IJSSR International Journal of Social Service and Research
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Vol. 4, No. 12, December 2024
e-ISSN: 2807-8691 | p-ISSN: 2807-839X

FROM INFLUENCE TO EXPLOITATION: UNVEILING CORRUPTION DYNAMICS IN THE PALM OIL INDUSTRY

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Keywords
corruption, social network analysis, state-corporate crime, palm oil industry

ABSTRACT
This study examines the complexity of corruption networks in the palm oil industry, focusing on the roles of state and corporate actors upstream and downstream. Using Social Network Analysis (SNA) of two corruption cases with data from investigation reports and court decisions, key actors and their relationships are analysed through degree centrality, eigenvector and modularity metrics. The results identified that actors have various roles, such as organisers, influencers, intermediaries, or simply communicators. Corporate actors dominate in upstream corruption involving illegal palm oil licences. Corporate actors dominate as initiators, exploiting regulatory weaknesses with state facilitation. In contrast, corruption in downstream palm oil revolves around crude palm oil (CPO) export fraud, with state actors as initiators organising systemic collusion so that corporate actors benefit from the manipulated system. The findings reveal adaptive corruption networks characterised by hierarchical structures and reciprocal solid relationships between actors. The study highlights the systemic nature of corporate-state crime in the palm oil industry by emphasising the dynamic role of influence and exploitation. Interventions against corruption cannot take a dyadic approach but must be comprehensive by disrupting corruption networks in weak governance.

INTRODUCTION

Indonesia's palm oil industry plays a vital role in the global market, accounting for 58% of the world's crude palm oil (CPO) supply by 2022-2023 (Kontan, 2022). The industry is a cornerstone of the national economy, supporting export earnings, creating jobs, and driving rural development (BPS, 2023). However, the rapid expansion of the sector has also exacerbated environmental and social challenges, including deforestation (Cisneros et al., 2021), biodiversity loss (Pramudya, 2018) and displacement of local communities (T. M. Li & Semedi, 2022). Moreover, these problems are exacerbated by the deep-rooted networks of corruption that thrive in the sector (Pachmann, 2021). The complexity of corruption is amplified by the involvement of multiple stakeholders - smallholders, multinational corporations and government officials - who interact through decentralised and often opaque regulatory frameworks (Whyte, 2014).

Corruption in the palm oil sector is closely linked to state policies that prioritise economic growth and inadvertently create pathways for exploitation (Astuti et al., 2022; Pacheco et al., 2020). Regulatory systems, especially those related to land use permits and export licences, are often hijacked by influential parties to serve private interests (Schoneveld et al., 2017). Large corporations with significant economic and political influence dominate these transactions, often with the complicity of state actors. This interaction between the state and corporations aligns with state-corporate crime (Michalowski & Kramer, 2007), where public officeholders and private entities collude to manipulate governance for mutual benefit (Pramudya et al., 2018). Such practices exacerbate inequality, environmental degradation and public distrust and entrench systemic corruption as the norm (Kartodihardjo et al., 2019).

Corruption networks in the palm oil industry are inherently adaptive and resilient, formed through complex relationships among state officials, corporate actors and intermediaries (Baker, 2020). These networks operate beyond individual transactions, creating an interconnected and interdependent resource exchange system (Ribeiro et al., 2023). Public officials often exploit regulatory loopholes, issuing licences in exchange for bribes or political support (Juniyanti et al., 2021). Corporations use their economic power to influence policy decisions, while intermediaries act as facilitators bridging the gap between key players to ensure the continuity of this corrupt system (Pirard et al., 2017). The adaptability of these networks allows them to persist despite changes in regulations or enforcement actions, underlining their structural complexity (Diviák, 2022).

Existing literature emphasises the need to move beyond an individualistic perspective on corruption to understand it as a network phenomenon (Helbing, 2013; Murillo, 2022). Traditional approaches focusing on dyadic exchanges fail to capture the systemic nature of corruption, especially in highly regulated sectors such as palm oil (Luna-Pla & Nicolás-Carlock, 2020). Social Network Analysis (SNA) offers a powerful lens through which to study corruption networks by examining relationships, centrality, and modularity (Duijn & Klerks, 2014). This perspective highlights how actors collaborate, switch roles and adapt to regulatory pressures, thus revealing the structural and dynamic patterns underlying corruption (Diviák & Lord, 2023). Such an approach is essential to see the interplay between formal and informal relationships that characterise corruption in the sector (Nicolás-Carlock & Luna-Pla, 2021).

This study explores the complexity of corruption networks in the Indonesian palm oil sector through the lens of corporate-state crime, a collaboration between the state and corporations that enable social distortions. This includes cases where corporations act illegally with state approval, or where the state fails to prevent corporate crime or actively colludes in wrongdoing. Law and governance often prioritize corporate interests over societal well-being, legitimizing exploitative practices. By analyzing two corruption cases—upstream and downstream—this study examines the role of key actors as initiators or facilitators. The findings aim to contribute to a deeper understanding of corruption as a systemic and complex problem and to inform targeted interventions to reform governance in the palm oil industry.

METHODS

To explore the complexity of corruption networks, we used social network analysis (SNA) on two palm oil corruption cases in Indonesia. Network metrics and visualisations are generated through computational processing with the Gephi application by counting the number of actors (nodes) and relationships (edges) in the network, identifying relationships between individuals, groups, and networks, and analysing sets, relationships between sets, and relationships between network types (Grandjean, 2015). Gephi used in this research is version 0.10.1 with the ForceAtlas2 algorithm, which is an algorithm used for small to large networks with thousands of nodes by simulating the physical system of forces acting on the nodes and edges of the network, transforming graphical data into map-like visualisations that are easy to read and interpret (Jacomy et al., 2014). In addition to the network layout being more aesthetically pleasing and easy to read, the ForceAtlas display helps researchers interpret patterns of structures, communities, bridges, and irregularities in network analyses more easily.

The dataset was carefully collected from selected cases representing upstream and downstream variance within the palm oil sector. Data was sourced from investigation reports and court proceedings, providing a rich basis for mapping interactions between actors. Summary Two cases include:

1) Upstream cases involve converting forest areas into oil palm plantations and other projects without regard to environmental sustainability and deforestation impacts. In the process of land conversion, the owner of the oil palm plantation corporation colluded with local officials to obtain an oil palm plantation permit in 2004, even though the plantation area is located in a state-protected forest area of more than 37,000 hectares. The oil palm plantation operated without obtaining business use rights but for more than two decades, from 2003 to the current year (2024).
2) Corruption in the downstream palm oil sector occurred in 2022, with charges of misuse of the Ministry of Trade's cooking oil export authorisation, resulting in a shortage of cooking oil

supply in Indonesia since 2021. This contradicts the fact that Indonesia is the world's largest supplier of CPO. The domestic market obligation (DMO) and domestic price obligation (DPO) arrangements towards producers led to the state having to subsidise bulk cooking oil due to the difference in the economic price of cooking oil. The subsidy scheme is 202 million litres monthly for six months at IDR 7.28 trillion. However, cooking oil producers still needed to fulfil the DMO or DPO were granted export approval while still receiving the subsidiary allocation.

The results of the SNA on two corruption cases can be tabulated as follows:

Table 1. Summary of corruption case data from investigation report documents and court decisions

Corruption Network	Actor Domination	Actors Involved				Actor Roles							Interaction Model			
		total	State Actor	Corporate Actor	Third Party Actor	Total		Organizer	Influencer	Intermediary	Communicator	Connector	Authority Ranking	Communal Sharing	Equal Matching	Market Price
Case 1 Upstream	State Actors	177	109	63	5	10	6%	2	2	4	1	1	54.60%	13.95%	30.86%	0.59%
Case 2 Downstream	Corporate Actors	128	41	81	6	12	9%	3	2	2	2	3	31.14%	14.04%	53.51%	1.32%

Based on the analysis of metrics by considering the significant centrality value of each actor to degree centrality, betweenness centrality, closeness and eigenvector as well as considering the dynamics of interaction and the context of relationships in the network, there are core actors who have various roles. The role of network organizer or as the main actor and network controller, influencer is a role that has influence on network decision-making and usually the actor is not real. The roles of communicators and connectors are actually almost the same as those of intermediaries, only intermediaries have more influence over the control of information flows and resources. Table2 details the centrality functions and significances of each core actor role in the network.

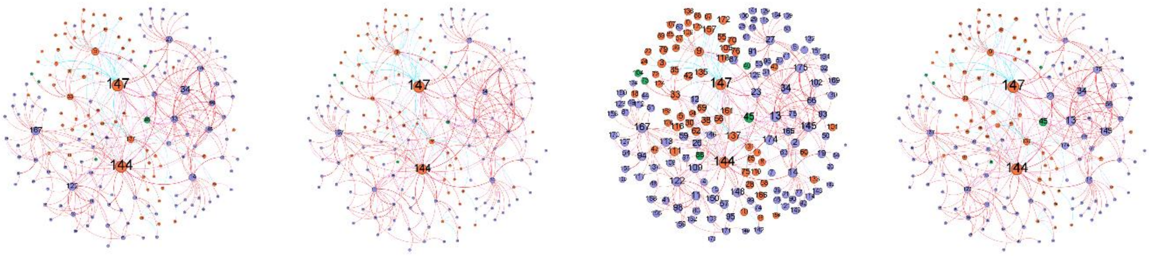
Table 2. Role and Function by Metric SNA

Role	Function	Centrality Significant
Organizer	Act as the network's core, facilitating communication, coordinating, and controlling the flow of information.	▪ Degree ▪ Eigenvector ▪ Closeness ▪ Betweenness
Communicator	Transmits information between core nodes and provides feedback, ensuring smooth information flow.	▪ Degree ▪ Closeness ▪ Betweenness
Connector	Links to all other nodes quickly, influencing by connecting with other influential actors.	▪ Closeness ▪ Degree
Intermediaries	Maintains network connectivity, ensuring smooth coordination and information exchange between unconnected nodes.	▪ Betweenness ▪ Eigenvector/Degree
Influencer	Supports network cohesion, playing a role in decision-making and collaboration.	▪ Eigenvector ▪ Degree ▪ Closeness

RESULTS

Configuration Network

Before proceeding with further analysis, it is important to acknowledge that the data represents corruption networks limited to actors explicitly named or investigated by law enforcement in the two cases. This means the scope of the network is shaped by investigative decisions, potentially excluding connections beyond the documented evidence. The dataset comprises state actors, corporate actors, and third parties, each playing varying roles across the cases. In the visualization, state actors are shown in purple, corporate actors in orange, and third-party actors in green. In Case-1 (Figure 1), the network involves 177 actors, with state actors dominating at 61.59%, followed by corporate actors at 35.23%, and third parties at 2.84%. This highlights the significant presence of state actors in the corruption network.



Degree centrality *Betweenness centrality* *Closeness centrality* *Eigenvector centrality*

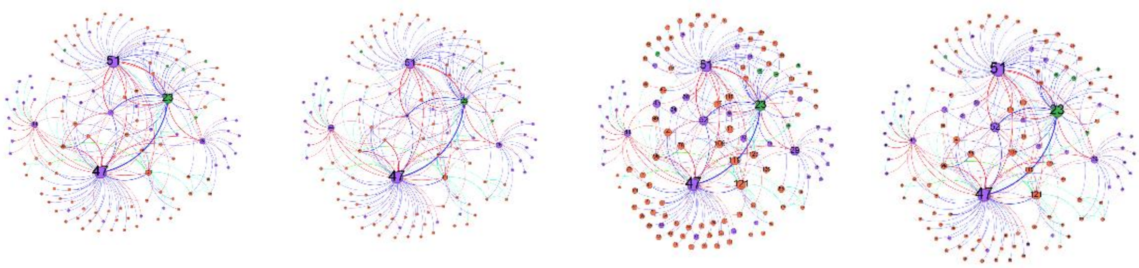
Purple = State Actor; Orange=Corporate Actor; Green=Third Party Actor

Figure 1. Network Configuration Case-1

The upstream palm oil corruption network reveals that corporate actors N147 and N144 are central figures who control the network. Other influential nodes include N13, an influencer, and N122 and N9, functioning as intermediaries. Additionally, N168 and N34 play dual roles, with N168 serving as a communicator or intermediary and N34 acting as both an influencer due to a high regional position and an intermediary facilitating communication with the central licensing authority. Over a 20-year period, this network demonstrates crime patterns consistent with Sutherland's (1983) theory of white-collar crime, where unethical behaviour develops through relationships, communication, and organizational norms. In 2004, N122, a local regent, issued an oil palm permit to N147's company, facilitated by N144 as the legal manager, despite violations of forest land provisions. Successor N168, in 2010, did not revoke the permit but instead adjusted it to fit regional map requirements, perpetuating the illegal activity.

In other words, through state actors acting as intermediaries, the exchange of information or resources remains stable and adaptive as time changes over twenty years. Allowing forest area violations is an instrument that facilitates corporations to hunt for leases by maintaining relationships with state actors who have access to permits (Kartodihardjo et al., 2015). This condition indicates the existence of corporate crimes facilitated by the state when the government (state actors) fails to control legal entities and is involved in illegal activities of issuing oil palm plantation business licenses (Lasslett, 2017).

The downstream palm oil sector shows the opposite (see Figure 2). Corruption cases in downstream palm oil involve 128 people, with a composition of 32.03% state actors, while corporate actors dominate the composition with 63.28% in the network and third parties as much as 4.69%.



Degree Centrality *Betweenness centrality* *Closeness centrality* *Eigenvector centrality*

Figure 2. Network Configuration Case-2

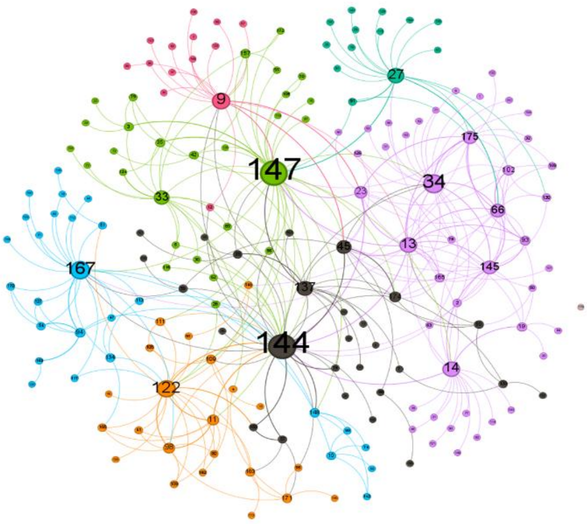
The Case-2 network highlights the interplay between state and corporate actors in securing CPO export permits, marked by regulatory or state capture. Key central figures include N51, the trade minister; N29, the coordinating minister for economic affairs and advisor to the state palm oil subsidy agency; and N47 and N44, officials managing export licenses within the Ministry of Trade. Additionally, N23, a third-party consultant to N29, exerts significant influence based on network metrics. While varying levels of centrality exist among the actors, the network consistently revolves around the core connections to N51, N47, and N23, underscoring their pivotal roles in the network's structure

Structure of Network

Network structures reflect patterns of relationships between actors that can be analyzed through the identification of patterns, relationship strengths, and structures that influence individual social or behavioral outcomes (Wasserman & Faust, 1989). In the context of corruption, this network describes the interaction of state actors, corporations, and third parties, both formal and informal, with core actors who have more influence than fringe actors who depend on relationships with core actors (Diviák et al., 2019). Modularity analysis helps identify groups or sub-communities in a network based on strong connections and hierarchies of interactions (Fortunato & Hric, 2016). In addition, the level of density and grouping coefficient provides an idea of the interconnectedness of the network, with high density indicating intense communication, while the grouping coefficient reflects the formation of close subgroups. These two aspects strengthen the network structure but can decrease modularity if the connectivity is too high (Faust, 2006).

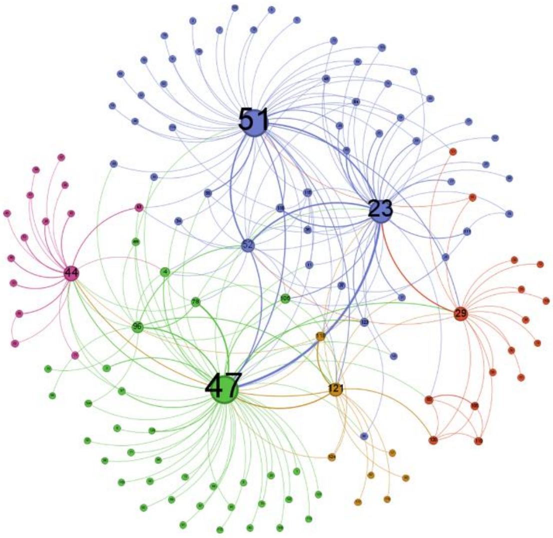
The Case-1 network topology (Figure 3) consists of eight modularity classes, distinguished by colour, revealing both core and peripheral structures. Cluster 4 (purple) dominates with 25% of the network population, indicating a tightly connected community of actors collaborating on corruption schemes, including N34, N13, N145, N175, and N66. This cluster represents state actors involved in granting permits for land-use changes, with N34 serving as a key "hub" linking other prominent clusters such as Cluster 3 (green), Cluster 5 (blue), and Cluster 7 (black), each with significant influence, exceeding 15% weight. In contrast, Cluster 0 and Cluster 2 are isolated and play no substantial role in the network, highlighting distinct subgroups within the corruption framework.

In the Case-1 network, the central actors, N144 in the green cluster and N147 in the black cluster, are corporate entities seeking permits for oil palm plantations. These core actors exhibit high centrality and serve as inter-cluster liaisons, controlling information flow across subgroups and maintaining connectivity between otherwise isolated subcommunities. The network demonstrates a well-defined community structure with a modularity score of 0.579, a density level of 0.022, with a clustering coefficient of 0.274. While relationships between actors are sparse, the core actors function as critical hubs, ensuring cohesion within clusters and maintaining links across the broader network.



Cluster	Weight
4	25,00%
3	15,91%
5	15,34%
7	15,34%
1	12,50%
0	7,95%
2	7,39%
6	0,57%

Figure 3. Modularity Class Case-1



Cluster	weight
3	41,41%
2	28,12%
0	12,50%
1	11,72%
4	6,25%

Figure 4. Modularity Class Case-2

As for case 2, the network is divided into five subclasses (see figure 4), which includes group 3 (green) with the largest weight of 41.41%, followed by group 2 (blue) with a weight of 28.12%. Both communities dominate the network and serve as the main structure within the network. The relatively equivalent community weights between group 0 (red) with a weight of 12.50%, group 1 (purple) with a weight of 11.72%, and group 4 (orange) with the lowest modularity weight of 6.25% reflect that nodes within a connected community are no more substantial than nodes outside the community. Overall, the actors N51, N47 and N23 are the core actors or nodes that play an important role in their communities and play an important role as liaisons between subcommunities.

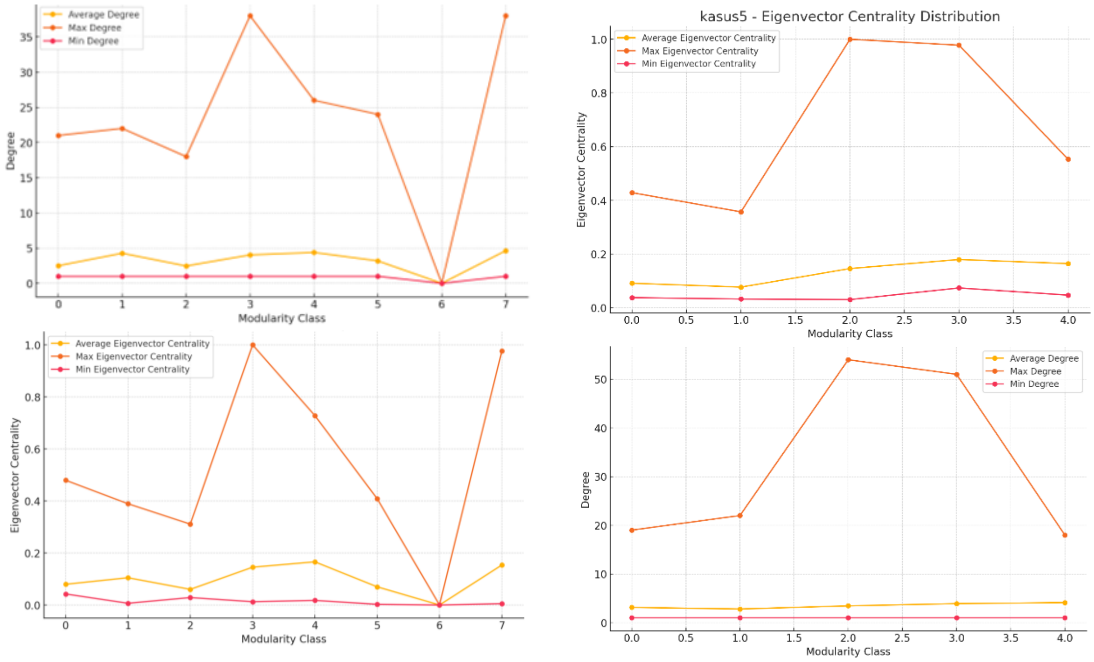
In the Case-2 network, N51 (blue cluster) and N47 (green cluster) act as community centres, connecting nodes within their respective groups while maintaining community interactions. The network shows well-separated yet interdependent subcommunities with a moderate modularity score of 0.449 and a low-density level of 0.028. Core actors serve as vital "hubs" for cross-community connections, ensuring the flow of information and influence, while peripheral actors remain less involved. Cluster 1 (pink), dominated by state actors, focuses on export approvals and cooking oil subsidies, whereas other clusters, including cluster 0 (orange), feature a stronger dominance of corporate actors, particularly in roles like managing the Oil Palm Plantation Fund. The network highlights the significant influence of corporate actors, albeit under the oversight of key state actors (N51 and N47).

From a State-Corporate crime perspective, the collaboration within this corruption network illustrates a symbiotic relationship between state and corporate entities. Analyzing the network structure and relationship patterns, both cases exhibit centralized network structures with strong modularity. However, the key distinction lies in the role of core actors as network hubs: in Case 1, corporate actors serve as the primary organizers, whereas in Case 2, state actors, supported by third-party actors, take on the central organizing role.

Dynamic of Network

The complexity of network dynamics is suspected by the non-linear characteristics and emergence of the network, which is shown through the disproportionate roles of nodes (actors) in connectivity with the emergence of patterns that are not determined from the external or the centre (Boccaletti et al., 2014). This includes the existence of a consistent, repetitive pattern among the actors or fractal dimensions, which indicates internal cohesion and structural network strength (Peeters, 2019) The fractal dimension through the Python algorithm in the corruption network reveals patterns of similar relationships at various levels (self-similarity), where the structure of small groups affects the larger network, creating similarities in their operations and interactions (D. Li et al., 2017)

Both cases exhibit non-linearity, as reflected in the disproportionate influence distribution between degree centrality and eigenvector centrality (see Figure 5). Emergence is evident through unexpected relationship patterns. In the Case-1 network, authority ranking dominates, with limited transactional behaviour, suggesting a power-driven system that includes some balanced partnerships. In Case 2, corporate dominance with an equal matching relationship model highlights the interdependence between state and corporate actors through social exchanges, with a clear division of roles. Both cases show nearly identical dimensional values (Case 1: 3.83, Case 2: 3.82), indicating complex, adaptive networks capable of reorganizing roles and responding dynamically to changes.



Case-1 *Case-2*

Figure 5. Degree and Eigenvector Distribution

CONCLUSION

The network analysis of corruption in the Indonesian palm oil sector reveals complex interactions among state actors, corporate entities, and third parties, highlighting distinct configurations in upstream and downstream cases. In the upstream scenario, a centralized network allows corporate actors to exploit systemic vulnerabilities, supported by state elites in a patron-client dynamic that fosters corruption through resource exchanges. Conversely, the downstream case features clusters of elites exerting control over public institutions through organized informal relations, enabling significant corporate influence over policies while state actors maintain formal authority. The study concludes that the roles of state and corporate actors shift based on context, emphasizing the adaptive nature of corruption networks. Addressing these challenges necessitates targeted interventions to disrupt entrenched systems. Future research could explore comparative analyses of corruption in various sectors, the impact of regulatory changes, the roles of civil society, longitudinal studies on network evolution, international influences, successful intervention case studies, technological solutions for transparency, informal networks, economic impact assessments, and evaluations of existing anti-corruption policies.

REFERENCES

Astuti, R., Miller, M. A., McGregor, A., Sukmara, M. D. P., Saputra, W., Sulistyanto, & Taylor, D. (2022). Making illegality visible: The governance dilemmas created by visualising illegal palm oil plantations in Central Kalimantan, Indonesia. *Land Use Policy*, *114*, 105942. https://doi.org/10.1016/j.landusepol.2021.105942

Baker, J. (2020). *Corrupt networks in the Indonesian forestry sector Politics and pulp in Pelalawan, Riau*.

Boccaletti, S., Bianconi, G., Criado, R., del Genio, C. I., Gómez-Gardeñes, J., Romance, M., Sendiña-Nadal, I., Wang, Z., & Zanin, M. (2014). The structure and dynamics of multilayer networks. *Physics Reports*, *544*(1), 1–122. https://doi.org/10.1016/j.physrep.2014.07.001

BPS. (2023). Perkembangan Ekspor dan Impor Indonesia. *Berita Resmi Statistik No. 61/09/Th. XXVI, 15 September 2023*, *64*, 1–8.

Cisneros, E., Kis-Katos, K., & Nuryartono, N. (2021). Palm oil and the politics of deforestation in Indonesia. *Journal of Environmental Economics and Management*, *108*, 102453. https://doi.org/10.1016/j.jeem.2021.102453

Diviák, T. (2022). Key aspects of covert networks data collection: Problems, challenges, and opportunities. *Social Networks*, *69*, 160–169. https://doi.org/10.1016/j.socnet.2019.10.002

Diviák, T., Dijkstra, J. K., & Snijders, T. A. B. (2019). Structure, multiplexity, and centrality in a corruption network: the Czech Rath affair. *Trends in Organized Crime*, *22*(3), 274–297. https://doi.org/10.1007/s12117-018-9334-y

Diviák, T., & Lord, N. (2023). From text to ties: Extraction of corruption network data from deferred prosecution agreements. *Data and Policy*, *5*. https://doi.org/10.1017/dap.2022.41

Duijn, P., & Klerks, P. (2014). Bridging science and investigative practice: Exploring the application of social network analysis in investigation. *Tijdschrift Voor Criminologie*, *56*(4). https://doi.org/10.5553/TvC/0165182X2014056004003

Faust, K. (2006). Comparing social networks: size, density, and local structure. *Metodološki Zvezki*, *3*(2), 185–216.

Fortunato, S., & Hric, D. (2016). Community detection in networks: A user guide. *Physics Reports*, *659*, 1–44. https://doi.org/10.1016/j.physrep.2016.09.002

Grandjean, M. (2015). *GEPHI – Introduction to network analysis and visualization*. Martin Grandjean - GEPHI Introduction.

Helbing, D. (2013). Globally networked risks and how to respond. *Nature*, *497*(7447), 51–59. https://doi.org/10.1038/nature12047

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLoS ONE*, *9*(6). https://doi.org/10.1371/journal.pone.0098679

Juniyanti, L., Purnomo, H., Kartodihardjo, H., Prasetyo, L. B., Suryadi, & Pambudi, E. (2021). Powerful actors and their networks in land use contestation for oil palm and industrial tree plantations in Riau. *Forest Policy and Economics*, *129*. https://doi.org/10.1016/j.forpol.2021.102512

Kartodihardjo, H., Ariati, N., & Abdullah, M. (2019). Kebijakan Pencegahan Korupsi Sektor Sumber Daya Alam Melalui Pendekatan Institusional dan Struktural. *Integritas*, *v*(2), 33–47. https://doi.org/https://doi.org/10.32697

Kartodihardjo, H., Nagara, G., & Situmorang, A. W. (2015). Transaction cost of forest utilization licenses: Institutional issues. *Jurnal Manajemen Hutan Tropika*, *21*(3), 184–191. https://doi.org/10.7226/jtfm.21.3.184

Kontan. (2022, November 24). Kontribusi Indonesia di Produksi Minyak Sawit Dunia Besar. *Https://Industri.Kontan.Co.Id/News/Kontribusi-Indonesia-Di-Produksi-Minyak-Sawit-Dunia-Besar*.

Lasslett, K. (2017). Uncovering the transnational networks, organisational techniques and state-corporate ties behind grand corruption: Building an investigative methodology. *International Journal for Crime, Justice and Social Democracy*, *6*(4), 29–54. https://doi.org/10.5204/ijcjsd.v6i4.445

Li, D., Wang, X., & Huang, P. (2017). A fractal growth model: Exploring the connection pattern of hubs in complex networks. *Physica A: Statistical Mechanics and Its Applications*, *471*, 200–211. https://doi.org/10.1016/j.physa.2016.12.038

Li, T. M., & Semedi, P. (2022). *Hidup bersama raksasa*. Duke University Press.

Luna-Pla, I., & Nicolás-Carlock, J. R. (2020). Corruption and complexity: a scientific framework for the analysis of corruption networks. *Applied Network Science*, *5*(1). https://doi.org/10.1007/s41109-020-00258-2

Michalowski, R. J., & Kramer, R. C. (2007). State-Corporate Crime and Criminological Inquiry. In H. N. Pontell & G. Geis (Eds.), *International Handbook of White-Collar and Corporate Crime* (p. 200).

Murillo, R. (2022). How to See Corruption: Networks and the Construction of Corruption in Spanish Italy. *Journal of Social History*, *55*(3), 565–585. https://doi.org/10.1093/jsh/shab026

Nicolás-Carlock, J. R., & Luna-Pla, I. (2021). Corruptomics. In N.-C. J. R. Granados O.M. (Ed.), *Understanding Complex Systems* (pp. 153–158). https://doi.org/10.1007/978-3-030-81484-7_9

Pacheco, P., Schoneveld, G., Dermawan, A., Komarudin, H., & Djama, M. (2020). Governing sustainable palm oil supply: Disconnects, complementarities, and antagonisms between state regulations and private standards. In *Regulation and Governance* (Vol. 14, Issue 3, pp. 568–598). Blackwell Publishing. https://doi.org/10.1111/rego.12220

Pachmann, A. (2021). Corruption and Deforestation in Indonesia. *Regional Formation and Development Studies*, *2*(2), 55–62. https://doi.org/10.15181/rfds.v25i2.1745

Peeters, C. F. W. (2019). *Social Network Analysis of Corruption Structures: Adjacency Matrices Supporting the Visualization and Quantification of Layeredness*. 1–13.

Pirard, R., Rivoalen, C., Lawry, S., Pacheco, P., & Zrust, M. (2017). A policy network analysis of the palm oil sector in Indonesia: What sustainability to expect? In *A policy network analysis of the palm oil sector in Indonesia: What sustainability to expect?* Center for International Forestry Research (CIFOR). https://doi.org/10.17528/cifor/006528

Pramudya, E. P. (2018). Balancing and counterbalancing : the Indonesian state addressing pressures to improve palm oil sector sustainability [Wageningen University]. In *Wageningen University & Research*. https://doi.org/10.18174/449954

Pramudya, E. P., Hospes, O., & Termeer, C. J. A. M. (2018). The disciplining of illegal palm oil plantations in Sumatra. *Third World Quarterly*, *39*(5), 920–940. https://doi.org/10.1080/01436597.2017.1401462

Ribeiro, H. V., Lopes, D. D., Pessa, A. A. B., Martins, A. F., da Cunha, B. R., Gonçalves, S., Lenzi, E. K., Hanley, Q. S., & Perc, M. (2023). Deep learning criminal networks. *Chaos, Solitons and Fractals*, *172*(April), 113579. https://doi.org/10.1016/j.chaos.2023.113579

Schoneveld, G., Jelsma, I., Komarudin, H., Andrianto, A., Orkada, B., & Ekowati, D. (2017). Public and private sustainability standards in the oil palm sector: Compliance barriers facing Indonesia's independent oil palm smallholders. *Public and Private Sustainability Standards in the Oil Palm Sector: Compliance Barriers Facing Indonesia's Independent Oil Palm Smallholders*, *182*. https://doi.org/10.17528/cifor/006556

Wasserman, S., & Faust, K. (1989). Canonical Analysis of the Composition and Structure of Social Networks. *Sociological Methodology*, *19*, 1–42.

Whyte, D. (2014). Regimes of Permission and State-Corporate Crime. *State Crime Journal*, *3*(2), 237–246.