

CENTRAL WAREHOUSE SELECTION WITH MULTIMODAL EMISSION CONSIDERATIONS

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ABSTRACT

The selection of a central warehouse location is a critical decision in logistics systems, as it is influenced by business process uncertainty, cost optimization, and environmental considerations such as CO₂ emissions. In the context of Bali Province, logistics activities involving the transportation of goods from Java are closely associated with these challenges. Addressing environmental concerns through sustainable logistics principles requires an analytical approach that accounts for uncertainty in logistics operations. This study applies simulation-based stochastic modeling using AnyLogic software integrated with Geographic Information System (GIS) features to evaluate alternative central warehouse locations based on CO₂ emission calculations. The logistics distribution model incorporates both land and sea transportation modes, reflecting the real distribution conditions between Java and Bali. The simulation results indicate that Mangupura is the preferred location for the central warehouse, despite Negara having a shorter average transportation distance.

Keywords: anylogic; central warehouse; CO₂ emissions; sustainable logistics

INTRODUCTION

Traditionally, a central warehouse in logistics distribution functions as a facility for receiving goods, storing commodities, dispatching outbound shipments, and processing customer orders. Along with the evolution of logistics systems, the role of central warehouses has expanded to include value-added activities such as consolidation, sorting, packaging, and information processing. This transformation is closely related to the advancement of Industry 4.0, which promotes the adoption of digital technologies and data-driven decision-making in logistics and warehousing operations (Politeknik Transportasi Darat Bali, 2020). As logistics systems grow in complexity, central warehouses increasingly operate as distribution centers that serve as transit points between suppliers and downstream facilities or customers. In this role, the central warehouse becomes the core node of commodity flows, container handling, inventory storage, and outbound distribution (Qian et al., 2017). Consequently, the selection of an appropriate warehouse location is a strategic decision, as it directly affects transportation efficiency, service performance, and overall logistics costs (Soimun, 2022). An improperly located warehouse may lead to excessive transportation distances, higher operational costs, and reduced system responsiveness (Rushton et al., 2014).

Rapid technological development under Industry 4.0 has also reshaped logistics decision-making processes. The availability of large-scale data, high computational capability, and advanced simulation software enables decision-makers to analyze complex logistics systems more comprehensively. As a result, warehouse location decisions can no longer rely on trial-and-error approaches or purely deterministic calculations. Instead, they require analytical tools capable of representing uncertainty in demand, transportation time, and operational conditions. In this context, decision support systems based on modeling and simulation have become essential for logistics planning (Borshchev, 2013). Simulation-based modeling offers significant advantages in analyzing logistics systems characterized by stochastic behavior (Grigoryev, 2018). Real-world logistics processes are inherently uncertain, as they involve

fluctuating customer demand, variable transportation times, and unpredictable supply conditions (Wagner & Taudes, 1987). Deterministic models often fail to capture these uncertainties, potentially leading to biased or inaccurate decision outcomes. (Ondrich & Ruggiero, 2001) Stochastic simulation models, by contrast, incorporate random variables and probability distributions, allowing decision-makers to evaluate system performance under more realistic conditions and to compare alternative scenarios more reliably. In the case of Bali Province, logistics distribution presents unique geographical and operational characteristics. Bali consists of nine regencies and cities distributed across the island and serves as an economic and population hub between Java and Lombok. A substantial portion of essential commodities and goods consumed in Bali is supplied from Java via sea transportation through the Banyuwangi–Gilimanuk route. This inter-island logistics structure makes the selection of a central warehouse location particularly critical, as it must efficiently connect sea-based supply flows with land-based distribution to regional branches.

Beyond economic and geographical considerations, contemporary logistics planning must also address environmental sustainability (Makmun, 2011). Global concerns regarding climate change and environmental degradation have emphasized the importance of reducing greenhouse gas emissions in transportation and logistics activities. The Sustainable Development Goals (SDGs), particularly those related to responsible consumption and production, encourage organizations to integrate environmental performance indicators into operational decision-making (Gasper et al., 2019). For Bali, which heavily depends on sustainable tourism and environmental preservation, logistics operations must align with these principles to support long-term regional development.

Previous studies on warehouse location selection in Bali primarily focused on minimizing transportation distance or total travel length. While distance-based criteria are useful, they do not fully capture the environmental impact of logistics operations. Transportation-related CO₂ emissions depend not only on distance but also on fuel consumption, vehicle utilization, and operational variability. Therefore, evaluating warehouse location alternatives solely based on distance such as in Gautama et al. (2023) may lead to suboptimal decisions from an environmental perspective. This study addresses this gap by determining the central warehouse location in Bali based on CO₂ emission calculations using a stochastic simulation approach. By integrating AnyLogic simulation software with Geographic Information System (GIS) features, this research models logistics distribution involving both land and sea transportation modes. CO₂ emissions are estimated by considering fuel consumption and emission factors within a stochastic framework. The results provide a comparative evaluation of alternative warehouse locations and demonstrate the importance of incorporating environmental criteria into logistics facility location planning.

METHOD

Several previous studies provide a mapping framework for this research. Ramadhan et al. (2020) used AnyLogic to model the supply chain of Honda automobiles. In this business model, there are three main entities: a factory, a warehouse, and dealers. The simulation method applied is discrete-event simulation, which is complemented by GIS maps to determine the location of each entity and statecharts to represent the behavior of each entity. The distribution process in the statechart involves statistical distribution calculations and the use of random numbers to reflect stochastic conditions. This study measures supply chain performance by evaluating the average time required for each car within the supply chain. The research is an extension of earlier studies that evaluated performance based on the distance traveled by vehicle units. Qian et al. (2017) combined life cycle assessment methods, carbon emission indices, cost

calculations, and linear programming in their study. Based on this research, the authors calculated carbon gas emissions generated by four parties: suppliers, logistics service providers, manufacturers, and distribution centers, for two types of commodities produced. Carbon emissions were calculated based on the quantity of commodities transported and the transportation distance, assuming that emissions from each transportation unit are constant. This calculation employed a deterministic approach. The results of the study show the total logistics cost, which includes carbon emission costs, transportation costs, and fixed costs. The option with the lowest total logistics cost was achieved by operating 3 out of the 4 planned logistics centers, namely centers 2, 3, and 4, while center 1 was not utilized.

This study is an extension of the simulation previously applied by Gautama et al. (2023), which determined the selection of a central warehouse based on the total travel distance of the entire transportation fleet during the distribution process. By utilizing a modified GIS map, the study found that the selected central warehouse location was Mangupura, as it resulted in the lowest total travel distance. In the present study, the authors compare the results obtained when the model is executed using calculations that consider emission value ranges and a stochastic approach. The inclusion of logistics distribution via maritime transport, representing supply from Java Island, is adopted from Gautama et al. (2024). Instead of using travel distance, decision-making in this study is based on the magnitude of CO₂ emissions.

This study applies a simulation-based stochastic approach to evaluate alternative central warehouse locations in Bali Province based on CO₂ emission performance. The overall research framework consists of four main stages: (1) system conceptualization, (2) simulation model development, (3) CO₂ emission estimation, and (4) statistical analysis of simulation outputs. The logistics system is modeled to represent the distribution of goods from Java to Bali using sea transportation, followed by land distribution from a central warehouse to regional branches across Bali. Two alternative locations for the central warehouse are evaluated, namely Negara and Mangupura. The comparison focuses on total CO₂ emissions generated during the distribution process rather than solely on transportation distance.

The simulation model is developed using AnyLogic software, which supports discrete-event simulation and stochastic modeling. Geographic Information Systems (GIS) are computer applications that function to capture, store, analyze, and display information related to positions on the Earth's surface (Huang et al., 2017). Another definition of GIS describes it as a technical system that captures, stores, manages, calculates, analyzes, displays, and explains geographic information related to the Earth's surface (Li et al., 2023). GIS can also be understood as an integrated computer system that performs operations including the analysis and storage of positional data, such as those implemented in Google Maps. It is therefore unsurprising that GIS plays a critical role in computer applications such as natural resource exploration and regional planning. Given the importance of GIS in simulation, several software packages, such as AnyLogic, have incorporated GIS features to support analysis in urban transportation, building and public facility planning, parking location determination, logistics route planning, and other applications.

AnyLogic modeling emerged after object-oriented programming languages such as Java gained popularity, alongside advances in processor performance and increased computer memory access speeds driven by the Fourth Industrial Revolution. Modeling, which previously existed only as a theoretical concept, began to materialize in practical form in the early 2000s (Grigoryev, 2018). AnyLogic modeling serves as a tool for representing complex and dynamic systems, particularly in the era of Industry 4.0 driven by advanced technologies. AnyLogic

integrates several modeling approaches—system dynamics, discrete-event simulation, and agent-based modeling—allowing researchers and practitioners to select the most appropriate method according to the context and objectives of their studies. AnyLogic is integrated with Geographic Information System (GIS) features to represent real geographical conditions, transportation routes, and distances between locations. The GIS map covers the island of Bali and the eastern part of Java, including the Banyuwangi–Gilimanuk sea crossing route.

Discrete-event simulation is selected as the primary modeling approach because it is suitable for representing logistics processes characterized by sequential events, resource utilization, and operational variability. Discrete-event simulation has evolved since the 1950s and involves interactive visual modeling, optimization, and integration with other software (Robinson, 2005). It is a stochastic approach used to represent complex and dynamic systems with an operational emphasis, for example in the healthcare sector (Vázquez-Serrano et al., 2021). Stochastic elements are incorporated into the model to reflect uncertainty in order arrivals, transportation activities, and emission factors. The logistics system consists of the following main entities:

1. Central warehouse, which receives orders from branches and dispatches trucks for land distribution.
2. Branch locations, representing regencies and cities in Bali that generate stochastic demand.
3. Sea transportation, representing cargo vessels delivering goods from Java to Bali.
4. Land transportation, represented by trucks distributing goods from the central warehouse to branches.
5. Several assumptions are applied to simplify the modeling process while maintaining realism:
6. Cargo vessels from Java arrive at Gilimanuk Port at intervals ranging from 2 to 4 days, with a constant sailing speed of 15 knots.
7. Each branch generates between 1 and 4 orders per week, with order arrivals determined randomly.
8. Truck movements follow the shortest available routes defined by the GIS network.
9. Fuel consumption for diesel trucks is assumed to be 1 liter per 8 km of travel.
10. The simulation duration is set to 100 days to capture sufficient operational variability.
11. Random number generation is used to represent stochastic behavior without fixed seeds. To obtain reliable results, multiple replications are conducted, and average values are used for analysis.

The modeling design begins with the configuration of the scenarios to be executed. Sea vessels from Java Island arrive every 2–4 days, with the vessel speed set at 15 knots. The number of orders received by branches from the central warehouse is assumed to range from 1 to 4 times per week. These orders are automatically generated by AnyLogic using random numbers, rather than the seed-based method used in previous studies. In the seed method, random numbers are generated in a fixed sequence and can be used for model comparison. In contrast, when pure random numbers are used, replications are required to obtain average values as the final results (Borshchev, 2013; Fatimah, 2021). The variables involved in this business process are divided into two categories: inputs and outputs. In the input stage, the business process begins when the central warehouse receives orders from branches, represented as agents called Orders. After receiving the orders, the central warehouse dispatches trucks to deliver goods to the ordering branches. During this process, information exchange occurs between the Order agents and truck agents at the central warehouse, ensuring that trucks are directed to the correct branches according to the orders. The movement of these trucks is also included in the calculation of

carbon gas (CO₂) emissions. The simulation scenario also incorporates the movement of sea vessels transporting commodities, as described in Gautama et al. (2024).

CO₂ emissions are estimated based on fuel consumption and emission factors following established guidelines. Emissions are calculated using the general formulation (Boer et al., 2012):

$$\text{"CO}_2 \text{ Emission"} = \text{"Fuel Consumption"} \times \text{"Calorific Value"} \times \text{"Emission Factor"}$$

Fuel consumption is derived from the total distance traveled by transportation units during the simulation. The calorific value of diesel fuel is set at 0.037 TJ/kL. Emission factors are adopted from the IPCC 2006 default values for diesel fuel, which range between 72,600 kg/TJ and 74,800 kg/TJ, with a default value of 74,100 kg/TJ. The assumption used is that 1 liter of diesel fuel allows a vehicle to travel a distance of 8 kilometers (Fitzgerald, 2024). Unlike deterministic approaches that use a single emission factor value, this study applies a triangular distribution to represent the emission factor range. This stochastic treatment allows the model to capture variability in emission outcomes and better reflect real-world uncertainty.

CO₂ emissions are calculated for both land and sea transportation components. Emissions generated by truck movements include round-trip distances between the central warehouse and branch locations, as well as trips between the warehouse and the port. Emissions from sea transportation are represented through vessel arrival activities and associated fuel usage assumptions. To compare the two alternative warehouse locations, the simulation is executed for each scenario with 30 independent replications. Each replication produces a total CO₂ emission value for the 100-day simulation period. The resulting emission values form two independent samples corresponding to the Negara and Mangupura warehouse locations. Before conducting statistical comparisons, the output data are tested for normality using the Shapiro–Wilk test, which is appropriate for sample sizes below 50. Homogeneity of variance is also examined to ensure the validity of parametric testing. An independent samples t-test is then applied to evaluate whether there is a statistically significant difference in mean CO₂ emissions between the two warehouse location scenarios. A significance level of 0.05 is used as the decision threshold.

RESULT AND DISCUSSION

The simulation experiments produced total CO₂ emission values for each warehouse location scenario based on 30 independent replications. Screenshot of the simulation experiments run in Anylogic is shown in Figure 1.



Figure 1. Simulation Experiment with Negara as Central Warehouse

These values represent the cumulative emissions generated by both land and sea transportation activities during the 100-day simulation period, as shown in Table 1.

Table 1.
 Simulation Experiment Result

No	Counrty	Mangupura
1	17,403.95	10,431.89
2	18,746.49	11,131.63
3	17,772.77	11,062.09
4	15,270.07	9,553.58
5	16,385.48	10,481.6
6	17,476.28	11,318.22
7	14,523.63	10,526.46
8	18,838.75	10,398.18
9	17,087.96	11,561.56
10	20,509.41	9,851.09
11	21,236.26	9,308.28
12	17,992.55	10,058.19
13	20,408.25	10,351.58
14	19,388.90	10,415.54
15	18,444.89	10,291.09
16	21,952.51	10,622.83
17	19,341.17	10,739.87
18	15,374.88	9,558.85
19	17,579.58	10,053.19
20	16,813.54	8,851.44
21	18,012.59	10,828.64
22	18,054.84	11,401.24
23	18,522.22	9,350.42
24	18,217.02	9,307.22
25	15,764.36	9,760.80
26	20,398.36	10,412.71
27	17,939.58	10,090.93
28	21,201.31	10,642.29
29	17,229.24	10,946.01
30	19,117.69	10,439.21

The results show a clear difference in emission performance between the two alternative warehouse locations. When Negara is selected as the central warehouse, the average total CO₂ emission is 18,233.48 kg, with a standard deviation of 1,829.31 kg. In contrast, the Mangupura scenario produces a substantially lower average emission of 10,324.89 kg, with a standard deviation of 672.03 kg. This indicates not only lower emissions but also reduced variability in emission outcomes for the Mangupura location. To verify the reliability of the simulation outputs, boundary analysis was conducted using deterministic minimum and maximum conditions. The simulated emission values fall within the analytically calculated lower and upper bounds, confirming the internal consistency of the model and supporting the validity of the simulation results. This study uses the minimum and maximum values of a triangular distribution. The determination of the upper and lower bounds also considers the maximum and minimum number of orders from each branch, ranging from once to four times per week.

The verification calculation process is carried out by computing the distance from Negara as the central point. The average distance from Negara to each destination city is obtained from

BPS Prov Bali (2023), which is 117.12 km. The manual calculation for the lower bound is performed by combining Equations (1) and (2) as follows:

$$\text{CO}_2 \text{ emissions} = 2 \times 117,120 / 8 \times 0.037 \times 72,600 / 1,000,000$$

$$\text{CO}_2 \text{ emissions} = 78.62 \text{ kg}$$

These emissions correspond to one trip or one order by one branch under the lower-bound condition. Using the same approach and replacing the value of 72,600 with 74,800, the CO₂ emissions at the upper bound are obtained as 81 kg. Under the lower-bound condition, each branch places only one order per week, or 14 orders per cycle (100 days). Thus, the manual calculation for the lower bound with Negara as the center is as follows:

$$\text{CO}_2 \text{ emissions} = 78.62 \times 14 \times 8 = 8,805.44 \text{ kg}$$

Emissions are also generated when ships arrive and trucks transport goods from Gilimanuk to Negara over a distance of 32 km. In the scenario with the least frequent ship arrivals, ships arrive once every four days, resulting in 25 arrivals during the simulation period. The emission calculation for the lower bound therefore becomes:

$$\text{CO}_2 \text{ emissions (1 trip)} = 2 \times 32,000 / 8 \times 0.037 \times 72,600 / 1,000,000 = 21.5 \text{ kg}$$

$$\text{CO}_2 \text{ emissions (25 trips)} = 21.5 \times 25 = 537.24 \text{ kg}$$

$$\text{Total CO}_2 \text{ emissions at the lower-bound value} = 8,805.44 + 537.24 = 9,342.68 \text{ kg}$$

Subsequent calculations are conducted to determine the upper bound with Negara as the central point. The upper-bound value uses an ordering frequency of four times per week, resulting in the following calculation:

$$\text{CO}_2 \text{ emissions} = 78.62 \times 96 \times 8 = 60,380.16 \text{ kg}$$

The upper-bound calculation is continued by assuming the most frequent ship arrivals (once every two days), or 50 arrivals during the simulation period:

$$\text{CO}_2 \text{ emissions} = 21.5 \times 50 = 1,075 \text{ kg}$$

$$\text{Total CO}_2 \text{ emissions at the upper-bound value} = 60,380.16 + 1,075 = 61,455.16 \text{ kg}$$

Based on the results shown in Table 1, the CO₂ emission values are verified, as they fall between the lower-bound value (9,342.68 kg) and the upper-bound value (61,455.16 kg).

The data presented in Table 1 were then processed using the SPSS software. The dataset with Negara as the center was labeled as Group 1, while the dataset with Mangupura as the center was labeled as Group 2. Subsequently, a normality test was conducted to determine whether the data were normally distributed, and the results of this test are presented in Table 2.

Table 2.
 Normality data testing

		Tests of Normality					
		Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	kelompok	Statistic	df	Sig.	Statistic	df	Sig.
nilai_rerata	Negara	.082	30	.200 ^a	.981	30	.845
	Mangupura	.116	30	.200 ^a	.977	30	.747

*. This is a lower bound of the true significance

a. Lilliefors Significance Correction

Prior to hypothesis testing, the normality of the simulation output data was examined using the Shapiro–Wilk test. The test results indicate that the emission data for both warehouse location scenarios are normally distributed, with significance values exceeding the 0.05 threshold. Therefore, parametric statistical testing is considered appropriate. An independent samples t-

test was then performed to evaluate whether the observed difference in mean CO₂ emissions between the two scenarios is statistically significant, as shown in Table 3.

Table 3.

T-Test Independent
Independent Sample Test

	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
nilai_rerata	15.8	.000							
Equal variances assumed			22.227	58	.000	7908.597	355.80907	7196.37	8620.83
Equal variances not assumed			22.227	36.7	.000	7908.597	355.80907	7196.37	8629.74

The test results show a significance value (p-value) below 0.05, leading to the rejection of the null hypothesis. This confirms that the difference in mean CO₂ emissions between the Negara and Mangupura warehouse locations is statistically significant. The mean difference between the two scenarios is 7,908.59 kg, indicating that the Mangupura location consistently generates lower CO₂ emissions compared to Negara under stochastic operating conditions, shown in Table 4.

Table 4.

Mean difference between 2 scenarios

Group statistics

	kelompok	N	Mean	Std. Deviation	Std. Error Mean
nilai_rerata	Negara	30	18233.48	1829.31268	333.98527
	Mangupura	30	10324.89	672.02520	122.69445

The results demonstrate that warehouse location decisions based solely on transportation distance may not yield environmentally optimal outcomes. Although Negara is geographically closer to the main sea port and benefits from shorter average distances for certain routes, the overall logistics system performance—when evaluated using CO₂ emissions—favors Mangupura. This finding can be explained by the interaction between transportation patterns, order frequency, and stochastic variability. The Mangupura location exhibits more balanced land distribution routes to multiple branches, resulting in lower cumulative travel distances under repeated stochastic demand scenarios. Additionally, the reduced variability observed in the Mangupura scenario suggests more stable logistics operations with respect to emission performance. From a sustainable logistics perspective, these results highlight the importance of incorporating environmental indicators into facility location planning. CO₂ emissions capture not only spatial factors but also operational characteristics such as trip frequency and vehicle utilization. Consequently, emission-based evaluation provides a more comprehensive decision criterion than distance alone. The use of stochastic simulation further strengthens the analysis by accounting for uncertainty in demand and transportation activities. Unlike deterministic approaches, which may underestimate or overestimate environmental impacts, the stochastic

framework used in this study offers a more realistic representation of real-world logistics operations.

CONCLUSION

This study investigated the determination of a central warehouse location in Bali Province by incorporating CO₂ emission calculations into a stochastic logistics distribution model. Using simulation-based modeling with AnyLogic integrated with GIS features, the study evaluated two alternative warehouse locations—Negara and Mangupura—under land and sea transportation scenarios.

The results demonstrate that Mangupura is the more environmentally efficient location, as it consistently produces lower average CO₂ emissions compared to Negara. Despite Negara's advantage in terms of shorter average distance to the main sea port, the overall emission performance of the logistics system favors Mangupura when operational variability and transportation frequency are taken into account. This finding confirms that transportation distance alone is insufficient as a decision criterion for warehouse location planning, particularly when environmental sustainability is considered.

The application of stochastic simulation provides a more realistic assessment of logistics system performance compared to deterministic approaches. By incorporating uncertainty in order arrivals and emission factors, the model captures variability in operational conditions and supports more robust decision-making. The results highlight the value of integrating environmental performance indicators, such as CO₂ emissions, into logistics facility location decisions, especially in regions with inter-island transportation characteristics. Future research may extend the current model in several directions. First, additional sea ports, such as Padang Bai in eastern Bali, can be incorporated to represent logistics flows between Bali and Lombok. Second, emission calculations for sea transportation can be refined by explicitly modeling fuel consumption and emission rates of cargo vessels during sea crossings. Finally, the model can be expanded to include economic cost factors and multi-objective optimization, enabling a more comprehensive evaluation of trade-offs between cost efficiency and environmental sustainability.

REFERENCES

- Boer, R., Dewi, R. G., Siagian, U., Ardiansyah, M., Surmaini, E., Ridha, D. M., . . . Parinderati, R. (2012). *Pedoman Penyelenggaraan Inventarisasi GRK Nasional*. Jakarta, Indonesia: Kementerian Lingkungan Hidup.
- Borshchev, A. (2013). *The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6 Edition*. Lightning Source Inc.
- BPS Prov Bali . (2023). Retrieved from Web Site Badan Pusat Statistik Provinsi Bali : <https://bali.bps.go.id/id/statistics-table/1/NDkjMQ==/jarak-antar-kabupaten-kota-di-provinsi-bali.html>
- Fatimah, F. (2021). *Analisis dan Interpretasi Data*. Tangerang Selatan: Universitas Terbuka.
- Fitzgerald, J. (2024, April 30). Retrieved from Car and Driver: <https://www.caranddriver.com/news/a60546916/heavy-duty-trucks-gas-diesel-highway-fuel-economy-test-results/>
- Gaspar, D., Shah, A., & Tankha, S. (2019). The Framing of Sustainable Consumption and Production in SDG 12. *Global Policy*. <https://doi.org/10.1111/1758-5899.12592>
- Gautama, N., Soimun, A., & Gilang, A. (2023). Analisis Lokasi Gudang Pusat Distribusi Logistik di Provinsi Bali. *Jurnal Teknologi Transportasi dan Logistik*. <https://doi.org/10.52920/jttl.v4i1.126>

- Gautama, N., Soimun, A., Darmayanti, N. L., & Jannah, A. I. (2024). Analysis of Central Warehouse Location and Logistics Distribution Land and Sea Modes. *Jurnal Teknologi Transportasi dan Logistik*, 5(1), 95-102. <https://doi.org/10.52920/jttl.v5i1.319>
- Grigoryev, I. (2018). *Anylogic in Three Days* (5 ed.). Retrieved July 1, 2021
- Huang, B., Cova, T., Tsou, M.-H., Bareth, G., Song, C., Song, Y., . . . Silva, E. (2017). *Comprehensive Geographic Information Systems*. Elsevier.
- Li, X., Yue, J., Wang, S., Luo, Y., Su, C., Zhou, J., . . . Lu, H. (2023). Development of Geographic Information System Architecture Feature Analysis and Evolution Trend Research. *Sustainability*. <https://doi.org/10.3390/su16010137>
- Makmun. (2011). Green Economy: Konsep, Impelentasi Dan Peran Kementerian Keuangan. *Jurnal Ekonomi Pembangunan LIPI*, 19(2), 1-15.
- Ondrich, J., & Ruggiero, J. (2001). Efficiency measurement in the stochastic frontier model. *European Journal of Operational Research*, 129, 434-442. [https://doi.org/10.1016/S0377-2217\(99\)00429-4](https://doi.org/10.1016/S0377-2217(99)00429-4)
- Politeknik Transportasi Darat Bali. (2020). *Buku Ajar Jurusan D3 Manajemen Logistik Manajemen Pergudangan*. Tabanan: PPSDMPD Kemenhub.
- Qian, X., Li, J., Ying, J., & Fu, P. (2017). Study on Carbon Analysis and site Selection of Logistics Center under Low-carbon Environment. *2nd International Conference on Mechatronics Engineering and Information Technology (ICMEIT 2017)* (pp. 401-407). Atlantis Press.
- Ramadhan, A., Aditya, S., & Afinil, M. (2020). Pemodelan dan Simulasi Rantai Pasok Mobil Honda. *Jurnal Manajemen Transportasi & Logistik*, 69-76.
- Robinson, S. (2005). Discrete-event simulation: from the pioneers to the present, what next? *Journal of the Operational Research Society*, 56, 619-629. <https://doi.org/10.1057/palgrave.jors.2601864>
- Rushton, A., Croucher, P., & Baker, P. (2014). *The Handbook of Logistics & Distribution Management* (5th ed.). London: KoganPage.
- Soimun, A. (2022). Infrastruktur Logistik. In *Kebangkitan Industri Logistik Pasca Pandemi Covid-19* (pp. 205-224). Bandung: CV. Media Sains Indonesia.
- Vázquez-Serrano, J., Peimbert-García, R., & Cárdenas-Barrón, L. (2021). Discrete-Event Simulation Modeling in Healthcare: A Comprehensive Review. *International Journal of Environmental Research and Public Health*, 18. <https://doi.org/10.3390/ijerph182212262>
- Wagner, U., & Taudes, A. (1987). Stochastic models of consumer behaviour. *European Journal of Operational Research*, 19(1), 1-23. [https://doi.org/https://doi.org/10.1016/0377-2217\(87\)90189-5](https://doi.org/https://doi.org/10.1016/0377-2217(87)90189-5)