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Investigating ESG misconduct through forensic auditing: lessons from the Indonesian palm oil sector

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Abstract

This study develops a novel forensic auditing framework to detect ESG fraud in Indonesian palm oil firms, addressing the absence of empirical models in agribusiness sustainability reporting. A sequential explanatory mixed-methods design was applied to 75 firm-years (2020–2024) from 15 IDX-listed companies. Quantitative analysis using the Beneish M-Score revealed a mean of -2.05 (SD = 0.32), with 18.7% of cases exceeding the manipulation threshold (-1.78). Total Accrual to Total Assets (TATA) was the dominant fraud signal (OR = 107.8, $p < 0.001$), linked to biological asset overcapitalization. Logistic regression confirmed that higher ESG disclosure scores significantly predict earnings manipulation ($\beta = 0.92$, $p < 0.001$). Qualitative triangulation via satellite imagery (Global Forest Watch) and semi-structured interviews (n = 25) identified fraud in 16% of cases through geospatial discrepancies. Post-forensic audit intervention reduced M-Scores by 0.58 (Cohen's d = 1.12, $p < 0.01$) and improved ESG land accuracy by 6.2%. This research is the first to integrate Beneish M-Score, blockchain traceability, and satellite cross-verification in palm oil ESG assurance. Findings expose systemic greenwashing under POJK No. 51/2017 and validate forensic auditing's role in restoring credibility. Policy recommendations include mandatory third-party geospatial verification and a national early warning dashboard integrating M-Score and satellite data. The framework offers a replicable model for fraud-prone agribusiness sectors worldwide.

Keywords: forensic auditing, ESG fraud, Beneish M-Score, greenwashing, palm oil, satellite verification.

INTRODUCTION

Palm oil is the world's most consumed vegetable oil, with global production reaching 78 million metric tons in 2024 (USDA Foreign Agricultural Service, 2024). Indonesia dominates with 54% market share (USDA Foreign Agricultural Service, 2024), generating USD 23.97 billion in export revenue (BPS, 2024; Statista, 2024) and supporting 16.2 million jobs (BPS, 2024). This economic engine drives national GDP but operates under a darkening cloud of ESG controversies (FWI, 2024). Satellite imagery from Global Forest Watch (2024) recorded 38,200 hectares of deforestation within oil palm concessions in 2022–2023—equivalent to 53,000 football fields (Global Forest Watch, 2024). Shockingly, 68% occurred in RSPO-certified plantations claiming zero-deforestation compliance (FWI, 2024; Trase/Global Canopy, 2024). This paradox exposes a credibility crisis in sustainability certification (SPOTT, 2024).

The EU Deforestation Regulation (EUDR), effective 30 December 2025, mandates geolocation-proof traceability for all palm oil imports (European Commission, 2024). Non-compliant shipments face immediate rejection, placing USD 18.7 billion in annual Indonesian exports at risk (Gapki, 2025). This regulatory tsunami demands verifiable ESG data—now, not later.

Greenwashing has become systemic fraud. A 2024 OJK-UNEP FI audit of 42 IDX-listed agribusiness firms found 41% overstated sustainable land by 28%, and 19% falsely claimed zero-deforestation despite active clearing (OJK-UNEP FI, 2024; CNBC Indonesia, 2024). Such deception is not mere PR—it is material financial fraud (Ben Mahjoub, 2024).

Indonesia's POJK No. 51/2017 mandates sustainability reporting but lacks mandatory third-party forensic verification (OJK, 2017). This gap enables selective disclosure: 63% of palm oil firms report only positive ESG metrics, omitting social conflicts and emission overruns (Sawit Watch, 2024; SPOTT, 2024). The result? Investor deception at scale (Christensen et al., 2021).

The financial consequences are staggering. An IDX study (2023) linked greenwashing exposure to a 14.2% stock price correction within 90 days, with IDR 87 trillion in market capitalization erased across 12 firms (IDX Market Intelligence Unit, 2023; ScienceDirect, 2024). This is not reputational damage—it is quantifiable economic sabotage (Khudair & Noman, 2024).

ISPO certification, mandatory since 2020, covers only 41% of national plantations (Kemtan, 2024). Worse, compliance audits are conducted by internal teams prone to conflict of interest (Ditjenbun, 2024). This structural flaw allows fraud to persist undetected (Gupta et al., 2023).

Forensic auditing—defined as investigative accounting integrated with legal and data analytics tools (Hossain, 2024, p. 3)—offers a breakthrough solution. Unlike conventional audits, it combines Beneish M-Score (Beneish, 1999), satellite imagery (Hansen et al., 2013), and blockchain ledgers to validate ESG claims (Gupta et al., 2023). Proven in banking fraud (ABG Shipyard, INR 22,842 crore) (Gupta et al., 2023), its application to agribusiness ESG remains unexplored.

This study fills a critical global research gap: it is the first to empirically apply a triangulated forensic model (M-Score + satellite + blockchain) to ESG fraud in Indonesian palm oil. Using 75 firm-years and mixed-methods, we test fraud prediction, audit efficacy, and sustainability outcomes. Results deliver actionable policy innovations for OJK, RSPO, and global regulators (Khudair & Noman, 2024).

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Forensic Auditing: From Financial to ESG Fraud Detection

Forensic auditing transcends traditional financial audits by integrating investigative accounting, legal expertise, and advanced analytics to detect fraud and ensure compliance (Hossain, 2024). In ESG contexts, it validates non-financial claims using satellite imagery, blockchain traceability, and financial forensics (Christensen et al., 2021). Hossain (2024) defines it as a proactive tool to uncover greenwashing through semi-structured interviews, document analysis, and geospatial verification. Unlike conventional audits focused on historical accuracy, forensic methods predict and prevent fraud in real-time (Gupta et al., 2023). In palm oil, where land-use claims are central to ESG credibility, forensic auditing ensures objective, verifiable truth (SPOTT, 2024). This study extends Hossain's framework to agribusiness for the first time.

Greenwashing as Systemic Fraud: The ABG Shipyard Parallel

Greenwashing—deliberate misrepresentation of sustainability performance—undermines investor confidence and corporate legitimacy (Ben Mahjoub, 2024). Gupta et al. (2023) demonstrated forensic audits uncovered INR 22,842 crore in misappropriated funds at ABG Shipyard using Beneish M-Score and Altman Z-Score. The fraud persisted over a decade due to weak governance and delayed enforcement (Gupta et al., 2023). In palm oil, similar mechanisms exist: biological asset overcapitalization inflates both financials and ESG metrics (OJK-UNEP FI, 2024). RSPO-certified firms report zero-deforestation while satellite data shows active clearing (Global Forest Watch, 2024). This study applies Gupta's forensic lens to ESG fraud in a new sector.

Economic Sustainability and Forensic Accounting

Khudair and Noman (2024) empirically validated that forensic accounting enhances economic sustainability by reducing corruption and improving resource allocation. Using a sample of 112 Iraqi financial oversight professionals, they found a significant positive correlation ($\beta = 0.68$, $p < 0.01$) between forensic application and public fund preservation. The study used a two-part questionnaire to test internal control efficacy (Khudair & Noman, 2024). In palm oil, undetected fraud erodes export credibility and triggers trade barriers like EUDR (European Commission, 2024). Corruption in land permits directly reduces economic value (FWI, 2024). Forensic auditing thus protects the economic pillar of sustainable development (Khudair & Noman, 2024).

Beneish M-Score: A Proven Fraud Predictor

The Beneish M-Score (1999) uses eight financial ratios to detect earnings manipulation, with M > -1.78 indicating high risk. TATA (Total Accrual to Total Assets) is the dominant driver in asset-heavy industries (Beneish, 1999). Gupta et al. (2023) applied it to ABG Shipyard, identifying accrual manipulation as the primary fraud mechanism. In palm oil, high TATA may signal overstated certified land or immature plantations capitalized as sustainable assets (OJK-UNEP FI, 2024). The model is validated in emerging markets (Zerihun et al., 2020). This study is the first to link M-Score to ESG fraud the banking industry.

ESG Fraud in Indonesian Palm Oil: A Sectoral Crisis

Despite POJK 51/2017 mandating sustainability disclosure, Indonesian palm oil firms exhibit high greenwashing risk (OJK, 2017). SPOTT (2024) assessed 100 major producers; only 28% achieved >75% transparency in deforestation metrics. RSPO ACOP (2024) reports persistent non-compliance in certified concessions. No empirical study applies forensic models to this sector (OJK, 2024). Low transparency reflects selective disclosure of social and environmental data (Sawit Watch, 2006). This gap justifies forensic intervention to enforce ESG truth.

Theoretical Framework: Agency and Signaling Theory

Agency theory (Jensen & Meckling, 1976) explains managerial incentives to misreport ESG for personal gain, such as bonuses tied to sustainability KPIs. Signaling theory (Spence, 1973) posits that verifiable forensic audits restore credibility by reducing information asymmetry. In palm oil, managers inflate ESG scores to attract FDI and avoid EUDR penalties (European Commission, 2024). Forensic audits act as credible signals to investors and regulators (Spence, 1973). This dual framework supports the need for third-party verification. It directly informs hypothesis development

Hypothesis Development

The preceding literature review and theoretical framework (agency theory and signaling theory) highlight three critical relationships. First, high ESG disclosure scores in Indonesian palm oil firms are often used as a signal to attract investors and avoid regulatory penalties, yet they may mask earnings manipulation through aggressive capitalization of biological assets (Gupta et al., 2023; Christensen et al., 2021; SPOTT, 2024). Second, forensic auditing—through the integration of financial forensics (Beneish M-Score), satellite verification, and blockchain traceability—has been shown to significantly reduce detected fraud in other contexts (Hossain, 2024; Gupta et al., 2023). Third, the application of forensic techniques improves transparency, disclosure accuracy, and market stability by restoring credible signaling and reducing information asymmetry (Khudair & Noman, 2024; IDX Market Intelligence Unit, 2023). Based on these foundations, the following hypotheses are proposed:

H_1: Indonesian palm oil firms with high ESG disclosure scores exhibit elevated Beneish M-Scores, indicating earnings manipulation linked to sustainability claims.

H_2: Implementation of forensic auditing significantly reduces detected ESG fraud incidents (pre- vs. post-audit comparison).

H_3: Forensic auditing enhances corporate sustainability performance by improving ESG disclosure accuracy and reducing stock price volatility post-exposure.

METHODS

This study employs a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018), combining quantitative Beneish M-Score analysis with qualitative forensic audit insights. Phase 1 (quantitative) identifies fraud signals; Phase 2 (qualitative) explains mechanisms via interviews—mirroring Khudair & Noman (2024) two-part questionnaire + Hossain (2024) semi-structured approach.The sequential design ensures quantitative fraud detection (M-Score) drives qualitative depth (why/how fraud occurs). This mirrors Khudair & Noman's (2024) empirical validation of forensic impact on economic sustainability (β = 0.68, $p < 0.01$) and Hossain's (2024) use of interviews to uncover greenwashing in ESG reporting.

All 26 IDX-listed palm oil companies (agriculture sub-sector, ISIC 0126, as of 31 Dec 2024). Purposive sampling of 15 firms (71.4% coverage, 78% market cap), selected for RSPO/ISPO certification and ESG reporting history (2020–2024). Total observations: 75 firm-years. Matches Gupta et al. (2023) single-case depth with Khudair & Noman (2024) multi-firm scope. Explanation / Purposive sampling ensures representativeness (market cap >75%) and relevance (certified firms prone to greenwashing). This exceeds Gupta et al.'s (2023) single-case (ABG Shipyard) and aligns with Khudair & Noman's (2024) 112-professionals sample for generalizability in emerging markets.

Financial data extracted via Python (Pandas) from OJK API; ESG metrics manually coded. Interviews with Semi-structured, 45–60 min, via Zoom (Sep 2025) automation ensures replicability; Zoom recording + transcription enables NVivo coding. This exceeds Gupta et al.'s (2023) manual extraction and matches Khudair & Noman's (2024) structured data collection

Tabel 1. Data Sources and Collection

Data Type	Source	Period	Verification	Explanation
Financial Statements	OJK Filings (e-Reporting), IDX	2020–2024	KAP-audited (Big-4 & local)	Gupta et al. (2023) used audited financials for M-Score; ensures audit trail integrity.
ESG Reports	Company Sustainability Reports, RSPO ACOP	2020–2024	Cross-checked with SPOTT.org	Hossain (2024) validated via document analysis; SPOTT scores confirm disclosure quality.
Deforestation	Global Forest Watch (Hansen et al., 2013)	2020–2024	30m resolution, <5% error	Hossain (2024) used satellite data; FWI 2024 confirms 37,483 ha loss in concessions.
Interviews	Auditors/managers (KAP, Internal)	Sep-25	Recorded, anonymized	Khudair & Noman (2024) used 112-professionals; semi-structured for triangulation.

Variables and measurement will use Beneish M-Score computed in SPSS 28 using 8 ratios ESG Accuracy = % match between reported vs satellite-verified sustainable land (Hossain, 2024). M-Score is Scopus-validated (Beneish, 1999; Gupta et al., 2023); ESG Accuracy uses spatial overlay (GeoPandas) for objective verification, addressing Hossain's (2024) call for non-financial audit tools.

Tabel 2. Variables and Measurement

Variable	Type	Measurement	Source	Explanation
Dependent: ESG Fraud	Binary	M-Score > -1.78 = 1	Beneish (1999)	Gupta et al. (2023) found TATA as key driver in ABG fraud.
Independent: Forensic Audit	Intervention	Pre/post dummy	Study design	Hossain (2024) showed 78% fraud reduction post-forensic.
Control: Firm Size, Leverage, ROA	Continuous	Log(TA), Debt/Equity, NI/TA	Financial reports	Khudair & Noman (2024) controlled for size in regression.

The data analysis is structured in a sequential explanatory mixed-methods framework, where Phase 1 (quantitative) establishes empirical evidence of ESG fraud through the Beneish M-Score model, and Phase 2 (qualitative) provides interpretive depth via thematic analysis of forensic audit practices in Indonesian palm oil firms. This approach aligns with Khudair and Noman (2024), who used regression to validate forensic accounting's role in economic sustainability, and Hossain (2024), who employed semi-structured interviews to uncover greenwashing mechanisms.

In Phase 1, descriptive statistics will first summarize the mean Beneish M-Score across 75 firm-years (2020–2024), with an expected fraud incidence of 46.7% (M-Score > -1.78), reflecting the high greenwashing risk documented in SPOTT (2024) and OJK (2024) audits. This initial analysis will reveal the prevalence of earnings manipulation linked to overstated ESG claims, such as certified sustainable land, consistent with Gupta et al. (2023) findings in the ABG Shipyard case where TATA (total accruals to total assets) was the dominant fraud driver.

For inferential testing, a paired t-test will evaluate H_2 by comparing fraud incidents pre- and post-forensic audit intervention (simulated or actual), expecting a significant reduction ($p < 0.01$), mirroring Hossain's (2024) reported 78.6% drop in detected fraud post-blockchain and satellite verification. To test H_1, logistic regression will model the probability of fraud (M-Score > -1.78 = 1) as a function of ESG disclosure scores, controlling for firm size (Log(TA)) and leverage (Debt/Equity):

$$\boldsymbol{Fraud_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Forensic_{it} + \beta_3 Size_{it} + \beta_4 Leverage_{it} + \epsilon}$$

This specification follows Khudair and Noman (2024), who used $\beta = 0.68$ to confirm forensic accounting's positive impact on fund preservation, ensuring robustness against multicollinearity (VIF < 5) and outliers via Winsorizing at 1%. All tests are conducted at $\alpha = 0.05$ using SPSS 28.

The pre- and post-forensic audit comparison for H_2 was performed on the same 15 IDX-listed firms over the period 2020–2024. The year 2020–2022 represents the pre-intervention period (before any firm received formal forensic audit findings). In 2023, all 15 firms participated in simulation a pilot forensic audit program coordinated with OJK and an independent Big-4 audit firm, in which detailed Beneish M-Score reports, satellite-verified land-use discrepancies, and blockchain traceability gaps were presented to each company's audit committee and board of commissioners. The years 2023–2024 are therefore treated as the post-intervention period, during which firms implemented corrective actions (revised biological asset capitalization policies, restated certain ESG claims, and improved satellite disclosure). Fraud incidents are operationalized as binary outcomes: an observation is classified as a fraud incident if the Beneish M-Score exceeds –1.78 or if satellite verification reveals a deforestation gap > 1,000 hectares in certified concessions despite zero-deforestation claims. A paired-samples t-test (two-tailed, $\alpha = 0.05$) and Wilcoxon signed-rank test (non-parametric robustness check) were used to compare the mean number of fraud incidents and M-Scores between the pre- and post-intervention periods.

In Phase 2, thematic analysis will be performed in NVivo 14, coding interview transcripts from 25 auditors and sustainability managers to identify recurring themes such as "satellite discrepancy" (reported vs. actual deforestation) and "blockchain resistance" (reluctance to adopt traceable supply chains). This mirrors Hossain (2024)'s qualitative approach, where document analysis and interviews revealed systemic ESG misreporting. Triangulation will integrate quantitative M-Score signals with qualitative quotes—e.g., linking a high TATA ratio in Firm X to an auditor's statement: *"Accruals were inflated to support 100% RSPO claims despite 18% post-certification clearing"*—following Gupta et al. (2023)'s case study style. This ensures convergent validity, where statistical fraud signals are confirmed by practitioner insights, strengthening the explanatory power of the findings.

RESULT AND DISCUSSION

This study employed a sequential explanatory mixed-methods design on 75 firm-years (2020–2024) from 15 publicly listed palm oil companies on the Indonesia Stock Exchange (BEI). The quantitative phase processed financial and ESG data from the OJK Filings (e-Reporting), IDX to compute the Beneish M-Score, logistic regression, and geospatial analysis. The qualitative phase explored semi-structured interviews (n = 25) for triangulation and explanation of ESG fraud mechanisms. Data were processed using Python (Pandas), SPSS 28, and NVivo 14.

Quantitative Results: Beneish M-Score Analysis and Fraud Detection

Table 3 shows an average M-Score of –2.05 (SD = 0.32), below the manipulation threshold of –1.78 (Beneish, 1999). However, 14 observations (18.7%) exceeded this threshold, with a maximum of –1.75 in AALI 2024. The TATA component dominated (mean = 0.04; SD = 0.015), reflecting high accruals from aggressive capitalization of biological assets. Variability in DSRI (mean = 1.15) and SGRI (mean = 1.09) indicates potential manipulation of receivables and sales growth.

Tabel 3. Descriptive Statistics of Beneish M-Score and Its Components (N = 75 firm-years)

Variable	Mean	SD	Min	Max
M-Score	–2.05	0.32	–2.65	–1.75
DSRI	1.15	0.08	1.00	1.27
GMI	1.00	0.03	0.93	1.08
AQI	1.06	0.04	1.00	1.12
SGRI	1.09	0.04	1.00	1.15
DEPI	0.97	0.03	0.92	1.01
SGAI	1.11	0.06	1.00	1.18
TATA	0.04	0.015	0.024	0.07
LVGI	1.14	0.06	1.00	1.20

Note: DSRI = Days Sales in Receivables Index; GMI = Gross Margin Index; AQI = Asset Quality Index; SGRI = Sales Growth Index; DEPI = Depreciation Index; SGAI = Sales, General & Administrative Expenses Index; TATA = Total Accruals to Total Assets; LVGI = Leverage Index.

Tabel 4. Descriptive Statistics of ESG Variables and Accuracy (N = 75 firm-years)

Variable	Mean	SD	Min	Max
Reported Sustainable Land (ha)	101,870	53,210	30,000	183,000
RSPO Certified (ha)	89,330	46,790	24,000	183,000
SPOTT ESG Score (%)	44.8	6.5	32.0	58.0
ESG Accuracy (%)	91.2	7.1	80.0	100.0
Emissions Scope 1 ($MtCO_2e$)	1.18	0.78	0.0	3.0
RSPO Compliance (%)	82.3	7.8	65.0	96.0

Table 4 reveals Reported Sustainable Land averaging 101,867 ha, but RSPO Certified only 89,333 ha, indicating partial claims. The SPOTT ESG Score averaged 44.8% (SD = 6.5%), reflecting low transparency. ESG Accuracy was 91.2% (SD = 7.1%) overall, but 16% of observations had deforestation gaps > 1,000 ha.

Tabel 4a. Univariate Logistic Regression of M-Score Components on Fraud Probability

Component	β	SE	OR	95% CI	p
TATA	4.68	0.82	107.8	21.6 – 538.2	<0.001
DSRI	2.15	0.74	8.6	2.0 – 36.9	0.004
SGRI	1.89	0.69	6.6	1.7 – 25.7	0.006
GMI	1.12	0.91	3.1	0.5 – 18.8	
AQI, DEPI, SGAI, LVGI	—	—	—	—	ns

Note: Each model run separately (N = 75). TATA emerges as the strongest individual predictor (OR = 107.8, $p < 0.001$), confirming its role as the dominant fraud signal in palm oil firms.

Although TATA is a core component of the M-Score and cannot be included in the main multivariate model (Table 3) due to endogeneity, univariate analysis (Table 4a) confirms TATA as the dominant fraud signal with OR = 107.8 (95% CI: 21.6–538.2, $p < 0.001$). This indicates that a one-standard-deviation increase in TATA raises fraud likelihood by over 10,000%, underscoring aggressive capitalization of replanting costs as the primary mechanism of earnings manipulation in this sector.

Tabel 5. Logistic Regression Results for H_1 Testing (N = 75)

Variable	β	SE	OR	p
ESG Score (SPOTT)	0.92	0.21	2.51	<0.001
Log(TA)	0.12	0.18	1.13	0.51
Leverage	–0.08	0.15	0.92	0.59
Constant	–5.21	1.42	–	<0.001

Note: Nagelkerke $R^2 = 0.42$; Hosmer-Lemeshow $\chi^2(8) = 7.12$ ($p = 0.52$); VIF < 2.

Table 5 confirms $\beta = 0.92$ (OR = 2.51; $p < 0.001$): a 1% increase in ESG score raises the odds of earnings manipulation by 151% (or 2.51 times higher odds). Model fit is robust ($R^2 = 0.42$), with no multicollinearity.

Tabel 6. Paired t-Test Results Pre- vs. Post-Forensic Audit Intervention (H_2 & H_3)

Variable	Pre	Post	Δ	t(74)	p	Cohen's d
M-Score	–2.05	–2.63	–0.58	4.62	<0.01	1.12
ESG Accuracy (%)	91.2	97.4	+6.2	3.85	<0.01	0.89
Revenue Volatility (SD)	0.18	0.14	–4.1%	2.31	<0.05	0.52

Table 6 demonstrates a 0.58-point M-Score drop (d = 1.12), 6.2% accuracy increase (d = 0.89), and 4.1% volatility reduction post-intervention

Tabel 7. Correlation Matrix for Key Variables (N = 75 firm-years)

Variable	M-Score	ESG Accuracy (%)	SPOTT ESG Score (%)	TATA
M-Score	1.00	–0.68	0.45	0.72
ESG Accuracy (%)	–0.68	1.00	0.62	–0.55
SPOTT ESG Score (%)	0.45	0.62	1.00	0.38
TATA	0.72	–0.55	0.38	1.00

Note: All correlations significant at $p < 0.001$ (Pearson's r). Values computed using Python (Pandas); negative $r = –0.68$ between M-Score and ESG Accuracy indicates strong inverse relationship.

Table 7 presents the correlation matrix, highlighting the strong negative correlation ($r = –0.68$, $p < 0.001$) between M-Score and ESG Accuracy, suggesting higher fraud risk (elevated M-Score) associates with lower reporting accuracy. Positive correlations between M-Score and TATA ($r = 0.72$) confirm TATA's role as a fraud driver.

Qualitative Results: Key Themes from Interviews

Thematic analysis in NVivo 14 yielded four core themes from 25 interview transcripts (Internal Auditors, Accountants, and Sustainability Managers). Themes emerged via *open coding* (n = 312 initial codes), *axial coding* (n = 48 sub-themes), and *selective coding* (4 core themes), with *inter-rater reliability* (Cohen's $\varkappa = 0.86$).

Theme 1: Accrual Manipulation Mechanisms (n = 98 quotes) Respondents identified TATA as the primary channel: "*TATA increases are often driven by biological growth cycles… replanting costs are aggressively capitalized to support RSPO claims*" (Internal Auditors). DSRI rose due to "*extending trade terms from 30 to 60 days to maintain sales volume despite falling CPO prices*" (Accounting). Sub-themes: (a) capitalization of biological assets (PSAK 69), (b) fictitious period-end receivables, (c) deferred depreciation.

Theme 2: Greenwashing Triggers (n = 86 quotes) "*GFW detects tree cover loss, but firms classify it as legal replanting on pre-cut-off degraded land*" (Internal Audit). RSPO claims were partial: "*Certification covers only core units; plasma is often excluded, yet reports claim 100% sustainability*" (Sustainability). Sub-themes: (a) definitional gaps (GFW vs. HCS/HCV), (b) *selective disclosure* of positive metrics, (c) sustainability KPI pressure.

Theme 3: Forensic Audit Barriers (n = 72 quotes) "*ESG data is manual and not integrated with ERP, making forensic tracing difficult*" (Accounting). "*Internal Audit staff lack GIS and blockchain skills; training is costly*" (Internal Audit). Sub-themes: (a) data fragmentation, (b) skill gaps, (c) high technology costs.

Theme 4: Stakeholder Pressures (n = 56 quotes) "*The Audit Committee demands explanations for TATA anomalies quarterly; institutional investors request satellite verification evidence*" (Internal Audit). "*OJK* *once requested clarification on gaps between ACOP and financial reports*" (Internal Audit). Sub-themes: (a) board oversight, (b) investor demands, (c) regulatory scrutiny.

Triangulation succeeded: high TATA (Table 1) aligns with aggressive capitalization narratives (Theme 1); deforestation *gaps* (Table 2) are explained by definitional discrepancies (Theme 2).

DISCUSSION

Interpretation of Quantitative Findings

Table 3 reveals an average M-Score of –2.05, consistent with Beneish (1999) for low-risk industries, yet 18.7% of cases exceeding –1.78 signals sector vulnerability. The dominance of TATA (mean = 0.04) reflects excessive capitalization of biological assets, aligning with OJK-UNEP FI (2024) findings that 41% of palm oil firms overstate sustainable land by up to 28%. Variability in DSRI and SGRI suggests manipulation of receivables and revenue recognition. The actual fraud incidence (18.7%) is notably lower than the 46.7% prevalence reported in prior industry-wide estimates (e.g., SPOTT, 2024), likely due to the heightened regulatory scrutiny and internal audit oversight in BEI-listed firms, which may suppress overt manipulation compared to non-listed entities.

Table 4 highlights an ESG paradox: a SPOTT ESG Score of 44.8% indicates poor transparency (SPOTT, 2024), while ESG Accuracy of 91.2% appears high. Sheet 3 analysis uncovers 16% of observations with deforestation *gaps* > 1,000 ha, confirming false *zero-deforestation* claims in 68% of RSPO-certified concessions (Trase/Global Canopy, 2024). The negative correlationin table 7 ($r = –0.68$) between ESG Accuracy and M-Score supports Hossain (2024) on the necessity of satellite verification.

Table 5 validates H_1: $\beta = 0.92$ (OR = 2.51) shows high ESG scores predict earnings manipulation, consistent with Christensen et al. (2021). POJK 51/2017 fails due to lacking *reasonable assurance* requirements. The robust model fit ($R^2 = 0.42$) positions ESG scores as a strong predictor, independent of size and leverage.

Table 6 confirms H_2 and H_3: a 0.58-point M-Score reduction ($d = 1.12$) and 6.2% accuracy gain ($d = 0.89$) post-intervention echo Khudair and Noman (2024) that forensic audits enhance economic sustainability ($\beta = 0.68$). The 4.1% volatility drop corroborates IDX (2023) that *greenwashing* exposure triggers 14.2% market corrections.

Overall, quantitative findings prove systemic ESG fraud via financial (TATA) and non-financial (*gap*) channels, with forensic audit as an effective remedy.

Integration with Qualitative Findings

Theme 1 (Accrual Manipulation) explains high TATA (Table 3) through aggressive replanting capitalization—akin to the ABG Shipyard case (Gupta et al., 2023). Respondents admitted "*capitalizing replanting costs to bolster RSPO claims*," confirming *earnings management* as a *greenwashing* tool. Deferred depreciation sub-themes reinforce low DEPI (Table 3).

Theme 2 (Greenwashing) exposes definitional loopholes behind deforestation *gaps* (Table 4). "*GFW vs. HCS/HCV*" enables "100% sustainable" claims despite active deforestation, matching Sawit Watch (2024). Partial RSPO certification explains RSPO Certified < Reported Sustainable Land (Table 4), evidencing *selective disclosure*.

Theme 3 (Forensic Barriers) highlights data fragmentation as a blockchain adoption obstacle (Gupta et al., 2023). "*Non-integrated ESG data*" hinders real-time triangulation, while skill shortages limit AI/satellite use. This supports the simulated intervention success (Table 6) despite constraints.

Theme 4 (Stakeholder Pressures) reflects *agency theory* (Jensen & Meckling, 1976): managerial incentives drive misreporting, but audit committee and investor oversight reduce information asymmetry (*signaling theory*, Spence, 1973). OJK demands reinforce the need for stricter regulation.

Theoretical and Practical Implications

Theoretically, this study extends Hossain (2024) and Khudair and Noman (2024) frameworks to agribusiness via M-Score + satellite + blockchain triangulation—a first in Indonesia. Findings affirm *greenwashing* as material financial fraud (Ben Mahjoub, 2024), not mere reputational risk. Integrating *agency* and *signaling theory* elucidates how forensic audit restores ESG signal credibility.

Practically, recommendations include: (1) OJK/BEI mandating *reasonable assurance* for high-risk ESG metrics (deforestation, emissions) and developing a national dashboard auto-integrating M-Score, GFW, and RSPO status—as per respondent suggestions; (2) firms enhancing Internal Audit with AI/satellite real-time monitoring and dual-competency training; (3) RSPO strengthening field audits, sanctions, and deforestation definitions; (4) investors conducting geospatial *due diligence* and requiring Internal Audit ESG verification reports. Implementation could prevent USD 18.7 billion export losses under EUDR (Gapki, 2025).

CONCLUSION

This study proves systemic ESG fraud in Indonesian palm oil firms (2020–2024) via TATA dominance (Table 3), deforestation *gaps* (Table 4), and ESG score-driven manipulation (Table 5). Quantitative evidence shows *greenwashing* as material earnings manipulation damaging market and export credibility.

Forensic audit effectively reduced M-Score by 0.58 points, boosted ESG accuracy by 6.2%, and cut market volatility (Table 6). Qualitative themes—accrual manipulation, definitional gaps, technological barriers, and stakeholder pressures—provide a holistic explanation of fraud drivers and prevention.

The M-Score + satellite + blockchain triangulation framework emerges as a globally replicable model for high-risk agribusiness. Policy implementation—national dashboards, *reasonable assurance*, and RSPO reforms—can mitigate EUDR risks and safeguard USD 18.7 billion in exports.

Ultimately, this research calls for a new ESG assurance paradigm: verification must match financial audit rigor, leverage technology, and be backed by stakeholder oversight. Only then can sustainability become a credible signal, not a *greenwashing* tool.

Limitations and Future Research

This study has limitations. First, ESG data is *self-reported*, prone to bias. Second, the forensic audit intervention was simulated, not real-time. Third, the sample is confined to BEI-listed firms, excluding non-public entities potentially more vulnerable. Fourth, interviews involved only 25 respondents, though thematic saturation was achieved.

Future research directions include:

- Testing blockchain traceability pilots in plasma supply chains for real-time verification.
- Expanding samples to non-listed firms and other commodities (soybean, cocoa) for forensic comparison.
- Developing machine learning models integrating M-Score, satellite data, and social media sentiment as an *early warning system*.
- Conducting longitudinal studies post-EUDR (2026) to assess regulatory impact on ESG accuracy.

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