 doi:10.20944/preprints202204.0218.v1

Article

A Sensitive Analysis of Drivers and Impact of Deforestation in Uganda's Virgin Tropical Rainforests Using Regression Analysis: Efforts Towards Zero Deforestation by 2030

Dastan Bamwesigye [1*], Evans Yeboah [1,2], Dalibor Safarik[1]

[1] Department of Forest and Wood Products Economics and Policy, Faculty of Forestry and Wood Technology, Mendel University in Brno. Zemědělská 3, 61300 Brno. xbamwesi@mendelu.cz
[2] Department of Business Economics, Faculty of Business and Economics, Mendel University in Brno. Zemědělská 1, 613 00 Brno, Czech Republic. xyeboah1@mendelu.cz
* Correspondence: xbamwesi@mendelu.cz

Abstract: Uganda possesses natural rainforests that serve enormous environmental ecosystems and biodiversity services. Moreover, the country is known for its various tropical rainforest hardwoods, birds, and animal species. Over the years, the trend in the natural forest land has declined at an alarming rate; hence need to investigate the possible drivers. The loss of such biodiversity and ecosystems risks desertification and extreme climatic condition. As the world moves towards Zero Deforestation 2030, understanding the determinants of deforestation and forest degradation is paramount. Therefore, the main objective of this study was to understand the impact and relationships between net forest conversion, energy emission, agriculture, and forest production of Roundwood. We used data from FAO for the period 2004-2016. Using the ADF and KPSS test, we checked for the unit root presence in the variables. Also, the study used two different regression models: multiple linear regression and dynamic linear model. To analyze the determinants of deforestation, we used net forest conversion in Uganda. There was 94 % variation in the dependent variable (Net Forest conversion). The outcome of the dynamic linear regression showed that agriculture and energy emission positively impact net forest conversion. Based on our findings, this study recommended the modernization of agriculture by the government of Uganda to stop cutting down the forests on a big scale. Also, the study suggested that the government strictly legislate Roundwood and wood fuels/charcoal and firewood to reduce huge dependency on forests toward Zero-Deforestation by 2030. If well-structured and implemented, government policies could solve the unnecessary over dependency on the rainforest, the heart of the region's climatic conditions.

Keywords: Agriculture; climate change; energy emission; forest transformation; policy actions; livelihood; wood fuel; Zero-Deforestation

---

1. Introduction

Forests globally play a critical role in human wellbeing and a sustainable environment through ecosystem and biodiversity services [1,2,3,4,5,6]. However, deforestation in Uganda has been on the rise for the past few decades, causing environmental degradation [4,7,8,9]. Various studies suggest that policy action with efforts toward the root causes could help the world mitigate and reduce deforestation to achieve Zero-Deforestation by 2030 [10,11,12,13,13,14,15,16,17,18]. Most of these were done in Latin America, where commercial agriculture value chains hurt forest biodiversity and ecosystems.

Uganda is a developing nation that heavily relies on wood fuel [7,8,9,19]. Like other African countries, wood fuel is the core energy source for heating at factories, commercial and household cooking in Uganda [9,19,20].

It is not surprising that deforestation in Uganda is striking, as many people continue to use fuelwood for cooking. Other studies indicate that deforestation is somewhat driven by farming systems, which increasingly clear forested land for farming [21]. Furthermore,

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

Waiswa et al. [22] explain that clearing forests for commercial agriculture remain a common practice in Uganda. It could account for about a higher percentage in Uganda and other countries.

Recent research indicates that deforestation has increased in the Northern Albertine region, in rural Western Uganda. Twongyirwe et al. [23] investigated and presented findings of perceptions from local people in the region on the causes of deforestation for the period between 1985 and 2014 [23]. Their results indicated that the increasing expansion of cash crop farming (28%-58.5%) is driving deforestation in the Northern Albertine region. Other driving factors mentioned in the study include population increase and moving forest protection boundaries. A few more studies investigated the core drivers of deforestation in the Lake Victoria Crescent in Uganda (1989 and 2009) [22]. The authors employed a case study approach to explore the issue. Their findings indicated that agricultural expansion into forest areas is one of the leading drivers. They also listed wood forest products and clearing forests for other non-agricultural activities as core contributing factors. Further, they categorized causes of deforestation as institutional, economic, and population growth as the leading factors.

Although these factors are critical in driving deforestation, it is projected that commercial logging contributes to clearing forests in East African counties, including Uganda [23,24,25]. Other factors such as cash crop plantation, cattle ranching, and road construction are also said to contribute a percentage (Figure 1). This is supported by various African studies [23,24,25,26]. For example, multiple studies indicate that governments in Africa support cash crops such as tea and sugarcane crops which contribute to clearing/cutting forests.

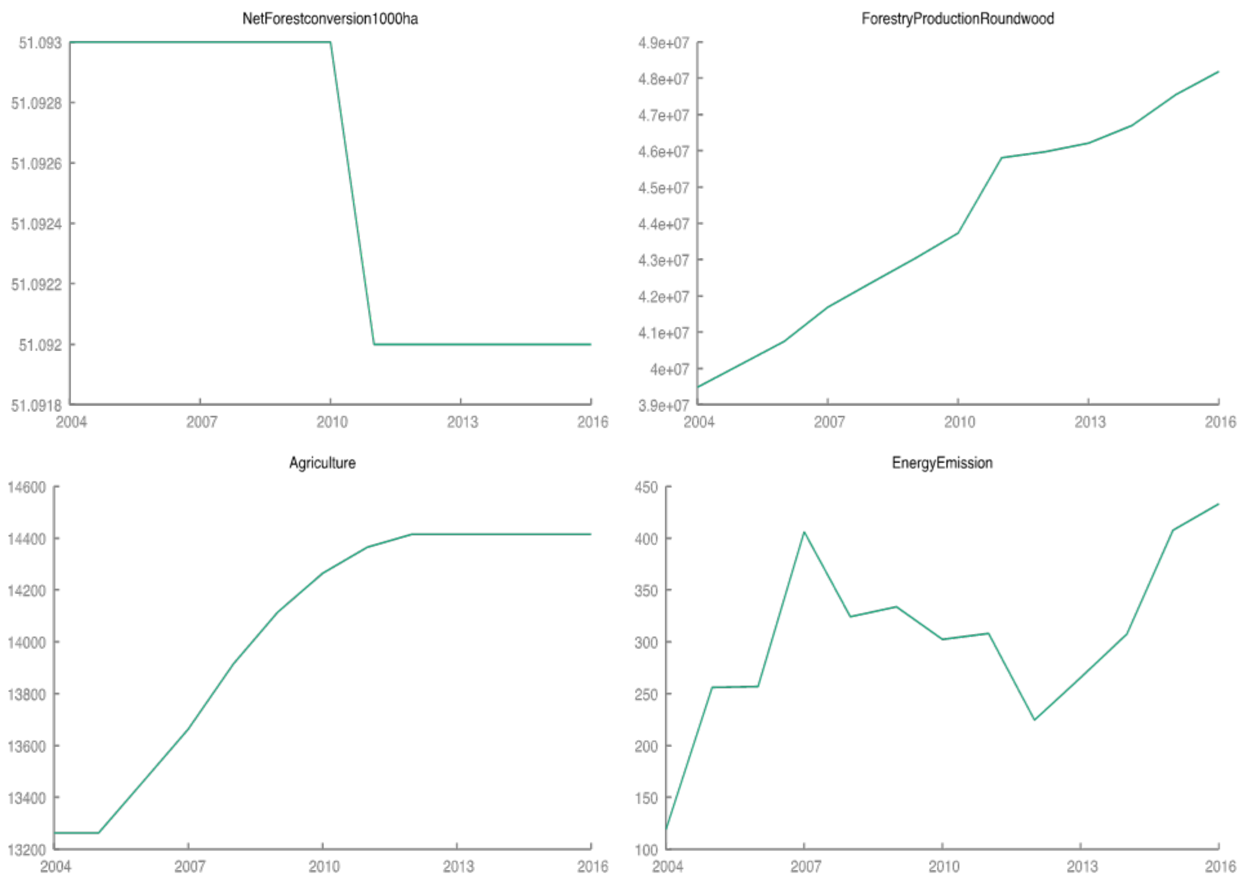

Figure 1: Trend in some of the causes and impacts of deforestation in Uganda (Own analysis)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

The activities of people generally drive deforestation. There seem to be consensuses that deforestation is one of the biggest causes of climate change in Uganda and other countries (20,22,27). There is a possible solution to stop it, especially at the political and policy levels in many nations, including Uganda. Nonetheless, actions such as regulating the logging business, strict protection of natural forests, and addressing some pressing human issues that drive deforestation in Uganda can help reduce the practice.

This study conducted a sensitive, quantitative assessment of some of the causes and impacts of deforestation. This study aimed to analyze sensitively the possible factors that fuel deforestation in Uganda and the region. We conducted multiple linear regression, dynamic linear regression (DLR), and multicollinearity statistical tests to understand the problem.

2.0 Literature Review

The section literature covers some of the major causes of deforestation that have been attempted to be studied before, such as population, agriculture, energy needs, wood/timber for export, and corruption.

2.1 Population increase

Prior studies indicate that population increase requires more land to establish housing and settlements, which causes deforestation [21,28,29]. These studies indicate increases in human activities, including road construction, urbanization, and farming. In other words, as people increases, their demand for food and farmland also grows, and this has been one of the drivers of deforestation in African countries, including Uganda. Moreover, cutting down forests for building materials, furniture, and other forest products has been pushed by the ever-growing population [30,31]. All these activities directly influence the increasing human population, which will be a threat to already encroached forests. Various scholars support this, suggesting that Uganda's forests are threatened by deforestation due to the increasing population [9,31]. However, Jagger & Kittner's [9] findings suggest that deforestation has severe implications for humans and the environment, especially in African countries' biomass-dependent and population-dense settings.

A study conducted in Budongo and Bugoma Forest Reserves revealed more than 10% of forest loss between 1985 and 2014 [23]. Another investigation was conducted in Bwindi Impenetrable Forest and indicated a loss of forests of 8% due to agriculture expansions [23]. Primarily, these human activities result from population growth in the country. According to the study conducted by Josephat [32], population growth in Uganda has increased the demand for agricultural land and wood fuel. Consequently, this has escalated the rate of deforestation in many parts of the country [9,31,32]. Although the government of Uganda has put some regulations to reduce the rate of deforestation, the demand for forest products keeps on increasing due to population growth.

2.2 Wood for export

Forest product exports continue to contribute to the current deforestation rate in Uganda [20,33]. The authors indicate that forest products such as commercially utilized biomass like timber for construction threaten forests in the country. Prior reports suggest that most of the timber and wood exported from Uganda mainly goes to Rwanda and Kenya [34]. However, most forest products, particularly timber traded in Africa, come from the eastern Democratic Republic of Congo [35]. Mostly, wood from Congo ends up in Uganda or sometimes transits through Uganda to other African countries. Recently, this trade has been widened by the growing international and regional demand.

Wood-based industries, especially paper and furniture, require a substantial wood quality. Despite the commercialization of these forest products, charcoal and firewood are primarily used for cooking and heating. Lukumbuzya and Sianga [34] showed that Uganda exports forest products to its neighboring countries [34]. For example, the same

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

study indicates that from 2010 to 2013, Uganda exported forest products worth between USD 500,000 to One Million USD per year. However, it is also revealed that the official export of Ugandan hardwood is zero because the government does not allow it. Most hardwood timber comes from other countries, particularly DRC and Uganda re-exports.

2.3 Agriculture and extensive farming

Agriculture is among the leading drivers of deforestation in developing countries, including Uganda [36,37]. One needs land to practice agriculture. With the development of agriculture to feed the ever-growing population, more and more land is required. Hosonuma et al. [37] 's study assessed various drivers of deforestation by analyzing empirical data from different countries as part of their REDD+ readiness activities. Their findings indicated that commercial agriculture is indeed one of the most important drivers of deforestation, followed by subsistence farming. Other research investigations confirm that population increase and per capita consumption significantly increase agricultural demand in Uganda [38].

Forests are cut down for agriculture to obtain land for farmers. Nonetheless, deforestation on a grand scale is visually dramatic. It brings many environmental changes, some of which are immediate and detrimental, but other incremental and not immediately apparent changes. However, it should be noted that cutting down forests also affects agriculture due to climate change. Interestingly, prior research suggests that if a forested area is regenerated through management techniques that include selective cutting and block cutting, that area is expected to revert to the full stocking before tree removal [39,40,41,42]. Despite the importance of these techniques, forests in Uganda remain threatened by commercial and subsistence agriculture.

2.4 Corruption in the land and resources sector

Land is one of the most significant resources that sustain millions of livelihoods in Uganda. However, the land resources sector in Uganda is heavily compromised by corruption [43]. Like most African countries, Uganda is faced with a high level of corruption. Corruption has been exhibited in many forms in the land and resources sector, i.e., power, money, and resource [44,45]. Studies indicate that any of these forms of corruption can lead those in power to work in favor of a few, thus compromising land rights [40,44,46]. For example, most corruption cases in Uganda's land and resources sector come from the administration and justice systems layers. Some studies indicated limited access to critical information, institutions, and procedures governing land ownership, a mixed tenures system, complex laws, as well as insufficient access to the justice system are some of the core factors contributing to the high level of corruption in Uganda's land and resources sector [40,44,46].

Prior research suggests that preventing or reducing corruption cases in the land and resources sector requires a collective effort and close supervision and monitoring of land administration agencies [47,48]. Such close supervision is critical in keeping officers in check while ensuring integrity in their services to the country. Like in most African countries, the consequences of corruption in Uganda are dire [47]. Moreover, these consequences are even worse in the land and resources sector. As Bhatt et al. [46] explain, land and resources corruption is a serious obstacle to the development of a nation. It affects the good livelihood and distorts economic development.

Rukundo & Kirumira [43] reported rampant corruption in Uganda's land sector while citing how the practice disproportionately impacts women. However, the government of Uganda has taken various measures to reduce corruption cases in the land and resources sector [47]. For example, Anti-corruption was put in place to investigate any

 doi:10.20944/preprints202204.0218.v1

corruption cases [46]. Nonetheless, measures have not been so effective, thus, leaving room for corruption to thrive [49].

2.5 Household energy

Household energy is one of the leading causes of deforestation in Uganda [8,9,19]. Bamwesigye et al. [19] indicated that charcoal and firewood fuel are the core drivers of deforestation in Uganda. The authors employed qualitative and quantitative research methods to investigate Uganda's charcoal and wood fuel energy use. Their findings revealed that more than 90% of households in Uganda use charcoal and firewood, which explains why there has been a rapid increase in deforestation. Many scholars have investigated household energy sources, and deforestation patterns reveal that fuelwood is one of the core energy sources for cooking, and forests are the main target [19,50]. For example, Sassen et al. [50] speculated that local communities, especially those who live around forests, often depend on them for firewood and charcoal sources.

Prior studies paint that the demand for fuelwood in African countries, especially sub-Saharan Africa, is expected to grow [19,51]. These studies indicate that wood fuel, especially charcoal and firewood, is the most utilized form of household energy [19,51]. Forests in Uganda are plugged into degradation as many people continue to cut down trees seeking charcoal and firewood in their homes [9,19,50,51]. While reflecting on these studies, there is a need for all stakeholders to find remedial solutions to the current ever-growing deforestation practices in the country.

3. Materials and Methods

The aim paper is to investigate some of the determinants of deforestation and forest development in Uganda. In achieving this objective, we consider some factors(variables) that are significant to the study using Granger. It is well-known that time series analysts have a different approach to analyzing economic data [52].

Assessing the impact of the independent variables, we considered several tests which aim at getting a linear regression using the Ordinary Least Squares (OLS). However, we used both multiple linear regression and a dynamic linear model to conduct our outline goal of the study. These tests include summary statistics, correlation matrix, the autocorrelation of the error terms, Unit root, and multicollinearity.

The study used a secondary data source from the Forest and Agriculture Organization of the United Nations (FAO) from 2004 to 2016 [53]. A summary statistic was carried out using the observation number of 13 of all the variables to obtain the mean and the standard deviation. A correlation matrix is to check the relationship between the variable and how they influence each other.

We employed the Augmented Dickey Fuller test (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to check for unit root test presence in the selected variables. Unit root tests help determine whether the time series is stationary or non-stationary. The method of testing whether a time series has a unit root or equal in value is that the variable follows a random walk [54]. We used the variants constant and trend (time), without constant and with constant. The equations below indicate the test for all the variants.

$$\Delta Y_t = \beta_1 Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-1} + \mu_t \quad (1)$$

$$\Delta Y_t = a_0 + \beta_1 Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-1} + \mu_t \quad (2)$$

$$\Delta Y_t = a_0 + a_1 t + \beta_1 Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-1} + \mu_t \quad (3)$$

However, under the KPSS unit root testing, the null hypothesis (H_0), μ_t is constant, and the variance of ε_t is zero. The alternative hypothesis (H_1), μ_t is a random walk, and the variance of ε_t is positive. The KPSS is shown in equation 4.

$X_t = r_t + \beta_t + \varepsilon_1 \ldots\ldots$ (4)

The KPSS test is built on linear regression, which breaks up the time series into three parts (a deterministic trend (β_t), a random walk(r_t), and a stationary error (ε_t) in the regression equation.

We performed a multicollinearity test using the variance inflation factors (VIF). It is greatly known that the symptoms of multicollinearity in a regression model is an increase of variance of regression coefficients. The approach of variance inflation factors VIF ($\hat{\beta}_j$) indicates the relative variance of the j-th coefficient of regression. It holds that VIF ($\hat{\beta}_j$) ≥ 1. If VIF ($\hat{\beta}_j$) exceeds the limit of 10, severe multicollinearity in the model. The variance of j-th regression coefficient can be written as in equation (5).

$$\text{Var} (\hat{\beta}_j) = \frac{\hat{\sigma}_e^2}{\left(1-R_j^2\right) \cdot \sum_{i=1}^{n}(x_j - \bar{x})2} = \text{Var} (\hat{\beta}_j) = \frac{\hat{\sigma}_e^2}{\sum_{i=1}^{n}(x_j - \bar{x})2} \quad \ldots. (5)$$

However, the multicollinearity assumption states that none of the regressors should be a perfect or linear combination. Multicollinearity violates the classical assumption.

Conversely, verifying for no autocorrelation between predicted variables and the error terms from the regression outputs in our first model, we used the Durbin-Watson (DW) autocorrelation test. The null hypothesis (H_0) There is no first-order autocorrelation, and the alternative hypothesis (H_1): there is first-order autocorrelation. The test statistic calculation is shown in equation two (6) below.

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_t^T e_t^2} \quad \ldots.. (6)$$

In the dynamic linear model, we used the Breusch-Godfrey test for autocorrelation up to order 5. The Durbin Watson is ruled out because it is not capable of testing for a regression model with a lag of the dependent variable at the right side of the equation. Breusch-Godfrey can test for autocorrelation of the highest order. The equations for the multiple linear regression and dynamic linear models are shown below in equations 7 and 8.

$$NFC_t = \beta_0 + \beta_1 Ag_t + \beta_2 Em_t + \beta_3 Fpr_t + \varepsilon_t \ldots\ldots.. (7)$$

Under the model equation (7) of the ordinary least squares, we expect agriculture to be positive, energy emission to be negative, and forest production at Roundwood. In contrast, we expect a negative coefficient for forest production Roundwood in the dynamic linear model.

$$NFC_t = \beta_0 + \beta_1 Ag_t + \beta_2 Fpr_t + \beta_3 Em_t + \beta_4 NFC_{t-1} + \varepsilon_t \ldots. (8)$$

Where NFC is the Net Forest conversion, Ag is Agriculture, Em is Energy emission and $\beta_4 NFC_{t-1}$ is the lag of the dependent variable. Also β_1, β_2, β_3, and β_4 are the regression coefficients while ε_t represents the error term, and β_0 representing the constant term of the obtained model. All the analyses were done using Gretl software.

The significance level used for this is 5%. The p-values can be used as an index of the "strength of the evidence" against the null hypothesis(H0) [55]. According the proposed level of p=0.05, or α"1 in 20 chance is being exceeded by chance", as a limit for statistical significance [56]. Fisher's reiterated p= 0.05 (5%) threshold explained the logic, stating that it is usual and convenient for experimenters to take 5% as a standard level of significance. They are prepared to ignore all outcomes that fail to reach this standard [55].

4. Results and Discussion

Table 1 provides a summary statistic for all the variables. We first observed that agriculture has a high mean than the means of the other three indicators. It appears that the forest production of Roundwood has the lowest mean value. Consequently, Agriculture

 doi:10.20944/preprints202204.0218.v1

had the highest median, followed by energy emission, net forest conversion, and forest production of Roundwood respectively.

Table 1. Summary Statistics.

Variable	Mean	Median	S.D.	Min	Max
Net Forest conversion	51.1	51.1	0.0005189	51.1	51.1
Forestry Production Roundwood	4.397e+07	4.373e+07	2.953e+06	3.948e+07	4.819e+07
Agriculture	14030	14265	462.3	13262	14415
Energy Emission	303.4	307.4	84.47	119.2	433.0

Source: Own analysis

The correlation coefficients using all the observation in table 2 with a 5% critical value (two-tailed) was equal to 0.5529. Forest production of Roundwood, agriculture, and energy emission negatively correlate with net forest conversion.

Table 2. Correlation matrix.

Net Forest conversion	Forestry Production Roundwood	Agriculture	Energy Emission	
1.0000	-0.9043	-0.7860	-0.2387	Net Forest conversion
	1.0000	0.9416	0.5210	Production Roundwood
		1.0000	0.4581	Agriculture
			1.0000	Energy Emission

Source: Own analysis

However, we will restrict our significance level to 5%. Based on the regression output from both ADF and KPSS tests showed that there was a unit root presence in the time series. The unit root presence showed that the time series were non-stationary. Under the ADF test for unit root, the null hypothesis of unit root presence is equal to 1, and the asymptotic p-value was used to check whether there is a unit root or not. The table of the ADF test showed there was a unit root. The KPSS test had the null hypothesis of no unit root present in variables based on the critical value. Analyzing the critical value from the KPSS table indicated a unit root presence.

Table 3. Unit root test results (ADF).

Variables	With constant trend	Without Constant	With constant
Net Forest Conversion	Constant (0.06886*), Time (0.0968*), asymptotic p-value (0.5634)	Net forest conversion (0.2852), asymptotic p-value (0.2852)	Constant (0.4241), Net Forest conversion (0.8091), asymptotic p-value (0.8091)
Agriculture	Constant (0.0684*), Time (0.2019), asymptotic p-value (0.2274)	Agriculture (0.9616), asymptotic p-value (0.9616)	Constant (1.76e-05***), agriculture (6.39e-16***), asymptotic p-value (6.388e-16)
Energy emission	Constant (0.0281**), Time (0.5249), asymptotic p-value (0.3352)	Energy emission (0.8526), asymptotic p-value (0.8526)	Constant (0.0188**), Energy emission (0.1121), asymptotic p-value (0.1121)
Forestry Production Roundwood	Constant (0.0529*), Time (0.0656*) asymptotic p-value (0.5094)	Forestry production roundwood (1) asymptotic p-value (1)	Constant (0.4120), Forestry production roundwood (0.8794), asymptotic p-value (0.8794)

Source: Own analysis

Table 4. KPSS Unit root test.

Variables	Without Trend	With Constant and Trend
Net Forest Conversion	Constant (1.68e-61***), test statistics (0.384119), Interpolated p-value (0.089)	Constant (3.43e-56***), time (0.0001***), test statistic (0.0991501), P-value (> .10)
Forestry Production Roundwood	Constant (1.15e-15***), test statistics (0.45005), Interpolated p-value (0.056)	Constant (5.81e-20***), time (4.57e-11***), test statistic (0.117718), P-value (> .10)
Agriculture	Constant (2.28e-19***), test statistics (0.407545), Interpolated p-value (0.078)	Constant (1.25e-18***), time (5.74e-06***), test statistic (0.13465), Interpolated p-value (0.084)
Energy emission	Constant (2.06e-08***), test statistics (0.310885), p-value (> .10)	Constant (0.0004***), time (0.0483**), test statistic (0.10082), P-value (> .10)

Significance codes: *** 1%, ** 5%, * 10%

The results showed no multicollinearity among the variables as they were lower than the set value for severe multicollinearity (Table 5).

Table 5. multicollinearity test.

Variables	Variance inflation factor
Agriculture	8.937
Energy Emission	1.390
Forestry Production Roundwood	9.692

Source: Own analysis

4.1 Regression Results

Model 1 of multiple regression seems good. This shows that the constant is significant, and so are the regressors' coefficients. However, the forest production of Roundwood has a negative impact on net forest conversion. Net conversion positively affects energy emissions and agriculture (Table 6). The dependent variable for the model is Net Forest conversion. Model 1 is not affected by autocorrelation, heteroskedasticity, and specification error. Normality from model 1 has a constant variance (Table 6 and Figure 2, respectively).

Conversely, the dynamic model approach was applied to investigate whether net forest conversion from the previous period has any effect on the current time period. The dynamic linear model in model 2 looks much better than model 1 because it has the lowest information criterion. The lower information criterion makes a model much better and fits it well. The regression output for model 2 is indicated (Table 7).

$$NFC_t = 51.0945 + 0.000000762 Ag_t + 0.00000215 Em_t - 0.000000000303 Fpr_t + \varepsilon_t \quad \text{(Model 1)}$$

Table 6. a: Multiple Linear Regression Estimation (Model 1).

Variables	Coefficient	Std. Error	t-ratio	p-value
constant	51.0945	0.00208528	2.450e+04	1.60e-36***
Agriculture	7.61799e-07	2.65769e-07	2.866	0.0186**
Energy Emission	2.14532e-06	5.73729e-07	3.739	0.0046***
Forestry Production Roundwood	−3.03214e-10	4.33369e-11	−6.997	6.35e-05***

Significance codes: *** 1%, ** 5%, * 10%

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

Table 6. b. model variants.

Mean dependent var	51.09254	S.D. dependent var	0.000519
Sum squared residual	1.82e-07	S.E. of regression	0.000142
R-squared	0.943528	Adjusted R-squared	0.924705
F (3, 9)	50.12414	P-value(F)	6.11e-06
Log-likelihood	99.08520	Akaike criterion	−190.1704
Schwarz criterion	−187.9106	Hannan-Quinn	−190.6349
rho	−0.170643	Durbin-Watson	2.091400

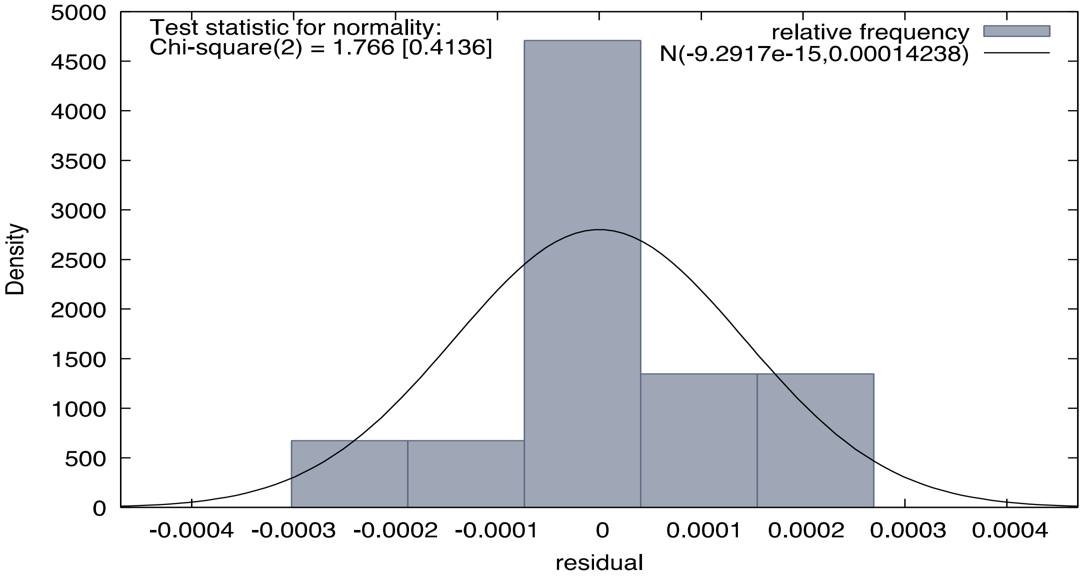

Figure 2. Normality test for model 1.

$$NFC_t = 58.0027\text{-}0.0000000003057Fpr_t + 0.000000987Ag_t + 0.00000279Em_t + \varepsilon_t \quad \text{(Model 2)}$$

Table 7a: Dynamic Linear Model (Model 2).

Variables	Coefficient	Std. Error	t-ratio	p-value
constant	58.0027	10.3134	5.624	0.0008***
Forestry Production Roundwood	−3.56524e-10	7.99721e-11	−4.458	0.0029***
Agriculture	9.86756e-07	3.64991e-07	2.704	0.0305**
Energy Emission	2.79492e-06	8.66787e-07	3.224	0.0146**
Net Forest conversion	−0.135229	0.201861	−0.6699	0.5244

Significance codes: *** 1%, ** 5%, * 10%

Table 7b: Model 2 variants.

Mean dependent var	51.09250	S.D. dependent var	0.000522
Sum squared residual	1.58e-07	S.E. of regression	0.000150
R-squared	0.947443	Adjusted R-squared	0.917411
F (4, 7)	31.54741	P-value(F)	7.09e-06
Log-likelihood	91.85875	Akaike criterion	−173.7175
Schwarz criterion	−171.2930	Hannan-Quinn	−174.6151
rho	−0.212254	Durbin's h	−1.028548

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

The output of the dynamic linear model gives similar impact signs to the coefficients of the regressors in model 1. However, the lag of the dependent variable is not statistically significant.

The coefficients in model 2 increased due to limited size, which may have caused bias in the regression coefficients (Table 7). However, there was no heteroskedasticity among the error term. This indicates that the error term has constant variance. The normality for model 2 shows that the error term is normally distributed based on the p-value (Figure 3).

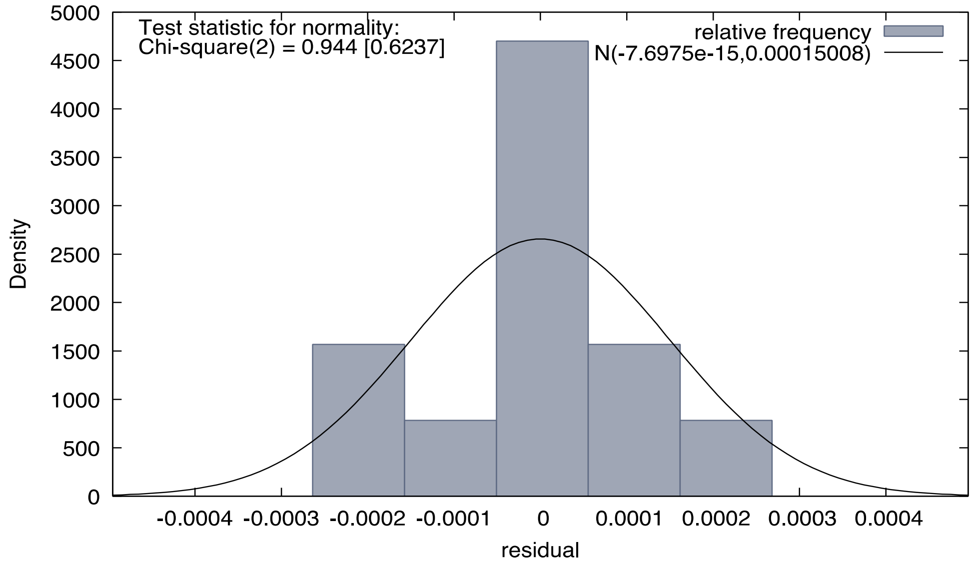

Figure 3. Normality of residual from the model 2 regression output.

Table 8. Breusch-Godfrey test.

Variables	coefficient	Standard error	t-ratio	p-value
constant	3.40209	13.7058	0.2482	0.8271
Forestry Production roundwood	$-4.87696\text{x}10^{11}$	$1.00606\text{x}10^{10}$	−0.4848	0.6757
Agriculture	$1.22528\text{x}10^{7}$	$3.90384\text{x}10^{7}$	0.3139	0.7833
Energy Emission	$-8.43410\text{x}10^{7}$	$6.52524\text{x}10^{7}$	−1.293	0.3254
Net Forest conversion_1	−0.0665740	0.268265	−0.2482	0.8272
uhat_1	−0.847832	0.457970	−1.851	0.2053
uhat_2	-1.45126	0.508613	−2.853	0.1040
uhat_3	−1.63631	0.522725	−3.130	0.0887 *
uhat_4	−1.30817	0.687414	−1.903	0.1974
uhat_5	−0.944448	0.434299	−2.175	0.1617

The Breusch-Godfrey test in table 8 indicates no autocorrelation among the error terms. The autocorrelation was performed up to lag 5. The p-values from the standard errors testing for serial correlation at 5% significance indicate no autocorrelation among the error terms.

This sensitive analysis confirmed some of the doubts, debates, and thoughts on significant causes of deforestation in Uganda, such as agriculture and energy needs. Deforestation has been indicated to be accelerating at a high rate in Uganda. The descriptive analysis also showed a steep increasing trend in wood production (Roundwood), agricultural land, and energy emissions from firewood/wood fuels.

Deforestation in Uganda is mainly caused by cutting down forests to create land for agriculture and other uses, such as wood exports, timber, and household energy [19,22].

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

It was revealed that charcoal and firewood fuel are among the core drivers of deforestation in Uganda [9,19,22]. Our study agrees with [9,19,22], who investigated household energy sources and deforestation patterns that revealed that fuelwood is one of the core energy sources for household cooking, which equally contributes to total energy emissions. Moreover, energy-related drivers of deforestation have been linked to population increase. For example, several studies indicated that human activities such as population increase requires more land to establish housing and settlements, agriculture, and energy needs are the lead causes of deforestation [21,28,29].

Although the land is one of the greatest resources that sustain millions of livelihoods in Uganda and globally, it is heavily compromised by corruption [43]. Corruption has been exhibited in many forms in the land and resources sector, i.e., power, money, and resource [43]. These forms of corruption can lead those in power to work in favor of a few, thus compromising land rights, among other political-economic decisions that would reduce pressure on forest resources. Arguably, most land and resources issues come from national forest institutions responsible for overseeing management-related activities. Besides, without proper land and resources management, deforestation in Uganda will continue and cause environmental effects detrimental to people's health and climate.

The limitation of this analysis can be a result of the small sample data size. However, further research needs to employ a large data sample size to carry out the same study to determine whether these variables would be statistically significant. Also, further research about this study could separately assess the short and long runs effect of the present situation on the future of Uganda's net forest conversion.

5. Conclusions

Deforestation is one of the biggest problems causing climate change in Tropical Africa and globally. Based on the evidence presented in the literature, deforestation in Uganda has been on the rise for the past few decades, hence causing environmental degradation. Uganda is one of the developing nations that heavily rely on wood fuel. It is worth noting that much has been lost to deforestation. This has caused degradation in most parts of the world, thus, calling for collective efforts to mitigate the impact. Although the effects of deforestation prompt people to develop various policies, regulations, and institutional reforms to reduce the current rate, most of the initiatives have not been successful.

Nonetheless, effective management of Uganda's forests should prioritize every citizen to save the environment. Even with such willingness to be part of initiatives to save the already threatened forests, most people in Uganda lack critical information in their decision-making. Therefore, protecting forests requires government, public, and private inputs.

The objective of this paper was to assess some determinants of deforestation and forest development in Uganda for the period 2004 to 2016. Using the ADF and KPSS test to check for the unit root presence in the variables, the results showed unit roots in the selected regressors.

Multiple linear regression was used to analyze the determinant of net forest conversion in Uganda compared to other techniques because it has several advantages over other alternative approaches. The was 94% variation explained in the dependent variable (Net Forest conversion).

The outcome of the dynamic linear regression showed that agriculture and energy emission had a positive impact on net forest conversion, whereas forest production of Roundwood had a negative effect. The test on multicollinearity shows no severe multicollinearity among the variables. However, the test for autocorrelation in the error term using Breusch-Godfrey indicates no sequential correction.

Based on our findings, this study concludes by recommending more modernized agriculture by the government and individuals as it would boost production activities. Policy reforms on energy innovations and investments in renewables and clean energy mix to reduce energy emissions. This will also help curb the massive dependency on wood fuel for firewood for household cooking which has contributed enormously to deforestation

Author Contributions: Conceptualization, D.B. and E.Y.; methodology, E.Y. and D.B.; software, D.B and E.Y.; validation, D.B., and E.Y.; formal analysis, D.B and E.Y.; investigation, D.B and E.Y.; resources, D.B.; data curation, D.B.; writing—original draft preparation, D.B and E.Y.; writing—review and editing, D.B. and E.Y; visualization, D.B.; D.S and E.Y; supervision, D.S.

Funding: Please add: This research received no external funding.

Data Availability Statement: Data will be available upon request.

Acknowledgments: We thank Mendel University in Brno for Open Access fuding. Also, we thank anonymous reviewers for their comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. García-Nieto AP, García-Llorente M, Iniesta-Arandia I, Martín-López B. Mapping forest ecosystem services: from providing units to beneficiaries. *Ecosystem Services*. 2013 Jun 1;4:126-38.
2. Guariguata MR, Balvanera P. Quantifying the flow of tropical forest ecosystem services. *Forest Ecology and Management*. 2009;258(9).
3. Börner J, Vosti SA. Managing tropical forest ecosystem services: An overview of options. *Governing the provision of ecosystem services*. 2013:21-46.
4. Bamwesigye, D., Hlavackova, P., Sujova, A., Fialova, J., & Kupec, P. Willingness to pay for forest existence value and sustainability. *Sustainability*, 2020, 12(3), 891.
5. Mutoko MC, Hein L, Shisanya CA. Tropical forest conservation versus conversion trade-offs: Insights from analysis of ecosystem services provided by Kakamega rainforest in Kenya. *Ecosystem services*. 2015 Aug 1;14:1-1.
6. Sekercioglu CH. Bird functional diversity and ecosystem services in tropical forests, agroforests and agricultural areas. *Journal of Ornithology*. 2012 Aug;153(1):153-61.
7. Bamwesigye, D., Boateng, K. A., & Hlaváčková, P. (2018). Timber and wood production in tropical African virgin forests. International Scientific Conference "Public recreation and landscape protection–with nature hand in hand (pp. 396-400).
8. Bamwesigye, D., Darkwah, A. S., Halvackova, P., & Kupcak, V. (2017). Firewood and charcoal production in Uganda. Int. Multidiscip. Sci. GeoConference SGEM, 17, 521-528.
9. Jagger, P., & Kittner, N. (2017). Deforestation and biomass fuel dynamics in Uganda. Biomass and Bioenergy, 105, 1-9.
10. Celentano D, Rousseau GX, Muniz FH, van Deursen Varga I, Martinez C, Carneiro MS, Miranda MV, Barros MN, Freitas L, da Silva Narvaes I, Adami M. Towards zero deforestation and forest restoration in the Amazon region of Maranhão state, Brazil. *Land use policy*. 2017 Nov 1;68:692-8.
11. zu Ermgassen EK, Ayre B, Godar J, Lima MG, Bauch S, Garrett R, Green J, Lathuillière MJ, Löfgren P, MacFarquhar C, Meyfroidt P. Using supply chain data to monitor zero deforestation commitments: an assessment of progress in the Brazilian soy sector. *Environmental Research Letters*. 2020 Feb 18;15(3):035003.
12. Furumo PR, Lambin EF. Scaling up zero-deforestation initiatives through public-private partnerships: A look inside post-conflict Colombia. *Global Environmental Change*. 2020 May 1;62:102055.
13. Paim MA. Zero deforestation in the Amazon: The Soy Moratorium and global forest governance. *Review of European, Comparative & International Environmental Law*. 2021 Jul;30(2):220-32.
14. Fernandes MM, de Moura Fernandes MR, Garcia JR, Matricardi EA, de Almeida AQ, Pinto AS, Menezes RS, de Jesus Silva A, de Souza Lima AH. Assessment of land use and land cover changes and valuation of carbon stocks in the Sergipe semiarid region, Brazil: 1992–2030. *Land use policy*. 2020 Dec 1;99:104795.
15. Silva RD, Barioni LG, Pellegrino GQ, Moran D. The role of agricultural intensification in Brazil's Nationally Determined Contribution on emissions mitigation. *Agricultural Systems*. 2018 Mar 1;161:102-12.
16. Karsenty A. Major food companies, PES and combating deforestation. Using PES to achieve "zero deforestation" agriculture. *Perspective*. 2015 Jan 1(36):1-4.
17. Garrett RD, Levy S, Carlson KM, Gardner TA, Godar J, Clapp J, Dauvergne P, Heilmayr R, de Waroux YL, Ayre B, Barr R. Criteria for effective zero-deforestation commitments. *Global environmental change*. 2019 Jan 1;54:135-47.
18. Newton P, Benzeev R. The role of zero-deforestation commitments in protecting and enhancing rural livelihoods. *Current Opinion in Environmental Sustainability*. 2018 Jun 1;32:126-33.
19. Bamwesigye, D., Kupec, P., Chekuimo, G., Pavlis, J., Asamoah, O., Darkwah, S. A., & Hlaváčková, P. (2020b). Charcoal and wood biomass utilization in Uganda: the socioeconomic and environmental dynamics and implications. Sustainability, 12(20), 8337.

20. Nabukalu, C., & Gieré, R. (2019). Charcoal as an energy resource: Global trade, production and socioeconomic practices observed in Uganda. *Resources*, *8*(4), 183.
21. Mwanjalolo, M. G. J., Bernard, B., Paul, M. I., Joshua, W., Sophie, K., Cotilda, N., ... & Barbara, N. (2018). Assessing the extent of historical, current, and future land use systems in Uganda. *Land*, *7*(4), 132.
22. Waiswa, D., Stern, M. J., & Prisley, S. P. (2015). Drivers of deforestation in the Lake Victoria crescent, Uganda. *Journal of Sustainable Forestry*, *34*(3), 259-275.
23. Twongyirwe, R., Majaliwa, J. G. M., Ebanyat, P., Tenywa, M. M., Sheil, D., Heist, M. V., ... & Kumar, L. (2011). Dynamics of forest cover conversion in and around Bwindi impenetrable forest, Southwestern Uganda. *Journal of Applied Sciences and Environmental Management*, *15*(1).
24. Teucher, M., Schmitt, C. B., Wiese, A., Apfelbeck, B., Maghenda, M., Pellikka, P., ... & Habel, J. C. (2020). Behind the fog: Forest degradation despite logging bans in an East African cloud forest. *Global Ecology and Conservation*, *22*, e01024.
25. Twongyirwe, R., Bithell, M., Richards, K. S., & Rees, W. G. (2015). Three decades of forest cover change in Uganda's Northern Albertine Rift Landscape. *Land Use Policy*, *49*, 236-251.
26. Mutesi, F., Tabuti, J. R. S., & Mfitumukiza, D. (2021). Extent and Rate of Deforestation and Forest Degradation (1986–2016) in West Bugwe Central Forest Reserve, Uganda. *International Journal of Forestry Research*, *2021*.
27. Specht, M. J., Pinto, S. R. R., Albuquerque, U. P., Tabarelli, M., & Melo, F. P. (2015). Burning biodiversity: Fuelwood harvesting causes forest degradation in human-dominated tropical landscapes. *Global Ecology and Conservation*, *3*, 200-209.
28. Jha, S., & Bawa, K. S. (2006). Population growth, human development, and deforestation in biodiversity hotspots. *Conservation Biology*, *20*(3), 906-912.
29. Rudel T. K. (2013). The national determinants of deforestation in sub-Saharan Africa. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *368*(1625), 20120405. https://doi.org/10.1098/rstb.2012.0405
30. Kaboggoza, J. (2011). Forest plantations and woodlots in Uganda. In *African Forest Forum* (Vol. 1, No. 17).
31. Gizachew, B., Solberg, S., & Puliti, S. (2018). Forest carbon gain and loss in protected areas of Uganda: Implications to carbon benefits of conservation. *Land*, *7*(4), 138.
32. Josephat, M. (2018). Deforestation in Uganda: population increase, forests loss and climate change. *Environ Risk Assess Remediat*, *2*(2), 46-50.
33. Bamwesigye, D., Akwari, F. N., & Hlaváčková, P. (2019). Forest product export performance in tropical Africa: an empirical analysis. *Forum Scientiae Oeconomia* (Vol. 7, No. 1, pp. 73-83).
34. Lukumbuzya, K., & Sianga, C. (2017). Overview of the timber trade in East and Southern Africa. *TRAFFIC, Cambridge, UK*.
35. Chang, Y., & Peng, R. (2015). Timber flow study: export/import discrepancy analysis. *London, UK: IIED .*
36. Doggart, N., Morgan-Brown, T., Lyimo, E., Mbilinyi, B., Meshack, C. K., Sallu, S. M., & Spracklen, D. V. (2020). Agriculture is the main driver of deforestation in Tanzania. *Environmental Research Letters*, *15*(3), 034028.
37. Hosonuma, N., Herold, M., De Sy, V., De Fries, R. S., Brockhaus, M., Verchot, L., ... & Romijn, E. (2012). An assessment of deforestation and forest degradation drivers in developing countries. *Environmental Research Letters*, *7*(4), 044009.
38. Hulme, M. F., Vickery, J. A., Green, R. E., Phalan, B., Chamberlain, D. E., Pomeroy, D. E., ... & Atkinson, P. W. (2013). Conserving the birds of Uganda's banana-coffee arc: land sparing and land sharing compared. *PloS one*, *8*(2), e54597.
39. Putz, F. E., Baker, T., Griscom, B. W., Gopalakrishna, T., Roopsind, A., Umunay, P. M., ... & Ellis, P. W. (2019). Intact forest in selective logging landscapes in the tropics. *Frontiers in Forests and Global Change*, *2*, 30.
40. Kabanda, N. (2013). Uganda's National Land Policy: Background, Highlights and Next Steps. *Focus on Land in Africa*.
41. Kobayashi, S. (Ed.). (2001). *Rehabilitation of degraded tropical forest ecosystems: workshop proceedings, 2-4 November 1999, Bogor, Indonesia*. Cifor.
42. Lexerød, N. L., & Eid, T. (2006). Assessing suitability for selective cutting using a stand level index. *Forest Ecology and Management*, *237*(1-3), 503-512.
43. Rukundo, B., & Kirumira, D. A. (2014). Reforming Land Management in Uganda: The difficult path towards harmonized institutional mechanisms and arrangements for land tenure security. In *Conference: Annual World Bank Conference on Land and PovertyAt. Washington DC*.
44. Wabineno, L. M., Musinguzi, M., & Ekback, P. (2011). Land Information Management in Uganda: Current Status. In *The First Conference on Advances in Geomatics Research; Gidudu, A., Otukei, JR, Musinguzi, M., Eds* (pp. 211-223).
45. Vaughan, J., & Stewart, T. (2011). Land Disputes in Acholiland, A Conflict and Market Assessment. *Mercy Corps. E. Food security I now want to ask you a few questions about eating patterns in the household*.
46. Bhatt, P., Chu, J., Mata, X., Nakajima, Y., Ro, A., & Schreier, M. (2017). The potential of ICTs to Combat land corruption in Uganda: a gendered approach. *Colombia University, New York*.
47. Martini, M. (2013). Uganda: Overview of corruption and anti-corruption. *U4 Expert Answer*, *379*, U4.
48. Mutungi, F., Baguma, R., Janowski, T., & University Krems, Austria, D. (2019, June). Towards digital anti-corruption typology for public service delivery. In *Proceedings of the 20th Annual International Conference on Digital Government Research* (pp. 484-494).
49. Persson, A., Rothstein, B., & Teorell, J. (2010). The failure of anti-corruption policies: a theoretical mischaracterization of the problem.
50. Sassen, M., Sheil, D., & Giller, K. E. (2015). Fuelwood collection and its impacts on a protected tropical mountain forest in Uganda. *Forest Ecology and Management*, *354*, 56-67.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 April 2022 doi:10.20944/preprints202204.0218.v1

51. Njenga, M., Iiyama, M., Gitau, J. K., & Mendum, R. (2018). Grassroots Innovations Improve Woodfuel in Sub-Saharan Africa. *The Global Innovation Index 2018: Energizing the World with Innovation*, 151.
52. Granger, c. (1981). Some properties of time series data and their use in econometric model specification. *Journal of econometrics*, 16, 121-130.
53. FAOSTAT. *The Food and Agriculture Organization (FAO) of the United Nations*. *2022*. https://www.fao.org/faostat/en/#compare
54. Dickey, W., & Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74, 427-431.
55. Fisher, R. (1925). Statistical Methods for Research Workers. Oliver & Boyd.
56. Fisher, R. (1935). The Design Experiment. Macmillan.