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The Relationship Between Tourism Development with Primary Forest in Indonesia

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Abstract: To further develop Indonesian tourism, the Indonesian government designed a program to develop 10 new Indonesian "Bali" destinations. The majority of these new 'Bali' destinations are located outside Java Island that contain primary forests with high endemic species. Since 2004, Indonesia's government have released several policies to further develop tourism destination outside of Bali such as *Rencana Induk Pembangunan Kepariwisataan Nasional* (RIPPARNAS) dan Destination Management Organization (DMO). The relationship between tourism development and forest cover is a subject of active discussion, and there is little empirical research on the topic. This study aims to examine the correlation of tourism development (hotel beds) with primary forest cover. The data used in the study are Global Forest Watch's forest cover image data, Global Administration Data System's land cover data, and Indonesia Central Agency of Statistics socio-economic publication data from 32 Indonesian provinces in 2011-2016. Through the use of a clustered fixed effects regression model, this study found that tourism has no significant relationship with primary forest area in Indonesia.

Keywords: Clustered fixed effect; Deforestation; Forest transition; Indonesia; Primary Forest; Tourism.

Introduction

Indonesia's forest and its biodiversity has provided Indonesia through a wide range of benefits like habitat formation, foods , biochemicals, and climate regulation (Nugroho et al., 2022). Biodiversity rates are higher in forest land that hasn't been changed by human activity, which is commonly called primary forest (Garg, 2019). Primary forest loss can substantially reduce carbon-storing stocks and impose disease outbreak threats (Dwiyahreni et al., 2021; Indrajaya et al., 2022). Once changed, primary forest can't be

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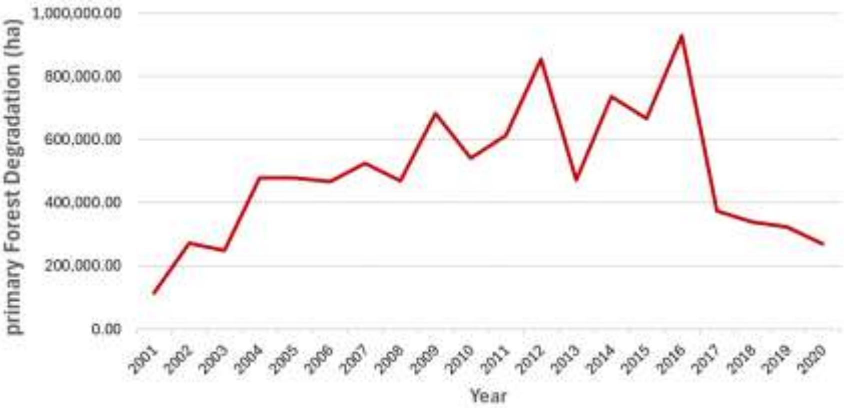
restored into its initial environmental potential *value* due to the loss of its original biodiversity and ecosystem that cannot be recovered through reforestation (Barbier et al., 2017).

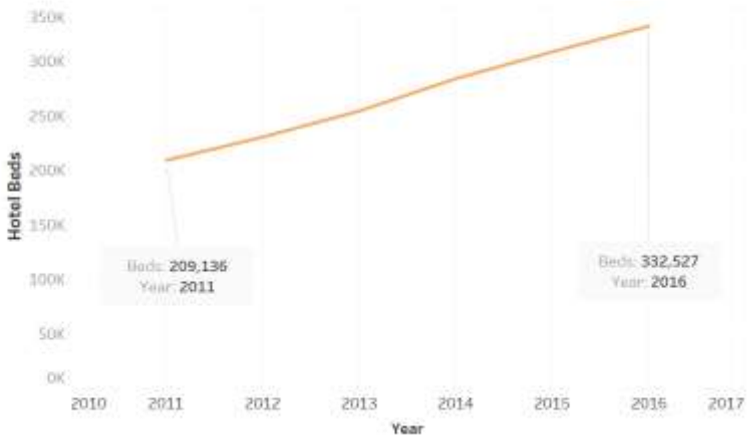
Indonesia have implemented policies to reduce deforestation since early 1980's by banning log export in 1982 and implementing forest protection laws in 1985. But despite the aforementioned efforts, primary forest degradation continues to be a problem. Indonesia's primary forest has been experiencing excessive extractive usage with its forest cover have been degraded about 9.86 million hectares during 2000 to 2020 (Hansen et al., 2013). Primary forest degradation's trend have been constantly increased from 2001 to 2016 and then followed by constant decreasing trend from 2017 (see Figure 1). Dwiyahreni *et al.* (2021) have found that Indonesia's primary forest degradation also happened in 43 national parks, which lost 1.62% of their total primary forest cover during 2012-2017. Indonesia still has deforestation problem that threaten its biodiversity value even in protected areas.



Source: Hansen et al. (2013)

Figure 1. Primary Forest Degradation's Trend in Indonesia 2001-2020

Indonesia government also additionally began establishing new approach for forest conservation through ecotourism by establishing national park (NP) starting from 1980 (Pamungkas & Jones, 2021). Indonesia government have also introduced several tourism development policies since then. Since 2004, Indonesia Government have issued several policies to increase Indonesia tourism in several destination, such as *Rencana Kebijakan Rencana Induk Pembangunan Kepariwisataan Nasional (RIPPARNAS)* and Destination Management Organization (DMO) (Judisseno, 2015). RIPPARNAS serves as a guideline for national and local tourism development in the 2011-2025 period. Meanwhile, DMO has been implemented since 2010 with the intention to further develop local tourism industry by increasing tourist visit, its length of stay, and its tourism spending (Pusat Studi Pariwisata Universitas Gadjah Mada, 2021). If measured using number of hotel beds, Indonesia tourism development experiences growth from 2011 to 2016 (see Figure 2).



Source: Annual Survey of Accommodation Service Providers (VHTL) (in Badan Pusat Statistik, 2025)

Figure 2. Hotel Beds Growth in Indonesia 2011-2016

Further discussion should be put more on tourism and its effect on the environment in Indonesia, especially on the forest. Various studies have showed that forest's degradation in protected areas such as NPs and conservation areas, can be caused by forest land use change to tourism infrastructure land (Marhaento et al., 2020; Purwanto et al., 2023). Radianto et al. (2019) showed that economic development led by tourism correlates with mangrove tree cover degradation. Furthermore, Dwiyahreni et al. (2021) found that Batimurung Bulusaraung NP, which has a consistent tourism activity, has one of the lowest primary forest degradation rates (p. 1239).

As an economic activity, tourism destination (especially ecotourism) utilize forest and natural sight as a resource for tourism activity (Inchausti-Sintes, 2023). Tourism can push for the conservation efforts of their natural destination and have a "positive externalities" effects, such as lowering unemployment rates and agriculture extensification (Gazoni & Brasileiro, 2018, 2022; Inchausti-Sintes, 2023; Kim et al., 2016; Mahadevan et al., 2017). But tourism activities can also cause further excessive deforestation from negative externalities, especially if the tourism activity exceeds the destination's natural capacity or what is commonly known as "overtourism" (Koens et al., 2018; Marsiglio, 2017; Nepal & Nepal, 2021). The relationship between tourism and forest cover is still being argued, as the relationship is tied with other socio-economic confounding variables (Bojanic & Warnick, 2020; Nguyen et al., 2022).

Deforestation phenomenon in Indonesia and other tropical countries

Deforestation is arguably common in a tropical developing country like Indonesia; forest woods are extracted to be imported to boost initial economic growth, and its lands are converted to accommodate initial growing population needs, such as for agricultural production and housing (E. B. Barbier & Burgess, 2022; Imai et al., 2018). Deforestation in Indonesia started in Java and Bali Island in the 1950's due to the high population density that increased the need for forest land use change (Santoro et al., 2023). Indonesia outer islands (islands beside java and Bali) began to experience deforestation from the 1960's to early 1980's due to rising timber production and export (Indrajaya et al., 2022; Tsujino et al., 2016).

Deforestation rate risen from 1977 to 1987, which is attributed to both timber industry and illegal logging activities (H. Hidayat, 2016; Tsujino et al., 2016). In the early

1980's, Indonesia government started to push for domestic owned timber production rather to replace the foreign owned timber corporations, that ultimately leads to a

There is a rise in deforestation from 1977 to 1987 that is attributed to timber industry but also to illegal logging. Indonesia government started to push for domestic timber market by encouraging capitalist to developed domestic plywood industry in the early 1980's and also banning roundwood export ban in 1985 to ensure supply for the domestic market (H. Hidayat, 2016). Early 1980's also marked a new wave of agriculture production outside of Java and Kalimantan, such as production of palm oil, plywood, and pulp production (H. Hidayat, 2016; T. A. Hidayat, 2019). Transmigration programs and rising demands for skilled laborers in the palm and plywood industry have risen outer island agriculture activity and subsequent deforestation (H. Hidayat, 2016; Koizumi, 2022; Simpson, 2021).

Since 1997, Indonesia experienced a massive growth of arable and crop land caused by a rise of large-scale palm oil production incentivized by rising crude palm oil prices (Gaveau et al., 2022; Guye & Kraus, 2022). The rise of crude palm oil prices in 2001 have also risen the opportunity cost of forest preservation, as landowners could earn more profit by converting it for palm oil cultivation (E. B. Barbier & Burgess, 2022). Furthermore, local political leaders favored to push for oil palm industry adaptation in their local economy due to its economic boost that will also ease their reelection (Gaveau et al., 2022). Government support for palm oil production and lack of forest protection policy have allowed palm oil fields expansion to be the driver for one-third of deforestation in Indonesia from 2001 to 2019 (Santosa et al., 2020; Tsujino et al., 2016).

After a rise of deforestation rate during 2010-2016, primary forest and natural forest land use change have been slowing down (Hansen et al., 2013). This can results from the decline of palm oil prices, the forest moratorium policy enacted in 2011, and other climate factors (Gaveau et al., 2022, 2019). The curve-like pattern of Indonesia deforestation rate from 1980 to 2017 can suggest the existence of Environmental Kuznets Curve (EKC) pattern in deforestation rate. The EKC hypothesis states that as the economy develops, the rate of environmental degradation will rise approximately until a turning point in economic development during which environmental degradation started to slowed down and eventually decreased (Caravaggio, 2020). Previous research by Adila et al (2021) have shown the validity of mentioned deforestation EKC in Indonesia.

The EKC hypothesis on deforestation also implies further theory of deforestation such as Forest Development Path (FDP) and Forest Transition (FT). Both hypothesis similarly states that the "turning point" of forest deforestation rates will decline and reach a negative value that can be inferred as reforestation (Caravaggio, 2020). But there hasn't been any research that supported the existence of FDP and FT in Indonesia. We can't also generalize the slowing down of primary forest deforestation rate as a sign of both theories existence in Indonesia, because there hasn't been any sign of Indonesia reaching the tipping point of reforestation yet (Walters, 2023).

Indonesia also additionally began establishing new approach for forest conservation through ecotourism by establishing national parks starting from 1980 (Pamungkas & Jones, 2021). This brings a new discussion about whether tourism development can help to protect primary forests. As a forest protection effort, tourism can decrease forest to agriculture land conversion by increasing job opportunities and shift agriculture employment to tourism and alternative jobs (Pandya et al., 2023). Tourism industry that uses environmental attributes as a resource (like beaches and forest) may also push for sustainable practice to keep their tourism spot's attractive value (Gazoni & Brasileiro, 2018, 2022; Inchausti-Sintes, 2023; Saavedra, 2022). Meanwhile in the international macroeconomics context, Kocak and Cavusoglu (2024) have found domestic tourism short run positive effect on deforestation in high income countries such as United States and United Kingdom.

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There are also previous contradictory findings that found tourism to cause or further push deforestation rates. First, tourism can induce land use change for tourism and its supporting infrastructure such as, agriculture, food manufacturing, and energy (Kocak & Cavusoglu, 2024; Nguyen et al., 2022). Tourism negative environmental externalities doesn't always come from direct tourism activity but can also come from indirect causes such as economic growth (Kyara et al., 2022). In deforestation case, Tourism can induce urban areas and road growth that can accelerate deforestation rates due to easier market access to forest land (Tuholske et al., 2017).

Previous research has also pointed out the dynamic aspect of tourism effect on forest, such as the existence of "curve" like pattern reminiscence of EKC and FT hypothesis. Tourism may have positive environmental effects in early stages, but it may reach a point where tourism development will have negative environmental impact, and vice versa (Liu et al., 2022). For example, Nguyen et al., (2022) found that although initially tourism doesn't have any relationship with forest change in high income economy, tourism will have a significant negative impact in the long run. However, "curve" hypothesis like FT and EKC forest land have been treated with skepticism as the correlation between economic growth and forest land is heterogenous across countries (Ajanaku & Collins, 2021; Assa, 2021; Pablo-Romero et al., 2023; Walters, 2023). The discussion on tourism effects on forest land presents a classic problem in human activity and landscape change research, which are the high degree of heterogeneity and context specific causes that bring difficulties for theoretical generalization (Walters, 2023).

There have been several studies conducted on the relationship between tourism and deforestation in Indonesia. However, those studies are focused on geographical aspect (Marhaento et al., 2020; Purwanto et al., 2023), other forest type such as mangrove (Radianto et al., 2019), limited to a particular region (Pamungkas & Jones, 2021), and only includes Indonesia as one of the individuals in an international macroeconomics research (Nguyen et al., 2022). It remains a challenge to empirically determine tourism effect to primary forest in Indonesia due to a lack of focused study on mentioned relationship.

Previous studies have put a great concern on the relationship between tourism growth and deforestation in Indonesia, such as in research by Pamungkas and Jones (2021) and Radianto et al. (2019). However, prior studies are focused on the general forest land and rather than primary forest, whose environmental benefit can't be fully restored by reforestation efforts. Therefore, we aim to study the correlation between tourism and primary forest cover in Indonesia. By doing so, we intend to fill knowledge gaps on the relationship between tourism and primary forest cover and provide further insight into tourism development policy. Considering that previous research by Pamungkas and Jones (2021) showed that tourism may cause primary forest in tourism hotspot, we hypothesize that tourism has a negative relationship with primary forest cover.

To ensure study accuracy, we use regression model with economic and socio-demographic control variables that correlate with deforestation. The heterogeneity of Indonesia's province can also limit the study accuracy, so we use panel data that consist observation of 32 province in 2011-2016 period. Proper regression methods will be picked based on the Best Linear Unbiased Regression (BLUE) assumptions and model suitability test. Ultimately, this study findings will serve as a foundation for us to provide policy recommendation for tourism development in Indonesia.

Research Method

Data description

We use panel regression to investigate Indonesia's tourism development relationship with deforestation. Panel regression, which utilizes panel data, can help to handle unobserved heterogeneity and individual effects. We choose to construct panel data based on province as the observation unit and year as the time unit. We use secondary data collected from three separate sources to construct this study's panel data. Primary forest cover, which is calculated from primary forest area and potential forest vegetation, is gathered from Global Land Analysis and Discovery (GLAD) database (Hansen et al., 2013). For the independent variables, we obtained them from Indonesia's Central Bureau of Statistics (BPS) various publication. A thorough reginal tourism data in BPS is only available after the year 2010 and then 2017's tourism data is missing due to halted data collection activities. Hence, we choose 2011-2016 as the time period for our observations sample to ensure complete data on each Indonesia province.

We choose to use all Indonesian's province observation except for Special Region of Yogyakarta due to it not having the primary forest cover (all the primary forest cover in it have been changed by human activity at the starting observation period). Furthermore, during the 2011-2016 observation period, North Kalimantan Province was established from the East Kalimantan's Province land in 2012. As it was once one province, we chose to merge the two provinces observation as East Kalimantan for this study. Therefore, this study's panel dataset is made up of observation time period of 2011 to 2016 (T=6) and includes 32 Province in Indonesia (N= 32), which summed up to 198 observations (6 x 32).

Primary Forest Cover

Previous research on the relationship between economy and forest area commonly used forest areas (ha/km), deforestation size, or deforestation rate as their dependent variable. But, Köthke et al. (2013) points out two weaknesses of using forest area and deforestation as the dependent variable in a cross-section study, which are: 1) The difference between the deforestation and reforestation phase starting point due to human activity; and 2) Unit's area limitations for forest growth due to geographical characteristics. Therefore, we choose to use Primary Forest Cover (PFC) as the dependent variable based on the Köthke et al. (2013) research.

In order to get a normalized PFC of each region, we first extracted primary forest area (ha) and the potential forest area (Fpot). We choose 2 dataset to calculate PFC which are Global Land Analysis and Discovery's land cover database (GLAD) database (Hansen et al., 2013). Hansen et al. (2013) database has detailed information on forest areas, which it divides into 3 groups based on the human activity impact, which are primary forest, secondary forest, and non-forest land. In accordance with the observation sample period, we use GLAD 2010 land cover data to obtain the potential forest cover data. We then divide the primary forest area with potential forest areas to get the PFC percentage. The PFC can be explained through equation (1).

$$\boxed{PFC_{i,t} = \frac{PFA_{i,t}}{Fpot_i}} \qquad (1)$$

Where: PFC = Primary Forest cover; PFA: Primary Forest area; Fpot =Potential area suitable for primary forest cover; i = Province; t = Year

Primary Forest is defined by Hansen et al. (2013) as mature natural humid tropical forest cover has not been completely cleared and regrown in recent history. Meanwhile potential forest areas are derived from areas that are suitable for forest growth, such as cropland, shrub cover, and secondary forest area (see Table 1). As in Ferrer Velasco et al. (2020) research, we excluded built-up land from potential forest area as it is not suitable for rapid land cover changes to accommodate forest growth (Hooke et al., 2012).

Table 1. Land and Forest Cover Used in this Study

Land cover category	**Land cover types**	**Characteristic**
Primary Forest	Primary Forest Area	As defined in (Hansen et al., 2013), Mature natural humid tropical forest cover that has not been completely cleared and regrown in recent history. Primary forest is a part of tree cover, which is an area that at least 30% covered with vegetation taller than 5 meters in height as of 2000.
Potential Forest	Tree cover (secondary forest)	Land cover that has vegetation taller than 5 meters and has a canopy percentage greater than 5 percent of total land cover pixel observation.
	Cropland	Land that is covered and used to produce annual crops for human consumption, and it includes both irrigated and non-irrigated fields.
	Plantation	Land that is covered and used to produce vegetation taller than 5 meters that is used for human consumption, forage, and biofuel.
	Shrubland	Land that is covered by short vegetation at least 75% of the pixel observation.

Source: Author's Analysis, 2024

Tourism (Hotel Beds Density)

Tourism activity can be measured by different metrics such as number of visit, tourist spending, and number of hotel. Borrego-Domínguez et al. (2022) found that hotel beds positively correlated with tourism demands. Hotel beds change has also been used previously as a proxy for tourism development in Minetos and Polyzos (2010) research. In this study, we use hotels beds controlled by province area as proxy of the density of tourism activity which will be called Hotel Beds Density (HBD). We use extracted datasets from BPS that included the number of beds in a rated hotel and province size (km^2).

Control Variable

We considered four socio-economic variables to control for confounding aspect of forest and tourism interaction. To control economic development, we use Regional Gross Domestic Product (GDPR) per capita, which is derived from dividing the total GDPR by the total population. We hypothesize that GDPR per capita has negative relationship with primary forest cover because that Indonesian economy is still developing and thus still prone to forest land use change (Adila et al., 2021; Liu et al., 2017). Agriculture expansion is also a common researched driver of deforestation in Indonesia. We use agriculture contribution to total GDPR to control agriculture intensification, that is derived from dividing regional agriculture sector GDPR to total GDPR. Agriculture GDPR contribution is assumed to have a negative relationship with Primary Forest Cover due to the rise of agriculture expansion that drives forest's land use change (Cisneros et al., 2021; Heilmayr et al., 2020; Leijten et al., 2021). For both economic variables, we use a GDPR value at constant 2010 prices from BPS.

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Population density can also drive deforestation by increasing pressure for the primary forest land to be utilize for wood production and converted for infrastructure (Ferrer Velasco et al., 2020; Köthke et al., 2013). In this study, we calculated population density as population pressure, which is derived from the total population divided by province areas. In regard of the socio-demographic aspect, we also utilize literacy rate as control variable because the conservation effort of primary forest is also supported by the local population understanding of local conservation laws and the importance of it (Assa, 2021).

Descriptive statistics of the whole Indonesia province shows that the population pressure and beds density have relatively much higher standard deviation (SD) than the mean. This can indicate high variability due to outliers and skewed distribution in mentioned variables. Tsujino et al. (2016) argued that the high variability of Indonesia's population density is caused by the high population density concentration in Indonesia's "inner island" (Java, Bali, and Lombok) that is attributed to its fertile volcanic soils (p.33). In the topic of inner and outer island of Indonesia, Hailu et al. (2018) exclude Java and Bali's from the study observation due to the high variable value difference between it and the "outer island". Therefore, we choose to investigate the "outer island" of Indonesia as a separate observation group. We define the "outer island" as province located outside of Java and Bali region (6 province excluded in the outer island observation group).

Descriptive statistic shows that "outer island" has lower hotel beds density, GDPR per capita, and Population pressure's mean than the whole observation. Which shows that the outer island has lower tourism and economic activity than the whole Indonesia observation. On the contrary, 'outer island' has a higher primary cover than the whole observation. This validates the previous assumption that the 'outer island' has relatively less disturbed forest areas than Java and Bali. But with the higher Agriculture GDPR contribution, the 'outer island' forest can be further threatened by agriculture extensification.

Table 2. Descriptive Statistics Samples of Indonesia and the Outer Island

		Whole Indonesia (N=192)		Outer Islands (N=156)	
Variable	**Unit**	**Mean**	**SD**	**Mean**	**SD**
Primary Forest Cover	Percentage (%)	35.613	25.273	42.740	22.59706
Hotel Beds density	Unit/km^2	2.647353	12.60721	0.137	.3365078
GDPR per capita	Billion rupiah/person	.0349691	.0286151	0.0326	.0246769
Regional Agriculture GDP Contribution	Percentage (%)	20.50538	9.668295	23.06923	8.555986
Population Pressure	Person/km^2	1941798	1.08e+07	554.9957	859.1127
Literacy Rate	Percentage (%)	94.44	5.93	94.47126	6.324933

Source: Author's Analysis, 2024

Model Specifications

This paper analyzes the relationship between tourism and primary forest cover using regression model with panel data. Our regression model assumes that tourism (hotel bed density) and primary forest cover have an instantaneous or short run relationship. That means we assume that primary forest's value will change in accordance with tourism variable and other independent control variables value within the time period unit. Various studies have studies previously investigates using deforestation and its correlated variables using changes in forest cover (forest cover's yearly difference) as the dependent variable and/or using dynamic regression model using lagged value of the dependent and independent variables (Aisbett et al., 2017). Aisbett et al. (2017) argues that by using changes in forest cover as the main dependent variable then the model is ad hoc and prone to both data snooping and misspecification (p. 3). Therefore, this study chooses to use static panel data regression using primary forest cover as the dependent variable.

Previous research has showed that forest deforestation in Indonesia is caused by several confounding factors such as economic development, agriculture extensification, and socio-demographic dynamics. Therefore, to ensure model accuracy, our model incorporates control variables to assess Omitted Variable Bias (OVB) in the model. Control variables that are used in this model are Regional Gross Regional Product (GDPR) *per capita*, agriculture sector GDPR contribution to total GDPR, population pressure, and literacy rate.

This study uses a regression model double-log functional form to ensure normal data distribution and homogeneity. Double-log function form is achieved by transforming variables' value to its natural logarithm form (ln), except for primary forest cover and literacy rate that have percentage value. Previous research regarding the relationship between tourism and deforestation and other environmental subjects have also used the double log model, such as in Kongbuamai et al. (2020), Leblois wt al. (2017), and Raihan et al. (2023). Based on the previous description, the double-log regression model can be specified as the following equation (2):

$$\boxed{\begin{aligned} PFC_{i,t} = \beta_0 + \beta_1 \ln bed_{dense i,t} &+ \beta_2 \ln GRPpc_{i,t} \\ &+ \beta_3 ContAgri_{i,t} + \beta_4 ln\ PopPr_{i,t} \\ &+ \beta_5 Lit\_rate_{i,t} + \varepsilon_{i,t} \end{aligned}} \tag{2}$$

Where: PFC = Primary forest cover; bed_dense: Rated hotel's bed density in a province *i* area; GDPRpc = gross domestic product of region (GDPR) per capita; ContAgri: Agriculture GDPR percentage on the total GDPR; PopPr: Population size divided by the primary forest area; Lit_Rate: Percentage of population that can read and write at least in one type of script; β1= constant value; β1- β_5 = Regression coefficient; ε = error terms; i = Province; t = Year

Based on the literature study, we hypothesize that tourism (proxied by hotel beds density) has a negative relationship with primary forest cover, in which tourism increase is correlated with primary forest cover decrease. Economic control variables, which are GDPR per capita and Agriculture GDPR contribution, are hypothesized to have a negative correlation with primary forest cover. Population pressure is also hypothesized to have a negative relationship with primary forest cover. On the contrary, we hypothesize that literacy rate has a positive relationship with primary forest cover.

To ensure model accuracy, we also conduct BLUE assumptions and model specification tests. We tested 3 BLUE assumption which are no multicollinearity, homoscedasticity, no autocorrelation. We utilize 3 tests for BLUE assumptions checking, which are Variance Inflation Factor (VIF), Breusch-Pagan/Cook-Weisberg, and Wooldridge test. BLUE assumption test is done to ensure model's suitability for a regression analysis. Meanwhile the model specification test consists of Moran's, Chow, and Hausmann test. We considered 3 regression methods for this study such as Spatial regression, Pooled OLS, and Fixed/Random Model. The best suited regression method will be chosen based on the mentioned model specification test results.

Results and Discussions

As previously mentioned, this study ensures model estimation compatibility by performing BLUE test followed by model specification test, which test results specified in table (3). The VIF test was performed first and showed that there is no variable that has VIF value over 5, on which we concluded that there is no multicollinearity problem in the model. However, Breusch-Pagan/Cook-Weisberg revealed that there is a heteroskedasticity problem in the model. This is followed by Wooldridge test that showed that there is autocorrelation in the model as well. Both problems will be further discussed in the following passage.

Table 3. BLUE assumption and Model Suitability Test Results

Test	Metric	P-value	Conclusion
Breusch–Pagan/Cook–Weisberg	Chi2 = 35.790	0.0000	Heteroskedasticity
Wooldridge	F test = 58.633	0.0000	Autocorrelated (AR1)
Moran's I test	$Chi^2(2) = 0.260$	0.8799	Errors terms are i.i.d
Chow test	F test = 25.820	0.0000	Individual Effect
Hausmann test	Chi2 = 45.140	0.0000	Fixed Effect

Source: Author's Analysis, 2024

Meanwhile Moran's I test shows that there is no spatial autocorrelation between observation's variable in the model, so it can be concluded that there is no need for spatial regression model to account for spatial autocorrelation. Furthermore, Chow test showed that Pooled OLS is not appropriate for the model due to the individual effect of the variables. The final test is the Hausmann test, that showed that fixed effect model is more suitable to use in the study than random effect model. To accommodate for heteroskedasticity and autocorrelation problem, we choose to use fixed effect model with clustered standard errors (Jackson, 2020). Clustered standard error estimator is used with the assumption that model residuals have correlation within the cluster but not between the cluster. Clustered standard error have also been used on other deforestation research such as in Alesina et al. (2014) and Kubitza et al. (2018).

Empirical Result

This study aims to investigate the relationship between tourism development and primary forest. As mentioned before, Indonesia deforestation phenomenon and its related variables are not distributed evenly between its provinces. Therefore, we conducted two fixed effect double log regressions on two different geographical contexts, one using every province observation and one only using province outside of Bali and Java or the "outer island". Both Hailu et al. (2018) and Wheeler et al. (2012) have use the "outer island" geographical context to avoid heterogeneity due to Java and Bali's higher economic development state. We conducted additional regression in "the outer island" to explore the dynamic between tourism development and primary forest cover in areas that economies are still developing and have higher primary forest cover than Java and Bali Island.

Estimation (1) concludes fixed effect regression result using only province observation outside of Java and Bali Island (N=156). That estimation has an F-test value of 0.000 which showed fixed effect regression is suited for the model. Estimation (1) R^2 value showed that the model can explain 83.01% of the variation in "the outer island" observations. Meanwhile estimation (2) is the main estimation that includes all Indonesia province observations (N=192). Estimation (2)'s F-test value also shows that fixed effect regression is suited for the model. According to Estimation (2) R^2 value, the model can explain 63.85% of the variations in the observation.

Estimation (1) shows that tourism doesn't have significant relationship with primary forest. At a significance level of 5%, a 1% increase in GDPR per capita correlated to a 0.157% decrease in primary forest cover. Both socio-economic variables have a significant relationship with primary forest cover. A 1% rise in population pressure is correlated with 15.587% decrease of primary forest cover at a 1% significance level. Conversely, a 1% rise in literacy rate is correlated with 0.197% increase of primary forest cover in 1% significance level. Meanwhile, it is estimated that Regional Agriculture GDP Contribution has no significant relationship with primary forest cover in estimation (1).

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Table 4. Fixed Effect Regression Estimations

Dependent Variable = Primary Forest Cover (%)		
	(1) Province outside Java and Bali Island	**(2)** All Observation
Tourism Variable		
Hotel's bed density (ln)	- 0.232 (0.179)	- 0.167 (0.208)
Control Variable		
GDPR per capita (ln)	- 0.157** (0.709)	- 0.053 (0.146)
Regional Agriculture GDP Contribution (ln)	- 0.067 (0.063)	0.065 (0.062)
Population pressure (ln)	-15.587*** (1.632)	- 15.27*** (1.616)
Literacy rate (%)	0.197*** (0.049)	0.181*** (0.043)
Constant	104.6962	115.2121
R^2	0.8031	0.6385
F	0.0000	0.0000
Clustered Fixed Effect	Yes	Yes
N	156	192

Source: Author's Analysis, 2024

Estimation (2) also found that tourism does not have a significant relationship with primary forest cover. Estimation (2) only found that only socio-economic variables have a significant relationship with primary forest cover. At 1% significance rate, a 1% rise of population pressure correlates with 15.27% decrease of primary forest cover. Meanwhile, a 1% increase in literacy rate correlates with a 0.181% increase in primary forest cover at 1% significance level. Meanwhile, both GDPR per capita and Regional Agriculture GDP contribution aren't found to be significant in estimation (2).

Discussion

We have explored the relationship between tourism development and primary forest cover through clustered fixed effect regression. Mentioned regression results showed that tourism don't have significant relationship with primary forest cover in either using the whole Indonesia province and the outer islands observations. Our finding is consistent with Nguyen et al. (2022) research, which states that tourism doesn't have significant short term relationship with forest changes in Upper Middle Economy (UME) countries which includes Indonesia. Moreover, Kocak and Cavusoglu (2024) found no tourism-forest land correlation in Thailand, another Southeast Asia country, but rather it is found on high income countries such as United Stated and several UAE countries. Our findings supported the notion that tourism doesn't have a significant short-term role in UME country like Indonesia.

Regression result showed that GDPR per capita only showed a negative relationship in the estimation that only uses the outer island's province observations. Previous findings have found that GDP has a negative correlation with forest land (Adila et al., 2021). But there's also several research that found no correlation between GDP with forest land or deforestation (Hidayati et al., 2017; Kurniawan, 2021). Our finding suggests that the heterogeneity of GDP correlation significance in previous studies to be caused by different development difference of inner and outer island as noted in Wheeler et al. (2012) research. The potential argument for the different economic development phase of inner and outer island is that outer island economy only began to rise due to the timber extraction rise and transmigration program started in the early 1970's (Simpson, 2021). But there is little empirical evidence on later hypothesis and our finding doesn't directly confirm it.

Population pressure has a consistent significant negative relationship with two estimation results. A negative relationship between population density and forest cover is found in both high-income regions such as Europe and developing regions like Southeast

Asia (Ferrer Velasco et al., 2020; Hellwig, Walz, & Markovic, 2019; Imai et al., 2018; J. Liu et al., 2017). Previous research have also found significant negative correlation between population density and forest land in Indonesia (Adila et al., 2021; Darmawan et al., 2016; Hidayati et al., 2017). Although there are several previous research have found no correlation of population density with forest land (Kurniawan, 2021; Surandoko, 2021), these findings can be caused by different independent variable in Kurniawan (2021) research and different regression type in Surandoko (2021).

Estimation results also showed that literation rate has a significant positive relationship with primary forest cover. This supports Assa (2021) findings that literacy rate to be positively correlated with forest cover in developing countries with tropical climate. But Fischer et al. (2021) found that literacy rate to be negatively correlated with forest area through deforestation. However, Fischer et al. (2021) concluded that since the study sample used had the relatively highest literacy rate then the negative correlation doesn't reflect the nature of literacy rate itself but rather it reflected forest land use of the educated settlers.

Conclusion

This study has found that there is no relationship between tourism and primary forest in Indonesia. Furthermore, this study has found several socio-economic variables that positively correlated with primary forest cover. GDPR per capita has a negative relationship with primary cover based on estimation using the outer island observation set. Population pressure also has a negative relationship with primary forest cover on both whole Indonesia and outer island estimations. Literacy rate is the only variable that is found to have a positive correlation with primary forest cover, and it is also found on both estimations.

We conclude several policy recommendations regarding tourism development and primary forest land use change based on this study findings. Although it is found that tourism development doesn't correlates with primary forest, Indonesian government should be aware of mentioned socio-economic variables that affected primary forest deforestation such as population pressure and GDPR per capita. Especially considering that both variables can be boosted by economic development through tourism. Outer island and/or province with relatively high primary forest cover is also more susceptible to deforestation as estimation showed that GDPR per capita is significant, and population pressure has a higher deforestation correlation in the "outer island" estimation.

We acknowledge that this study has certain limitations, which can serve as guide for further research. This study uses static panel data regress, which does not account for the dynamic aspect of deforestation such as time lag and other time dynamic determinants. Furthermore, the use of province as an observation unit means that we are assuming that variable's values in that unit are homogeneous across the province area. Which is not always true, in some cases the use of more detailed geographical units (such as smaller regional observations unit and grid squares) can reveal primary forest hotspots or urban areas that have high population and regional GDP.

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