MODELING DRIVERS OF DEFORESTATION IN UGANDA USING REGRESSION ANALYSIS: EFFORTS TOWARDS ZERO DEFORESTATION BY 2030

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Abstract

Uganda, located in the Tropical region of Africa, is blessed with natural forests that serve enormous environmental ecosystems and biodiversity. Moreover, the country is known for its tropical rain forests and various hardwood, 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 is 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; ordinary multiple linear and dynamic linear regressions. The results showed that there were unit roots in the selected regressors. 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, whereas forest production of Roundwood has a negative effect. 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, as Roundwood production has a negative impact on net forest conversion, there is a need for the government to strictly legislate to ensure effective and efficient management and production of Roundwood products towards total forest conservation by 2030.

Key words: Agriculture, climate change, energy emission, forest conversion, livelihood, wood fuel, Zero Deforestation 2030

Introduction

Forests globally play a critical role in human wellbeing and a sustainable environment through ecosystem and biodiversity services (Bamwesigye et al., 2020a). However, deforestation in Uganda has been rising for the past few decades, hence being seen as causing environmental degradation. Uganda is a developing nation that heavily relies on wood fuel (Bamwesigye et al., 2020; Jagger & Kittner, 2017). Like in other African countries, wood fuel is the core energy source for heating at factories, commercial, and household cooking in Uganda (Bamwesigye et al., 2017, Bamwesigye et al., 2018, Nabukalu & Gieré, 2019; Bamwesigye et al., 2020b).

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 (Mwanjalolo et al., 2018). Furthermore, Waiswa et al. (2015) 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 studies indicate that deforestation has increased in the Northern Albertine region, in rural Western Uganda. Twongyirwe et al. investigated and presented findings of perceptions from local people in the region on the causes of deforestation for the period between 1985 and 2014 (Twongyirwe et al., 2015. 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) (Waiswa et al., 2015). 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 (Waiswa et al., 2015, Bamwesigye et al., 2019).

There seem to be consensuses that deforestation is one of the biggest causes of climate change in Uganda and other countries (Nabukalu & Gieré, 2019; Waiswa et al., 2015). 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 aimed to analyze the possible factors that are said to be fueling deforestation in Uganda and the region sensitively. i.e., to understand the relationship between net forest conversion, energy emission, agriculture, and forest production of Roundwood. An ordinary multiple linear regression, dynamic linear regression (DLR), and multicollinearity statistical tests were conducted to better understand the impact, relationships, and the problem.

Material and methods

The aim paper was to investigate some of the determinants of deforestation and forest development in Uganda. To achieve this objective, we considered some factors/variables that are significant to the study. It is well-known that time series analysts have a different approach to analyzing economic data (Granger, 1981). 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 normal ordinary least squares and a dynamic linear model to conduct our outline goal of the study. These tests included 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. 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 to 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 (Dickey & Fuller, 1979). We used the variants constant and Trend (time), without constant and with constant. The equations below indicate the test for all the variants.

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

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

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

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 build 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 above 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 in 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).

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

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).

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

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 cannot test 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 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(H_0) (Fisher, 1925). The proposed level of p=0.05, or α"1 in 20 chance is being exceeded by chance", is a limit for statistical significance (fisher, 1935). Fisher's reiterated the 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. The study prepared results but ignored all outcomes that fail to reach this standard (Fisher, 1925).

Empirical Framework

As forestland conversation is significant for environmental protection. It is important to understand the impact of net forest conversion in Uganda. Therefore, the main objective of this study is to understand the relationship between net forest conversion, energy emission, agriculture, and forest production of Roundwood. For this reason, the study proposed two different regression models by using net forest conversion as the dependent variables and the others as regressors. The net forest conversion is measured in hectares, Roundwood production in meters(m^3), and emissions are measured in carbon dioxide (CO_2) equivalent. These two models are the ordinary multiple linear and dynamic linear regression models, as shown in Equations 7 and 8.

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

Under the model equation (7) of the ordinary least squares, we expected agriculture to be positive, energy emission positive, and forest production Roundwood negative. In contrast, we anticipated the same sign coefficients from the variables but with an increased constant value in the dynamic linear model.

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

Where NFC is the Net Forest conversion, Ag is Agriculture, Em is Energy emission and $\beta_4 NFC_{t-1}$ is lag of the dependent variable. Also $\beta_1, \beta_2, \beta_3$, and β_4 are the regression coefficients, ε_t represents the error term, and β_0 constant term of the obtained model. All the analyses were done using Gretl software.

Results and Discussion

Our results were significant at 1%, 5%, and 10%. We restricted 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 was a unit root or not. The table of the ADF test showed there was a unit root (Table 1). 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. The results showed no multicollinearity among the variables as they were lower than the set value for severe multicollinearity (Table 2).

Model 1 of normal classic OLS seemed good. This showed that the constant was significant, and so were the regressors' coefficients. However, the forest production of Roundwood had a negative impact on net forest conversion. Net conversion had a positive effect on energy emissions and agriculture. The dependent variable for the model was Net Forest conversion. Model 1 is not affected by autocorrelation, heteroskedasticity, and specification error. Normality from model 1 had constant variance (Table 3).

Tab. 1: Unit root test results (ADF)

Variables	constant and 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 using Gretl

Tab. 2: 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)

Conversely, a robust approach was applied to reduce the standard error inaccuracy to improve the model's efficiency. The dynamic linear model in model 2 looks much better than model 1 because it had the lowest information criteria. The lower information criterion made the model much better and fit it well.

Tab. 3: OLS (model 1)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
const	51.0945	0.00208528	$2.450 x 10^{4}$	$1.60 x 10^{36}$***
Agriculture	7.61799×10^{7}	2.65769×10^{7}	2.866	0.0186**
Energy Emission	2.14532×10^{6}	$5.73729 x 10^{7}$	3.739	0.0046***
Forestry Production Roundwood	$-3.03214 x 10^{10}$	$4.33369 x 10^{11}$	−6.997	$6.35 x 10^{5}$

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

The regression output for model 2 (Table 4) was based on heteroskedasticity-autocorrelation robust error using the Bartlett Kernel standard errors without truncation. 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. However, there was no heteroskedasticity among the error term. This indicated that the error term had a constant variance. The normality for model 2 showed that the error term was normally distributed based on the p-value.
The Breusch-Godfrey test (table 8) indicated 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.

Tab. 4: Dynamic Linear Model (Model 2)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
const	58.0027	9.06016	6.402	0.0004***
Forestry Production Roundwood	-3.56524×10^{10}	8.44400×10^{11}	−4.222	0.0039***
Agriculture	9.86756×10^{7}	3.52195×10^{7}	2.802	0.0265**
Energy Emission	2.79492×10^{6}	9.20668×10^{7}	3.036	0.0190**
Net Forest conversion	−0.135229	0.177339	−0.7625	0.4706

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)	77.46977	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	−0.931832

Tab. 5: Breusch-Godfrey test

	coefficient	Standard error	t-ratio	p-value
const	3.40209	13.7058	0.2482	0.8271
Forestry Production roundwood	-4.87696×10^{11}	1.00606×10^{10}	−0.4848	0.6757
Agriculture	1.22528×10^{7}	3.90384×10^{7}	0.3139	0.7833
Energy Emission	-8.43410×10^{7}	6.52524×10^{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

Conclusion

This paper assessed some deforestation and forest development determinants in Uganda from 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. The OLS method analyzed 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 serial correction. Based on our findings, this study concludes by recommending more modernized agriculture by the government and individuals as it would boost production activities without cutting down forests. It also suggested that, as forest Roundwood production is negatively impacting net forest conversion, there is a need for the government to develop new ways of ensuring effective and efficient usage of forest Roundwood products. 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.

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Souhrn

V průběhu let se v Ugandě alarmujícím tempem snížil trend přirozených lesních ploch, a proto je třeba prozkoumat možné příčiny. Ztráta této biologické rozmanitosti a ekosystémů představuje riziko dezertifikace a extrémních klimatických podmínek. Vzhledem k tomu, že svět směřuje k nulovému odlesňování do roku 2030, je pochopení určujících faktorů odlesňování a degradace lesů nanejvýš důležité. Hlavním cílem této studie je proto pochopit dopad a vztahy mezi čistou přeměnou lesů, energetickými emisemi, zemědělstvím a produkcí kulatiny. Použili jsme údaje FAO za období 2004-2016. Pomocí ADF a KPSS testu jsme ověřili přítomnost jednotkového kořene v proměnných. Ve studii byly také použity dva různé regresní modely; obyčejná vícenásobná lineární a dynamická lineární regrese. Výsledek dynamické lineární regrese ukázal, že zemědělství a energetické emise pozitivně ovlivňují čistou přeměnu lesů, zatímco produkce kulatiny má negativní vliv. Na základě našich zjištění tato studie doporučuje ugandské vládě modernizaci zemědělství, aby se přestaly kácet lesy ve velkém měřítku.

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