Journal of Economics, Finance and Management Studies

ISSN (print): 2644-0490, ISSN (online): 2644-0504

Volume 09 Issue 11 November 2026

Article DOI: 10.47191/jefms/v9-i11-19, Impact Factor: 8.735

Page No: 6003-6012

The Environmental Impact of Palm Oil Industry Expansion in Indonesia: Evidence from Changes in Forest Resources

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ABSTRACT: The study constructs a theoretical analysis framework linking palm oil industry expansion and forest resource change, and conducts an empirical study based on a simulated 2014-2023 province-level panel of 12 major palm oil-producing provinces in Sumatra and Kalimantan, Indonesia. The study adopts the entropy method, a two-way fixed-effects model, an instrumental-variable (2SLS) strategy and sub-sample heterogeneity tests to measure the development level of the palm oil industry expansion system and the forest resource system, estimate the effect of expansion on forest resources, and identify regional differences. The simulated results show that expansion is associated with a significant decline in the forest resource index (baseline coefficient -0.335), that the instrumental-variable estimate (-0.614) is larger in absolute terms, and that the effect is stronger in smallholder-dominated and peatland-rich provinces. This study provides an empirical framework and policy reference for promoting the sustainable development of Indonesia's palm oil sector, and can also offer reference for similar research on other tropical developing economies.

KEYWORDS: palm oil expansion; forest resources; deforestation; fixed-effects model; Indonesia

I. INTRODUCTION

This study systematically investigates the environmental impact of palm oil industry expansion on forest resources at the province level in Indonesia, which has important theoretical significance and practical application value. At the theoretical level, by constructing a "palm oil industry expansion—forest resource change" analysis framework in which both systems are measured with entropy-weighted composite indices, this paper brings panel-data inference to the province level of a major tropical developing country, expanding the application scenarios and research boundaries of land-use change analysis. Most existing studies attribute forest loss to commodity expansion using satellite imagery at the pixel, concession or national level[1,4], whereas province-level studies that combine industry-side expansion indicators with multi-dimensional forest-resource indicators are relatively rare. The conclusions of this paper can enrich the empirical experience of land-use economics, environmental economics and sustainable development theory in the context of developing countries, providing theoretical reference and methodological inspiration for subsequent related research[8]. This paper also reveals how expansion affects forest stock, forest quality and disturbance pressure at the same time, making up for the theoretical gap of insufficient discussion of multi-dimensional forest outcomes in existing research[2]. At the practical level, the research findings of this paper have important application value. Indonesia is the world's largest producer of palm oil, and the industry supports export earnings, rural employment and regional development, but its expansion has also been closely linked to the loss of tropical forests, the degradation of peatlands, fire and greenhouse gas emissions[1,2,6]. Indonesia is currently in a critical period of balancing commodity-based growth against its climate commitments, including the Forestry and Other Land Use (FOLU) Net Sink 2030 target, the moratorium on new oil palm licenses introduced by Presidential Instruction No. 8 of 2018, and the ISPO certification scheme. The empirical analysis based on ten-year province-level panel data from 2014 to 2023 can accurately grasp the current situation, problems and regional differences in the relationship between expansion and forest change across provinces, providing a scientific basis for the Indonesian government to formulate differentiated provincial land-use, licensing and enforcement policies[11]. Against the background of growing demand for deforestation-free commodities in importing markets, and since a large share of tropical deforestation is embodied in internationally traded agricultural products[17], the conclusions of this paper also have demonstration significance for the sustainable governance of palm oil supply chains in Southeast Asia and can provide empirical support for regional cooperation on sustainable commodity production. Finally, for other tropical developing countries where oil palm is expanding, such as those in

West Africa and Latin America[18], Indonesia's experience has important reference value. The successful experience and existing problems summarized in this paper can provide reference for countries at similar development stages to reconcile agricultural expansion with forest conservation and to achieve green transformation. This paper focuses on the important practical issue of the environmental externalities of a major agribusiness sector, and extends firm-level supply-chain sustainability analysis to the regional level, providing a new research perspective for studying regional industrial policy and sustainable development strategy, and making a positive contribution to enriching applied research in the field of regional economic development in business administration discipline.

II. LITERATURE REVIEW

A. Palm Oil Industry Expansion

The oil palm is the most land-efficient of the major vegetable oil crops, producing far more oil per hectare than its main substitutes, which is why it has become central to the global vegetable oil market[3]. In Indonesia, the area under oil palm has expanded rapidly since the 1990s, first on Sumatra and then increasingly in Kalimantan, with both large estates and smallholders contributing to the expansion[18]. In terms of conceptual definition, palm oil industry expansion refers to the growth of the planted area, output and processing capacity of the sector, and its impact on regional land use is determined not only by how much land is planted but also by how fast the frontier moves. Regarding the measurement of expansion, academia has formed a relatively mature set of indicators. Commonly used indicators include the share of planted area in total land, the annual expansion rate, crude palm oil (CPO) output per unit of land, the density of processing mills and the share of the sector in regional output. Satellite-based mapping has made it possible to delineate plantations consistently across large regions[18], and global forest-change datasets provide the standard measurement of tree-cover loss[5]. A single indicator often cannot fully reflect the multi-dimensional nature of expansion, so existing studies usually adopt multi-indicator comprehensive evaluation, combining objective weighting methods such as the entropy method to obtain a composite index, which improves the scientificity and reliability of measurement results. Concerning the drivers of expansion, the literature highlights world vegetable oil prices, the suitability of land for oil palm, road access, and the decentralization of licensing authority to districts[12]. Expansion responds strongly to price cycles: the slowdown of deforestation in Indonesia after 2017 has been linked to declining oil palm expansion and lower oil prices[2]. In terms expansion raises rural incomes and regional output, and some studies argue that replacing palm oil with other vegetable oils could require even more land overall[3]. This makes it essential to evaluate the environmental cost of expansion on empirical grounds rather than by assumption.

B. Palm Oil Expansion and Forest Resources

Regarding the direction of the impact of palm oil expansion on forest resources, most scholars believe that expansion has a significant negative effect on forests. Expansion affects forests through three main channels: the direct land-conversion effect, in which plantations replace natural forest[6,7]; the indirect access effect, in which roads, mills and in-migration open neighboring forests to logging and conversion[10,12]; and the peatland-fire effect, in which the drainage of peat swamp forests for plantations raises fire risk and carbon emissions[14,15]. A study of the drivers of Indonesian deforestation found commodity plantations among the leading proximate causes of forest loss[1]; an analysis of primary forest over 2000-2012 documented a rising rate of primary forest loss in Indonesia[4]; and in West Kalimantan a considerable share of oil palm expansion took place on forest land[7]. Projections for Kalimantan further show that expansion conflicts with climate mitigation goals unless it is steered towards already-degraded land[13]. Beyond forest area, expansion also reduces biodiversity relative to the forests it replaces[8,9,20] and releases stored carbon[16]. However, there are differences and controversies in the conclusions drawn by different studies. Oil palm is not the only driver of forest loss: logging, pulpwood plantations and mining also contribute substantially[10], and part of the expansion takes place on previously cleared land. Policy evidence is also mixed: the moratorium on new concessions is estimated to have affected deforestation emissions, although the size of the effect depends on enforcement[11]. From the perspective of regional heterogeneity, the impact depends on the peatland share, the structure of producers (estates versus smallholders) and the quality of local governance[12]. Taken together, the literature suggests three testable propositions: palm oil expansion lowers the level of forest resources; the estimated effect is robust to endogeneity concerns; and the effect differs across provinces with different peatland and producer structures. These propositions guide the empirical design below.

III. DATA SOURCE AND VARIABLE MEASUREMENTS

A. The Formula

Standardization processing distinguishes between positive indicators and negative indicators, using different formulas for processing. For positive indicators (larger values indicate a higher level of the system), the standardization formula is:

$_i - ()$

$'_i = _____$

$m() - ()$

For negative indicators (smaller values indicate a higher level of the system), the standardization formula is:

$m() - _i$

$'_i = _____$

$m() - ()$

Where, x_{ij} is the original value of the j-th indicator of the i-th sample, min(x_j) and max(x_j) are the minimum and maximum values of the j-th indicator respectively, and x'_{ij} is the standardized indicator value, with a value range of [0,1]. Through the above standardization processing, all indicators are comparable, laying a foundation for subsequent weight calculation and comprehensive index construction. After the above processing, this study finally obtains balanced panel data, with a sample size of 12 provinces × 10 years = 120 observations, which meets the sample size requirements for panel data econometric analysis. The 12 provinces are Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra and Bengkulu on Sumatra, and West, Central, South, East and North Kalimantan on Kalimantan. Data note. The province-level panel used in the empirical analysis of this paper is simulated. The datagenerating process was designed with plausible orders of magnitude for Indonesian provinces, including a world CPO price cycle, province-specific suitability for oil palm, peatland shares, producer structures, and fire years in 2015, 2019 and 2023, and the simulated series are used to demonstrate the full empirical design. All estimates reported in Chapter IV should therefore be read as illustrative results of simulated data and not as evidence about actual Indonesian provinces; they should be replaced by estimates from official statistics and remote-sensing datasets before any substantive conclusion is drawn.

B. Index System Construction

Each system includes multiple dimensions and specific indicators, following the principles of scientificity, systematicness, and operability, ensuring that the index system can comprehensively and accurately reflect the development level of each system. Palm Oil Industry Expansion System (U_1). The palm oil industry expansion system constructs an index system from three dimensions: expansion scale, expansion speed, and industrial intensity, specifically including the following five indicators: Planted Area Share (X_{11}): Expressed as the share of oil palm planted area in the province's total land area (%), measuring the scale of the industry's land footprint. A higher share indicates a larger scale of expansion, which is a positive indicator. Annual Expansion Rate (X_{12}): Expressed as the annual growth rate of the planted area (%), reflecting the speed at which the plantation frontier moves, which is a positive indicator. CPO Output Density (X_{13}): Expressed as crude palm oil output per square kilometer of land (tons/km²), reflecting the intensity of production, which is a positive indicator. Mill Density (X_{14}): Expressed as the number of palm oil mills per 1,000 km², reflecting the processing capacity and infrastructure that tie a province to the industry, which is a positive indicator. Palm Oil ValueAdded Share (X_{15}): Expressed as the share of the palm oil sector's value added in provincial gross regional domestic product (%), reflecting the economic dependence of the province on the sector, which is a positive indicator. Forest Resource System (U_2). The forest resource system constructs an index system from three dimensions: forest stock, forest quality, and disturbance pressure, specifically including the following four indicators: Forest Cover Rate (X_{21}): Expressed as the proportion of forest area in the province's land area (%), reflecting the stock of forest resources. A higher forest cover rate indicates a better forest resource base, which is a positive indicator. Primary Forest Share (X_{22}): Expressed as the proportion of primary forest in total forest area (%), reflecting forest quality, carbon density and biodiversity value, which is a positive indicator. Tree Cover Loss Rate (X_{23}): Expressed as annual gross tree-cover loss as a percentage of forest area, in the spirit of global forest-change measurement[5]. A lower rate indicates less pressure on forests, so this indicator is a negative indicator. Fire Hotspot Density (X_{24}): Expressed as the number of fire hotspots per 100 km², reflecting disturbance pressure from fire, which is a negative indicator. Control variables and instrument. To isolate the effect of expansion, three control variables are included: Per Capita GRDP (X_{31}, ln PGDP), measuring the level of regional economic development; Population Density (X_{32}, PD), expressed as persons per km²; and Road Density (X_{33}, RD), expressed as kilometers of road per 100 km², which captures accessibility of the forest frontier[12]. To address the endogeneity of expansion, an instrumental variable Z is constructed as the product of a province's time-invariant agro-climatic suitability for oil palm (Suit, ranging from 0 to 1) and the log of the one-year lagged world CPO price index (2014 = 100). Price shocks raise the returns to expansion more in suitable provinces, while the exclusion restriction assumes that they affect forest resources only through expansion. In summary, the evaluation index system constructed in this study includes 2 subsystems, 6 dimensions, and 9 specific indicators, supplemented by 3 control variables and 1 instrumental variable.

C. Model Specification and Testing

This study sequentially uses the entropy method, a two-way fixed-effects model, an instrumental-variable (2SLS) estimation, and sub-sample heterogeneity tests for empirical analysis. This subsection sequentially describes the specification forms, testing

methods, and implementation ideas of each step. The entropy method is used to calculate the weight of each indicator and obtain the comprehensive development index of the two subsystems. The specific steps are as follows: Step 1: Standardize the original indicators. The processing method is as described above and the standardized matrix $X = (x'_{ij})_{m\times n}$ is obtained, where m is the number of samples and n is the number of indicators. Step 2: Calculate the proportion p_{ij} of the i-th sample under the j-th indicator:

$'_i$

$i =$ _____

$=1\ 'i$

1

____

$= -$ ii

$=1$

When $p_{ij} = 0$, let $p_{ij} \ln p_{ij} = 0$.

Step 4: Calculate the difference coefficient g_j of the j-th indicator: $g_j = 1 - e_j$. The larger the difference coefficient, the more important the indicator is.

Step 5: Calculate the weight w_j of the j-th indicator:

$=$ _____

$=1$

Step 6: Calculate the comprehensive development index U_k of each subsystem:

$=$ $i'i$

$=1$

Where, k = 1, 2 correspond to the palm oil industry expansion system (POEI) and the forest resource system (FRI) respectively, n_k is the number of indicators of the k-th subsystem, w_{kj} is the weight of the j-th indicator of the k-th subsystem, and x'_{kj} is the standardized indicator value. Through the entropy method calculation, the comprehensive development index of each subsystem for each province in each year is obtained, providing a basis for the subsequent regression analysis. Baseline model. To estimate the effect of palm oil expansion on forest resources, the following two-way fixed-effects model is specified:

$2,i = + 1,i + CiCti + + + i$

Where i denotes the province and t the year; μ_i is the province fixed effect, which controls for time-invariant characteristics such as soil, peat conditions and historical land tenure, and λ_t is the year fixed effect, which absorbs national shocks such as the world price cycle, El Niño fire years and national policy changes. The coefficient of interest is β, which is expected to be negative. Standard errors are clustered at the province level in the full-sample regressions; with only 12 clusters, inference is approximate[19]. Instrumentalvariable estimation. Because expansion may respond to forest conditions, the baseline estimate may be biased. The following twostage specification is therefore used, with the instrument Z defined in the previous subsection:

$1,i = i + CiCti + + + i$

$_i = Si \times (-_1/100)$

The second stage replaces the expansion index in the baseline model with its fitted value from the first stage. The strength of the instrument is assessed with the first-stage F statistic. Heterogeneity tests are conducted by splitting the sample by region (Sumatra and Kalimantan) and by the median peatland share and smallholder share of the provinces, and by estimating the baseline model on each sub-sample.

IV. RESULT ANALYSIS

A. Descriptive Statistics and Correlation Analysis

Descriptive statistical analysis serves as the foundational step in empirical research, helping us understand the basic distribution characteristics and trends of the data, which lays the groundwork for subsequent in-depth analysis. This study uses balanced panel data from 12 Indonesian provinces from 2014 to 2023, resulting in a total of 120 observations. The main variables include the palm oil expansion index, the forest resource index, and relevant control variables. The descriptive statistical results for each variable are presented in Table 1.

Table 1. Descriptive Statistics of Main Variables

Variable Name	Obs	Mean	Std. Dev.	Min	Max
POEI (U_1)	3120	0.375	0.145	0.129	0.760
FRI (U_2)	3120	0.514	0.244	0.064	0.984
POAS (%)	3120	12.14	4.98	2.91	24.63
EXP (%)	3120	5.38	2.96	1.33	17.92
FCR (%)	3120	35.67	15.79	12.18	69.47
PFS (%)	3120	42.96	20.67	2.00	79.50
TCL (%)	3120	3.02	1.64	0.45	7.01
FHD	3120	1.96	1.75	0.28	8.98
PGDP (million IDR)	3120	80.03	39.16	29.48	196.48
PD (persons/km²)	3120	83.89	53.49	9.17	221.23
RD (km/100 km²)	3120	22.17	10.96	4.09	49.02

Note: POEI and FRI are entropy-weighted composite indices; POAS = planted area share; EXP = annual expansion rate; FCR = forest cover rate; PFS = primary forest share; TCL = tree cover loss rate; FHD = fire hotspots per 100 km². The data are simulated (see Section III.A).

From the descriptive statistical results, it can be observed that there are considerable differences in the values of each variable across different provinces, which is generally consistent with the contrast between the long-established plantation provinces of Sumatra and the newer, forest-richer frontier of Kalimantan. Specifically, the palm oil expansion index has a mean value of 0.375 with a standard deviation of 0.145, ranging from a minimum of 0.129 to a maximum of 0.760, indicating significant differences in the degree of expansion across provinces. This disparity primarily stems from differences in suitability for oil palm, historical development foundations and licensing practice: provinces such as North Sumatra and Riau have long-standing plantation sectors, while North Kalimantan and Aceh have remained at an early stage of expansion. The forest resource index has a mean value of 0.514 with a standard deviation of 0.244, with a minimum of 0.064 and a maximum of 0.984, showing even larger variation, which reflects that provinces differ greatly in the remaining forest stock. The average forest cover rate is 35.67%, and the average planted area share is 12.14% of land area. The correlation analysis shows that the expansion index and the forest resource index are negatively correlated (r = -0.60), and that the planted area share is negatively correlated with the forest cover rate (r = -0.62), which is consistent with the expectation that expansion is accompanied by forest loss. At the same time, population density and road density are highly correlated with each other (r = 0.98), which points to a multicollinearity risk among the control variables that is discussed in the limitations below. Because simple correlations cannot separate expansion from other province-level characteristics, Table 2 reports the baseline regression results.

Table 2. Correlation Analysis and Baseline Regression of Main Variables

Variable	(1) FRI	(2) FRI	(3) FRI
POEI (U_1)	-1.003***	-0.401	-0.335***
	(0.279)	(0.443)	(0.095)
ln PGDP		-0.011	0.157*
		(0.059)	(0.078)
Population Density		0.007**	-0.004***
		(0.003)	(0.001)
Road Density		-0.046**	-0.007
		(0.019)	(0.004)
Controls	No	Yes	Yes
Province FE	No	No	Yes
Year FE	Yes	Yes	Yes
Obs	120	120	120
R-squared	0.367	0.622	0.995

Note: Standard errors clustered at the province level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The data are simulated (see Section III.A).

In column (1), which only includes year fixed effects, the coefficient of expansion on the forest resource index is -1.003 and is significant at the 1% level. In column (2), after adding the control variables, the coefficient falls to -0.401 and is no longer statistically significant, because population density and road density, which are strongly related to expansion across provinces, absorb much of the cross-sectional variation. In column (3), which controls for province fixed effects, the coefficient is -0.335 and is significant at the 1% level: within the same province, a higher level of expansion is associated with a lower level of forest resources. In terms of economic magnitude, a one-standard-deviation increase in the expansion index (0.145) is associated with a decline of 0.049 in the forest resource index, about 0.20 of its standard deviation. Among the controls, population density has a significantly negative coefficient, while per capita GRDP has a positive coefficient that is only significant at the 10% level.

B. Measurement and Analysis of the Two Systems' Development Level

Following the index system and measurement method constructed in Chapter III, this study first calculates the weight of each indicator using the entropy method, then obtains the comprehensive development index of each subsystem through weighted aggregation. For the expansion system, the entropy weights are relatively balanced: planted area share 0.180, expansion rate 0.262, CPO output density 0.185, mill density 0.192, and value-added share 0.181. For the forest resource system, the weights are more concentrated: forest cover rate 0.444, primary forest share 0.274, tree cover loss rate 0.202, and fire hotspot density 0.080, indicating that the forest stock accounts for the largest share of the cross-province variation. The final measurement results of the average development levels of the two systems in Indonesia from 2014 to 2023 are shown in Table 3.

Table 3. Average Measurement Results

Year	Average POEI (U_1)	Average FRI (U_2)	Average Forest Cover (%)
2014	0.329	0.577	39.30
2015	0.338	0.534	38.45
2016	0.354	0.557	37.66
2017	0.360	0.543	36.84
2018	0.374	0.521	35.97
2019	0.360	0.504	35.23
2020	0.374	0.511	34.50
2021	0.408	0.490	33.72
2022	0.420	0.472	32.94
2023	0.432	0.435	32.11
Annual Growth Rate (%)	3.07	-3.08	-2.22

Note: The results are computed from the simulated panel (see Section III.A); the annual growth rate is the compound annual growth rate from 2014 to 2023.

Comparing the development levels of the two systems, during the sample period the average level of palm oil expansion rose from 0.329 in 2014 to 0.432 in 2023, an annual growth rate of 3.07%, while the average level of forest resources declined from 0.577 to 0.435, an annual change of -3.08%. The average forest cover rate fell from 39.30% to 32.11%, a decline of about 7.2 percentage points over ten years. This indicates that, in the simulated panel, expansion and forest loss move in opposite directions, and the forest resource base of the major producing provinces is being steadily eroded. Regarding the time trend, the growth of the expansion index was slow between 2016 and 2020, a period of lower world prices that also coincided with the moratorium on new licenses, and accelerated after 2021 when prices rose sharply, in line with the evidence that expansion follows price cycles[2]. The forest resource index shows two pronounced drops, in 2015 (from 0.577 to 0.534) and in 2023 (from 0.472 to 0.435), which correspond to the severe fire seasons built into the simulated data. This pattern is consistent with the view that fire-prone peatland provinces are vulnerable in dry years, and that structural expansion pressure is superimposed on episodic fire shocks[14,15].

C. Sub-regional Development Level Analysis

To reveal regional differences in the relationship between expansion and forest resources, this study divides the 12 provinces into two regions: Sumatra (7 provinces) and Kalimantan (5 provinces). The average development levels of the two systems in the two regions are calculated separately. The average expansion index is 0.40 in Sumatra and 0.34 in Kalimantan, while the average forest resource index is 0.446 in Sumatra and 0.610 in Kalimantan; the average forest cover rate is 30.21% and 43.32%, and the average planted area share is 13.36% and 10.45%, respectively. Sumatra, where the industry is older, therefore combines a higher

level of expansion with a lower level of forest resources. To address the endogeneity of expansion, the instrumental-variable results for the two regions are presented in Table 4.

Table 4. Sub-regional Instrumental-Variable Regression Results

Variable	First Stage Sumatra (1) POEI	Second Stage Sumatra (2) FRI	First Stage Kalimantan (3) POEI	Second Stage Kalimantan (4) FRI
Instrument Z	).631*** (0.153)		..353*** (0.273)	
POEI (U_1), instrumented		).037*** (0.205)		).265*** (0.092)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	1570	1570	1550	1550
First-stage F	16.9		24.6	
R-squared	0.984	0.991	0.935	0.998

Note: Heteroskedasticity-robust standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The data are simulated (see Section III.A).

The first-stage results show that the instrument is a strong predictor of expansion in both regions: the coefficient of Z is 0.631*** in Sumatra and 1.353*** in Kalimantan, with first-stage F statistics of 16.9 and 24.6, both above the conventional threshold of 10. In the second stage, the instrumented expansion index has a significantly negative effect on the forest resource index in both regions, -1.037*** in Sumatra and -0.265*** in Kalimantan. In the full sample the two-stage estimate is -0.614*** with a first-stage F statistic of 32.6, which is larger in absolute value than the fixed-effects estimate of -0.335 in Table 2. A larger instrumental-variable estimate is consistent with attenuation from measurement error in the composite expansion index, but it may also reflect violations of the exclusion restriction, for example if world prices affect forests through channels other than palm oil, so the two estimates should be read as a range rather than a point. The effect is considerably larger in Sumatra than in Kalimantan. A possible explanation is that in Sumatra, where forests are already scarce and fragmented, each additional increment of plantation land removes a larger share of the remaining forest resource, while Kalimantan still holds large forest stocks and its expansion frontier is at an earlier stage[13]. This also implies that the smaller coefficient in Kalimantan should not be read as lower risk: the firststage coefficient is more than twice as large in Kalimantan, which shows that expansion there is more sensitive to price signals.

D. Heterogeneity Test

The results reveal significant disparities across provinces with different land and producer structures. The provinces are split at the median peatland share (7% of land area) and at the median smallholder share of planted area (39%). The high-peatland group consists of Riau, Jambi, South Sumatra, West Kalimantan, Central Kalimantan and South Kalimantan, and the high-smallholder group consists of Aceh, North Sumatra, West Sumatra, Riau, Jambi and Bengkulu. Table 5 highlights differential responses across groups: the coefficient of expansion is -0.427*** in high-peatland provinces and -0.317*** in low-peatland provinces, so the negative effect is larger where drained peat forest is converted and where fire risk is higher[14]. The coefficient is -0.592*** in smallholderdominated provinces and -0.183*** in estate-dominated provinces, suggesting that fragmented expansion by many small producers is harder to regulate than expansion by a limited number of large concessions, which can be monitored and certified[12]. These patterns are suggestive rather than conclusive: in pooled interaction models with common control coefficients, the difference between the peatland groups is -0.302 ($p = 0.133$) and the difference between the smallholder groups is 0.004 ($p = 0.985$), neither of which is statistically significant.Several robustness checks support the baseline result. Using the forest cover rate directly as the outcome, a one-percentage-point increase in the planted area share is associated with a 0.871 percentage-point decline in forest cover ($p < 0.01$). Using the tree cover loss rate as the outcome, the coefficient of the expansion index is 6.023***. Replacing the expansion index with its one-year lag gives a coefficient of -0.377***. In contrast, the expansion index has no significant effect on fire hotspot density once province and year effects are included (coefficient 1.013, $p = 0.608$),

which is consistent with fire intensity being driven mainly by climatic years that are absorbed by the year fixed effects. The regression results of the four sub-samples are reported in Table 5.

Table 5. Heterogeneity Test

Variable	High Peatland	Low Peatland	High Smallholder	Low Smallholder
	(1)	(2)	(3)	(4)
POEI (U_1)	).427*** (0.102)	).317*** (0.073)	).592*** (0.102)	).183*** (0.053)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	1360	1560	1360	1560
R-squared	0.995	0.996	0.995	0.998

Note: Heteroskedasticity-robust standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The data are simulated (see Section III.A).

However, the model has notable limitations: multicollinearity between population density and road density (r = 0.98) may compromise the reliability of the control coefficients; the exclusion restriction of the price-based instrument cannot be tested directly; the number of provinces is small, so clustered inference is approximate; and the analysis does not model spatial spillovers between neighboring provinces. Future research should integrate spatial econometrics and dynamic panel techniques, and replace the simulated panel with official statistics and remote-sensing datasets to strengthen causal inference. In policy terms, Sumatra, where forests are already scarce, needs stricter protection of the remaining forest and peatland and support for smallholder compliance, while Kalimantan needs preventive measures such as steering new plantations to degraded land, because its large forest stock is the most exposed to the next price boom. Policymakers also need to strengthen enforcement of the licensing moratorium, improve land-use planning and traceability, and provide incentives for productivity improvement on existing plantations to bridge the gap between economic and environmental goals.

CONCLUSIONS

This study analyzes the environmental impact of palm oil industry expansion on forest resources in Indonesia (2014-2023) using a simulated province-level panel of 12 provinces. Key findings include: The palm oil expansion index rises steadily (annual 3.07%), while the forest resource index declines (annual -3.08%) and the average forest cover rate falls from 39.30% to 32.11%. Expansion slowed in the low-price years of 2016-2020 and accelerated after 2021. On average, Sumatra shows a higher level of expansion and a lower level of forest resources than Kalimantan. The provinces with the largest declines in forest cover are North Sumatra (-10.60 percentage points) and South Kalimantan (-8.96 percentage points), while North Kalimantan shows the smallest (-4.47 percentage points). In the two-way fixed-effects model the coefficient of expansion on the forest resource index is -0.335, and the instrumentalvariable estimate is -0.614, with strong first-stage relevance. The effect is larger in peatland-rich and smallholder-dominated provinces, although the differences are suggestive rather than conclusive. Expansion has no significant effect on fire hotspot density once year effects are controlled. Theoretical Contributions & Practical Implications: first, this paper builds a province-level framework linking palm oil expansion with forest stock, forest quality and disturbance pressure through entropy-weighted indices, expanding the application of panel-data methods to land-use change in tropical developing countries. Second, it combines fixedeffects and price-based instrumental-variable strategies and reports sub-sample heterogeneity, deepening the understanding of the conditions under which expansion damages forests. Third, it guides differentiated provincial policies: stricter protection of remaining forest and peatland in Sumatra, and preventive planning in Kalimantan, together with enforcement of the moratorium and support for smallholder compliance, to help Indonesia reach its FOLU Net Sink 2030 target. It also offers lessons for other palm oil-producing countries in Southeast Asia and tropical regions, and provides business administration insights for sustainable sourcing strategies and government policy design, bridging firm-level supply-chain sustainability with regional environmental outcomes. Because the panel is simulated, the numerical results are illustrative, and the framework should be re-estimated with official and remote-sensing data before being used for policy conclusions.

ACKNOWLEDGMENT

I would like to extend my profound gratitude to my supervisor for their unwavering guidance and assistance throughout this research journey—from the initial conception to the final draft. Academic acumen and practical insights have significantly

influenced the focus of this study on the environmental impact of palm oil industry expansion on forest resources in Indonesia. I am also deeply appreciative of all individuals and institutions that contributed valuable advice and support during the course of this work.

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