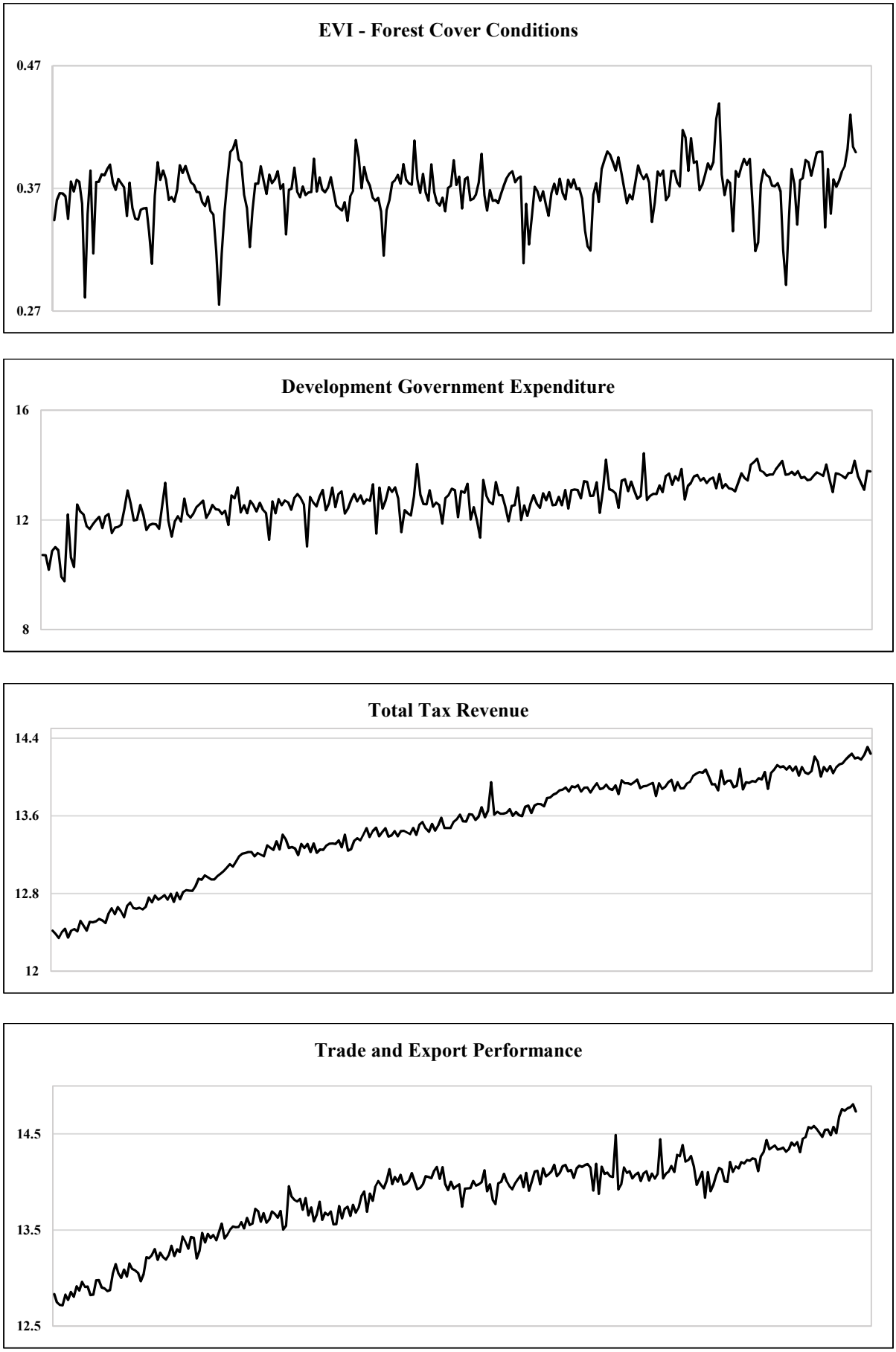
4.1.1. Trend Analysis

The time series properties of the variables are examined through visual inspection of **Figure 2,** prior to formal unit root testing. Forest cover dynamics exhibits persistent high frequency fluctuations around a relatively stable mean, with no discernible upward or downward trend over the sample period.

Development government expenditure displays a gradual upward trend accompanied by moderate volatility, consistent with a progressive expansion in public investment over time. Trade and export performance similarly follows a broadly upward trajectory, reflecting sustained growth in external economic activity, albeit with intermittent fluctuations.

Tax revenue, by contrast, exhibits a strong and near monotonic upward trend throughout the sample period, with no visual evidence of mean reversion. The sustained upward trajectory in tax revenue reflects persistent growth in fiscal collections, driven by economic expansion and improvements in tax administration over the study period.

Figure 2: Time Series Trends of Variables at Levels.



4.1.2. Model Specification and Pre-Estimation Tests

Prior to model estimation, the time-series characteristics of all variables included in the analysis were assessed to ensure correct model specification and to prevent the occurrence of spurious relationships. This was done using the ADF and PP unit root tests, with the corresponding outcomes reported in **Table 3**. Each test was implemented under two specifications, one including only a constant term, and another incorporating both a constant and a deterministic trend to account for different data generating processes.

The PP test serves as a robustness check for the ADF approach, as it adjusts for serial correlation of higher order and remains reliable in the presence of heteroskedasticity and possible structural shifts. The lag structure was selected based on the Schwarz Information Criterion, ensuring an optimal balance between fit and parsimony.

The findings reveal that the variables exhibit mixed integration properties, with some being stationary at level form I(0), while others achieve stationarity only after first differencing I(1). This combination of integration orders indicates heterogeneous time-series characteristics among variables.

Table 3: Stationarity Test Results for the Variables.

		ADF		**Phillips-Perron**	
Variables	**Deterministic**	**Level**	**Difference**	**Level**	**Difference**
Forest Cover Dynamics (EVI)	Intercept	-9.268(0)***		-9.266(5)***	
	Trend and intercept	-9.581(0)***		-9.131(8)***	
Development Government Expenditure	Intercept	-0.496(11)	-9.653(10)***	-5.726(10)***	-133.7(146)***
	Trend and Intercept	-15.31(0)***	-9.619(10)***	-15.32(1)***	-134.5(148)***
Total Tax Revenue	Intercept	-2.789(5)*	-24.71(1)***	-1.600(34)	-35.22(70)***
	Trend and intercept	-0.864(5)	-11.87(1)***	-3.772(40)**	-47.30(56)***
Trade and Export performance	Intercept	-1.394(10)	-5.524(12)***	-1.653(16)	-35.13(31)***
	Trend and intercept	-1.965(10)	-5.534(12)***	-5.432(1)***	-35.33(31)***

Note: ***, **, and * stand for statistical significance at 1%, 5% and 10% respectively; Numbers in parentheses show lag lengths, selected using the Schwarz Bayesian Criterion for the ADF tests and the Newey-West method for the PP tests.

The lag length selection was guided by the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan-Quinn Information Criterion (HQIC) and Likelihood Ratio test statistic (LR). Although the information criteria suggested optimal lag lengths of 3 and 6, a lag length of 6 was ultimately selected, as it adequately eliminated serial

correlation in the residuals. This choice is consistent with standard VAR practice, where diagnostic checks are prioritized to ensure model validity (Hamilton, 1994; Lütkepohl, 2005). The selected lag structure was therefore adopted for all subsequent estimations.

The VAR model is estimated in levels, with all variables included in their level forms. The analysis is conducted using IRFs and forecast error variance decomposition to capture the dynamic effects of shocks and assess the relative contribution of fiscal policy innovations to changes in forest cover conditions and dynamics over time. The use of a VAR framework in levels is justified in line with (Sims, 1980), who argues that VAR models estimated in levels remain appropriate for analysing dynamic relationships without imposing restrictive prior assumptions, and (Lütkepohl, 2005), who shows that VARs in levels can yield consistent impulse response estimates and reliable dynamic analysis provided the system is stable. In this regard, Sims *et al*. (1990) provide foundational support, asserting that the presence of unit roots among variables does not invalidate the estimation of a VAR in levels, thus lending additional theoretical grounding to the analytical framework employed in this study.

4.1.3. The results of the VAR Model for Aggregate Fiscal Policy

The baseline results reveal a strong degree of persistence in forest cover dynamics. The first lag of forest cover dynamics is positive and statistically significant at the 1% level, indicating strong short-run dependence in forest cover dynamics over time, on average ceteris paribus. This finding is consistent with the notion that forest cover conditions evolve gradually, with current states closely reflecting recent past conditions.

The results further indicate that a percentage increase in development expenditure is associated with an improvement in forest cover conditions and dynamics at the second lag, on average ceteris paribus, although the relationship is only marginally statistically significant.

In contrast, total tax revenue is statistically insignificant across the considered lags, indicating that its estimated coefficients do not show a statistically meaningful short-run association with forest cover conditions within the specified model framework. Similarly, trade and export performance remain statistically insignificant across all lags, suggesting that the estimated effects of short-run external trade dynamics on forest cover conditions and dynamics are not statistically distinguishable from zero.

Table 4: VAR Estimation Results.

Variable	Coefficient	Standard Error	t-Statistic
Forest Cover Dynamics (EVI_FOREST)			
EVI_FOREST(-1)	0.494137	0.06469	7.63866***
EVI_FOREST(-2)	-0.037753	0.07207	-0.52382
EVI_FOREST(-3)	0.035212	0.07303	0.48218
EVI_FOREST(-4)	-0.032143	0.07276	-0.44175
EVI_FOREST(-5)	-0.048574	0.07302	-0.66520
EVI_FOREST(-6)	-0.080051	0.06450	-1.24114
Development Expenditure (LNDVP)			
LNDVP(-1)	0.001502	0.00218	0.68989
LNDVP(-2)	0.003570	0.00221	1.69660*
LNDVP(-3)	0.000374	0.00222	0.16853
LNDVP(-4)	-0.001032	0.00185	-0.55653
LNDVP(-5)	-0.001640	0.00183	-0.89773
LNDVP(-6)	-0.001169	0.00183	-0.63983
Tax Revenue (LNTAX)			
LNTAX(-1)	0.002553	0.02127	0.12001
LNTAX(-2)	-0.005913	0.02144	-0.27581
LNTAX(-3)	0.016950	0.02169	0.78129
LNTAX(-4)	-0.020216	0.02121	-0.95303
LNTAX(-5)	0.002139	0.02076	0.10305
LNTAX(-6)	0.006102	0.02035	0.29982
Trade and Export Performance (LNEXP)			
LNEXP(-1)	-0.001441	0.00940	-0.15328
LNEXP(-2)	0.009261	0.01102	0.84067
LNEXP(-3)	-0.010854	0.01112	-0.97649
LNEXP(-4)	-0.008838	0.01112	-0.79497
LNEXP(-5)	-0.002481	0.01097	-0.22616
LNEXP(-6)	0.013430	0.00960	1.39947
Constant			
C	0.219178	0.08862	2.47321**

Note: ***, ** and * stand for statistical significance at 1%, 5% and 10% respectively.

4.1.4. Variance Decomposition and Impulse Responses for Aggregate Fiscal Policy Model

The Variance Decomposition and IRFs jointly describe the dynamic interactions among fiscal policy, economic activity, and forest cover conditions within the VAR framework. Both analyses are based on the Cholesky decomposition of the residual covariance matrix to ensure orthogonal structural shocks. The recursive identification follows an economically motivated ordering commonly used in VAR literature, where government development expenditure is assumed not to respond contemporaneously to other shocks, while trade and export performance and total tax revenue respond sequentially, and forest cover conditions and dynamics responds contemporaneously to all fiscal and economic shocks. This approach,

consistent with the empirical literature Attílio *et al*. (2024) facilitates meaningful interpretation of structural shocks and their transmission mechanisms.

As reported in **Table 5**, forest cover dynamics are predominantly explained by their own innovations in the short run, accounting for 89.94% of total variation in period 1. The contributions of development government expenditure, total tax revenue and trade and export performance are comparatively small at this stage.

As the forecast horizon increases, the findings suggest that, the influence of fiscal variables becomes more substantial. Development government expenditure emerges as the dominant external driver, rising to 12.05% in period 4 and stabilising at a consistently high level of approximately 12.95% by period 24. Total tax revenue also shows a gradual increase, while trade and export performance remains negligible.

Notably, as indicated by results, development expenditure contributes approximately 12.95%, representing a substantial share among the explanatory variables and underscoring its importance in shaping forest cover conditions and dynamics in the long run. This finding aligns with Attílio *et al*. (2024) who reports that government spending accounts for 12.58% of deforestation in the Amazon after two years. A similar pattern Attílio *et al*. (2024) observed in the Atlantic Forest, where government spending explains 18.47% of deforestation variation over the same period.

Table 5: Variance Decomposition of Forest Cover Conditions and Dynamics.

Period	Development Government Expenditure	Trade and Export performance	Total Tax Revenue	Forest Cover Dynamics
1	07.75	0.14	02.17	89.94
4	12.05	0.38	02.31	85.26
8	12.70	01.05	02.26	83.99
12	12.94	01.19	02.27	83.60
24	12.95	01.25	02.29	83.51

The IRFs in **Figures 3**, illustrate that forest cover conditions and dynamics responds differently to fiscal and economic shocks over a 24 period horizon, while the purple lines represent the ±2 standard error bands (approximately a 95% confidence interval).

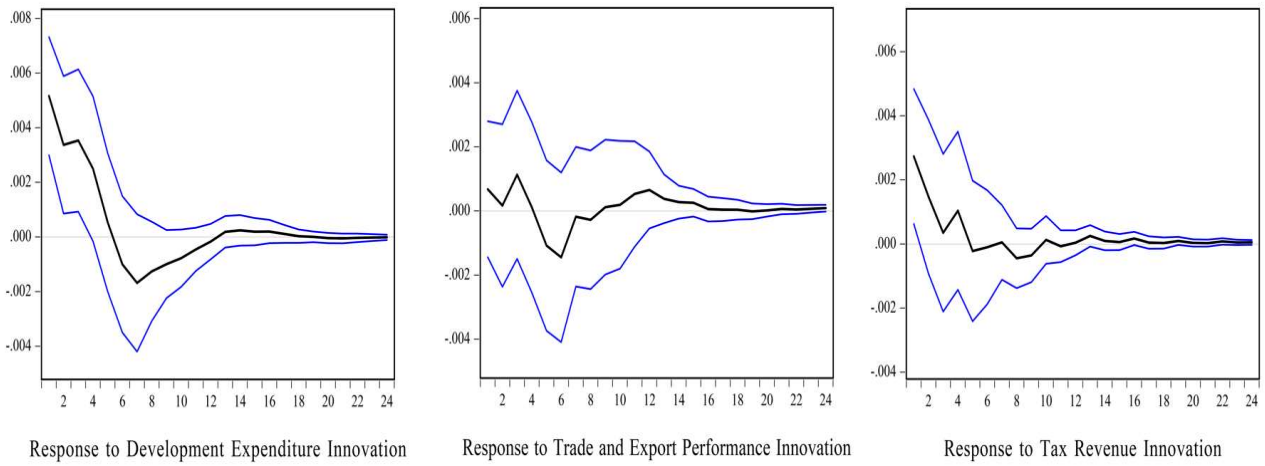
Tax revenue shocks generate a positive and statistically significant response only in the first period. Thereafter, the response declines rapidly and oscillates slightly around zero, remaining statistically insignificant in subsequent periods before converging to zero in the long run.

Development expenditure shocks produce a positive and statistically significant effect on forest cover condition from periods 1 to 3, while the fourth period remains weakly significant at the 10% level. Afterward, the response turns negative around periods 5 to 7, before gradually recovering, crossing back toward zero around the middle periods, and eventually converging to zero.

In contrast, trade and export performance shocks remain statistically insignificant throughout the entire horizon. The response fluctuates mildly between positive and negative values before gradually converging toward zero.

Overall, our results underscore the importance of fiscal policy in shaping environmental outcomes in Tanzania. The findings suggest that fiscal instruments, particularly revenue generation and development expenditure, can contribute to improved forest conservation outcomes. These results are consistent with the broader literature suggesting that fiscal policy can reduce environmental degradation through enhanced public investment (Attílio *et al*., 2024; Halkos & Paizanos, 2016; Katircioglu & Katircioglu, 2018). Moreover, a stronger and more efficient revenue system can support environmental management by improving the government's capacity to finance conservation and sustainable resource management initiatives (Binswanger, 1991; Fatima *et al*., 2023; Zhang *et al*., 2022). They also support the view that fiscal policy plays a meaningful role in promoting sustainable environmental and natural resource outcomes.

Figure 3: IRFs of Forest Cover Conditions & Dynamics to one S.D Shocks in Development Government Expenditure, Trade and Export Performance and Total Tax Revenue. The solid black line represents the estimated impulse response; the purple lines represent the ±2 standard error confidence bands.

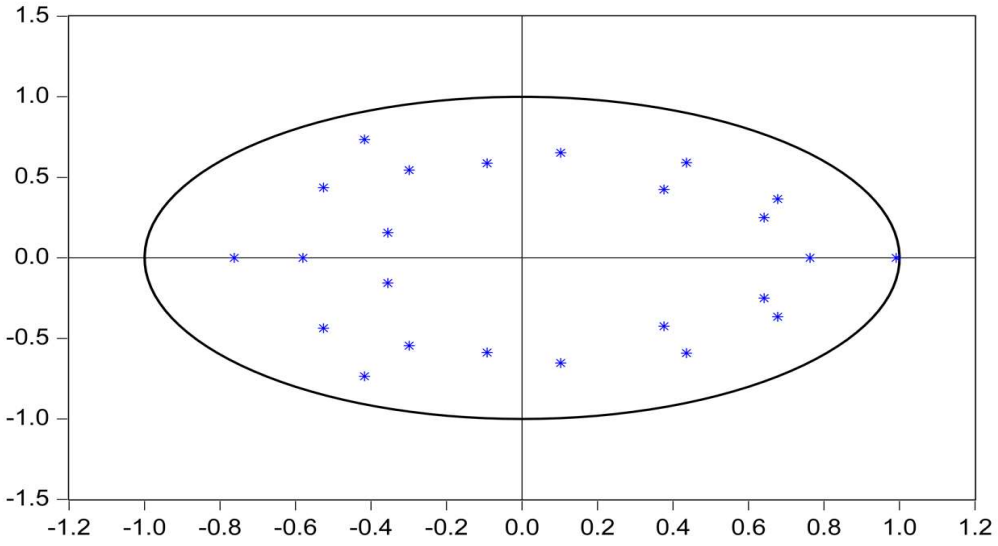


4.1.5. Model Stability Test

The stability of the estimated VAR model was assessed to ensure that the system is well-behaved. Following (Lütkepohl, 2005) and (Hamilton, 1994), a VAR is stable if all eigenvalues of the companion matrix lie strictly within the unit circle. Stability guarantees a valid infinite-order vector moving average representation, which is a necessary condition for the meaningful interpretation of IRFs and variance decompositions.

Figure 4 presents the inverse roots of the AR characteristic polynomial. All roots lie strictly inside the unit circle, confirming that the estimated VAR model satisfies the stability condition and that the estimated responses to shocks are both reliable and interpretable.

Figure 4: Inverse Roots of AR Characteristic Polynomial.



4.1.6. Diagnostic Tests

The Lagrange Multiplier (LM) test was conducted to check for serial autocorrelation in the VAR model residuals under two complementary approaches. Panel A tests for autocorrelation at each individual lag h, providing a targeted assessment of residual behaviour at each specific horizon. Panel B tests sequentially from lag 1 to h, offering a comprehensive evaluation of residual autocorrelation across all lags up to the chosen horizon. Together, these two approaches provide a robust assessment of the model's residual properties, as recommended by (Lütkepohl, 2005).

As reported in **Table 6**, the p-values across all lags under both Panels A and B exceed the 5% significance level, confirming that the residuals of the VAR model are free from serial

correlation at all tested lags. This result supports the adequacy of the lag structure and validates the use of the estimated model for inference.

Table 6: LM Test Results for Serial Correlation in VAR Residuals.

Panel A: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
6	14.94489	16	0.5287	0.934604	(16, 764.4)	0.5287

Panel B: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	18.09480	16	0.3184	1.133909	(16, 764.4)	0.3184
2	24.67815	32	0.8189	0.768894	(32, 908.8)	0.8189
3	48.17539	48	0.4657	1.004606	(48, 934.2)	0.4661
4	58.76234	64	0.6616	0.916281	(64, 934.0)	0.6623
5	83.32299	80	0.3776	1.043863	(80, 925.5)	0.3790
6	104.7181	96	0.2550	1.096101	(96, 913.7)	0.2570

Note: A p-value greater than 0.05 indicates no significant autocorrelation.

The White heteroskedasticity test was conducted within the VAR framework to assess whether the residuals are homoskedastic. The joint test, reported in Table 7, yields a p-value of 0.3255, which exceeds the 5% significance level. This result confirms that the null hypothesis of homoskedasticity cannot be rejected, indicating that the VAR residuals do not exhibit significant heteroskedasticity. Normality of the residuals was further assumed on the basis of the Central Limit Theorem, providing justification for standard statistical inference given the large sample size.

Table 7: White Heteroskedasticity Test Results.

Joint test;		
Chi-sq	**df**	**P-value.**
493.4754	480	0.3255

Note: A p-value greater than 0.05 indicates no evidence of heteroskedasticity.

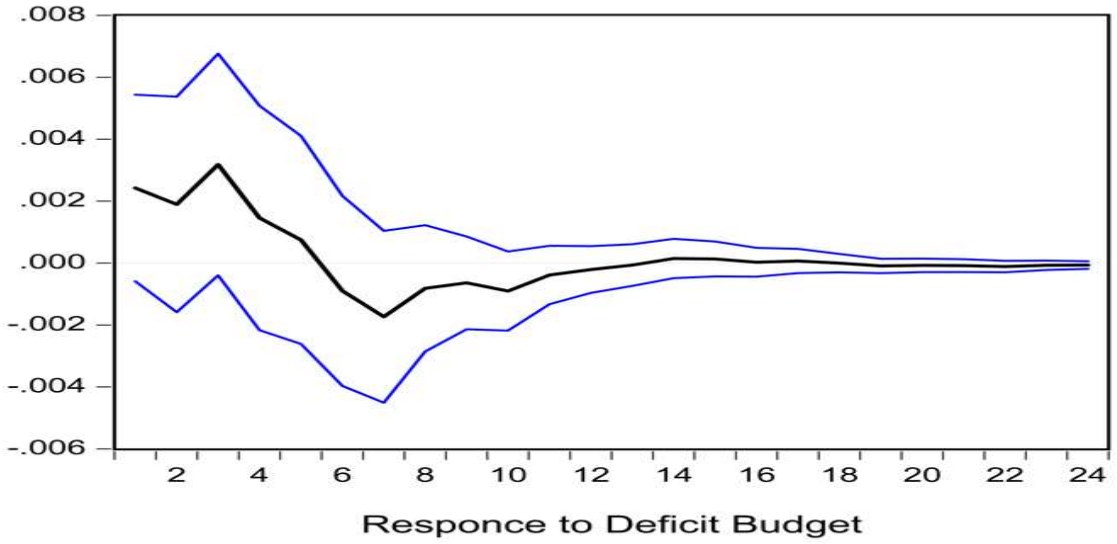
4.2. Composite Fiscal Policy Shocks: Deficit and Balanced Budget Scenarios

In the final part of this section, the combined effects of government expenditure and taxation on forest cover conditions and dynamics are examined through two fiscal policy scenarios. The first scenario reflects a deficit driven fiscal impulse, where government expenditure increases while tax revenue decreases, representing an expansionary fiscal stance

financed through a larger deficit. The second scenario represents a balanced budget approach, where higher government expenditure is matched by an equivalent increase in tax revenue, thereby ensuring fiscal neutrality.

The IRFs for the deficit-financed scenario, presented in **Figure 5**, indicate that forest cover conditions and dynamics initially respond positively to the shock in the short run. The response subsequently turns negative in the medium term before gradually stabilising and converging toward zero in the long run. Overall, this pattern suggests that deficit financing does not generate a sustained or significant effect on forest cover dynamics within the model horizon.

Figure 5: IRFs of Forest Cover Conditions & Dynamics to one S.D Shocks in Deficit-Financed scenario. The solid black line represents the estimated impulse response; the purple lines represent the ±2 standard error confidence bands.

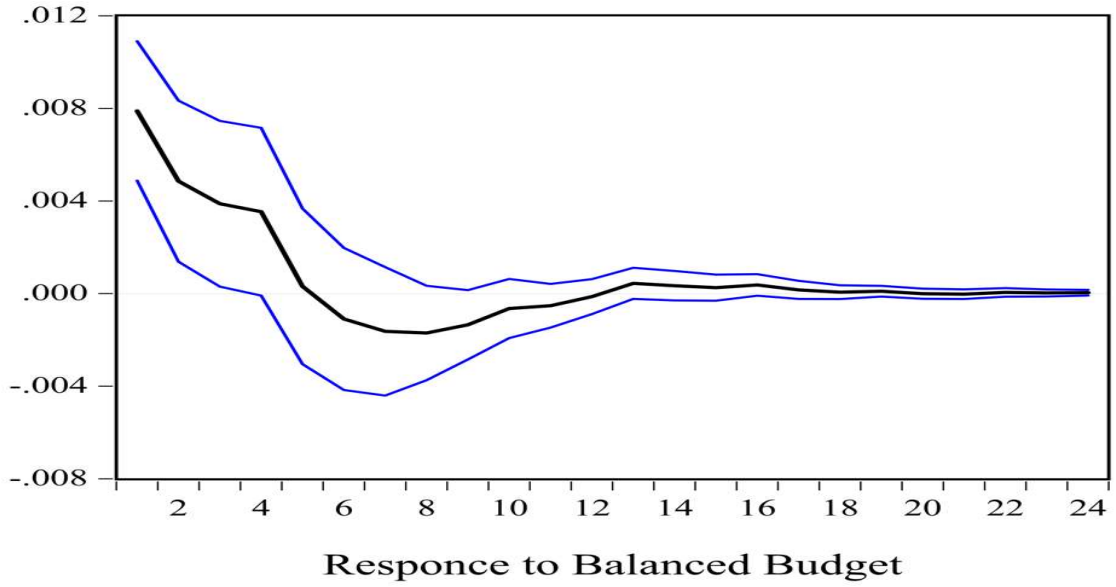


In contrast, the estimates for the impact of a balanced budget scenario are presented in **Figure 6**. The results indicate that forest cover conditions improve immediately following the shock and remain above the baseline in the short run, before turning negative in the medium term and gradually stabilising as the response converges toward zero in the long run. The response is statistically significant during the first four periods, indicating a meaningful improvement in forest outcomes. These findings suggest that, when higher public spending is offset by an equivalent increase in tax revenue, a balanced fiscal stance can enhance forest cover conditions and dynamics without deteriorating the fiscal position.

These findings are fully consistent with the existing empirical literature. Attílio *et al.* (2024) report that balanced-budget fiscal impulses can be effective in reducing deforestation, while Katircioglu & Katircioglu (2018) find that balanced fiscal adjustments improve environmental quality. Halkos & Paizanos (2016) similarly suggest that well-designed fiscal

policy can mitigate environmental degradation without harming fiscal stability. Taken together, the evidence from Tanzania corroborates these conclusions, confirming that a balanced fiscal expansion can generate a positive and statistically significant effect on forest cover conditions and dynamics in the short run.

Figure 6: IRFs of Forest Cover Conditions & Dynamics to one S.D Shocks in Balanced Financed scenario. The solid black line represents the estimated impulse response; the purple lines represent the ±2 standard error confidence bands.



4.3. Robustness Check: IRFs of the VAR(3) Model.

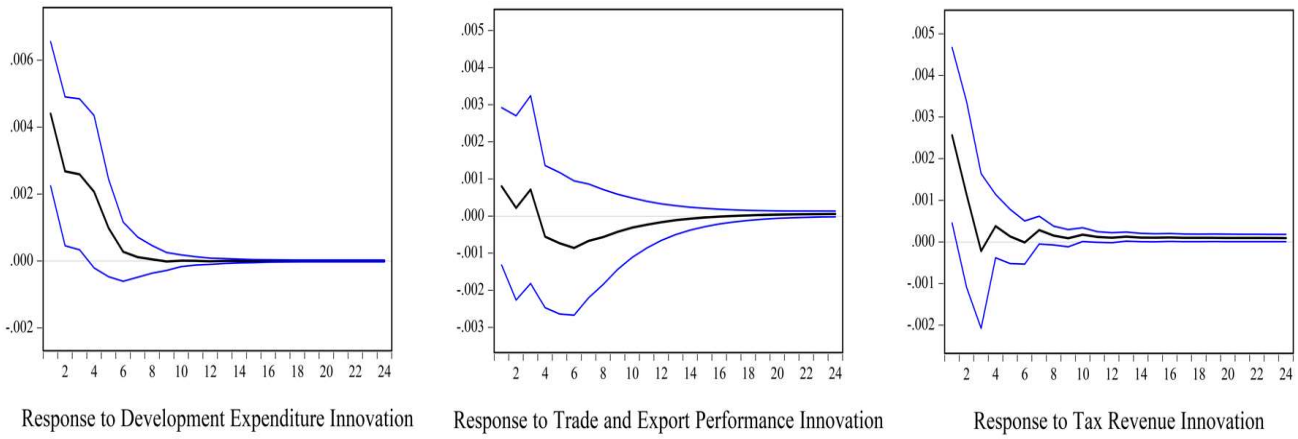
Tax revenue shocks generate a positive response in forest cover in the first period. Thereafter, the response declines rapidly and oscillates slightly around zero before converging to zero in the long-run.

Development government expenditure shocks produce a positive effect on forest cover dynamics from periods 1 to 4. Beyond this point, the response turns negative over periods 5 to 7, before gradually recovering and converging toward zero in the long run.

These patterns are robust to the choice of lag length. The VAR(3) robustness check produces qualitatively similar impulse responses. Development expenditure shocks generate a positive response that declines monotonically from period 1 before converging toward zero in the long run. Trade and export performance shocks produce a mildly positive initial response that turns negative in the medium term before recovering and converging to zero. Tax revenue shocks display a positive initial response that quickly turns negative around periods 3 to 4, before stabilising and converging toward zero. The consistency of the direction and shape of

these responses with the baseline VAR(6) results strengthens confidence in the robustness of the estimated dynamic relationships.

Figure 7: IRFs of Forest Cover Conditions & Dynamics to one S.D Shocks in Development Government Expenditure, Trade and Export Performance and Total Tax Revenue, based on a VAR model estimated with 3 lags. The solid black line represents the estimated impulse response; the purple lines represent the ±2 standard error confidence bands.



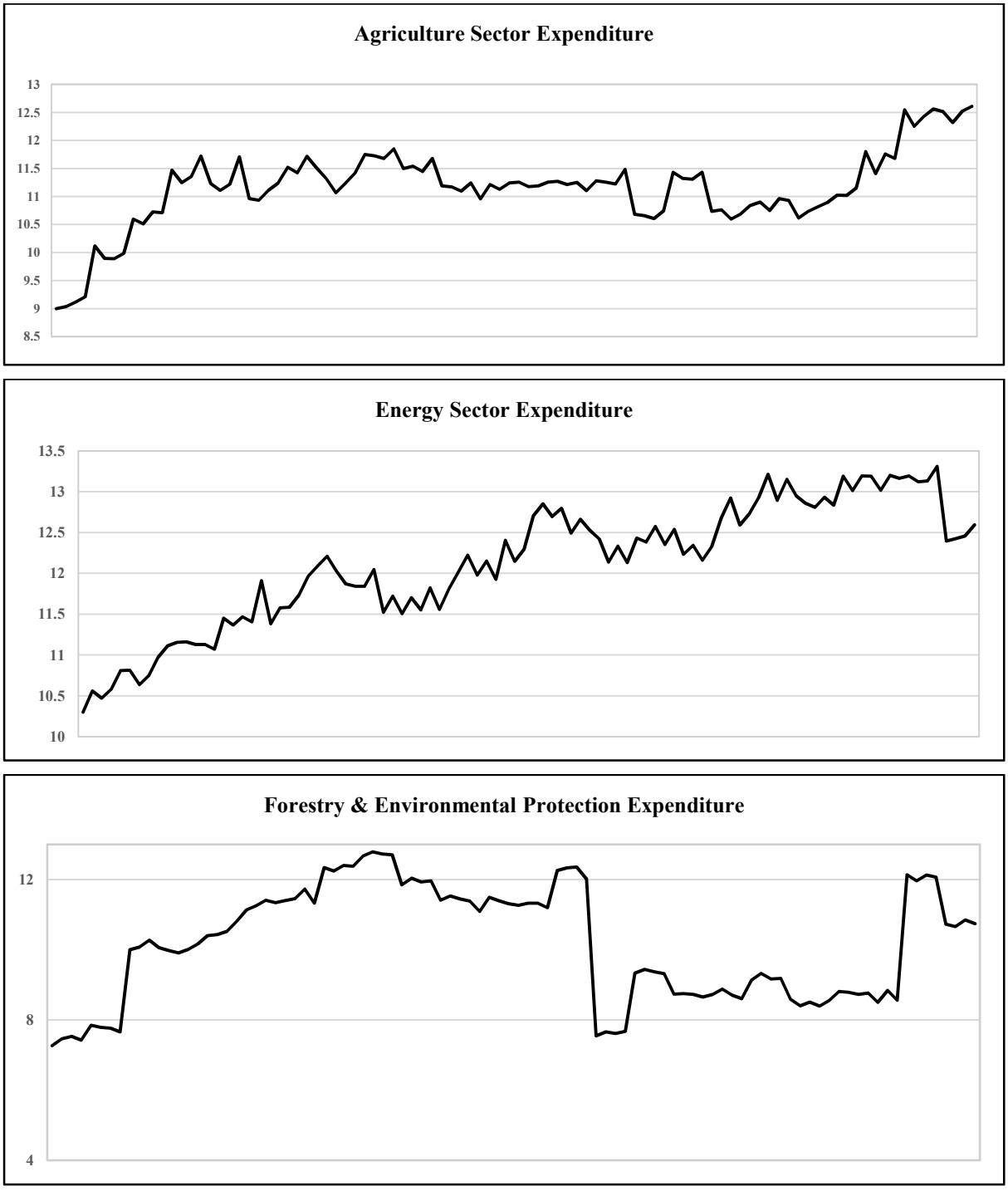
4.4. Estimation using Sectoral Government Expenditure

To examine the heterogeneous effects of government expenditure on environmental outcomes, the baseline VAR model was extended by disaggregating development expenditure into three sectoral components, agriculture sector expenditure, forestry and environmental protection expenditure, and energy sector expenditure. This disaggregation enables a more granular assessment of how targeted fiscal allocations transmit to sectoral outcomes, moving beyond the aggregate impulse examined in the baseline model. Similarly, this analysis employs the EVI as a proxy for forest cover dynamics. Due to data availability constraints, the analysis utilises quarterly data spanning January 2001 to December 2024.

4.4.1. Trend Analysis

Visual inspection of the series, as shown in **Figure 8**, reveals that agricultural and forestry expenditures fluctuate moderately around a constant mean, indicating relative stability without strong upward or downward trends. In contrast, energy expenditure displays a noticeable upward trajectory, suggesting persistent growth over the sample period.

Figure 8: Time Series Trends of Variables at Levels.



4.4.2. Model Specification and Pre-Estimation Tests

To assess the stationarity properties of the variables, the ADF and PP unit root tests were employed. As indicated in Table 8, and consistent with the baseline model discussed in Section 4.1.2, the results reveal mixed integration properties, with variables exhibiting heterogeneous time-series characteristics across levels and first differences.

Table 8: Stationarity Test Results for the Variables.

Variables	Deterministic	ADF		Phillips-Perron	
		Level	Difference	Level	Difference
Forest Cover Dynamics (EVI)	Intercept	-6.097(1)***		-6.659(1)***	
	Trend and intercept	-6.989(1)***		-7.060(3)***	
Agriculture Sector Expenditure	Intercept	-2.672 (1)*	-12.75(0)***	-2.686(4)*	-12.75(2)***
	Trend and intercept	-2.699(1)	-12.72(0)***	-2.796(3)	-12.72(2)***
Energy Sector Expenditure	Intercept	-2.220(1)	-14.86(0)***	-2.452(17)	-15.06(5)***
	Trend and intercept	-2.209(1)	-15.03(0)***	-3.671(2)**	-15.99(7)***
Forestry & Environmental Protection Expenditure	Intercept	-2.573(0)	-9.861(0)***	-2.587(1)*	-9.861(1)***
	Trend and intercept	-2.636(0)	-9.840(0)***	-2.646(1)	-9.839(2)***
Trade and Export performance	Intercept	-1.263(1)	-13.16(0)***	-1.211(26)	-13.44(8)***
	Trend and intercept	-2.347(1)	-13.11(0)***	-2.612(9)	-13.48(9)***

Note: ***, **, and * stand for statistical significance at 1%, 5% and 10% respectively; Numbers in parentheses show lag lengths, selected using the Schwarz Bayesian Criterion for the ADF tests and the Newey-West method for the PP tests.

The lag length of two was selected based on the unanimous recommendation of all information criteria, a choice further validated through residual diagnostic checks. Consistent with the estimation strategy detailed in Section 4.1.2, the model is estimated in levels in accordance with (Sims, 1980), (Sims *et al*., 1990), and Lütkepohl (2005). Dynamic analysis is conducted through impulse response functions and forecast error variance decomposition to assess the transmission of sectoral expenditure shocks to forest cover dynamics over time.

4.4.3. Results of the VAR Model for Sectoral Government Expenditure

The results reveal strong own persistence in forest cover dynamics, driven predominantly by the second lag, which is negative and highly significant, indicating that on average and ceteris paribus, a unit increase in forest cover two periods prior causes a sharp mean-reverting correction in the current period, reflecting strong short-run dependence over time. The first lag is positive but insignificant, suggesting no immediate self-reinforcing effect, ceteris paribus.

Regarding sectoral expenditure, energy expenditure is the only fiscal variable that exhibits a statistically significant relationship with forest cover dynamics in the short run. Its first lag is negative and significant at the 5% level, indicating that on average and ceteris

paribus, a percentage increase in energy expenditure in the preceding quarter is associated with a decline in forest cover dynamics. The second lag is positive and marginally significant, implying a weak short-run reversal effect, ceteris paribus.

Agricultural expenditure, forestry and environmental protection expenditure, and trade and export performance all yield statistically insignificant coefficients across both lags, indicating no noticeable short-run relationship with forest cover dynamics, ceteris paribus. The broader transmission of sectoral fiscal allocations to environmental outcomes is therefore better examined through the impulse response functions and forecast error variance decomposition presented in the subsequent sections.

Table 9: VAR Estimation Results.

Variable	Coefficient	Standard Error	t-Statistic
Forest Cover (EVI_FOREST)			
EVI_FOREST(-1)	0.040121	0.03815	1.05168
EVI_FOREST(-2)	-0.938708	0.03894	-24.1082***
Agriculture Sector Expenditure (LNAGRI)			
LNAGRI(-1)	-0.000570	0.01002	-0.05692
LNAGRI(-2)	0.000811	0.01052	0.07703
Energy Sector Expenditure (LNENER)			
LNENER(-1)	-0.031350	0.01292	-2.42568***
LNENER(-2)	0.020755	0.01249	1.66120*
Forestry & Environmental Protection Expenditure (LNFOR)			
LNFOR(-1)	-0.001706	0.00390	-0.43695
LNFOR(-2)	0.000490	0.00386	0.12693
Trade and Export Performance (LNEXP)			
LNEXP(-1)	0.000767	0.03364	0.02280
LNEXP(-2)	0.036688	0.03454	1.06231
Constant			
C	0.283204	0.13513	2.09586**

Note: ***, ** and * stand for statistical significance at 1%, 5% and 10% respectively.

4.4.4. Variance Decomposition and Impulse Responses for Sectoral Government Expenditure

The variance decomposition and IRFs jointly describe the dynamic interactions among sectoral fiscal allocations, economic activity, and forest cover dynamics within the VAR framework. Both analyses are based on the Cholesky decomposition of the residual covariance matrix, with the recursive identification following an economically motivated ordering where sectoral expenditure variables are assumed not to respond contemporaneously to other shocks,

while trade and export performance responds sequentially, and forest cover conditions respond contemporaneously to all fiscal and economic shocks, consistent with Attílio *et al*. (2024)

As reported in **Table 10**, forest cover dynamics are predominantly explained by their own innovations in the short run, accounting for 92.82% of total variation in period 1, with contributions from energy, agricultural, and forestry expenditures and trade and export performance remaining comparatively negligible at this stage.

As the forecast horizon extends, the influence of sectoral fiscal variables becomes increasingly apparent. Energy expenditure emerges as the dominant external driver, contributing approximately 11.14% from period 2 and stabilising at around 10.57% by period 12. Agricultural expenditure exhibits a gradual increase, reaching 0.90% by period 12, while forestry expenditure and trade and export performance remain modest contributors throughout the horizon.

Own innovations of forest cover nonetheless remain the dominant source of variation across all horizons, explaining approximately 85.64% of forecast error variance by period 12, underscoring strong endogenous persistence in forest cover dynamics. The growing contribution of energy expenditure highlights its role as the principal fiscal driver of forest cover dynamics in the long-run.

Table 10: Variance Decomposition of Forest Cover Conditions and Dynamics.

Period	Energy Sector Expenditure	Agriculture Sector Expenditure	Forestry & Environmental Protection Expenditure	Trade and Export performance	Forest Cover Dynamics
1	5.083825	0.040414	0.000026	2.051263	92.82447
2	11.14357	0.056465	0.008735	2.177460	86.61377
3	10.59638	0.424349	0.173241	1.898683	86.93975
4	10.73325	0.439109	0.219164	2.141974	86.46650
5	10.43652	0.434518	0.213160	2.317031	86.59877
6	10.65833	0.514653	0.214217	2.358194	86.25461
7	10.62786	0.610052	0.229441	2.379225	86.15342
8	10.61503	0.659912	0.234983	2.458572	86.03151
12	10.56700	0.896834	0.246186	2.645646	85.64433

The IRFs trace the dynamic response of forest cover to shocks in energy, agriculture, forestry, environmental sector expenditures, and trade and export performance over a 12 period horizon, as shown in **Figure 9**. The solid line represents the estimated response, while the dashed lines denote the 95% confidence intervals.

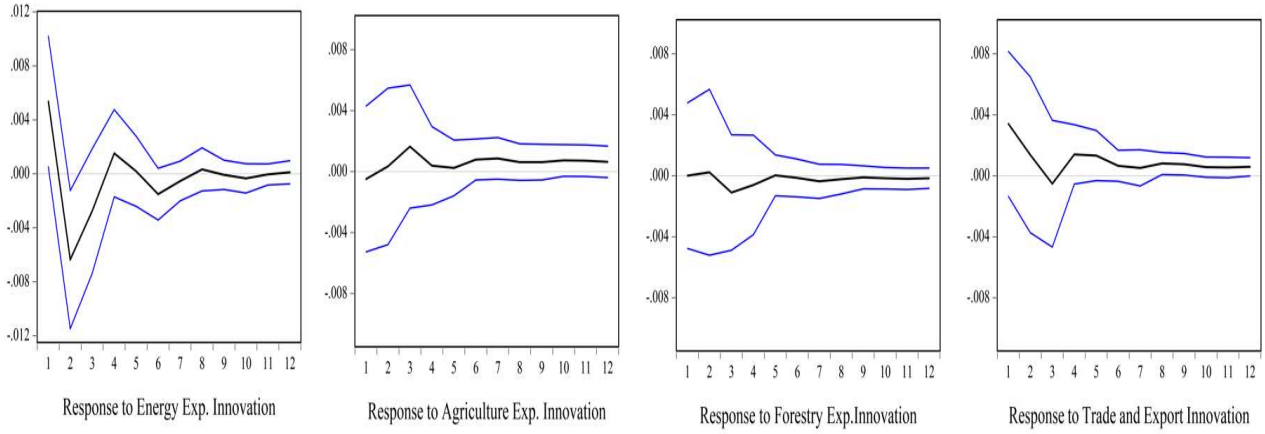
A shock to energy sector expenditure produces a positive and relatively pronounced response in forest cover dynamics at period 1, which reverses sharply into a significant trough at period 2, before rebounding to a secondary positive peak around period 4 and thereafter gradually converging toward zero. This oscillating short-run dynamic suggests that while the initial fiscal impulse momentarily favours forest cover, the subsequent negative response at period 2 indicates that energy expenditure does not immediately translate into reduced pressure on forest resources, with any positive effects only emerging gradually in the medium term.

Shocks to agricultural expenditure produce responses that remain statistically indistinguishable from zero throughout the entire horizon, with confidence bands consistently straddling zero. This absence of a meaningful signal indicates that fiscal allocations to the agricultural sector exert no discernible impact on forest cover dynamics in either the short or medium term.

Forestry expenditure shocks similarly yield a negligible and near-zero response across the full horizon. The persistently wide confidence bands suggest that public spending in this sector fails to translate into measurable forest cover outcomes within the observed period, most plausibly attributable to institutional and implementation lags between budget disbursement and effective conservation delivery on the ground.

A shock to trade and export performance generates a moderate positive response at period 1, which subsequently declines toward a trough around period 3 before gradually recovering and stabilising near zero in the medium term. Although this pattern hints at an initial trade induced boost to forest cover dynamics, the response remains statistically insignificant throughout, precluding any firm conclusions regarding the directional influence of export performance on forest cover over this horizon.

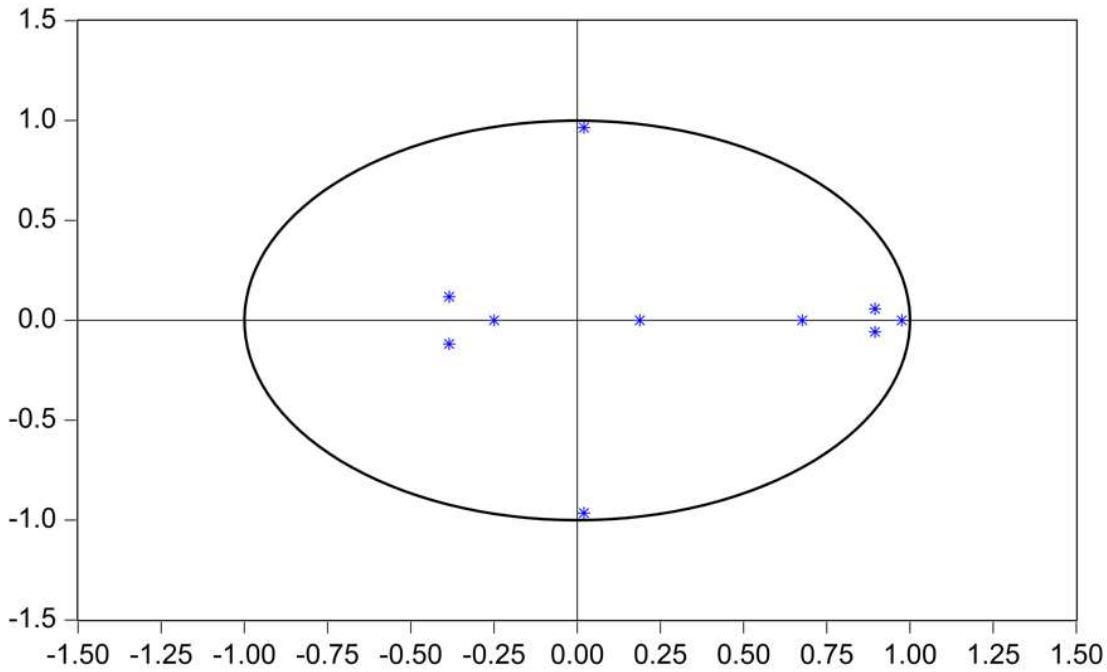
Figure 9: IRFs of Forest Cover Conditions & Dynamics to one S.D Shocks in Energy Sector Expenditure, Agriculture Sector Expenditure, Forestry & Environmental Protection Expenditure and Trade and Export performance. The solid black line represents the estimated impulse response; the purple lines represent the ±2 standard error confidence bands.



4.4.5. Model Stability Test

The inverse roots of the AR characteristic polynomial for the sectoral model are presented in **Figure 10**. All roots lie strictly inside the unit circle, confirming that the estimated VAR satisfies the stability condition and that the IRFs and FEVD are reliable and interpretable.

Figure 10: Inverse Roots of AR Characteristic Polynomial.



4.4.6. Diagnostic Tests

The Lagrange Multiplier (LM) test was conducted to assess residual serial correlation under two complementary approaches. Panel A tests at each individual lag h, while Panel B tests sequentially from lag 1 to h (Lütkepohl, 2005). As reported in **Table 11**, all p-values across both panels exceed the 5% significance level, confirming the absence of serial correlation in the VAR residuals and validating the adequacy of the selected lag structure for inference.

Table 11: LM Test Results for Serial Correlation in VAR Residuals.

Panel A: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
2	27.12047	25	0.3499	1.092118	(25, 276.4)	0.3507

Panel B: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	31.04292	25	0.1876	1.258761	(25, 276.4)	0.1883
2	62.78694	50	0.1058	1.281664	(50, 318.1)	0.1078

Note: A p-value greater than 0.05 indicates no significant autocorrelation.

The White heteroskedasticity test results, as reported in **Table 12**, indicate that the null hypothesis of homoskedasticity cannot be rejected at the 5% significance level, confirming that the VAR residuals do not exhibit significant heteroskedasticity. Similarly to Section 4.1, normality of residuals is assumed on the basis of the Central Limit Theorem, providing justification for standard statistical inference

Table 12: Results of Homoskedasticity Test.

Joint test;		
Chi-sq	**df**	**P-value.**
990.6797	975	0.3563

Note: A p-value greater than 0.05 indicates no evidence of heteroskedasticity.

4.5. Discussion of the Results

As Tanzania strives to balance economic growth with environmental sustainability, understanding the ecological implications of fiscal policy remains crucial. The findings reveal that fiscal policy instruments exert heterogeneous effects on forest cover dynamics, with outcomes varying across expenditure types, financing structures, and time horizons. Overall development expenditure and tax revenue mobilization both contribute positively to forest conservation, suggesting that well directed public investment and stronger domestic resource mobilization enhance the government's capacity to finance environmental protection. However, the environmental effectiveness of fiscal policy is shown to depend critically on its financing structure, as meaningful differences emerge between deficit-financed and balanced-budget scenarios. At the sectoral level, energy expenditure exhibits a complex short-run dynamic, where an initial positive response quickly reverses into a significant negative effect in the second period before gradually recovering toward equilibrium, indicating that energy investments do not immediately alleviate pressure on forest resources. These findings collectively underscore that achieving sustained forest conservation outcomes requires not only increased fiscal allocations but also careful alignment of expenditure composition and financing mechanisms with environmental objectives, as discussed below.

The positive relationship between development expenditure and forest cover suggests that government spending plays an important role in shaping environmental outcomes in Tanzania. This finding supports the view that fiscal policy can contribute to environmental sustainability when public resources are allocated in ways that strengthen environmental governance, support conservation efforts, and promote sustainable development. The result is consistent with previous studies highlighting the potential of public expenditure to improve environmental quality through investments in environmental management, institutional capacity, and sustainable resource use (Attílio *et al*., 2024; Halkos & Paizanos, 2016; Katircioglu & Katircioglu, 2018).

From a theoretical perspective, development expenditure can influence forest conservation through several channels. Government spending may enhance the capacity of environmental institutions, improve forest monitoring and enforcement mechanisms, support afforestation and reforestation programs, and create alternative livelihood opportunities that reduce dependence on forest resources. Such investments can contribute to improved forest management and help mitigate pressures associated with population growth and economic expansion. However, the environmental effectiveness of such spending is not automatic, it depends critically on expenditure composition, implementation quality, and the degree to which environmental

considerations are embedded within broader development priorities, consistent with earlier work emphasizing that fiscal instruments can either mitigate or worsen environmental degradation depending on how they are structured (Lans Bovenberg & Goulder, 2002; Xepapadeas, 2005).

In the Tanzanian context, development expenditure has expanded significantly over the last two decades under national development frameworks such as the Tanzania Development Vision 2025, rising from approximately TZS 323 billion in 2002/03 to over TZS 14.6 trillion in 2023/24. Investments in infrastructure, education, agriculture, environmental management, and institutional development have collectively contributed to the country's socio-economic transformation. While certain expenditure categories, particularly infrastructure and energy investments, may generate environmental trade-offs through land conversion and resource extraction pressures, the overall positive association observed in this study suggests that, on balance, government spending has been supportive of forest conservation. This outcome likely reflects the increasing integration of environmental considerations into development planning and the growing allocation of resources toward environmental protection and sustainable land management initiatives, including forestry and environmental protection expenditure which peaked at over TZS 929 billion in 2023.

These findings reinforce the argument that public expenditure can serve as an important policy instrument for achieving both economic development and environmental sustainability. Nevertheless, maximizing these benefits requires continued attention to expenditure quality, effective implementation, and stronger policy coordination to ensure that development investments remain aligned with long-term forest conservation objectives. As López et al. (2011) notes, the environmental benefits of fiscal policy are not automatic but depend fundamentally on how expenditure is allocated across competing development priorities, underscoring the need for deliberate mainstreaming of environmental considerations into Tanzania's broader fiscal planning framework.

The findings on the revenue side indicate a positive effect of tax revenue on forest cover, although its overall contribution remains relatively modest, accounting for approximately 2% of the forecast error variance decomposition. This suggests that while tax revenue mobilization is not the dominant driver of forest cover dynamics, it nonetheless plays a meaningful supporting role in shaping environmental outcomes through broader fiscal capacity. The positive association between tax revenue and forest cover indicates that strengthening domestic resource mobilization enhances environmental governance and supports sustainable land management, consistent with earlier research showing that well-

structured tax systems and environmentally oriented fiscal reforms can promote conservation and improve environmental quality (Fatima *et al*., 2023; Zhang *et al*., 2022)

The transmission mechanism through which tax revenue influences forest outcomes operates primarily through the fiscal capacity channel, whereby improved revenue collection expands the government's ability to finance environmental protection, forest monitoring, and conservation initiatives. Studies by Halkos & Paizanos (2016) and López *et al*. (2011) emphasize that the effectiveness of fiscal instruments depends not only on expenditure levels but also on the strength of revenue mobilization, fiscal discipline, and institutional capacity. These insights reinforce the view that stronger tax systems are essential for achieving both fiscal sustainability and environmental protection, as reliable domestic revenues provide governments with the resources and flexibility needed to invest in long-term conservation and sustainable land-use initiatives.

In contrast, distortionary fiscal incentives that subsidize land clearing and resource extraction have historically accelerated deforestation, as documented in Brazil (Binswanger, 1991), underscoring that the environmental outcomes of fiscal policy depend fundamentally on its structure. Revenue enhancing and environmentally aligned systems foster sustainability, while poorly designed incentives undermine it. In the Tanzanian context, improved revenue mobilization therefore emerges as a central pathway for fostering forest and environmental conservation, particularly given its crucial role in supporting effective environmental governance without heavy dependence on external aid. Increased domestic revenue can also facilitate the implementation of the National Forest Policy Strategy by providing the necessary funding for key conservation targets, including afforestation and broader tree-planting initiatives, thereby contributing to Tanzania's long-term sustainable forest management objectives.

The findings indicate that the environmental effects of fiscal policy in Tanzania are more clearly observed under a balanced-budget framework, in which increases in public expenditure are matched by equivalent revenue generation. Under this fiscal arrangement, improvements in forest cover suggest that balanced fiscal operations can generate environmentally favourable outcomes, at least in the short to medium term. This implies that when fiscal expansion is accompanied by corresponding revenue adjustments, public spending is more likely to support sustainable resource management and contribute positively to forest conservation. The result highlights the importance of fiscal discipline in ensuring that government expenditure translates into tangible environmental benefits rather than creating imbalances that may weaken policy effectiveness.

Overall, the Tanzanian evidence reinforces the view that fiscal design, rather than expenditure magnitude alone, is critical in determining the durability of environmental outcomes. These results are consistent with existing empirical literature. (Attílio *et al*., 2024) show that balanced-budget fiscal impulses can be effective in reducing deforestation, while Katircioglu & Katircioglu (2018) find that balanced fiscal adjustments improve environmental quality. Similarly, Halkos & Paizanos (2016) argue that well-designed fiscal interventions can mitigate environmental degradation without compromising fiscal stability. Taken together, the evidence from Tanzania corroborates these conclusions, confirming that achieving sustained forest conservation outcomes requires not only increased fiscal allocations but also a deliberate commitment to fiscally responsible financing mechanisms that align public spending with long-term environmental objectives.

At the sectoral level, energy expenditure exhibits a complex dynamic, where an initial positive response quickly reverses into a significant negative effect in the second period before gradually recovering toward equilibrium, indicating that energy investments do not immediately alleviate pressure on forest resources. This pattern reflects the structural disconnect between public expenditure on energy and the actual transition away from biomass fuels at the household level, suggesting that under current conditions, increases in energy expenditure are unlikely to generate favourable environmental outcomes in the short to medium term.

This is reflected in Tanzania's electricity development trajectory, where despite increased energy sector expenditure and notable progress in access rising from 67.5% to 78.4% between 2016/17 and 2019/20, with rural access reaching 69.8% and 58.8% of villages connected (URT, 2020) electricity has not displaced biomass as the dominant cooking fuel. Household connectivity remains limited at 37.7% overall, with rural connectivity as low as 24.5%, and where electricity is available, it is predominantly used for lighting (76.6%) rather than cooking (URT, 2020)**.** Cooking energy patterns remain largely unchanged, with 63.5% of households relying on firewood and 26.2% on charcoal, compared to only 3.0% using electricity (URT, 2020)**.** This reveals that electricity development, while expanding in coverage, has not penetrated the cooking sector the primary driver of biomass demand and forest degradation and therefore cannot yet be expected to reverse the negative environmental impulse observed in the short run.

The persistence of biomass dependence reflects deep structural and economic barriers that energy expenditure alone cannot overcome, and which are likely to continue shaping environmental outcomes unless directly addressed. Charcoal retains a significant cost

advantage over cleaner alternatives, is widely available, and benefits from weak royalty enforcement and effective VAT exemption, sustaining its affordability and demand. LPG tax incentives have encouraged only partial fuel substitution, with most households adopting energy stacking rather than full transition (Doggart, Ruhinduka, *et al*., 2020), meaning that fiscal measures targeting cleaner fuels have yet to produce the scale of behavioural change necessary to reduce biomass pressure meaningfully. Efforts to promote Improved Cook Stoves (ICS) further illustrate how slowly behavioural and technological adjustments occur despite their potential to reduce charcoal consumption by more than 50%, adoption remains limited due to affordability constraints, low awareness, and weak institutional support (URT MNRT, 2021b)**,** suggesting that even cost-effective interventions will not deliver rapid environmental gains without stronger policy coordination. Consequently, unless energy sector investments are explicitly directed toward making clean cooking alternatives affordable and accessible particularly in rural areas where biomass dependence is deepest future increases in energy expenditure are likely to continue reproducing the same delayed and temporarily negative environmental response, leaving forest pressures from biomass consumption largely unaddressed in the short to medium term.

5. CONCLUSION AND POLICY IMPLICATIONS

5.1. Summary of the Key Findings

Tanzania continues to experience significant negative forest cover conditions and dynamics despite the existence of national and sub-national sustainable forest management policies and regulations, wood-product traceability systems, and ongoing policy interventions such as afforestation programs and REDD+ initiatives. While forests remain essential for rural livelihoods, ecosystem services, biodiversity conservation, and climate regulation, persistent pressures arising from energy demand, population growth, and land-use change continue to coincide with forest degradation and deforestation. Although previous studies have mainly focused on drivers such as agricultural expansion and charcoal production, this study contributes to the literature by examining the association between fiscal policy and forest outcomes, extending the environmental macroeconomics literature by using forest cover conditions and dynamics as indicators of environmental quality in a resource-dependent developing economy.

This study employs a VAR framework, complemented by impulse response analysis and forecast error variance decomposition, to examine the dynamic association between fiscal policy and forest outcomes in Tanzania between 2001 and 2024. As a reduced-form time-series approach, the VAR framework captures the statistical association and dynamic co-movement between fiscal variables and forest cover, rather than establishing causal relationships between them.

Four key findings emerge from this study. Development expenditure shows a positive significant short-run association with EVI-based forest cover conditions, though the strength and direction of this association evolve over the medium term, with the response moving through a temporary negative and insignificant phase before settling back toward zero. This pattern points to a short-run, evolving relationship between public expenditure and forest cover dynamics, rather than a single, uniform trajectory of improvement.

Tax revenue mobilization shows a positive but modest association with forest cover, accounting for approximately 2% of forecast error variance, suggesting that periods of stronger domestic resource mobilization tend to coincide with somewhat improved government capacity to finance conservation, though this association appears meaningful only where additional revenue is channelled toward environmental objectives.

Fiscal sustainability also plays a relevant role in relation to forest cover conditions, with fiscally balanced conditions being associated with more stable patterns in forest cover dynamics than

deficit-financed expansion, the response to a balanced-budget innovation builds significantly initially, dips mildly and becomes insignificant, and gradually converges toward zero, indicating that the financing structure of public expenditure, alongside the level of spending itself, is relevant for understanding forest cover conditions in Tanzania.

At the sectoral level, forestry and environmental protection expenditure shows no statistically significant association with forest cover conditions, despite its substantial growth in recent national budgets, while energy expenditure shows a complex short-run pattern an initial positive association that reverses into a significant negative association before gradually returning toward equilibrium consistent with a structural disconnect between electricity infrastructure investment and household level shifts away from biomass fuels. Despite improved electricity access, most households continue to rely on firewood and charcoal for cooking, a pattern consistent with the cost advantage of charcoal, weak royalty enforcement, limited LPG penetration, and low uptake of improved cook stoves.

5.2. Policy Implications

These findings carry important implications for Tanzania's public financial management and forest governance institutions, particularly in relation to meeting the targets set under the National Forest Policy Implementation Strategy.

Development expenditure and forest restoration targets. From a policy perspective, the findings indicate that development expenditure is associated with favourable forest cover conditions in Tanzania in the short run, particularly when allocated toward environmentally relevant sectors. However, this association is not sustained automatically and weakens over the medium term, suggesting that the composition of development spending, and not merely its overall level, is central to achieving lasting environmental benefits. Mainstreaming environmental considerations into development expenditure across sectors would therefore support Tanzania's progress toward the Strategy's targets of restoring 5.2 million hectares of forest land and reducing the annual deforestation rate of 469,000 hectares per year by 70% by June 2031.

Financing structure and fiscal sustainability. The comparatively more stable pattern observed under balanced-budget conditions, relative to deficit-financed expansion, has a bearing on how the Ministry of Finance structures development spending. As Tanzania continues to rely on a mix of domestic borrowing, external loans, and development partner support, debt-financed fiscal expansions, even when nominally development oriented, appear

to coincide with weaker and less stable environmental patterns than expenditure financed through sustainable domestic revenue, an important consideration given the reliability of funding needed to sustain progress toward the Strategy's targets. It is recognised that, as a developing country, Tanzania cannot meet its development financing needs through domestic revenue alone and will continue to rely on borrowing to some extent. However, gradually building up environmentally oriented expenditure financed through sustainable domestic revenue, even on a modest scale, would offer a more durable foundation for environmental protection than large debt-financed expansions alone.

Energy expenditure and demand side interventions. The reversal observed in energy expenditure's short-run association has a specific implication for the Rural Energy Agency and the Ministry of Energy, the continued investment in electrification, while valuable for other development goals, does not appear to be accompanied by a reduction in household reliance on charcoal and firewood, meaning energy budgets risk limited environmental relevance unless a meaningful share is redirected toward demand side interventions such as LPG subsidies and improved cook stove adoption. To align energy expenditure more closely with national targets, it is recommended that a defined share of the energy budget be explicitly earmarked for achieving 50% sustainable charcoal production and for developing and implementing the mechanism to increase consumption of alternative charcoal in urban areas from 100 to 200,000 tonnes, both by June 2031, rather than allocating energy expenditure predominantly toward electrification infrastructure alone.

Taken together, these results suggest that forest conservation outcomes in Tanzania are associated not merely with how much government spends, but with which institutions receive funding, how that funding is financed, whether it is absorbed and implemented effectively, and whether sectoral allocations are designed with an explicit environmental lens. Strengthening the observed environmental relevance of fiscal policy will therefore require closer integration of environmental objectives into national fiscal planning, including mainstreaming environmental considerations into budget formulation and expenditure reviews, and strengthening institutional capacity for environmental monitoring, implementation, and enforcement across sectors, particularly within forestry-specific budget lines where spending has grown without a corresponding statistical association with outcomes.

5.3. Directions for Future Research

Future research should combine subnational fiscal data with geographically disaggregated forest cover measures to exploit spatial variation across Tanzania's diverse landscapes, offering insight into how local governance capacity mediates the observed relationship between public investment and conservation outcomes. Extending the analysis using panel data across East, West, Central, and Southern African regions, given their relatively high exposure to negative forest cover dynamics, would further strengthen identification and enhance generalizability across different institutional and ecological contexts. While this study already disaggregates fiscal expenditure by sector (agriculture, energy, and forestry and environmental protection), future work could further disaggregate fiscal instruments by function within each sector, including a closer examination of why forestry-specific expenditure shows no measurable association with forest cover, to allow more precise identification of the specific channels through which fiscal policy relates to forest cover dynamics.

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APPENDIX A: Supplementary Tables and Google Earth Engine Script.

A1: VAR Lag Order Selection Criteria.

Table A13: VAR Lag Order Selection Criteria; Model 1 (Monthly VAR).

VAR Lag Order Selection Criteria
Endogenous variables: LNDVP LNTEP LNTAX EVI_SA
Exogenous variables: C
Date: 07/21/26 Time: 20:21
Sample: 2001M01 2024M12
Included observations: 280

Lag	LogL	LR	FPE	AIC	SC	HQ
0	148.5145	NA	4.19e-06	-1.032247	-0.980321	-1.011419
1	1046.067	1763.049	7.71e-09	-7.329047	-7.069420	-7.224910
2	1098.724	101.9298	5.94e-09	-7.590886	-7.123556*	-7.403439
3	1139.756	78.25295	4.96e-09*	-7.769683*	-7.094650	-7.498926*
4	1149.250	17.83642	5.20e-09	-7.723216	-6.840481	-7.369150
5	1160.080	20.03533	5.40e-09	-7.686287	-6.595850	-7.248911
6	1182.058	40.03196*	5.18e-09	-7.728989	-6.430850	-7.208304
7	1191.740	17.35735	5.42e-09	-7.683856	-6.178015	-7.079861
8	1197.699	10.51395	5.84e-09	-7.612137	-5.898593	-6.924832

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table A14: VAR Lag Order Selection Criteria; Model 2 (Quarterly VAR).

VAR Lag Order Selection Criteria
Endogenous variables: LNENER LNAGRI LNFORES LNTEP EVI_SA
Exogenous variables: C
Date: 07/21/26 Time: 21:13
Sample: 2001Q1 2024Q4
Included observations: 92

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-173.5741	NA	3.34e-05	3.882045	4.019099	3.937361
1	141.9316	589.8585	6.04e-08	-2.433296	-1.610974	-2.101400
2	261.4170	210.3981*	7.79e-09*	-4.487325*	-2.979734*	-3.878849*
3	280.8111	32.04248	8.90e-09	-4.365459	-2.172599	-3.480402
4	303.1325	34.45261	9.66e-09	-4.307228	-1.429100	-3.145591

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

A2: Impulse Response Function (IRF) Results.

Table A15: Response of Forest Cover Dynamics (EVI) to Cholesky One S.D. Innovations; Model 1 (Monthly, 24-period horizon).

Response of EVI_SA to Cholesky One S.D. (d.f. adjusted) Innovations

Period	LNDVP	LNTEP	LNTAX
1	0.005159	0.000680	0.002733
	(0.00108)	(0.00106)	(0.00105)
2	0.003377	0.000173	0.001481
	(0.00126)	(0.00127)	(0.00120)
3	0.003534	0.001132	0.000350
	(0.00130)	(0.00131)	(0.00123)
4	0.002499	0.000115	0.001041
	(0.00133)	(0.00133)	(0.00123)
5	0.000533	-0.001079	-0.000217
	(0.00127)	(0.00133)	(0.00110)
6	-0.000996	-0.001444	-9.84E-05
	(0.00125)	(0.00132)	(0.00089)
7	-0.001681	-0.000176	5.20E-05
	(0.00126)	(0.00109)	(0.00058)
8	-0.001257	-0.000273	-0.000444
	(0.00091)	(0.00108)	(0.00046)
9	-0.000992	0.000122	-0.000354
	(0.00062)	(0.00105)	(0.00042)
10	-0.000772	0.000194	0.000130
	(0.00052)	(0.00100)	(0.00037)
11	-0.000453	0.000532	-6.94E-05
	(0.00040)	(0.00082)	(0.00025)
12	-0.000168	0.000657	3.94E-05
	(0.00032)	(0.00060)	(0.00020)
13	0.000191	0.000381	0.000254
	(0.00029)	(0.00038)	(0.00017)
14	0.000246	0.000277	9.68E-05
	(0.00028)	(0.00026)	(0.00015)
15	0.000196	0.000257	6.20E-05
	(0.00025)	(0.00021)	(0.00013)
16	0.000202	6.11E-05	0.000174
	(0.00021)	(0.00019)	(0.00010)
17	0.000115	4.32E-05	4.67E-05
	(0.00017)	(0.00018)	(9.7E-05)
18	3.15E-05	4.13E-05	3.22E-05
	(0.00012)	(0.00015)	(8.8E-05)
19	6.14E-06	-9.20E-06	9.80E-05
	(9.8E-05)	(0.00012)	(6.2E-05)
20	-3.76E-05	2.01E-05	3.48E-05
	(9.3E-05)	(9.7E-05)	(5.7E-05)
21	-5.15E-05	6.36E-05	2.90E-05
	(8.9E-05)	(8.2E-05)	(5.4E-05)
22	-2.84E-05	4.79E-05	8.25E-05
	(7.8E-05)	(6.9E-05)	(5.0E-05)
23	-2.03E-05	7.06E-05	4.97E-05
	(6.3E-05)	(6.0E-05)	(4.1E-05)
24	-1.04E-05	8.89E-05	5.18E-05
	(4.8E-05)	(5.2E-05)	(3.8E-05)

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: LNDVP LNTEP LNTAX EVI_SA
Standard errors: Analytic

Table A16: Response of Forest Cover Dynamics (EVI) to Cholesky One S.D. Innovations; Model 2 (Quarterly, 12-period horizon).

Response of EVI_SA to Cholesky One S.D. (d.f. adjusted) Innovations

Period	LNENER	LNAGRI	LNFORES	LNTEP	EVI_SA
1	0.005363	-0.000478	1.20E-05	0.003407	0.022916
	(0.00242)	(0.00239)	(0.00239)	(0.00238)	(0.00167)
2	-0.006349	0.000348	0.000232	0.001376	-0.003428
	(0.00256)	(0.00256)	(0.00272)	(0.00255)	(0.00196)
3	-0.002739	0.001651	-0.001096	-0.000516	-0.009662
	(0.00231)	(0.00202)	(0.00189)	(0.00208)	(0.00431)
4	0.001530	0.000391	-0.000596	0.001409	0.002354
	(0.00162)	(0.00128)	(0.00163)	(0.00097)	(0.00194)
5	0.000191	0.000242	3.41E-05	0.001334	0.004402
	(0.00130)	(0.00091)	(0.00067)	(0.00082)	(0.00372)
6	-0.001497	0.000796	-0.000139	0.000660	-0.001394
	(0.00096)	(0.00067)	(0.00062)	(0.00051)	(0.00141)
7	-0.000528	0.000870	-0.000356	0.000524	-0.001835
	(0.00074)	(0.00068)	(0.00056)	(0.00059)	(0.00250)
8	0.000342	0.000629	-0.000217	0.000811	0.000900
	(0.00080)	(0.00060)	(0.00048)	(0.00036)	(0.00104)
9	-6.77E-05	0.000623	-9.99E-05	0.000762	0.000855
	(0.00054)	(0.00059)	(0.00038)	(0.00035)	(0.00147)
10	-0.000329	0.000736	-0.000158	0.000570	-0.000408
	(0.00054)	(0.00052)	(0.00035)	(0.00033)	(0.00070)
11	-3.78E-05	0.000717	-0.000195	0.000553	-0.000279
	(0.00039)	(0.00052)	(0.00035)	(0.00034)	(0.00083)
12	0.000122	0.000648	-0.000158	0.000592	0.000293
	(0.00043)	(0.00052)	(0.00033)	(0.00030)	(0.00045)

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: LNENER LNAGRI LNFORES LNTEP EVI_SA
Standard errors: Analytic

A3: Google Earth Engine Script for Monthly EVI Generation.

MONTHLY EVI SCRIPT

```
// ============================================================
// Tanzania Forest-Only Monthly MODIS EVI Time Series
// ============================================================

// ---- 1. Boundary ----
var tanzania = ee.FeatureCollection("FAO/GAUL/2015/level0")
  .filter(ee.Filter.eq('ADM0_NAME', 'United Republic of Tanzania'));

Map.centerObject(tanzania, 6);
Map.addLayer(tanzania, {}, 'Tanzania Boundary');

// ---- 2. Forest mask (Hansen Global Forest Change, v1.12, 2000-2024) ----
var gfc = ee.Image('UMD/hansen/global_forest_change_2024_v1_12');
var treeCover2000 = gfc.select('treecover2000');
var forestMask = treeCover2000.gte(30);   // adjust threshold if needed

Map.addLayer(forestMask.selfMask().clip(tanzania), {palette: ['green']}, 'Forest Mask (>=30%,
2000)');

// ---- 3. Study period ----
var startYear = 2001;
var endYear   = 2024;
var years  = ee.List.sequence(startYear, endYear);
var months = ee.List.sequence(1, 12);

// ---- 4. Load MODIS EVI, scale, mask to forest ----
var modis = ee.ImageCollection("MODIS/061/MOD13Q1")
  .select('EVI')
  .filterDate(startYear + '-01-01', (endYear + 1) + '-01-01')
```

```
  .filterBounds(tanzania);

var scaleAndMask = function(image) {
  var evi = image.multiply(0.0001);            // apply MODIS scale factor
  var masked = evi.updateMask(forestMask);      // keep forest pixels only
  return masked.copyProperties(image, ['system:time_start']);
};

var modisForest = modis.map(scaleAndMask);

// ---- 5. Build monthly mean composites (forest-only) ----
var monthlyEVI = ee.ImageCollection.fromImages(
  years.map(function(y) {
    return months.map(function(m) {
      var filtered = modisForest
        .filter(ee.Filter.calendarRange(y, y, 'year'))
        .filter(ee.Filter.calendarRange(m, m, 'month'));
      var monthlyMean = filtered.mean()
        .set('year', y)
        .set('month', m)
        .set('system:time_start', ee.Date.fromYMD(y, m, 1));
      return monthlyMean;
    });
  }).flatten()
);

// ---- 6. Reduce each monthly image to a single national (forest-only) mean ----
var eviTimeSeries = monthlyEVI.map(function(image) {
  var mean = image.reduceRegion({
    reducer: ee.Reducer.mean(),
    geometry: tanzania.geometry(),
```

```
    scale: 250,
    maxPixels: 1e9
  });
  var y = image.get('year');
  var m = image.get('month');
  return ee.Feature(null, {
    'year': y,
    'month': m,
    'date': ee.Date.fromYMD(ee.Number(y), ee.Number(m), 1).format('YYYY-MM'),
    'EVI': mean.get('EVI')
  });
});

var eviFC = ee.FeatureCollection(eviTimeSeries);

// ---- 7. Sort by date and export ----
var finalFC = eviFC.map(function(f) {
  var sortKey = ee.Number(f.get('year')).multiply(100).add(ee.Number(f.get('month')));
  return f.set('sort_key', sortKey);
}).sort('sort_key');

print('Preview', finalFC.limit(5));

Export.table.toDrive({
  collection: finalFC,
  description: 'Tanzania_Forest_EVI_Monthly',
  folder: 'GEE_exports',
  fileFormat: 'CSV',
  selectors: ['date', 'year', 'month', 'EVI']
});
```

forests

MDPI

Article

The Effects of Fiscal Policy on Forest Cover Conditions and Dynamics: Evidence from Tanzania

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Abstract

Forest cover conditions in Tanzania remain predominantly negative, with significant implications for biodiversity, rural livelihoods, and climate stability. Despite national forest management policies, traceability systems, afforestation programs, REDD+ initiatives, and the National Carbon Monitoring Centre, forest conditions continue to deteriorate. Naturally regenerating forests declined to 42.8 million hectares in 2025, while annual deforestation rose to approximately 469 thousand hectares in the post-2015 period. Fire disturbances remain evident, with around 4014 hectares burned in 2025, and forest growing stock declined to 3143 million m^3. Existing studies largely attribute these trends to agricultural expansion, population pressure, and charcoal dependence, while the role of fiscal policy has received limited empirical attention. This study addresses this gap by examining the relationship between fiscal policy and forest cover conditions in Tanzania from 2001 to 2024 using a VAR framework. The results indicate that increases in government development expenditure are associated with short-run improvements in forest cover conditions, suggesting that public investment can contribute to positive environmental outcomes, while balanced budget condition is associated with more stable improvements. These findings point to strengthened domestic revenue systems, greater fiscal discipline, and closer alignment of public expenditure with environmental objectives as relevant areas for further policy attention.

Keywords: EVI; development government expenditure; fiscal policy; forest cover conditions and dynamics; Tanzania; VAR

Check for updates

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1. Introduction

Forests are among the most critical natural resources globally, covering approximately 30.8% of the terrestrial surface, equivalent to about 4.06 billion hectares [1]. However, their distribution is highly uneven, with more than half of global forest cover concentrated in a few countries. Forest ecosystems play a fundamental role in sustaining biodiversity, hosting nearly 80% of amphibian species, 75% of bird species, and 68% of mammal species, as well as over 60,000 tree species worldwide [2–4]. Beyond their ecological importance, forests are essential for human well-being, providing food, fuel, medicine, and income, while