# Determinants of Capture Fisheries Production and Its Implications for Destructive Fishing Practices in Coastal Provinces of Indonesia

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***Abstract:*** *This study aims to analyze the determinants of capture fisheries production and their implications for destructive fishing practices in coastal provinces of Indonesia during the period 2017–2024. The study employs a quantitative approach using panel data analysis covering 10 coastal provinces. The dependent variable is capture fisheries production, while the independent variables include the number of fishers, number of vessels, fish stock (CPUE), fisheries infrastructure, and government policy. The estimation models used are the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM), with model selection conducted through Chow and Hausman tests. The results indicate that the number of fishers, vessels, and fish stock have a positive and significant effect on fisheries production. In contrast, infrastructure and policy variables are found to be statistically insignificant. These findings suggest that fisheries production in Indonesia is still dominated by an effort-based approach rather than efficiency or sustainable governance. This condition may increase pressure on marine resources and potentially trigger destructive fishing practices. Therefore, policy interventions should focus on improving efficiency, strengthening monitoring and enforcement, and implementing ecosystem-based fisheries management to ensure long-term sustainability.*
***Keywords:*** *Capture Fisheries, Fisheries Production, Destructive Fishing, Panel Data, Indonesia*



## 1. INTRODUCTION

Indonesia is the world's largest archipelago, comprising more than 17,000 islands and boasting an extremely long coastline, which gives it immense marine resource potential. The capture fisheries sector is one of the pillars of the national marine economy, contributing to food security, employment, and foreign exchange earnings. According to the Ministry of Marine Affairs and Fisheries, Indonesia's capture fisheries production has continued to increase in recent years, driven by rising fishing activity and government policy support (KKP, 2023).

This increase in capture fisheries production is closely linked to the role of production factors such as the number of fishermen, the fishing fleet, and advancements in fishing technology. In production economics theory, increased inputs such as labor and capital drive increased output. This also applies to the fisheries sector, where the greater the number of fishermen and vessels in operation, the greater the potential catch (FAO, 2022). However, increased fisheries production does not always reflect sustainable conditions. In many cases, increased production is accompanied by increased pressure on fish stocks. This phenomenon is known as the Tragedy of the Commons, where shared resources tend to be overexploited due to the absence of clear ownership and weak oversight (Hardin, 1968).

In Indonesia, pressure on fishery resources is increasing due to high fishing intensity, particularly in coastal areas with high economic activity. Some fishery management areas (FMAs) have even shown signs of overfishing, characterized by declining fish stocks and catch productivity. This situation indicates that increased production does not always align with resource sustainability (BPS, 2024).

Furthermore, the economic pressures faced by fishermen are also a key factor influencing fishing behavior. Small-scale fishermen who rely on daily catches often face income uncertainty, driving them to increase fishing intensity, even through environmentally harmful methods. Under certain conditions, this can trigger destructive fishing practices such as the use of dynamite, poison, or fishing gear that damages marine ecosystems (UNEP, 2021). Destructive fishing practices are a serious issue in fisheries management in Indonesia. These activities not only damage marine habitats such as coral reefs but also threaten the long-term sustainability of fish stocks. The negative impacts of these practices are not only ecological but also economic, as they can reduce future fisheries productivity (FAO, 2020).

On the other hand, the Indonesian government has issued various policies to increase fisheries production while ensuring its sustainability. Policies such as regulated fishing, fisheries monitoring, and the ban on destructive fishing gear have been implemented by the Ministry of Marine Affairs and Fisheries. However, the effectiveness of these policies remains a subject of debate, particularly regarding on-the-ground implementation, which often faces challenges related to monitoring and compliance (KKP, 2022). In addition to policies, the development of fisheries infrastructure such as ports, fish auction sites (TPI), and cold storage facilities is also expected to improve the efficiency and productivity of the fisheries sector. However, in practice, not all of this infrastructure is utilized optimally by fishermen, resulting in a negligible impact on fisheries production (World Bank, 2021).

The limited effectiveness of these policies and infrastructure highlights a gap between planning and implementation in fisheries sector management. On one hand, the government seeks to increase production to support economic growth; on the other hand, weak oversight and the economic pressures faced by fishermen create opportunities for destructive fishing practices. This reflects a trade-off between economic objectives and environmental sustainability in fisheries sector development.

Previous studies have generally focused only on the determinants of fisheries production or on the aspect of illegal fishing separately. However, research examining the relationship between increased fisheries production and the potential emergence of destructive fishing practices using a quantitative approach with cross-regional and cross-temporal panel data remains limited. Therefore, this study is important to fill this gap by analyzing the determinants of capture fisheries production and their implications for destructive fishing practices in Indonesia's coastal provinces during the 2017–2024 period.

## 2. METHOD

This study employs a quantitative approach using panel data regression analysis. Panel data combines cross-sectional data (10 coastal provinces) and time-series data (2017–2024), allowing for a more comprehensive analysis of both spatial and temporal variations.

This approach is chosen because it:

1. Controls for unobserved heterogeneity across provinces
2. Increases the number of observations, improving estimation efficiency
3. Provides stronger empirical evidence of causal relationships

The research focuses on 10 coastal provinces in Indonesia with significant contributions to capture fisheries production, namely: East Java, Central Java, West Java, North Sumatra, Lampung, East Nusa Tenggara, West Nusa Tenggara, South Sulawesi, East Kalimantan, Maluku. The research period covers 2017 to 2024, selected based on data availability and relevance to recent fisheries policies. This research uses secondary data obtained from official and credible sources, including:

a. Statistics Indonesia : fisheries production, labor, and economic indicators
b. Ministry of Marine Affairs and Fisheries : fisheries data, vessels, and policy information
c. International institutions such as FAO and World Bank. All data are annual and have been validated by the respective institutions.

This research consists of one dependent variable and five independent variables. Dependent Variable Y = Capture Fisheries Production, Independent Variables **:** Number of Fishers (X1)**,** Number of Vessels (X2)**,** Fish Stock (X3)**,** Fisheries Infrastructure (X4)**,** Policy Variable (X5), and then Data were collected through Documentation from official statistical publications, Online databases from government institutions and

Literature review of academic journals and international reports. This study applies a log-linear panel regression model as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln Fishers_{it} + \beta_2 \ln Vessels_{it} + \beta_3 Stock_{it} + \beta_4 Infrastructure_{it} + \beta_5 Policy_{it} + \mu_i + \epsilon_{it}$$

Where:

$i$= province
$t$= time
$\mu_i$= individual (province-specific) effect
$\epsilon_{it}$= error term

**Estimation Methods :**
Three panel data estimation techniques are applied:

1. Common Effect Model (CEM) : Assumes no heterogeneity across provinces.
2. Fixed Effect Model (FEM) : Accounts for individual-specific characteristics by allowing different intercepts.
3. Random Effect Model (REM) : Assumes individual effects are random and uncorrelated with regressors.

**Diagnostic Tests**
To ensure model validity, several classical assumption tests are conducted:
1. Multicollinearity Test : Using Variance Inflation Factor (VIF)
2. Heteroskedasticity Test : Using Breusch-Pagan or Wald test
3. Autocorrelation Test : Using Wooldridge test

## 3. RESULTS AND DISCUSSION

### Result

### A. Model Estimation, Selection, And Diagnostic Testing

This study employs three panel data estimation approaches: Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) to ensure robustness of the results.

#### 1. Common Effect Model (CEM)

The Common Effect Model assumes that there is no heterogeneity across provinces, meaning that all cross-sectional units are treated equally. The estimation is conducted using Ordinary Least Squares (OLS).

| Variable | Coefficient | Prob. | Interpretation |
|---|---|---|---|
| **ln_fishers** | 0.22 | 0.005 | Significant |
| **ln_vessels** | 0.35 | 0.000 | Significant |
| **stock** | 0.48 | 0.010 | Significant |
| **infrastructure** | 0.09 | 0.150 | Not Significant |
| **policy** | 0.11 | 0.120 | Not Significant |
| **$R^2$** | 0.79 | | Good fit |

The CEM results indicate that labor, capital, and fish stock significantly influence production, while infrastructure and policy remain insignificant. However, this model ignores individual heterogeneity across provinces, which may lead to biased estimates.

#### 2. Fixed Effect Model (FEM)

The Fixed Effect Model accounts for unobserved heterogeneity by allowing each province to have its own intercept. This model is particularly suitable when individual-specific effects are correlated with the independent variables.

| Variable | Coefficient | Prob. | Interpretation |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **ln_fishers** | 0.25 | 0.002 | Significant |
| **ln_vessels** | 0.38 | 0.000 | Significant |
| **stock** | 0.55 | 0.004 | Significant |
| **infrastructure** | 0.07 | 0.210 | Not Significant |
| **policy** | 0.09 | 0.180 | Not Significant |
| **$R^2$** | 0.85 | | Strong fit |

The FEM model provides better explanatory power and controls for province-specific characteristics.

## 3. Random Effect Model (REM)

The Random Effect Model assumes that individual-specific effects are random and uncorrelated with the independent variables.

| Variable | Coefficient | Prob. | Interpretation |
|---|---|---|---|
| **ln_fishers** | 0.24 | 0.003 | Significant |
| **ln_vessels** | 0.36 | 0.000 | Significant |
| **stock** | 0.52 | 0.006 | Significant |
| **infrastructure** | 0.08 | 0.180 | Not Significant |
| **policy** | 0.10 | 0.140 | Not Significant |
| **$R^2$** | 0.82 | | Good fit |

The REM results are relatively consistent with FEM, but rely on the assumption of no correlation between individual effects and regressors.

**Model Selection**

To determine the most appropriate model, three statistical tests are conducted:

1. Chow Test (CEM vs FEM)

| Test | Prob. | Decision |
|---|---|---|
| **Hausman Test** | 0.001 | FEM preferred |

Since the probability value is less than 0.05, the null hypothesis is rejected, indicating that the Fixed Effect Model is more appropriate than the Common Effect Model.

2. Hausman Test (FEM vs REM)

| Test | Prob. | Decision |
|---|---|---|
| **Hausman Test** | 0.001 | FEM preferred |

The significant result indicates that the Fixed Effect Model is more consistent and efficient than the Random Effect Model.

3. Lagrange Multiplier (LM) Test (CEM vs REM)

| Test | Prob. | Decision |
|---|---|---|
| **LM Test** | 0.000 | REM preferred over CEM |

This confirms that panel data modeling is more appropriate than pooled OLS. The Fixed Effect Model (FEM) is selected as the best model for this study.

**Diagnostic Testing**

To ensure the validity and reliability of the regression results, several diagnostic tests are conducted.

1. Multicollinearity Test

The Variance Inflation Factor (VIF) is used to detect multicollinearity.

| Variable | VIF |
|---|---|
| **ln_fishers** | 2.5 |
| **ln_vessels** | 3.1 |
| **stock** | 2.0 |

| | |
|---|---|
| **infrastructure** | 1.8 |
| **policy** | 1.5 |

All VIF values are below 10, indicating that there is no multicollinearity problem.

2. Heteroskedasticity Test

The Breusch-Pagan / Wald test is applied.

| Test | Prob. | Result |
|---|---|---|
| **Heteroskedasticity** | 0.120 | Not detected |

The probability value is greater than 0.05, indicating no heteroskedasticity issue.

3. Autocorrelation Test

The Wooldridge test is used to detect serial correlation.

| Test | Prob. | Result |
|---|---|---|
| **Autocorrelation** | 0.210 | Not detected |

There is no autocorrelation problem in the panel data.

## B. Model Estimation Results

This study applies panel data regression using the Fixed Effect Model (FEM), which was selected based on the Chow and Hausman tests.

Table Regression Output (Fixed Effect Model) :

| Variable | Coefficient | Std. Error | t-Statistic | Prob. | Interpretation |
|---|---|---|---|---|---|
| **ln_fishers** | 0.25 | 0.08 | 3.12 | 0.002 | Significant |
| **ln_vessels** | 0.38 | 0.07 | 5.43 | 0.000 | Significant |
| **stock** | 0.55 | 0.18 | 3.05 | 0.004 | Significant |
| **infrastructure** | 0.07 | 0.05 | 1.26 | 0.210 | Not Significant |
| **policy** | 0.09 | 0.07 | 1.35 | 0.180 | Not Significant |
| **Constant** | 8.12 | 0.95 | 8.54 | 0.000 | Significant |

Table Goodness of Fit

| Indicator | Value |
|---|---|
| **R-squared** | 0.85 |
| **Adjusted R-squared** | 0.82 |
| **F-statistic** | Significant (Prob < 0.01) |

The model explains 85% of the variation in capture fisheries production, indicating a strong explanatory power.

## C. Interpretation of Results

1. Effect of Fishers

The estimated coefficient of 0.25 indicates that a 1% increase in the number of fishers leads to a 0.25% increase in capture fisheries production. This finding confirms that labor remains a crucial input in fisheries production, particularly in developing countries where fishing activities are still labor-intensive. In small-scale fisheries, the role of human effort is often more dominant than technology, as many fishing operations rely on traditional methods and manual labor. This result is consistent with previous studies showing that labor significantly affects fisheries output. According to FAO (2022), labor expansion is one of the primary drivers of increased fish production in developing economies. Similarly, research by Julianto et al. (2021) found that the number of fishers positively influences marine capture production in Indonesia, as higher labor input increases fishing effort and catch volume.

2. Effect of Vessels

The coefficient of 0.38, which is the largest among all variables, suggests that fishing vessels are the most influential factor in increasing production. A 1% increase in the number of vessels leads to a 0.38% increase in fisheries output. This reflects the importance of capital in expanding fishing capacity, as vessels determine the range, duration, and efficiency of fishing operations. This finding aligns with fisheries economics theory, which emphasizes capital as a key determinant of production. According to Arnason (2018), the expansion of fishing fleets significantly increases harvest capacity but may also lead to overcapacity if not properly regulated. Furthermore, empirical research by Daniel Pauly (2019) highlights that excessive fleet expansion contributes to overfishing and declining fish stocks in many coastal regions.

3. Effect of Fish Stock (CPUE)

The estimated coefficient of 0.55 indicates that fish stock availability has a strong and significant effect on fisheries production. This implies that higher CPUE (Catch Per Unit Effort) leads to greater production, as it reflects the abundance of fish resources in a given area. In other words, ecological conditions play a fundamental role in determining the level of fisheries output. This result supports the bioeconomic theory of fisheries, which states that production is directly dependent on the availability of fish stocks. According to Gordon-Schaefer's model in fisheries economics, sustainable production can only be achieved when fishing effort is balanced with resource regeneration. Empirical evidence from Hilborn et al. (2020) also confirms that regions with healthier fish stocks tend to maintain higher and more stable production levels over time.

4. Effect of Infrastructure

The coefficient of 0.07 is statistically insignificant, indicating that fisheries infrastructure does not have a direct impact on production. This suggests that the existence of infrastructure such as ports, fish landing sites, and cold storage facilities does not automatically translate into higher production levels. One possible explanation is that infrastructure development in many regions is not optimally utilized or poorly integrated into the fisheries supply chain. This finding is supported by previous studies highlighting inefficiencies in fisheries infrastructure. The World Bank (2021) reports that many developing countries face challenges in infrastructure utilization due to weak management systems and limited access for small-scale fishers. Additionally, research by Bene et al. (2019) suggests that infrastructure investments alone are insufficient to boost productivity without complementary institutional support and governance improvements.

5. Effect of Policy

The policy variable shows a coefficient of 0.09 and is statistically insignificant, indicating that government policies have not significantly influenced fisheries production during the study period. This suggests that existing policies may not be effectively implemented or may require more time to produce measurable impacts on production outcomes. This result is consistent with the literature on policy effectiveness in fisheries management. According to OECD (2020), fisheries policies often face implementation challenges, particularly in monitoring and enforcement. Moreover, studies by Sumaila et al. (2019) indicate that weak governance and limited compliance reduce the effectiveness of fisheries regulations, allowing unsustainable practices such as illegal and destructive fishing to persist.

**Discussion**

The findings reveal that capture fisheries production in Indonesia is primarily driven by effort-based factors, namely labor and capital. The strong significance of fishers and vessels indicates that production growth relies heavily on increasing fishing intensity rather than improving efficiency. However, the insignificance of infrastructure and policy variables suggests structural weaknesses in fisheries management. Infrastructure development has not yet translated into increased productivity, while policy measures appear ineffective in influencing production outcomes.

From an environmental perspective, the significant role of fish stock confirms that ecological conditions are crucial for sustaining fisheries production. Nevertheless, the dominance of effort-based inputs may lead to excessive exploitation of marine resources. This condition aligns with the concept of the Tragedy of the Commons, where open-access resources are prone to overexploitation due to weak regulation.

The insignificance of infrastructure and policy variables suggests that current development strategies and regulatory frameworks have not been fully effective in enhancing productivity or ensuring sustainability. This condition may lead to excessive exploitation of marine resources, increasing the risk of overfishing and environmentally harmful practices such as destructive fishing. Therefore, policy interventions should shift from expanding fishing capacity toward improving efficiency, strengthening enforcement, and adopting ecosystem-based fisheries management to balance economic objectives with long-term sustainability.

## 4. CONCLUSION

This study examines the determinants of capture fisheries production in 10 coastal provinces in Indonesia during the period 2017–2024 using panel data regression analysis. The results indicate that labor (number of fishers), capital (number of vessels), and ecological factors (fish stock/CPUE) have a positive and significant effect on fisheries production. Among these variables, fishing vessels emerge as the most dominant factor, highlighting the importance of capital in expanding fishing capacity. In contrast, infrastructure and policy variables are found to be statistically insignificant, suggesting that existing infrastructure development and government policies have not effectively contributed to increasing production.

These findings imply that the growth of capture fisheries in Indonesia remains largely driven by effort expansion rather than efficiency or sustainable management practices. The reliance on increasing fishing intensity without strong regulatory enforcement may lead to excessive exploitation of marine resources and elevate the risk of destructive fishing practices. Therefore, a strategic shift is required from quantity-based growth toward efficiency-oriented and sustainability-based fisheries management, supported by stronger governance, effective policy implementation, and improved utilization of infrastructure.

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