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INDONESIA'S FOREST MANAGEMENT PROGRESS: EMPIRICAL ANALYSIS OF ENVIRONMENTAL KUZNETS CURVE

Purpose. *High dependence on land resources is often the main cause of large-scale land conversion and deforestation in Indonesia. However, as a country vulnerable to climate change, Indonesia continues to increase its efforts to improve forest management and reduce deforestation. This is also in line with Indonesia's commitment to reduce emission levels to achieve Net-Zero Emissions by 2060, where the forestry sector will be the base of this achievement. This study aims to measure Indonesia's progress during 1970–2018, especially in reducing deforestation. With this study, we can see trends in forest management in developing countries, especially Indonesia. In addition, based on available data, we can see which factors are most closely related to Indonesia's deforestation rate.*

Methodology / approach. *This study uses a time-series data analysis with Error Correction Method (ECM). This ECM is used to detect the existence of the Environmental Kuznets Curve (EKC), which describes the relationship between environmental degradation and economic variables. In this study, EKC is used to assess further relationship pattern between the Gross Domestic Product (GDP) per capita and deforestation. The relation pattern between this GDP and deforestation is tested using quadratic and cubic models.*

Results. *Under the quadratic model, a classic inverted U-shape EKC is detected in this study. It means that with economic growth and technological improvement, deforestation can be reduced. In other words, Indonesia has improved its forest management. However, as the N-shape relation was also detected in further cubic model simulation, it is also an indication that, at some point, Indonesia is also prone to increase its deforestation again. Another finding from the model is that the palm oil plantation area strongly relates to the deforested area. At the same time, the simulation detects a negative relationship between the horticulture cropland and the deforested area. The result may capture an insight into the forest transition period in Indonesia. In this transition, the government has started to slow down the speed at which forests are exploited in various ways.*

Originality / scientific novelty. *Although the forestry sector is an important economic sector for Indonesia, there is still limited research on this topic, especially at the national level. This study uses more updated statistical information to better describe the Indonesian forestry condition. Moreover, the analysis is aligned with the Indonesian land policy by introducing additional variables from palm oil and crop areas. Moreover, the previous EKC assessments in Indonesia usually only use the quadratic model, which has some limitations in detecting other turning points and seeing the existence of N-shaped or inverted N-shaped EKC. This study also tries to add a bit on cubic model assessment to detect this N-shaped EKC in Indonesia.*

Practical value / implications. *This study gives broader information based on the available data and statistics on the country's deforestation situation and how the economic situation affects it. Policymakers can use the materials from this study to develop an effective forest management system throughout Indonesia.*

Key words: *agroforestry, Environmental Kuznets Curve (EKC), Error Correction Model*

(ECM), forest management, Indonesia.

Introduction and review of literature. Deforestation has become one of Indonesia's main environmental problems. The country's reliance on land resources to boost the economy has increased land conversion and deforestation rates. Indonesia's main export commodities are mostly non-oil and gas products, dominated by products from commercial plantations (e.g., palm oil). As the business grows rapidly, Indonesia focuses on expanding its commercial crops to fill national and international demand. The country has also planned to open the wetlands and peatlands for agricultural land expansion and further boost food production as one of its missions to achieve food sufficiency and become the future 'world food barn' (Husnain, 2020).

The Indonesian government claims that the country has already made progress in forest management and reducing emissions from deforestation and forest degradation (REDD) programmes. This claim is supported by recent national statistics showing a significant decline in deforestation (Figure 1h). Deforestation mainly occurs in areas designated for other use (OTH) and production forests (PF), as those areas are intended for cultivation. However, deforestation patterns are different in each area. For example, although the forest area is small in Java compared to other areas in Indonesia, there is a significantly increasing trend of deforestation in the OTH, PF, and protected forests (PNF). This increase is most likely caused by progressive and aggressive infrastructure development (e.g. the Trans-Java Toll Road development) (Prabowo, 2018), which will affect the land use pattern outside the province. Some areas in outer Java will need to be cultivated for agriculture as a substitute for the cropland in the Java area, which has the highest productivity in the country. This phenomenon might affect the land-use change pattern throughout the area, including the rate of deforestation.

Deforestation has increased in the PNF in Bali and Nusa Tenggara (Figure 1e) because of economic activity, which has resulted in the increased demand for land (Nurrochmat et al., 2019). Sulawesi also observed an increase in deforestation, especially from 2010–2016, as this area is often considered to have a high potential for agricultural expansion, timber harvesting, infrastructure development and the expansion of palm oil plantations, especially in the West Sulawesi area (Siregar, 2019). In other words, deforestation in Indonesia is often triggered by economic decisions.

There is a common belief that with increasing economic growth, a country will focus more on environmental sustainability. Similar to Indonesia, in recent years, the government also put some effort into reducing deforestation by applying some policies like issuance of a moratorium policy on limiting primary forest clearcutting. In some areas like Sumatera, Java, Bali, and Nusa Tenggara, there was also some afforestation in all forest types (can be seen in negative value in Figure 1). But the number of this afforestation cannot offset the number of deforestation in the country. However, Indonesia has unique conditions because its economy relies highly on the land sector, especially because its biggest export income comes from its commercial plantation. This is why deforestation in Indonesia needs constant monitoring, and the country's tendency to reduce deforestation and focus on its economic improvement needs additional verification.

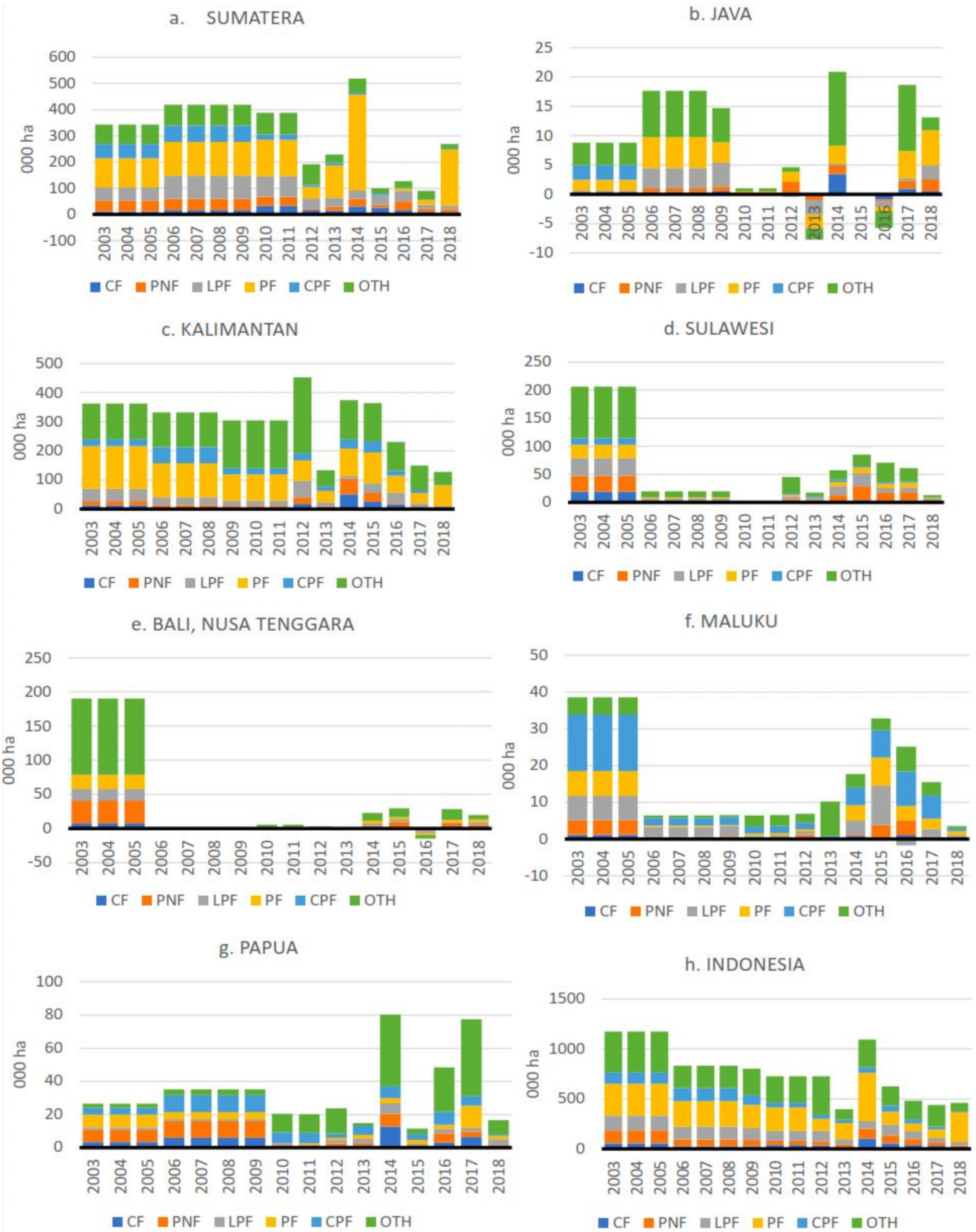


Figure 1. Deforestation rates for each forest type in each region of Indonesia

Note. CF – Conservation forest; PNF – Protected natural forest; LPF – Limited production forest; PF – Production forest, CPF – Convertible production forest; OTH – Area designated for other use; TOT – Total. The negative value in the graphic indicates afforestation.

Source: compiled from Damarraya et al. (2018); KLHK (2014a, 2017, 2020).

There are several methods to assess the relationship between the environmental degradation phenomenon and economic activity. One commonly used method is the Environmental Kuznets curve (EKC). In this study, EKC analyses are conducted to check Indonesia's tendency to manage its forested areas and economic growth. Moreover, the analysis is adjusted with the Indonesian land policy by introducing additional variables from palm oil and crop areas. Using the econometric analysis and recent time-series statistics, it is hoped that this study can give further insight into forest management progress in Indonesia and give some recommendations that suit the Indonesia condition.

1. General Description on Deforestation in Indonesia and the Environmental Kuznets Curve Analysis.

1.1. Deforestation in Indonesia. Based on global trends, countries with tropical forests experience a faster deforestation rate than non-tropical ones. Deforestation in Indonesia is considered a global environmental concern because it has the world's third-largest tropical forest area, and it has unique biodiversity compared to other countries. When compared with the five countries with the largest tropical forest areas in the world, it can be seen that there is a downward trend in the total forest area, especially in Brazil and Indonesia.

If we compare the trend with the one in the Asia region, despite a positive trend in forest area in the region due to a significant increase of forest cover in central Asia (e.g., Tajikistan and Kyrgyzstan) and South Asia (e.g., India and Pakistan) (Potapov et al., 2022), Indonesia still needs to manage a constant decrease in its forest area (Figure 2a).

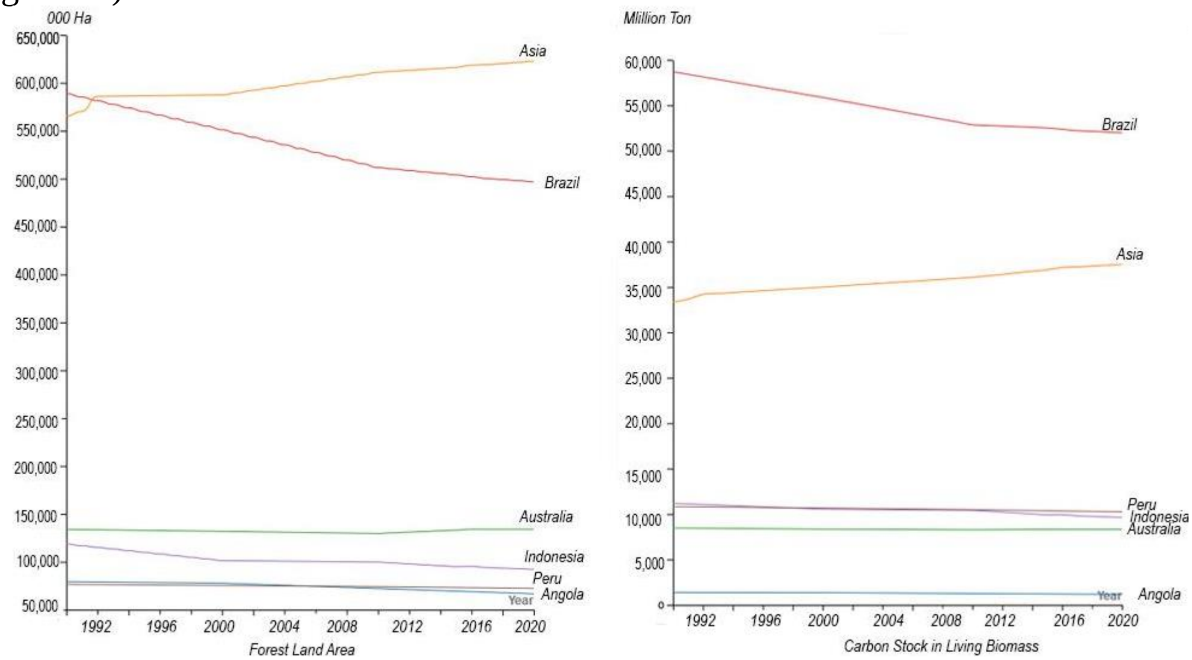


Figure 2. Comparison of forest areas and carbon stock between countries with the widest tropical forest and Asia

Source: FAO (2020).

In addition to the problem of forest area, which tends to decrease annually, according to statistics, Indonesia has also experienced a decrease in carbon stock. As illustrated in Figure 2b, even though Indonesia's forest area is larger than Peru, Indonesia's total carbon stock seems to be lower than that of that country, although it is still higher than Australia's carbon stock which has a wider area of the tropical forest than Indonesia. This at least gives an idea of the decreasing of the density of the forest due to deforestation, either intentional (e.g., land conversion for economic activity) or unintentional (e.g., illegal logging, forest, and peat fire) (Durán & Gianoli, 2013).

Indonesian forests also have quite complex characteristics as they are heterogenic, and many are in peatland areas (Wade et al., 2020). Although peatland areas have a big carbon stock, they are vulnerable to forest fires caused by human activities and temperature changes due to certain climatic phenomena (e.g., El Nino). Forest fires in Indonesia often become a regional problem because the smoke spreads to neighbouring countries and is difficult to extinguish. Furthermore, the high rate of land-use change, deforestation, and forest fires increase Indonesia's emissions. Land-Use Change and Forestry (LUCF) dominate the emission levels, which is a challenge because Indonesia has committed to reducing emissions by 29 % compared to the business-as-usual (BAU) level by 2030 (Republic of Indonesia, 2015).

Historically, Indonesia's high forest deforestation rate allegedly stems from industrialisation since 1970. At first, deforestation was driven by logging for wood harvesting, but since the 1980s, the Indonesian economy has become more export-oriented, and commercial plantation products are cultivated because they are the most in-demand export commodities. Palm oil is in high demand and has become Indonesia's main export commodity, which has driven massive deforestation in commercial plantation areas (Tsujino et al., 2016).

The existence of commercial plantations is considered to be the main cause of forest conversion, and the high rate of deforestation is often used to indicate that the Indonesian government is still more concerned with the economy than environmental sustainability. Indonesian forest governance is complicated because it involves many parties, including local governments, local communities and many political hierarchies (Maxton-Lee, 2018). However, the Indonesian government also pays special attention to the forestry sector because it closely relates to their commitment to the national emission reduction target.

The Indonesian government has paid special attention to reducing deforestation rates to reduce national emission levels and issued a moratorium on clearing palm oil land because the plantations are mostly taken from former forest areas. The moratorium mainly focused on palm oil-producing centres, such as Riau and Kalimantan, and it successfully reduced deforestation. Research on sustainable palm oil is also growing. Nurrochmat et al. (2020) stated that to achieve palm oil production targets, Indonesia did not need to change the function of forest land but could allocate non-forested areas and abandoned land to palm oil plantations.

Although the national deforestation rate has allegedly decreased since the moratorium was introduced, new deforestation sites have started to appear, such as in Sulawesi, Maluku and Papua. Although these areas do not have as large a forest area as Kalimantan, if we add them up, they account for about one-third of Indonesia's primary forest area and have very high biodiversity. It would be unfortunate if land conversion and deforestation shifted to other areas with natural forest ecosystems (Wijaya et al., 2019). Indonesia also needs to realise that the national economy cannot continue to rely on land resources and raw materials, considering that international prices for these commodities will decrease over time as the global community's concern for environmental sustainability increases.

1.2. Environmental Kuznets Curve.

1.2.1. Econometric and Data Analysis Approach for EKC. The method to detect and analyse the EKC varies depending on the variable conditions and the scope. For example, in the case of multiple regions or countries, a panel data analysis method is commonly used, as conducted by Culas (2007). Moreover, the method is more varied when using time-series data because it needs a variable diagnosis before choosing the appropriate regression technique. Some methods that are often used for the time series data are Auto-Regressive Distributed Lag (ARDL) (Waluyo & Terawaki, 2016), vector error correction model (VECM) (Ahmed et al., 2015), Vector Auto-Regressive (VAR) (Minlah et al., 2021a) and also Error Correction Model (ECM) (Bekhet et al., 2020; Koilo, 2019).

The used econometric approach is fully determined based on the data type (time series or panel data), econometric classical assumptions test (e.g., autocorrelation test, multicollinearity test, etc.), and model selection (e.g., common, fixed, or random effect for panel data, VAR, ARDL, or ECM for time series data) (Wooldridge, 2013).

1.2.2. Application of EKC Analysis on Environmental Degradation. As mentioned, the EKC analysis shows the relationship between environmental degradation and economic growth. The EKC hypothesis states that a relationship exists between environmental degradation and income per capita and that environmental degradation increases in the early stage of economic growth. On some levels, countries will improve their environmental quality; therefore, an inverted U-shaped curve represents the relationship between environmental degradation and economic growth. However, in other cases, along with the country's effort to boost the economy, the environmental degradation may worsen, making an inverted U-shaped EKC irrelevant to explain the environment depletion-economic nexus. It makes the EKC study interesting as it is possible to see the pattern between economic growth and environmental problems. A more detailed explanation of the EKC pattern will be explained further in the next section.

The most common environmental depletion assessed using the EKC is the phenomenon of GHG emissions and pollution. Although the most common result of the assessment is the detection of an inverted U-shaped EKC (the emission/pollution increasing at some point but gradually decreasing along with the economic growth), the other pattern of EKC also can be detected. For example, the study of Alam et al. (2016) related to the relationship between GHG emissions and economic growth. The study detected a classic inverted U-shaped EKC in Indonesia, China, and Brazil but the U-shaped EKC in India. There is also a case that the EKC could not be detected, just like found in the study of Liu et al. (2017) when trying to detect the EKC of CO_2 emission in ASEAN-4 (Indonesia, Malaysia, the Philippines, and Thailand) countries and stated that the CO_2 emission level in these countries is more correlated by the supply of non-renewable energies rather than the economic factors.

The EKC analysis also can be further conducted to see the tendency in the future by looking at the N-shaped (a tendency of increasing environmental depletion after the inverted U-shaped pattern) or vice versa (a tendency of decreasing environmental depletion after the U-shaped pattern) as conducted in the study of Allard et al. (2018). Their assessment results show that in low-middle income countries, an N-shaped EKC is detected, which means that although there is a trend that the CO_2 emission started to decrease along with the GDP growth, there is a high tendency that it will increase again at some points in the future, signalling that the countries should always be aware on their CO_2 emission level.

Moreover, the EKC analysis is also used to assess deforestation and forest degradation problems. One of the earliest studies on EKC deforestation was conducted by Cropper & Griffith (1994) by assessing the deforestation pattern in several countries in Africa, Latin America, and Asia. Their findings brought up an important issue to be discussed further. They found that the hump-shaped EKC (inverted U-shaped) was detected in the case of deforestation in Latin America and Africa, indicating that, at some point, income growth may gradually solve environmental problems. However, the assessment needs to be updated and expanded because although economic growth is an important variable, the dynamic of deforestation is very complex and needs further research. After this study, the studies on EKC deforestation are further expanded by introducing more variables.

Culas (2007) used EKC to see the relationship between forest and economic transition and found that there are different EKC patterns between Asia regions (U-shaped curve) and Latin and African regions (Inverted U-shaped curve). That result is similar to the study conducted by Bhattarai & Hammig (2001), except that the Asian region has an Inverted U-shaped EKC instead of a U-shaped one. Ehrhardt-Martinez et al. (2002) also tried to assess the EKC pattern in less developed countries and stated that the inverted U-shaped EKC are detected in those countries. At the country level, especially in the Asian region, there are studies conducted by Waluyo & Terawaki (2016) for the case of Indonesia and Ahmed et al. (2015) for the case of Pakistan. Both country-level assessments detected an Inverted U-shaped relationship between economic growth and deforestation. Outside Asia, a country-level assessment was also conducted by Minlah et al. (2021) to assess the deforestation situation in Ghana and found that a U-shaped EKC curve was detected in the country. Thus, the relationship between deforestation and economic growth can vary between countries, and more analysis is needed. However, due to data limitations, the EKC analysis for deforestation is lesser than the analysis for emission and other environmental depletions. There are also few studies on EKC-deforestation that conduct a further assessment step to determine N-shaped EKC as what will be carried out in this study. One study that further assesses the N-shaped EKC deforestation was conducted by Caravaggio (2020) and became one important input for this research. By assessing the long-term EKC deforestation, this study found that there is a tendency for N-shaped EKC to exist in the case of deforestation. However, as an elevated turning point was detected, it raised some important concerns as well as an opportunity regarding future forest management to prevent another environmental depletion.

A summary of the literature about EKC analysis for environmental depletion can be found in Table 1. This literature summary is not exhaustive. However, it shows some evidence of the methodological approaches and results regarding the EKC assessment.

Table 1

Summary of selected literature related to EKC for deforestation and other environmental depletion

Authors	Econometric Method	Geographical Scope	EKC shape*				Notes
			U	Inv-U	N	Inv-N	
Deforestation/ Forest Degradation							
Cropper and Griffith (1994)	Panel data analysis	Regional (Selected countries in Africa, Latin America, and Asia)		X			Inverted U-shaped: Africa and Latin America
Culas (2007)	Panel data analysis	Regional (Latin America, Africa, Asian)	X	X			Inverted U-shaped: Latin American and Africa U-shaped: Asian
Ehrhardt-Martinez et al. (2002)	Ordinary least squares (OLS)	Multi countries (less developed countries)		X			
Ahmed et al. (2015)	Auto-Regressive Distributed Lag (ARDL) model and vector error correction model (VECM)	Country (Pakistan)		X			
Waluyo & Terawaki (2016)	ARDL	Country (Indonesia)		X			
Minlah et al. (2021)	Vector Auto-Regressive (VAR)	Country (Ghana)	X				
Bhattarai & Hammig (2001)	Weighted least square (GLS)	Regional (Latin America, Africa, Asian)		X			
Caravaggio (2020)	Panel data analysis	Regional (low, medium, and high-income countries)			X		
Other Environmental Depletion (CO_2 emission)							
Liu et al., (2017)	Ordinary least squares (OLS) extensive model	Regional (ASEAN-4)	Not detected				
Alam et al., (2016)	ARDL model	Multi Countries (Indonesia, China, Brazil, and India)	X	X			Inverted U-shaped: Indonesia, China, and Brazil U-shaped: India

Continuation of Table 1

Bekhet et al., (2020)	Error correction model (ECM)	Country (Malaysia)		X			
Koilo (2019)	ECM	Regional (Eastern Europe and Central Asia)		X			
Allard et al., (2018)	Panel Data (cubic model)	Multi Countries (low-, middle-, and high-income countries)			X		

Notes. U – U-shaped; Inv-U – Inverted U-shaped; N – N-shaped; Inv-N – Inverted N-shaped.
Source: systematized by the author.

1.3. Limitation of EKC analysis on environment depletion assessment.

Despite its popularity in assessing the relationship between environmental degradation and the economy, the EKC has been criticized because linear mathematical modelling cannot be simply assessed for environmental degradation and economic growth. The EKC also sees a one-sided relationship between environmental degradation and the economy. Thus, it assumes that environmental damage does not sufficiently reduce economic activity to stop economic growth (Ulucak & Bilgili, 2018). Alternatively, some literature argues that EKC analysis is needed because some countries, especially developing countries, often sacrifice environmental sustainability to boost economic growth, especially countries that largely depend on land resources, such as Indonesia. Thus, along with its strength and weaknesses, more literature on EKC analysis is needed to monitor the government's progress in managing the environment (Zhao & Yang, 2017). The variables involved in EKC analysis also need to be adjusted to fit the current condition. The researcher should be sensitive to the specific circumstances related to current conditions because economic growth is not a single factor in improving the environment or curbing environmental degradation (Choumert et al., 2013).

The purpose of the article. This study aimed to detect the Environmental Kuznets curve of deforestation in Indonesia from 1970–2018 using the Error Correction Method.

Methodology.

1. Data. This study uses time-series data compiled from various sources, primarily national statistics. The data were collected from 1970 to 2018 and transformed into log forms to reduce the outliers in the dependent and independent variables. The data was possibly gathered from interpolation or forecasting methods that create skewed data. Log transformation helps minimise that effect and normalise the data.

For the EKC analysis, the primary data required are environmental disturbances (in this study, the deforested area (DEFF)), the gross domestic product (GDP) per capita and the squared form of GDP per capita. The information will create a quadratic equation to detect the U-shaped curve. To provide more insight into the model, the crop areas (rice fields, horticultural areas, other food crops and palm oil areas) are added as independent variables. Data descriptions can be found in Table 2.

Due to technical issues, the data on deforested areas (DEFF) was compiled from many sources. In Indonesia, forest-related statistics are scattered in several sources due to some transformation in ministry organisation. In the beginning, the forest is managed by the Ministry of Forestry (MoFo), but since 2014, the organisation is then merged with the Ministry of Environment (MoEF). Therefore, the time series data of deforestation and forest area must be traced through many sources. Fortunately, some publications well-documented those data. In their review and study, Tsujino et al. (2016) shared Indonesia's deforestation and forest statistics from 1970 to 2000, which were compiled from the national forest reports written by Indonesia MoFo during that period. The data before 2014 are gathered from reports or journals published in cooperation with the Indonesia Ministry of Forestry. Some data, especially through the period 2000–2015, are also well archived in the FAOSTAT database, as Indonesia had a strong cooperation with the FAO related to land-use-related data compilation during this period. The data after 2014 were more accessible as it is well documented and always updated through the forest reports published by the Indonesia MoEF on their website.

Moreover, although many factors affect Indonesia's deforestation, only limited variables can be introduced for the regression, as many predictor variables will lead to a high intercorrelation between variables. The selection of additional variables for this empirical model after making several considerations, including those related to the serial correlation (Uyanık & Güler, 2013).

Table 2

Description of dependent and independent data

Data	Description	Source	Notes
DEFF	Log form of deforested area, mln ha	Data from 1970 to 2000 gathered from Tsujino et al. (2016). Data after 2000 are compiled from Damarraya et al., 2018; FAO, 2020; KLHK, 2014, 2015, 2017, 2020)	- Dependent variables - Original data in mln ha - To deal with the missing data for several years, the interpolation method is used
GDPCAP	Log form GDP per capita	The World Bank (2020)	- Original data in trillion Indonesian Rupiah (IDR) - In constant LCU (local currency unit)
GDPSQRT	Squared log form of GDP per capita (Log^2GDPCAP)	-	Gained by processing GDPCAP data
HOR	Log form area for horticulture cultivation	(Ministry of Agriculture, 2020b)	Original data in million hectares, mln ha
OFC	Log form area for food crop cultivation (excluding paddy fields)	(Ministry of Agriculture, 2020a)	Original data in mln ha
PAD	Log form area for rice cultivation	(Ministry of Agriculture, 2020a)	Original data in mln ha
PAL	Log form area for palm oil plantation	(Putra et al., 2019)	Original data in mln ha, including all forms of palm oil plantations (smallholders, big and government-owned plantations)

Source: systematized by the author.

2. *Method*. When using the time-series analysis method, several steps must be carried out to ensure that the data used are representative. After ensuring the data, the next step is to decide the time-series estimation appropriate for use and finally specify the model. The EKC form can be seen after the result of the model calculation.

The timeseries classic assumption tests become very crucial in this analysis as it is ensuring the data reliability and as a crucial step to choose the model estimation way. In general, the very first step is to conduct unit root and cointegration tests. The unit root test is used to check whether the mean and variance change over time by taking the autoregressive structure of the time series into account. If all the variables are stationary at level (I(0)), Ordinary Least Squares (OLS) regression can be performed. However, if some variables are stationary at this level while others are stationary in the first difference, the ARDL model, Vector Autoregressive (VAR) model, Error Correction Model (ECM) and Vector Error Correction Model (VECM) are possible methods that can be used to analyse the data. Thus, the unit root test must be followed by the cointegration test.

The cointegration test checks if there is a correlation between two or more nonstationary time series in the long run or for a specified period. If cointegration exists, a decision can be made using the ECM or VECM. This decision depends on whether the focus is on a single operation or a system of equations. The ECM method is chosen if only a single operation is needed (Figure 3).

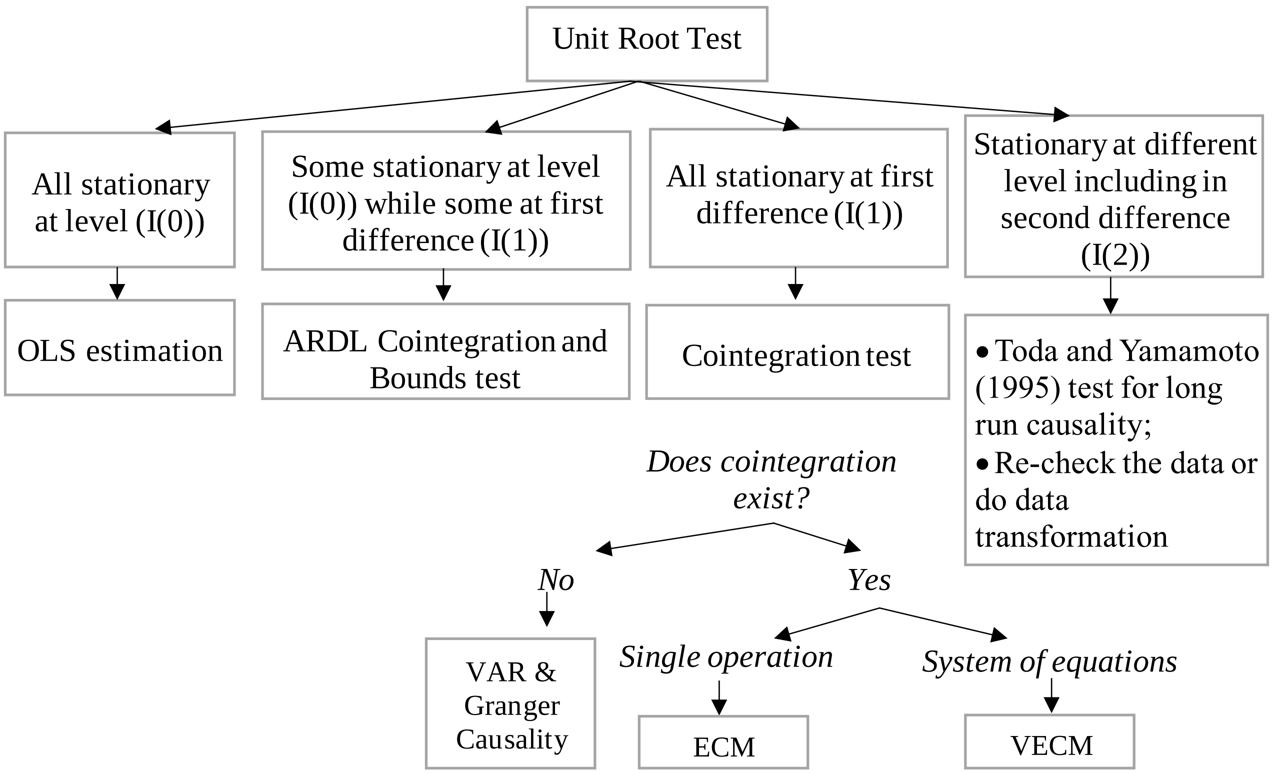


Figure 3. The flow of model selection is based on the unit root and cointegration tests

Source: Jalil & Rao (2019).

After the unit root and cointegration tests, the data still need to pass some diagnostic tests (serial correlation, heteroskedasticity and normality) to ensure that the Best Linear Unbiased Estimators (BLUE) are obtained before the model specification can be made. A more detailed explanation of the diagnostic tests and the model specification is explained in the next subsection.

2.1. Classical Assumption Test.

2.1.1. Unit root, lag length test, and cointegration tests. As previously mentioned, the very first step in the time-series analysis is the unit root and cointegration tests. As the unit root test ensures that the data has a stationary property, its variance and autocorrelation structure should not change, and it should remain constant over time (Prins, 2012). Data need to be stationary to obtain meaningful sample statistics (Mushtaq, 2012). Some data are gained from the official national statistics, and some are obtained from the interpolation process. Thus, it is sometimes impossible to maintain stationarity at a certain level, so the data would then be stationary in the first or second difference.

Unit root tests can determine if the trending data should first be differentiated or regressed on deterministic functions of time. Cointegration techniques can assess the long-run relationships if the variables are I(1). There are several stationarity testing methods, but the most common method is the augmented Dickey-Fuller (ADF) t-statistic. The ADF test verifies the null hypothesis that a time series y is I(1) against the alternative I(0), assuming that the dynamics in the data have an autoregressive moving average (ARMA) structure (Mushtaq, 2012). The simple autoregressive (AR) equation is written as follows:

$$yt = \rho yt - 1 + xt'\sigma + \varepsilon t, \qquad (1)$$

where yt is the endogenous variable and xt is an exogenous regressor that may consist of a constant or trend. Furthermore, ρ are the estimated parameters and εt is assumed to be white noise. The standard DF test estimates the AR equation after subtracting from both sides of the equation (Dickey & Fuller, 1979).

$$\Delta yt = \alpha yt - 1 + xt'\sigma + \varepsilon t, \qquad (2)$$

In the equation above, $\alpha = \rho - 1$. The null and alternative hypotheses may be written as follows:

H0: $\alpha = 0$ (nonstationary);

H1: $\alpha < 0$ (stationary).

In the test, the null hypothesis must be rejected because the p-value needs to be less than 0.05 or depend on the other probability levels chosen (0.01 or 0.1) (Zivot & Wang, 2006).

Besides the ADF test, this study also uses the Phillips-Perron (PP) stationarity test. The PP unit root test slightly differs from the ADF in dealing with serial correlation and heteroskedasticity in the errors. While the ADF tests use a parametric autoregression to approximate the structure of the errors in the regression test, the PP tests omitted any serial autocorrelation. It makes the PP tests more robust to general forms of heteroskedasticity in the error term εt. But at the same time, this test is also more sensitive to the model misspecification (order of any Autoregressive- Moving

Average (ARMA) model) (Hamilton, 1994). Thus, applying both tests to check the stationarity of a model is more advised.

After unit root test, the next stage is to check the lag length. It is a common practice that the ECM used lag=1 when differentiating the transient term and lagging the equilibrium term. However, depending on the length of the data and the system of the model, the lag length needs to be checked additionally. Generally, too many lags inflate the standard errors of coefficient estimates and thus imply an increase in the forecast error. However, omitting the lags that should be included in the model may also lead to estimation bias (Hanck et al., 2022). To confirm the lag length, a common lag test such as Akaike Information Criterion (AIC), Schwarz Criterion (SC) and Hannan Quinn (HQ) are used (Chandio et al., 2019).

The next step is the cointegration test. Theoretically, if time-series data has cointegration, it suggests that the datasets will move together around a long-run equilibrium. This study uses an F-bound test to detect cointegration in the long-run equilibrium. The bounds test is mainly based on the joint F-statistic in that its asymptotic distribution is non-standard under the null hypothesis of no cointegration (Belloumi, 2014).

2.1.2. Regression diagnostic test. After the stationarity and cointegration tests, the model must undergo a further diagnostic test to minimise bias. The regression diagnostic test is applied to any time-series data, and the OLS derivative method ensures that the model is free of serial correlation and heteroskedasticity and that the residuals are normally distributed.

Serial correlation happens when error terms from different, usually adjacent, time-series or cross-section observations are correlated (correlated error term). Although it will not affect the OLS estimators' consistency and unbiasedness, a serial correlation will make the standard error smaller than the 'true' standard error and may cause a tendency to reject the H0 when it should not be rejected (Williams, 2015).

Any OLS regression assumes that all residuals are drawn from a constant variance population. If the error terms do not have constant variance, the estimation will remain unbiased and consistent. However, this reduces the estimators' efficiency, which will decrease the validity of the hypothesis tests conducted on the model, such as the t-test and F-test. In other words, the existence of heteroskedasticity will make the hypothesis test invalid (Barreto & Howland, 2005). To increase the validity of the regression, residual normality is also tested. A straightforward interpretation can be made once the diagnostic analysis shows no correlation, no heteroskedasticity (homoscedasticity) and is a normally distributed (Lobato & Velasco, 2004). As the concepts of ECM, ARDL, VAR and VECM are based on the OLS, a diagnostic test can be performed on the OLS. The Ramsey Rest test was also performed to ensure that it has a correct functional form. Moreover, to test model stability, this study utilised the cumulative sum of recursive residuals (CUSUM), and the cumulative sum of squares of recursive residuals (CUSUMQ) tests as advised by R. L. Brown et al. (1975).

A robustness analysis can be carried out to check the regression result's consistency in estimating the single cointegrating vector. Special forms of the linear regression method can be used, such as the Dynamic Ordinary Least Square (DOLS) estimator and Fully Modified Ordinary Least Squares (FMOLS) regression (Ahmad et al., 2017; EVIEWS, 2019), as these are suitable for ensuring the provision of unbiased estimates of the cointegrating coefficients (Inagaki, 2010).

2.2. Model Specification.

2.2.1. Short-term and long-term equations in ECM. After all the diagnostic tests have been conducted, the model can be specified. In this study, the data transformation was performed using log transformation. The relationship between the dependent and independent variables in this study can be written as follows:

$$DEFF = \alpha + \beta\_1\ GDPCAP + \beta\_2\ GDPSQRT + \beta\_3\ HOR + \beta\_4\ OFC + \beta\_5\ PAD + \beta\_6\ PAL + \varepsilon t, \quad (3)$$

In the above equation:

$DEFF$ – Log of deforested area;

$GDPCAP$ – Log of GDP per capita;

$GDPSQRT$ – $Log^2\ GDPCAP$ (squared from GDP per capita);

HOR – Log of horticulture area;

OFC – Log of food crops area (excluding rice fields and paddy cultivation areas);

PAD – Log of rice field area;

PAL – Log of palm oil plantation area;

α – Constanta;

β – Estimated parameters;

εt – White noise error.

If the model detects cointegration, the equation above is formulated as the long-term equation. Thus, a short-term equation needs to be decided. The short-term relationship between variables for this study can be written as:

$$\Delta DEFF = \alpha + \beta\_1\ \Delta GDPCAP + \beta\_2\ \Delta GDPSQRT + \beta\_3\ \Delta HOR + \beta\_4\ \Delta OFC + \beta\_5\ \Delta PAD + \beta\_6\ \Delta PAL + \beta\_7\ ECT + \varepsilon t, \quad (4)$$

where Δ indicates the first difference form and ECT represents the error correction term. The ECT shows the model adjustment and demonstrates that the model converges to a long equilibrium path when there is a disturbance in the short run (Ahmad et al., 2017). Thus, if ECT's value is significant under the chosen significance level, usually 5%, the short-run model indicates the long-run relationship. Moreover, this ECT value is bounded between 0 and -1, which ensures that the system is convergent (Lebo & Kraft, 2017).

Furthermore, the decision about the EKC's existence is made by comparing the values of $\beta 1$ and $\beta 2$ (Koilo, 2019; Sinha et al., 2019). The details are as follows:

If $\beta_2 = \beta_1 = 0$, there is no relationship between economic growth and environmental degradation.

If $\beta_2 = 0$ and $\beta_1 > 0$, there is a linear relationship.

If $\beta_1 > 0$ and $\beta_2 < 0$, there is an inverted U-shaped, and the EKC hypothesis can be accepted.

If $\beta_1 < 0$ and $\beta_2 > 0$, there is a positive U-shaped relationship.

In most cases, $\beta_1 > 0$ and $\beta_2 < 0$, and an inverted U-shaped EKC curved is detected. It describes the ability to improve environmental quality or gradually reduce environmental depletion and economic growth. However, if the U-shaped curve is shown, it does not prove the EKC hypothesis but may show that a higher dependency on environmental resources results in more exploitation of natural resources (Figure 4).

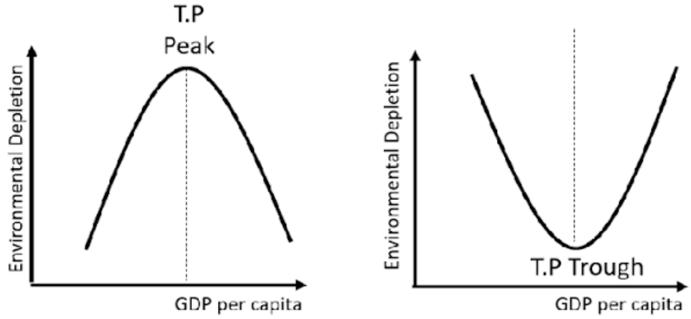


Figure 4. Comparison of classic forms of EKC curve: Inverted U-shaped (left) and U-shaped (right) EKC

Note. T.P – Turning point.

Source: Miah et al. (2011).

The turning point level of the EKC can be obtained by using a similar way to calculate the turning point on the parabola. Thus, in this study, the turning point is calculated by $TP = -\beta_1 / 2\beta_2$. As the equation in this study is already transformed into a log form, the exponential of TP (exp(TP)) is calculated to return the value. The turning point is the monetary value representing that point (Kilinc-Ata & Likhachev, 2022).

2.2.2. N-shaped EKC test (Cubic Model). Because the model uses the logarithmic data, an additional N-shaped model is conducted further to explore the relationship pattern between deforestation and the GDP. This N-shaped model is done by using the cubic model, in which additional cubic form for the GDP per capita (GDP^3) is added. This cubic GDP is written as GDPCUBIC in the equation below:

$$DEFF = \alpha + \beta\_1 \;\; GDPCAP + \beta\_2 \;\; GDPSQRT + \beta\_3 \;\; GDPCUBIC + \beta\_4 \;\; HOR + \beta\_5 \;\; OFC + \beta\_6 \;\; PAD + \beta\_7 \; PAL + \varepsilon t. \qquad (5)$$

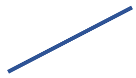
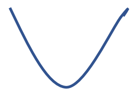
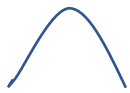
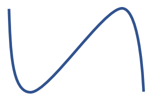
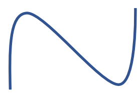
This N-shaped test is recommended for the logarithmic EKC to minimise the potential problem that often arises while using the logarithmic specification that makes the estimation generalised and cannot give a detailed description of the turning points condition. Although there are still some limitations on the EKC estimation using the logarithmic model, it often cannot be avoided, especially in the case of developing countries with limited reliable statistics. Adding a higher polynomial logarithmic is a reasonable way to test the model further and better understand the result's pattern using a "general-to-specific" methodology (Hasanov et al., 2021). Furthermore, as the EKC analysis for deforestation is more complicated as there are many external variables affecting deforestation, an EKC model for deforestation case is suggested to have multiple stages of testing, including using a polynomial approach (Dinda, 2004).

In the cubic case, the relation between deforested area (DEFF) and GDP follows an N-shaped curve if $\beta_3 > 0$. Other patterns also can be seen by looking at the pattern of β_1, β_2, and β_3 (Table 3). An N-shape is detected if $\beta_1 > 0 \; and \; \beta_2^2 - 3\beta_1\beta_3 >$

0. The importance of this N-shaped test is to signify that environmental degradation (in this case, deforestation) starts rising again after a reduction to a specific level, as this pattern cannot be detected by only using a quadratic model (Sterpu et al., 2018). If detected an N-shaped relationship is detected, this cubic model implies that the advantages of increasing GDP per capita to reduce deforestation tend to disappear, or at least get lower, for the highest GDP per capita levels (Pablo-Romero et al., 2023).

Table 3

The relationship between deforestation and the GDP per capita under the cubic model

Values of β_1, β_2 and β_3	The relationship pattern	Graphic (x = GDP, y = deforestation)
$\beta_1 = \beta_2 = \beta_3 = 0$	No relationship between deforestation and GDP	N/A
$\beta_1 < 0$; $\beta_2 = \beta_3 = 0$	Deforestation decreases monotonously along with the GDP growth	
$\beta_1 > 0$; $\beta_2 = \beta_3 = 0$	Deforestation increases monotonously along with the GDP growth	
$\beta_1 < 0$; $\beta_2 > 0$; $\beta_3 = 0$	U-shaped relationship between deforestation and GDP	
$\beta_1 > 0$; $\beta_2 < 0$; $\beta_3 = 0$	Inverted U-shaped relationship between deforestation and GDP	
$\beta_1 < 0$; $\beta_2 > 0$; $\beta_3 < 0$	Inverted N-shaped relationship between deforestation and GDP	
$\beta_1 > 0$; $\beta_2 < 0$; $\beta_3 > 0$	N-shaped relationship between deforestation and GDP	

Source: summarised from Liu (2020).

Results and discussion.

1. General Description of the Raw Data. To get a general description of the situation in Indonesia, the raw data (before being transformed to log form) are firstly illustrated in Figure 5. The dependent variable in this study is the deforested area. As can be seen, during the period 1970–2018, the deforested area in Indonesia decreased, although there was some increase from 2005 until 2010, when the forest moratorium was implemented in Indonesia. After 2010, the decreasing trend keeps continued until now.

On the other hand, Indonesia's GDP per capita is experiencing an increasing trend, although the growth fell in 1998 during the monetary crisis. The increasing trend can also be seen in paddy and palm oil plantation areas. Although there are some dynamics in planting area for paddy due to the land competition for cropland and other uses (e.g., infrastructure and settlements) as the main staple foods for most Indonesian, the area under rice cultivation relatively continues to increase as the government always prioritises the cropland allocation for paddy rice compared to other food crops and horticulture (e.g., vegetables and fruits). That's why we can see in Figure 5 that there are a lot of dynamics for horticulture and other food crops. While for palm oil plantations, it can be seen that there is an obvious constant increase in palm oil plantation areas in Indonesia. Especially since 1980, the growth rate has been growing rapidly and continues until 2018. The explanation behind this trend is that since 1980, palm oil has gradually transformed into one of Indonesia's main export commodities (Baudoin et al., 2017), and the government has also paid special attention to maintaining palm oil production. In some cases, there is forest clearing for the land allocation for palm oil until the government needs to issue the palm oil moratorium policy and keep extending it until September 2021(Safitri, 2021). As the data plotting is not enough to describe the relationship between each variable, the relationship between deforestation with other variables needs to be investigated ad verified further through the empirical assessment described in the next section.

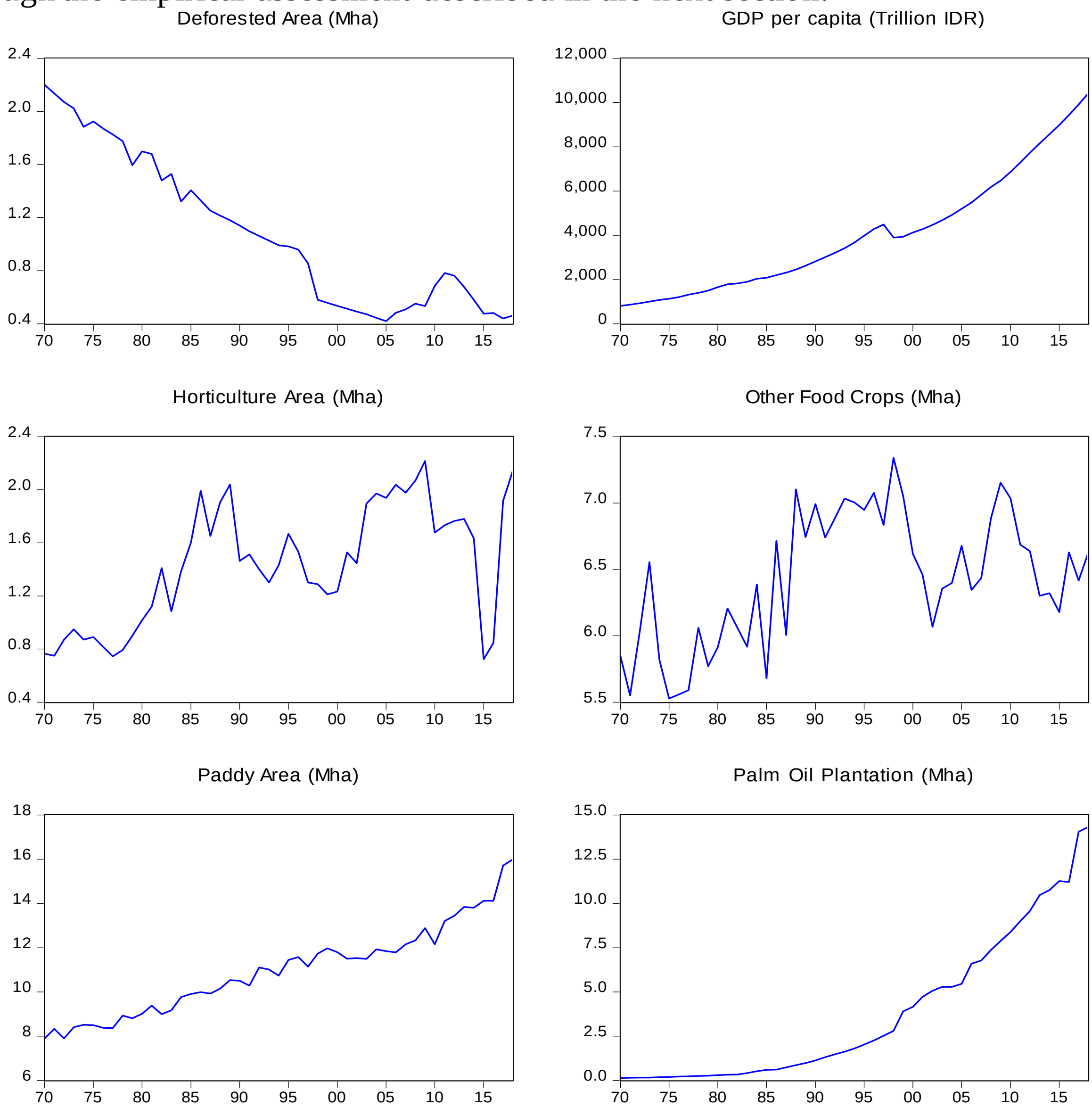


Figure 5. Illustration of the Raw Data for each variable from 1970–2018

Notes. X – axis represent the year.

Source: developed by the author.

Moreover, Table 4, shows the descriptive statistic of each variable. The average of Indonesia's GDP per capita is 3,672 trillion IDR. Moreover, on average, from 1970–2018, 10.98 Mha of land is used for paddy cultivation, 6.43 Mha for other food crops, 3.79 Mha for Palm Oil plantation, while only 1.43 Mha for horticulture (including the cultivation of fruits, nuts, and vegetables). During that period, on average, 1.08 Mha of forest are deforested annually. By looking at the maximum value, it is also seen that the area allocated for palm oil plantation almost overtakes the land area for paddy. Considering the big gap between the minimum and maximum value and higher standard deviation of areas of paddy, other food crops, and horticulture indicates the very rapid growth of this sector.

Table 4

Descriptive Statistic for each variable in the study

Description	GDPCAP	DEFF	HOR	OFC	PAD	PAL
Mean	4034.315	1.080	1.433	6.432	10.976	3.794
Median	3672.538	0.991	1.447	6.434	11.103	1.804
Maximum	10425.40	2.200	2.217	7.341	15.994	14.327
Minimum	805.733	0.419	0.723	5.527	7.897	1.333
Std. Dev.	2683.524	0.563	0.449	0.492	2.021	4.152

Note. GDPCAP – GDP/capita, trillion IDR; DEFF – deforested area, Mha; HOR – horticulture area, Mha; OFC – other food crops area, Mha; PAL – palm oil plantation area, Mha.

Source: developed by the author.

2. Unit root, cointegration, and stability tests. This study used the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test to check the data's stationarity level. Both the ADF and PP tests show that all the variables are stationary in the first difference, as indicated by the probability (ρ) of less than a 5 % significance level (Table 5).

Table 5

Results of the stationarity test

Variable	Augmented Dickey-Fuller (ADF)				Philips-Perron (PP)			
	Level I(0)		First difference I(1)		Level I(0)		First difference I(1)	
	t-statistic	probability	t-statistic	probability	t-statistic	probability	t-statistic	probability
DEFF	-0.923	0.772	-5.425	0.000***	-0.977	0.754	-5.425	0.000***
GDPCAP	-1.689	0.431	-4.917	0.000***	-1.536	0.507	-4.939	0.000***
GDPSQRT	-0.520	0.878	-8.081	0.000***	-0.499	0.882	-5.051	0.000***
GDPCUB[1]	-1.689	0.431	-4.917	0.000***	-1.689	0.431	-4.917	0.000***
HOR	-2.418	0.142	-6.358	0.000***	-2.249	0.192	-7.284	0.000***
OFC	-2.230	0.199	-11.799	0.000***	-2.538	0.113	-11.798	0.000***
PAD	-0.768	0.992	-7.609	0.000***	-1.244	0.998	-9.340	0.000***
PAL	-1.022	0.738	-6.986	0.000***	-1.045	0.730	-6.989	0.000***

Note. ** 5% level of significance; ***1% level of significance; 1) use for cubic model in the N-test.

Source: simulation result using EViews 11 University.

After the stationarity test, the lag of the model was also checked. In this study, the lag is checked based on some lag test criteria: AIC, SC, and HQ. Generally, we choose the lag length for which the values of most of these lag length criteria are minimized, which is indicated by an asterisk sign when checked by EViews software. All of the lag tests select lag 1 as the best lag length for the model (Table 6).

Table 6

Lag Length Test based on Lag length Criteria

Lag	AIC	SC	HQ
0	-8.467	-8.229	-8.378
1	-18.005*	-16.335*	-17.379*
2	-17.764	-14.664	-16.602
3	-17.572	-13.041	-15.875

Notes. *Indicates the selected lag by the criterion.

Criterion: AIC – Akaike Information Criterion; SC – Schwarz Information Criterion, HQ – Hannan-Quinn Information Criterion.

Source: simulation result using EViews 11 University.

As all the variables are stationary at the first difference (I(1)), the cointegration test must be conducted to detect each variable's relationship in the long-term equilibrium. The cointegration test in this study was carried out using an F-bound test, and from the result, it is evident that there is a clear long-run relationship between the variables when DEFF is the dependent variable. This is because its F-statistic (6.529) is higher than the upper-bound critical value (3.99) at the 1 % level. This implies that the null hypothesis (h_0) of no cointegration among the equation's variables is rejected (Table 7).

Table 7

F-bound test for DEFF

Variable	Lags	F-stat
DEFF	1	6.529
Lower-bound critical value at 1 %	2.88	
Upper-bound critical value at 1 %	3.99	

Note. Lower- and upper-bound critical values are taken from Pesaran et al. (2001).

Source: simulation result using EViews 11 University.

As the stationarity test shows that all the variables are stationary at the first difference (I(1)) and cointegration exists, the analysis can be continued using the ECM or VECM methods. However, as this study focuses on DEFF's affecting factors, only a single equation will be involved. Thus, the ECM will be useful for analysing the long-run relationship confirmed by the test.

Another important step that must be taken to ensure the model's validity is conducting diagnostic tests for serial correlation, heteroskedasticity, normality, and the specification test. This study used the Breusch–Godfrey test for the serial test, the Breusch–Pagan–Godfrey test and Harvey test for heteroskedasticity and the histogram normality test to check residual normality. Moreover, the Ramsey RESET (regression Specification Error Test) is done to check the model specification. The test results reveal that the probability was higher than the 0.5 % significance level; therefore, the decision was made not to reject H0 in all the tests (Table 8).

As already mentioned before, the stability of the CUSUM and the CUSUMQ are also conducted to check the stability of the model. These stability test results are shown in Figure 6, and as indicated in both cases, the model was found to be stable within the critical bound at the 5 % level.

Table 8

Diagnostic test for DEFF

Diagnostic test	Null hypothesis	F-stat	Probability	Decision
Breusch–Godfrey serial correlation LM test	H0: No serial correlation	1.559	0.223	Do not reject H_0
Heteroskedasticity test: Breusch–Pagan–Godfrey	H0: Homoskedasticity	1.978	0.092	Do not reject H_0
Heteroskedasticity test: Harvey	H0: Homoskedasticity	1.227	0.313	Do not reject H_0
Normality test	H0: Residuals are normally distributed	-	0.191	Do not reject H_0
Ramsey RESET Test	H0: No omitted variables	2.723	0.107	Do not Reject H_0

Source: developed by the author.

As the testing shows that the model is stable enough, thus it can be said that it is already well-specified and therefore, stable. Thus, we can continue to interpret the result.

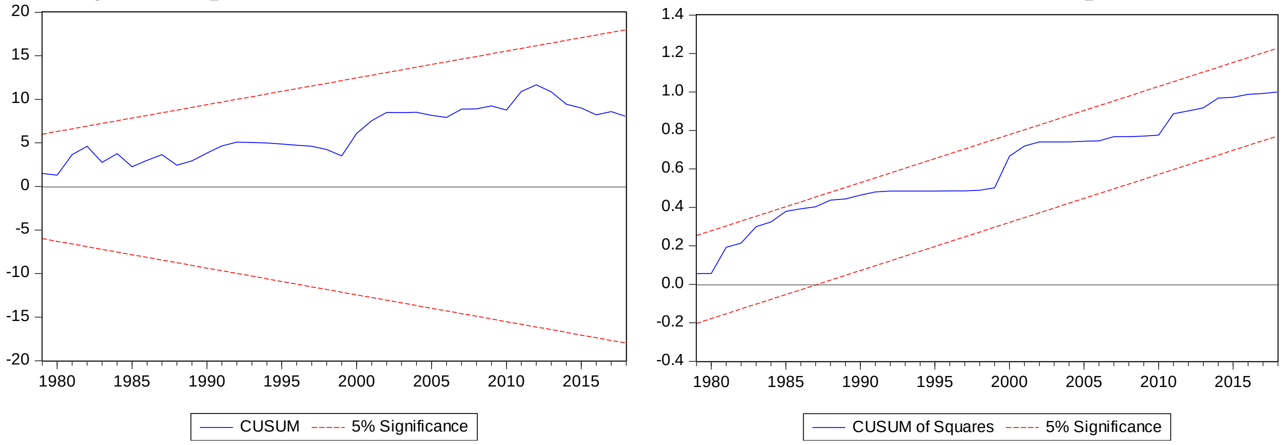


Figure 6. Result of CUSUM test (left) and CUSUMQ test (right)

Source: developed by the author.

3. Estimation result.

3.1. ECM's estimation result. The ECM's estimation result is summarised in Table 6. The error correction value is negative (-0.384) and significant at a 5 % significance level in the short-run equation. This confirms the validity of the long-run relationship in the equation. Another significant result in the short-run equation is DEFF(-1), which indicates that in the short-run, the deforested area was primarily affected by deforestation in previous years. More insight can be gained by interpreting the long-run estimation (Table 6).

The first insight from the long-run result is that DEFF has a positive relationship with GDPCAP (β_1) and a negative relationship with GDPSQRT (β_2). As $\beta_1 > 0$ and $\beta_2 < 0$, both values are significant at a 5 % significance level; therefore, the model indicates an N-shaped relationship between economic growth and deforestation. Thus, the EKC hypothesis can be accepted. Furthermore, the model detects a very significant positive relationship between the DEFF and PAL, which indicates that a bigger area for palm oil plantations increased the DEFF in the simulation period of 1970–2018.

HOR has a significant negative relationship with the DEFF, which indicates that adding land for horticulture decreased the deforested area during the simulation period. Thus, it may provide insight into the positive impact of agroforestry, which was introduced on a large scale in one of the main REDD programmes.

Moreover, for the short-term analysis, it is important to see the value of the Error Correction Term (ECT). As mentioned, the range of this ECT value is bounded between 0 and -1 that indicates the convergency of the system. In this study, the ECT value is significant, with the value -0.384 confirming the model's cointegration. This ECT also refers to the return to equilibrium when there is a shock (the speed of convergence) (Khan et al., 2022). The ECT result here indicates that the error from the previous period is corrected by 38.4 % in the current period (Table 9).

As mentioned, an additional N-shape test by running the cubic logarithmic model is also conducted. This simulation is to check whether there is also an N-shaped or inverted N-shaped pattern. The inverted U-curve followed by the N-shaped shows that, although there is a tendency for the level of environmental degradation to decrease as the economy develops, at certain points, the country tends to re-exploit the environment. This check is useful, especially for detecting the tendency of environmental exploitation in developing countries (Allard et al., 2018). By seeing the simulation result under the cubic model, it can be seen that $\beta_1 > 0$; $\beta_2 < 0$; $\beta_3 > 0$. Thus, it can be said that an N-shaped of relationship is detected in this model.

Table 9

Short-run and long-run ECM estimation results

Variable	Coefficient	Probability	Coefficient	Probability
	Quadratic		*Cubic*[1)]	
Long-run estimation				
GDPCAP (β_1)	**33.276**	**0.004****	**16.872**	**0.052***
GDPSQRT (β_2)	**-23.162**	**0.000*****	-8.636	0.829
GDPCUB (β_3)	**-**	**-**	**0.007**	**0.003*****
HOR	**-4.414**	**0.031****	0.107	0.287
OFC	-10.128	0.254	0.642	0.481
PAD	-11.002	0.581	-0.828	0.972
PAL	**19.618**	**0.000*****	**0.718**	**0.000*****
Adj. R^2		*0.925*		0.946
Short-run estimation				
ΔDEFF (-1)	**0.487**	**0.019****	**0.427**	**0.013****
ΔGDPCAP (-1)	2.999	0.936	0.143	0.318
ΔGDPSQRT (-1)	0.349	0.986	-1.100	0.326
ΔGDPCUB (-1)	-	-	**0.007**	**0.001*****
ΔHOR (-1)	0.049	0.979	0.039	0.467
ΔOFC (-1)	2.236	0.719	0.141	0.411
ΔPAD (-1)	-4.078	0.714	-0.407	0.189
ΔPAL (-1)	0.236	0.967	0.190	0.513
ECT	**-0.384**	**0.014****	**-0.157**	**0.041****

Notes. **5% level of significance; ***1% level of significance; **bold** indicates a significant value. [1)] N – shaped test.

Source: simulation result using Eviews 11 University.

3.2. Robustness check for long-run coefficient. Another form of the regression process was carried out as an additional step to check the robustness of the long-run coefficient result and its consistency. This additional check is only done to the quadratic model as it is only to test model reliability further. In this study, the long-run result was compared with FMOLS and DOLS. The long-run regression analysis results follow a similar trend of a positive relationship between the DEFF and PAL and a negative relationship between the DEFF and HOR. These results also support the indication of EKC for deforestation in Indonesia during 1970–2018, as there is a significant negative value for β_2 (GDPSQRT) and a positive value for β_1 (GDPCAP) (Table 10).

Table 10

Regression results in the FMOLS and DOLS simulation

Variables	FMOLS	P-values	DOLS	P-values
GDPCAP	**34.924**	**0.034****	**35.911**	**0.004****
GDPSQRT	**-25.244**	**0.005*****	**-24.185**	**0.001*****
HOR	**-6.730**	**0.014****	**-5.113**	**0.088***
OFC	24.153	0.116	15. 275	0.258
PAD	-16.038	0.313	-16.377	0.540
PAL	**18.732**	**0.000*****	**16.518**	**0.000*****
Adj. R2	0.933		0.940	

Notes. *10 % level of significance; **5 % level of significance; ***1 % level of significance; **bold** indicates a significant value.

Source: simulation result using EViews 11 University.

Discussion. Under the quadratic model, the simulation result demonstrates that in the long run, GDP (β_1) > 0 and GDPSQRT (β_2) < 0, which indicates that the EKC has an inverted U-shape in Indonesia. Using the equation of turning point $x = -\beta_1 / 2\beta_2$, we get $x = 0.692$. Returning this log form by using exponential gives $x = 1.998$ with x as GDP per capita (in Trillion IDR). This result is strengthened by the robustness test using FMOLS and DOLS. The result of these tests indicates that when technological advancement and improved production factors are available (long-term effect), Indonesia tends to reduce deforestation along with economic growth. The model detected a strong correlation between deforestation and palm oil plantation areas and a negative relationship between deforestation and horticulture. However, based on the data used in this study, there was not enough evidence to see the correlation between deforestation and rice field cultivation or other food crop areas.

This result is driven by the Indonesian economy's high dependency on the land-based sector, especially commercial plantations, industrial forests and agriculture. However, along with the use of more advanced technology in land management, Indonesia has started to find a way to maintain its deforestation rate. Nevertheless, we also need to consider research by Bhattarai & Hammig (2001), who found that it was also possible that in a country experiencing a transitional EKC curve, the N-shaped curve could be changed into a U-shaped curve if there was a lack of institutional effort on forest management or the country continued to rely heavily on the natural resource extraction with significant improvements in technology. The importance of institutional policy and regulation is also stated by Adedoyin et al. (2020), who suggest that regulation has a strong relationship with environmental damage. Therefore, we also need to monitor other factors that influence deforestation in Indonesia, especially variables that are positively associated with deforestation.

The simulation showed that the PAL positively correlated with the DEFF, which indicates that between 1970 and 2018, the expansion of palm oil plantations resulted in more deforestation. This result also aligns with the fact that palm oil has already become one of Indonesia's main economic and export commodities (Malahayati, 2018). Palm oil plantation areas have expanded vastly throughout the country, from only 120,000 ha in 1969 to around 1.1 Mha in 1990 and reaching more than 10 Mha in 2013. During these periods, the global demand for palm oil products increased rapidly in the food industries and biofuel. Indonesia tried to take advantage of this by supplying more palm oil products, aiming to use the supplementary income to reduce poverty and boost economic growth. Unfortunately, the lack of sustainable forest management during that period resulted in high deforestation for commercial plantation expansion (Susanti & Maryudi, 2016).

However, as Indonesia is committed to reducing its emissions through Nationally Determined Commitments (NDCs), the country must take specific actions, including reducing land-use change emissions. The country has also realised the importance of conserving natural forests and peatlands. In 2011, Indonesia enacted Presidential Instruction No. 10/2011 as the first phase of the forest moratorium policy, with palm oil plantations as the main object of attention. Under this instruction, land conversion in natural forests and peatland areas was terminated for two years. Although this decision was rejected by some industries, the government insisted on enacting the policy and making adjustments to more sustainable development (Joyosemito et al., 2014). Using technology to increase crop yield and participate in rejuvenation programmes was also initiated (Novika, 2020). The policy had a positive socio-environmental impact, and the deforestation rate decreased in regions with high commercial plantation areas, such as Central Kalimantan (Sumarga & Hein, 2016) and the Riau province (Ramdani & Hino, 2013). If all the Nurrochmat et al. (2020), land clearing for palm oil can be reduced sustainably. Even if land extension is required, palm oil plantations can take advantage of non-forest land.

The long-run simulation also indicates a negative relationship between horticulture and deforestation. In other words, the deforestation rate tends to decrease during land expansion for agriculture. This result is expected to be closely related to the increasing adoption of agroforestry in Indonesia. It is easier for horticulture plants to be planted inside the forest without putting too much pressure on the natural forest. Traditional home gardens, to some extent, also resemble the vegetation structure and composition of natural forests. Thus, these factors make it easier for horticulture plants to grow alongside natural forest vegetation (Wirono et al., 2016). The introduction of agroforestry to crop diversification has caused little disturbance in the forest ecosystem, and agroforestry can also sustain the hydrological cycle between forests and rainfed agriculture (Samsuri et al., 2014). This method is also believed to increase smallholder farmers' incomes (Paembonan et al., 2017). This finding also aligns with a previous study by Waluyo & Terawaki (2016), who found no indication that agriculture positively relates to deforestation. In their paper, they state that technological progress in agriculture must reduce the speed of deforestation.

The empirical simulation result also shows no significant relationship between paddy and other food crops. Indonesia's central rice cultivation centres are on Java Island, and its cultivation requires more complex technologies and treatment than other crops (Boer et al., 2016). It is unlikely that it can be carried out on a large scale outside Java, as land characteristics, temperature and geographical conditions are different. Although specific cultivation technologies for rice plantations are required outside the Javan area, through the Indonesian Ministry of Agriculture, the Indonesian government has continued to expand the paddy field area outside the island of Java. However, this effort is constrained by budget limitations (Widiatmaka et al., 2016).

Due to the climate and soil conditions, other food crops (e.g., corn and tubers) will most likely be expanded outside Java. However, the cultivation of non-paddy crops as food alternatives is constrained by several factors such as demand, marketing and lack of labour. Most labourers outside Java prefer to move to Java to find jobs. As Indonesia's staple food demand is still dominated by rice, farmers outside Java face lower demands for their produce if they cultivate other crops as substitutes for paddy. Furthermore, Indonesia is a vast archipelagic country, making the transportation of any crops between provinces challenging. A lack of advanced storage and food processing technologies makes food crops susceptible to damage when transported over a long distance (Budhi, 2016).

Furthermore, in the short-run simulation, the model indicates that no variables impacted the deforestation rate, except deforestation from previous years and GDP per capita. This result may prove that only Indonesia's production factors and technological advancements may have a significant role in avoiding the aggravation of deforestation. Moreover, converting forests into land for other use will require years, as this will involve the land clearing process, new crops, plant cultivation and waiting time for the harvest (Brown & Lugo, 1994). Thus, this can only be implemented by adding labour or more efficient production factors.

Another interesting finding is, a further check of through the cubic model simulation found that $\beta_1 = 0.007$ and $\beta_2^2 - 3\beta_1\beta_3 = 0.354$. This fulfils the condition for N-shaped EKC that is $\beta_1 > 0$ *and* $\beta_2^2 - 3\beta_1\beta_3 > 0$. This "N-shaped" EKC means that in Indonesia, there is a tendency for the country to increase again the deforestation rate. Study by Caravaggio (2020) stated that it is a common pattern in low-middle income countries: when the forests begin to increase and recover, the exploitation might happen again, especially if the country does not have a modern policies and management to address this issue.

Policy implications. Although the empirical simulation results in an inverted U-shaped, indicating the reduction of deforestation alongside an increase in GDP per capita, the government must still be very careful when making policies. Especially because a further check on the model show that there is a tendency that the deforestation might increase again in the future (N-shaped EKC).

As mentioned before, Indonesia's government often relies on land to boost the economy. In the wake of the COVID-19 pandemic, the government has planned to open more than 900,000 ha of wetlands and peatlands (Nurhadi, 2020; Rosana & Widyastuti, 2020), which is in line with their plan to expand the global food and agricultural market and their ambition to become a global leader in the palm oil market (Ministry of Agriculture, 2019). This policy can potentially create another wave of deforestation and peatland exploitation. Thus, the government must consider the land expansion plan and focus on the technological improvements needed to increase yield, store crops and diversify food production. In terms of palm oil, the need for land expansion is because its yield is very small, especially in smallholder plantations. In 2017, around 40.6 % of the palm oil plantations in Indonesia were smallholder plantations, but at the same time, the average growth rate of these plantations was very high (around 7.03 % per year from 2010–2019) (Putra et al., 2019). Therefore, the government must pay attention to smallholdings, and some REDD incentives must be introduced to encourage farmers to carry out land rejuvenation according to the requirements.

The agroforestry system with the joint planting of multipurpose trees, shrubs and annual and perennial crops (i.e., home–garden agroforestry) can be introduced to the forest society. According to this simulation, the home–garden agroforestry system can reduce deforestation while empowering communities to maintain and utilise forest land. Moreover, based on recent findings, this kind of diversification also believed to enhance biodiversity in cropping systems, is suggested to promote ecosystem services, thereby reducing dependency on agronomic inputs while maintaining high crop yields. Widespread adoption of any diversification practices contributes to biodiversity conservation and food security (Tamburini et al., 2020). The Indonesian government plans to introduce an agroforestry system and has already launched many agroforestry systems like social and community forests. As the system shows a positive impact on reducing the deforestation rate, it is recommended that the government maintain and improve this effort. With the right management, the forest society can still undertake its economic activity in the forest ecosystem without large-scale forest clearance.

Indonesian forests are transforming. According to the results of this study, after periods of decreasing forest cover, the government has started to slow down forest exploitation. However, perennial crops, such as palm oil, sometimes need more space, which drives additional deforestation. This kind of forest transition is very common, especially in developing countries (Barbier et al., 2010), so the government needs to ensure that there will be no overexploitation in any form around the forest area. As already mentioned, a detected N-shaped EKC curve indicates a tendency for deforestation to increase again. However, it can also be seen as an opportunity to learn and prepare, so the country can avoid the second turning point, which means another phase of increasing deforestation.

Learning from other countries experiences, sometimes the REDD effort only focuses on increasing forest cover but not on the recovery of the forest's quality, diversity and productivity. For example, although the government already invest a lot in afforestation projects, China is still experiencing huge forest exploitation due to rapid growth in non-timber products and agroforest tourism (Ke et al., 2020). This situation could be repeated in Indonesia if forest areas are not monitored properly or there is a lack of evaluation processes. Thus, forest planning, monitoring and evaluation are needed to maintain and improve progress. This can also help control the rate of unplanned deforestation, which still occurs regularly in Indonesia. Zafeiriou et al. (2022) stated that when an N-shaped EKC is detected, a country needs to keep updating the forest management system and increase the productivity of industrial forests and other lands so the deforestation rate can be keep maintained at a manageable level.

Conclusions. This study aimed to detect the EKC of deforestation in Indonesia from 1970–2018 using the ECM. The regression result detected the existence of a reserved U-shaped EKC (under the quadratic model) and N-shaped EKC (under the cubic model), indicating that after periods of massive deforestation, Indonesia has started to slow down deforestation along with its GDP growth. However, the government still needs to be careful as there is a probability that this deforestation will increase again if the Indonesian government does not provide more advanced technologies to improve the land productivity and forest management system.

This result aligns with the Indonesian government's decision to enact the forest moratorium policy in 2011, which has been extended several times. According to the moratorium policy, land conversion should be minimised in terms of land clearing in natural forests and peatlands. The simulation also captures the palm oil plantation area’s tendency to correlate with the deforested area positively, and there is an indication that horticulture areas negatively correlate with deforested areas. The result reveals that the expansion of palm oil plantations has become one of the drivers of deforestation in Indonesia. However, introducing agroforestry by cultivating horticulture crops may reduce the deforestation rate.

The results of this study provide evidence that Indonesia is progressing in slowing down the deforestation rate. However, the country still tends to make economic policies that rely heavily on land use; for example, opening wetlands and peatlands to boost food crop production. The rate of national deforestation will increase significantly if this policy is not revised. Increased crop productivity through improved pre- and post-harvest technologies as well as improved crop storage and transportation technologies may be policy choices that the government can implement before making large-scale land-use changes.

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