Full Length Article

All maritime crimes are local: Understanding the causal link between illegal fishing and maritime piracy

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A B S T R A C T

Two types of maritime crime, piracy and illegal fishing, are common and pose risks to marine security. Past studies show a correlational link between the two activities, but the causal direction is far from clear. A popular narrative of the event is that foreign fishing events deplete local resources, causing local fishers to turn to piracy. We propose another mechanism that links the two events by focusing on local perpetrators. We argue that maritime piracy is a high-risk, high-reward substitute for local actors who engage in illegal fishing. Empirically, this would mean that a constraint placed on illegal fishing at the local level should lead to a higher likelihood of pirate attacks if the area provides an abundant opportunity. For evidence, we explore these relationships in Indonesian waters. Our unit of analysis is the 0.5° × 0.5° grid cell year within Indonesian EEZ from 1990 to 2017. Results support our hypotheses. When there is a decline in Illegal, Unreported, and Unregulated (IUU) fishing in an area, we find a greater likelihood of ship attacks, especially if vessel traffic in the grid cell is high. Importantly, we fail to see a similar relationship with legal fishing, which tells us that local capacity and conditions, rather than environmental factors, are likely the driving force behind piracy attacks. We also find little evidence of a reverse relationship where piracy drives IUU fishing.

1. Introduction

A growing body of literature on maritime crime and security posits a link between Illegal, Unreported, and Unregulated (IUU) fishing and sea piracy. But the causal picture remains far from clear. For instance, one conjecture is that illegal and eco-system-destuctive fishing by foreign vessels generates income loss for artisanal fishers, thereby creating conditions for increased maritime crime. This narrative has been the most common, delineating the causal link between illegal fishing and piracy: industrial fishing by foreign trawlers exhausts local resources, forcing local fishers into sea crime (Bahadur, 2011, p. 302; Bizious, 2013; Desai & Sambaugh, 2021; Hughes, 2011; Weldemichael, 2019). This description of foreign fishing fleets producing pirates out of local fishers comes from the Somali case. But the Somali case is quite unique since the capacity of the central state in Mogadishu has remained far below the modal coastal state worldwide. The Somali model, therefore, has little explanatory power outside of the Greater Gulf of Aden. Alternatively, it is often the case that homegrown perpetrators engage in illicit fishing and piracy distinctly in response to local constraints and opportunities. We, therefore, seek to understand the link between maritime piracy and local fishers, not foreign ones, as they move in and out of illegal fishing depending on the level of state enforcement. We investigate the temporal and spatial relationship between illegal fishing and sea piracy within Indonesian waters to clarify the causal narrative.

The costs of illicit maritime activities, such as illegal and unreported fishing and piracy have been substantial in Southeast Asia (Belhabib & Le Billon, 2022). A recent study published by the World Resources Institute estimates that countries in the Western Pacific, including Indonesia, Malaysia, the Philippines, Cambodia, Papua New Guinea, Thailand, and Vietnam sustain annual loss in gross revenue between $2.4 and $4.5 billion US dollars as a consequence of illegal fishing (Konar et al., 2019). The overall annual economic impact for the entire Pacific Ocean, according to the study may be as high as SUS 21 billion. Indonesia, the largest archipelagic country in the world, has accordingly taken several policy measures to address this resource plundering. For instance, the Indonesian Ministry of Marine Affairs and Fisheries...
(MMAF) started the Vessel Monitoring System to regulate fishing in 2003 and further refined the regulation in subsequent years (Soemarmi et al., 2020).

The government has implemented even more drastic measures since 2014, authorizing the Indonesian Navy to sink any vessels that engage in illegal fishing. For instance, from October 2014 to August 2018, the Ministry of Maritime Affairs and Fisheries sunk 488 ships detained for illegal fishing, of which 272 were Vietnamese, 90 Filipino, 23 Thai, 25 Indonesian, 2 Papua New Guinean, 1 Chinese and 73 Malaysian flagged ships (Madjid et al., 2019). These governmental efforts undoubtedly brought changes in the amount of illegal fish caught in the country’s waters (Suherman et al., 2020). How have these changes affected the number of maritime pirate attacks in the region?

We compile longitudinal micro-level grid-cell data for Indonesia’s Exclusive Economic Zone (EEZ) and test our conjectures to ascertain which causal story obtains. Information on IUU fishing is taken from the Sea Around Us (Pauly et al., 2015, p. 869), while piracy data come from the Maritime Piracy Event and Location Database (MPELD). Our work suggests an association between IUU fishing and maritime piracy. The primary findings from the statistical models show that a decrease in illegal fishing, and nearby vessel traffic, independently increase the odds of piracy events in an area. But more importantly, the interaction of these two events nearly doubles the likelihood of sea-piracy incidents in the area. Importantly, we fail to find a similar relationship with legal fishing, which tells us that local capacity and a criminal milieu, rather than structural factors like grievances, are likely the driving forces behind pirate attacks. Additionally, we find little evidence of a reverse relationship that piracy drives IUU fishing. These findings have important implications for our understanding of factors that affect the onset of pirate attacks in an area. For policymakers, it cautions that local efforts to combat IUU fishing can inadvertently shift criminal activity to ship raiding. We conclude with some thoughts about the direction of future research.

2. Deprivation can drive maritime crime

Fishery is a critical industry and an important food source for populations located in the Indo-Pacific. The two countries in the region Indonesia and Viet Nam are among the top ten global aquatic capture producers in 2020, with Indonesia being the second largest, after China.

According to a recent FAO report, global consumption of aquatic products increased at an average annual rate of 3 % from 1961 until 2019, almost twice the rate of world population growth (FAO, 2022). However, the report shows that the global marine catch has been on the decline, from an average annual rate of 88.9 million tonnes in the 1990s to 78.8 million tonnes in 2020, indicating depleting marine stocks. There simply aren’t enough fish anymore, and overfishing has become the main problem. Moreover, IUU fishing undermines efforts to manage fisheries sustainably. For instance, in Indonesia alone, on average 20 %-38 % of the wild-caught seafood exported from Indonesia in 2011 is estimated to be caught illegally (Pramod et al., 2014, p. 106). The archipelagic setting of countries in the Indo-Pacific and the territorial disputes make combatting IUU fishing particularly difficult (Phayal et al., 2022). Foreign vessels easily invade Indonesian and Filipino EEZs because of the size of their maritime spaces, and both governments do not have the capacity to police their waters adequately.¹

Importantly, IUU fishing produces revenue loss and ecosystem harm, leading to other costly externalities. If local fishers are driven out of work by foreign fishing fleets or fish stocks are significantly depleted by over-fishing, the effects can be significant and push at least some former fishers into maritime crime (Okafor-Yarwood et al., 2022). Prior studies have established a correlational link between piracy and IUU fishing (Mitchell & Schmidt, 2023). As marine resources get depleted through industrial over-use, local artisanal fishers are forced to migrate elsewhere or find alternative sources of income. Some former fishers can turn to maritime crime, such as piracy, armed robbery on ships, drug smuggling, and human trafficking, to earn an income and support their families (See, Learn, 2020).

Past studies discuss the economic incentives for engaging in maritime crime. They suggest that individuals in piracy-prone states are drawn to sea crime mainly due to the opportunity costs associated with the local labor market (Gold et al., 2023; Jablonski & Oliver, 2013). Potential perpetrators of piracy when the payoff is relatively high and the risk of capture remains sufficiently low. For instance, Jablonski and Oliver (2013) find that price changes in labor- and commodity-intensive goods in piracy-prone countries affect the number of piracy events. The cost of labor-intensive commodities, measured by rice and sugar prices, is negatively correlated with the number of piracy events in rice- and sugar-producing countries. When the prices of such labor-intensive commodities are low, individuals have a greater incentive to engage in piracy. Alternatively, when prices rise, individuals stay in the legal economy. For capital-intensive goods, such as oil, price increases make it more lucrative for pirates to attack oil tankers, thus increasing the number of piracy attacks in oil-exporting countries where there are price hikes (Jablonski & Oliver, 2013, p. 682). In sum, perpetrators of pirate attacks seem to be driven by economic incentives.

The incentive mechanism also reveals the motive or the grievance explanation behind piracy incidents. The evidence collected to date suggests that joblessness, poverty, and wage-stagnation contribute to crime on land and crime on the water (Daxecker & Prins, 2021; Iyigun & Ratisukipimol, 2010; Jablonski & Oliver, 2013). Subsequent research has focused specifically on the relationship between piracy and the fishing industry. Daxecker and Prins (2013) posit that sea-piracy should be sensitive to the price of fish in the local market since the direction of the market’s movement impacts individuals employed in the fishing industry. These individuals have the necessary boat-handling skills to engage in sea crime. They are, therefore, more likely to pivot to pirate attacks as the opportunity costs for fishing become too high. As expected, the authors find that reductions in fish values, as noted in the FAO data, tend to increase the number of piracy incidents, an effect similar to the change in the country’s GDP per capita. Other studies have also found a similar relationship between the legal fishing market and the number of piracy events observed (Tominaga, 2018). Findings in these studies support an economic theory of crime that individuals are more inclined to engage in piracy when it is much more lucrative than other marketplace activities like legal fishing.

More recent work highlights the need to include illegal fishing in analyses of sea piracy. For example, Denton and Harris (2021) note inconsistencies in previous studies examining the relationship between fisheries and maritime crime. They note that “in 2013 Daxecker and Prins find that decreases in fish catches correlate with the increase in piracy (2013) while in 2021 evidence from Daxecker and Prins reveals no relationship between per capita value of fisheries production and piracy (2015)” (p. 942). Denton and Harris (2021) argue that such contradictions result from failing to incorporate illegal fishing into the...
fishing data. When including both reported and illegal fishing values in the Gulf of Guinea, they show that increased industrial fishing increases piracy incidents. But an increase in subsistence fishing actually lowers piracy incidents. The theoretical argument for the distinctive effects of industrial and subsistence fishing is that they have the opposite impact on the economy of the local fishing industry. Large industrial fishing, both reported and unreported, harms the local market and economy, thereby driving locals into maritime crime. According to the authors, as “industrial fish catch increases, the relative amount of fish available for local fishermen declines. We believe this will cause piracy to increase” (p. 943). On the contrary, increased subsistence fishing has the opposite effect: it tends to lower the rate of piracy since the profits from the fish harvest remain in the local economy.

We seek to build upon these past studies by focusing on several unanswered questions. For example, findings in the Denton and Harris (2021) study imply that these different categories of fishing activities—legal, illegal, industrial, and subsistence—occur at different times and locations, and that piracy events tend to cluster spatially (Di Salvatore & Jessica, 2018). But the study, similar to other studies discussed above, is at the aggregate country-year level, which does not allow geographical or temporal disaggregation. It is unclear whether the legal and illegal fishing in the region is temporally or spatially distant from piracy incidents. More importantly, the study by Denton and Harris builds the case for including illegal fishing when analyzing the fishing-piracy relationship but does not address the critical question posed in this paper: how might illegal fishing at the local level affect piracy incidents?

3. Illegal fishing and its impact on piracy

IUU fishing involves harvesting prohibited species, overfishing or high-grading permitted species, unregulated fishing, falsifying catch weights, fishing without a license or out of season, and utilizing banned gear (Batsleer et al., 2015; Liddick, 2014a). Research in recent years has begun to examine the link between illegal fishing and piracy. Mitchell and Schmidt (2023) examine coastal states worldwide and, using annual data, find that IUU fish catch explains the number of piracy events in those states. Desai and Shambaugh (2021) examine the relationship with more fine-grained micro-level data and find a correlation between IUU fishing and sea piracy. The authors use grid-cell level analysis for five-year-panel data from 2005 to 2014 and find that the spatial locations with the highest risk of piracy are also the areas with the highest risk of IUU activities.

A key argument proposed in these studies is that illegal fishing by foreign trawlers tends to deplete scarce marine resources, leading local fishers to turn to sea crime. Fishers-turned-pirates “act as an effective deterrence to foreign industrial or illegal fishing fleets, and thus joining pirate gangs may be a response to fear of foreign exploitation” (Desai & Shambaugh, 2021, 3). This narrative was prevalent during the peak of Somali piracy, as the pirates sought to legitimate their activities by naming their groups after common military units, such as the “Somali Marines,” “Central Somali Coast Guard,” or “Defenders of Somali Territorial Waters” (Mitchell & Schmidt, 2023). In other words, these studies on the relationship between IUU fishing and sea piracy have assumed that pirate attacks are driven primarily by the actions of foreign trawlers (Daxecker & Prins, 2013; Ploch et al., 2011; Weir, 2009). While the foreign trawler story may explain some of the piracy in the Greater Gulf of Aden, it remains unclear how much leverage this narrative has for maritime crime in other regions like the Indo-Pacific. In fact, in Indonesia, most illegal fishing is a local problem with local perpetrators (Nadiari et al., 2021). In this study, we focus on the local level, as we connect local fishers to sea piracy through increased surveillance of maritime spaces.

Methodologically, we employ data that are both temporally and spatially disaggregated. Mitchell and Schmidt (2023) work on IUU fishing and piracy includes temporal disaggregation as they utilize longitudinal data to show the association between IUU fishing and piracy. But the data used in the study does not have spatial disaggregation. Since the study is at the country level, we do not know whether these events occur in a country’s same or different maritime regions. Moreover, the research does not include a control for the opportunity structure of piracy, such as geographic chokepoints or shipping traffic. Desai and Shambaugh (2021) fill this gap by using spatially disaggregated data at the grid-cell level, showing that IUU fishing and piracy tend to occur in similar regions while also controlling for shipping traffic in the area. However, their dataset remains temporally static, as they pool all piracy and IUU fishing events from 1995 to 2014, thus making it hard to distinguish the temporal sequence of events. Desai and Shambaugh’s research design uses spatial disaggregation but ignores temporal variation.

A more recent work exploring the relationship between IUU fishing and piracy in the Gulf of Guinea does not find any correlation between the two events (Jespersen & Henriksen, 2022). The authors argue that rather than pure grievance arising from depleted fisheries due to illegal foreign fishing, other more specific incentives at an individual level might better explain individual decisions to perpetrate piracy attacks. Our research expands on these significant studies by focusing on the local level. Instead of dismissing the notion that foreign illegal trawlers lead to piracy incidents, we emphasize the involvement of local perpetrators in illegal fishing and argue that constraints on illegal fishing can displace the perpetrators to piracy. To explore the association between sea piracy and illegal fishing, we start with the assumption that illegal fishing and piracy originate from the same local coastal regions. This assumption is distinct from past studies discussed above, which suggest that increased piracy events result from overfishing in coastal areas by foreign trawlers, leading to reduced fish catch. Rather than refuting the foreign trawler claim, we argue that the association between piracy and foreign trawlers is more likely in the case of weak states like Somalia, where the state’s capacity to either politically or physically deter illegal trawlers is minimal or non-existent. The boundary between legal and illegal fishing in such contexts is blurred or non-existent. In such countries, overfishing and the depletion of resources due to illegal foreign vessels can create economic strain on fishers involved in both legal and illicit activities, pushing them towards piracy. But modal states around the world have some level of state capacity. For instance, commercial trawlers in Indonesia have been banned since the 1980s. Although there are a few cases of foreign trawlers in Indonesian waters, most appear in the region of North Sumatra, around the Malacca Strait (Liddick, 2014b). However, maritime piracy is not limited to North Sumatra and the Malacca Straits region. Our study explores this puzzle to understand the link between illegal fishing and sea piracy.

We develop a more comprehensive theory that connects pirate attacks to the interaction of a state’s constraints on illegal fishing and the incentive provided by opportunity targets that motivate such attacks. At a more aggregate state level, variation in IUU fishing events likely explains piracy incidents in a country’s EEZ, as suggested by past studies. At the local level, the association between the two is more complex, and the interplay of two other factors, constraint and opportunity, helps elucidate the relationship between piracy and illegal fishing. We argue that individuals engaged in IUU fishing are more prone to perpetrating pirate attacks when there is an external constraint on illegal fishing. Such restrictions could be due to legal enforcement or other reasons, like environment-related fish depletion. In our analysis, we remain agnostic about the precise mechanism but propose that such constraints on the perpetrators leads to an observed decline in IUU fishing in an area. This apparent decline in illegal fishing propels individuals to engage in more rewarding pirate activities, especially when they are closer to target-rich
areas like regions with high vessel traffic.

A sociological approach to crime suggests that community-level poverty is one common factor that increases crime at the local level (Belhabib et al., 2019; Carrabine et al., 2014; Galster & George, 2012). But rather than addressing root causes, approaches to deter or constrain an activity through detention and criminal prosecution can displace crime into other areas. Government efforts to counter the illicit harvesting of marine resources without addressing genuine economic grievances at the local level can inadvertently shift effort from fishing to piracy (See Belhabib et al., 2019). Piracy can be risky for the perpetrators, and the legal penalty can be serious (Fenton & Chapsos, 2019). Those formerly engaged in IUU fishing are more likely to accept the risk of piracy, mainly because it offers significant monetary rewards, either by participating individually or by creating a pool of willing volunteers that engage in sea piracy as a part of an organized criminal group. In sum, while the earlier hypothesis, that illegal foreign fishing leads to fishery depletion and increased pirate activities, is based on the grievance-based narrative, our theoretical proposition linking illegal fishing and sea-piracy is closer to literature on crime displacement and diffusion (Guerette & Kate, 2009). 📑

Opportunistic pirate attacks involving local individuals are common in high shipping traffic areas. At an individual level, windows of opportunity are often the main drivers of crime (Felson & Clarke, 1998). In a report on piracy in Southeast Asia, Liss (2007) calls them desperate fishermen, who launch “small-scale attacks on other fishing vessels, yachts or small to medium-sized ships, including merchant vessels, passing through waters near their communities. Most of these attacks are opportunistic, hit-and-run affairs in which the pirates take whatever they find onboard.” Liss further illustrates using an example of attacks on merchant vessels conducted by opportunistic pirate-fishermen from Kampung Hitam, on Pulau Babi in the Riau Archipelago, where the waters are polluted and over-fished, and the legal catch of local fishers is often not adequate to sustain the fishers and their families. Some of these desperate fishers likely turn to piracy to supplement their incomes. We add that the chances of such opportunistic attacks are higher if the region harbors both a pool of individuals who have engaged in illegal fishing and sees abundant vessel movement. 📑

Organized criminal groups at sea are often transnational organizations (Belhabib & Le Billon, 2020; Witbooi et al., 2020). They target local fishers to recruit them as members of illegal fishing teams and for their local knowledge of the marine environment. Therefore, when the government takes measures to curb such transnational crime, it can take away a lucrative source of employment for local fishers, increasing their likelihood of engaging in other forms of crime, such as piracy. This dynamic is evident in a recent study in Indonesia. According to Chapsos and Hamilton (2019), organized criminal groups employ local fishers and vessels to hide from government patrol boats and transship the illegal catch to a larger vessel, violating Indonesian regulations stipulating that they must unload their catch in specified ports. Another recent study on Indonesia also highlights the complex involvement of local individuals in illegal fishing with transnational groups. According to Pusiansyah (2021, 635), illegal fishing connotes fishing by foreigners or ships carrying foreign flags contrary to the conservation and management provision of the country, regional organization, or international law. But the involvement of local citizens is often overlooked. For instance, foreign vessels operating illegally in Indonesia tend to utilize a legal fishing permit owned by a local entrepreneur, a practice often referred to as the “flag of convenience” (Miller, & Rashid Sumaila, 2014). Another common practice of transshipment enables local fishers to sell their catch to foreign vessels at sea at a higher price than at a local fish auction. This practice in Indonesia is believed to be more organized since local fishers involved in transshipment are funded by foreign businessmen (Chapsos et al., 2019, p. 5). Therefore, government measures to clamp down on local organized groups can create a pool of local anglers that can no longer fish and are now ready to launch risky, opportunistic pirate attacks.

Moreover, law enforcement approaches focused on combatting illegal fishing may not necessarily prevent piracy. This is because illegal fishing is often associated with poor ocean governance, and the countermeasures include a national-level plan of action, tighter control at ports, and monitoring fishing vessel activities. Compared to such a wide-scale governance problem, pirate attacks are rare and more elusive. Sometimes, the government’s effort to counter these crimes is simply a matter of priority. For instance, according to Supriyanto (2016) Indonesia’s Guidelines on Deployment of the Indonesian National Defense Forces indicate that “counter-piracy is not Indonesia’s top security priority. Issues such as smuggling, illegal fishing and boundary disputes are far more pressing security concerns for Indonesia.” Therefore, effective measures to reduce illegal fishing may not work to check piracy. In fact, as discussed above, such measures and the subsequent “shock” effect of a sudden decline in illegal fishing in an area should increase the risk of pirate attack in that same maritime space.

The above discussions lead to the following hypotheses:

H1. Piracy incidents are more likely to occur in areas where illegal fishing has declined.

H2. Piracy incidents are more likely to occur in areas with high commercial vessel traffic.

H3. Piracy incidents are more likely to occur in areas with high vessel traffic and a decline in illegal fishing.

4. Data and research design

To explore how illegal fishing impacts the occurrence of piracy in an area, we examine Indonesia’s maritime region. The country has the world’s largest archipelago as well as the busiest vessel traffic in the area near the Singapore Strait. Moreover, Indonesia supplies approximately 34% of ASEAN’s overall fish products that reach the global market, and it is the world’s second-largest seafood producer. According to the Indonesian Ministry of Maritime Affairs and Fisheries, illegal fishing costs the country more than 3 billion US dollars annually. The Indonesian government has implemented various measures to address illegal fishing (Chapsos et al., 2019; Sodik, 2009), as summarized in the following sections (see Fig. 1).

Like illegal fishing, piracy incidents are also common in Indonesian waters. According to Daxecker and Prins (2021), contemporary piracy was first observed in Indonesia in the late 1980s. But the rate of piracy incidents has ebbed and flowed over the years. The piracy data in this study is from the MPELD project (Daxecker & Prins, 2021), whereas the annual data for unreported fishing comes from the Sea Around Us project based on their cell-based catch data (Zeller et al., 2016) updated through 2017. The country’s yearly aggregate data for these two

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8 Fenton and Chapsos (2019) state that piracy perpetrators in Indonesia can be punished with a maximum of fifteen years of imprisonment. However, the authors analyze some court case documents in Indonesia to find the actual sentencing to be more lenient.

9 Somali author, Awet Weldemichael (2019), documents several instances of local fishers turning to sea-piracy. Martin Murphy (2009) also notes local illegal fishers in the Malacca and Singapore Straits. While Murphy generally finds local fishers to be victims of pirates, we argue that local fishers can be perpetrators of piracy as well.


11 Available https://www.reportingasean.net/illegal-fishing-costs-indonesia-3-billion-dollars-a-year/ [Accessed March 5, 2022].

12 See www.searoundus.org.
variables are depicted in Fig. 2, which shows annual unreported fishing in tonnes and the number of piracy attacks in the country’s EEZ from 1990 to 2017. The figure shows a gradual decline in illegal fishing, measured in gross tonnes, between 2000 and 2010. The declining rate of illegal fishing slows after 2010. On the contrary, the total count of pirate attacks increases steeply until 2005, then declines until 2009, after which it starts to climb again, peaking in the year 2015 before the recent decline. However, since we are interested in piracy onset in each grid-cell, the bar chart (not scaled) shows the count of cells that have at least one piracy event. Note that the bar chart represents the yearly trend of piracy present in each grid-cell and it is not scaled to show the exact number. On average, the dataset has 34.18 grid-cells with at least one piracy event, ranging from a minimum of 6–82. The piracy onset trend shows that the number of grid-cells with piracy was the highest in 2004, and it gradually declined until 2009, after which it remained fairly stable.

We spatially disaggregate the yearly piracy incidents and IUU fishing data in Indonesia’s EEZ by mapping them into 55 km × 55 km grid cells. This disaggregation allows us to explore if a change in illegal fishing in a grid-cell explains the occurrence of a piracy incident. Since the study’s dependent variable is the presence or absence of piracy incidents in a grid cell, we code the variable, piracy, for a grid-cell year as 1 if it had any piracy attacks in the year and zero otherwise. Of the total 66,248 grid-cell years in the dataset, piracy incidents were present in 933. To test the hypotheses, we use two key explanatory variables in the regression analysis: the annual decline in IUU fishing and the yearly mean vessel traffic in a grid cell. Below, we discuss these two explanatory variables along with several other control variables used in the study.

To operationalize the change in the amount of IUU fishing in grid-cell years, one of the two explanatory variables in this study, we create a binary variable, decrease in IUU fishing. It is coded as 1 if a grid cell year experiences a 10 % or more decline in IUU catch (in log scale) compared to the preceding year. From 1990 to 2017, unreported industrial fishing in the country’s grid cell years ranged from 0 to 20,513 tonnes, which on a log scale converts from −2.99 (log of 0.05) to 9.93. For simplicity, let us assume that a grid-cell year has 148 tonnes of IUU fish catch (5 in log scale) in the preceding year. In that case, the variable decrease in IUU fishing for the grid-cell year will be coded as 1 only if IUU fishing in the grid cell is 90 tonnes or less in the current year; otherwise, it is coded as 0. In the dataset, only 1.71 % of all Indonesian grid cell years have 10 % or more decline in IUU catch compared to the preceding year.

The second key explanatory variable captures the presence of opportunity targets for piracy in a grid cell year. Past studies have used broader geographical choke points like the Malacca Straits or the Bab el Mandab waterway to operationalize opportunities for pirates (U. E. Daxecker & Prins, 2015; Guzansky et al., 2011; Vagg, 1995). In contrast, our study uses more granular vessel traffic data to create a more reliable and universal measure of opportunity. We use monthly vessel traffic data for 2019, and 2020 generated by the Automatic Identification System (AIS) installed on vessels, utilizing both satellite and terrestrial AIS data. We then aggregate the data into a yearly average to create a variable Yearly mean traffic at the grid-cell level. Fig. 3 visualizes the vessel density data in log scale, where darker shades in the EEZ grid cell represent higher traffic areas. As expected, it correctly depicts grid cells around the Singapore Straits as having the heaviest vessel traffic in the region.

5. Control variables

We include several control variables in our analyses. First, a factor that directly influences the likelihood of a pirate attack is the location of a port or anchorage in a grid cell. According to Daxecker and Prins (2021), nearly 40 % of piracy attacks worldwide from 1995 to 2020 were against anchored ships located off coastal ports. We, therefore, include the port counts in a grid cell as a control variable. In total, the dataset in this study has 56 grid cell years with three coastal ports, 221 with two, and 2172 with only one. Second, we include control for the information about the presence of security bases in a grid cell, mainly those operated by the Indonesian Directorate General of Marine and Fisheries Resources Surveillance (Direktorat Jenderal Pengawasan Sumber Daya Kelautan dan Perikanan – PSDKP). The variable PSDKP base is coded as 1 if a grid cell year has one or more PSDKP bases and 0 otherwise. We do not have clear information on when these bases were established. But since the Directorate began implementing these IUU regulatory measures in 2002, we code the presence of these bases only from 2002. In total, there are 1168 grid-cell years with PSDKP bases.

Lastly, we control for the coastal economy and market using satellite nightlight data. Past studies have shown that these factors significantly affect incidents of piracy in nearby waters. Desai and Shambaugh (2021) argue that piracy requires a functioning market and population center areas where pirates can recruit members, sell stolen goods, and acquire financing, weapons, and other equipment necessary for launching attacks. Like Desai and Shambaugh (2021), we use night-time light emissions as a proxy for economic activity on land areas close to waters. The authors use a three-degree coastal buffer, approximately 330 km from land to the water, as the water grid cell’s nightlight value. But we take a slightly different approach. We first mark all nearby land mass from a water grid cell that falls within its 3-degree radius. We then calculate the average night light emission of that land mass and code it as the variable near nightlights for the grid-cell year. We believe this approach more accurately depicts how nearby land activity affects events in water grid cells. For example, we illustrate this approach in Fig. 4, which shows Indonesian grid cells for 2009, where darker shades of red represent grid cells closer to population center areas with higher average night light values. Note that we use the standardized calibrated nightlight data, which ranges from 0 to 1 (Elvidge et al., 2014; Tollefsen et al., 2012). We repeat this step for all Indonesian grid-cell years from 1990 to 2017.

Table 1 shows the summary statistics of all variables used in this study. Following past works on piracy (Coggins, 2016; Daxecker & Prins, 2013; Daxecker and Prins, 2017; Okeelalham & Otwombe, 2016), we use these variables in a generalized estimating equation (GEE) panel analysis to assess the probability of pirate activity occurring in a grid cell, as a function of the decline in illegal fishing. In particular, we use a mixed linear GEE estimator using a binomial distribution with an AR(1) error.
Fig. 1. Mechanism linking IUU fishing to the piracy attack probability in an area.

Fig. 2. Unreported fishing and piracy in Indonesia from 1990 to 2018
Note: Fig. 2 above illustrates the trend in unreported fishing, measured in million tonnes denoted by the solid line (corresponding to y-axis on the left), and the total count of actual piracy events indicated by the dashed line (y-axis on the right). The x-axis spans the years from 1990 to 2017. The graph indicates a general decline in unreported fishing but reveals a non-linear trend of total piracy events over the same period. But since we are interested in piracy onset in each grid cell, the bar chart (not scaled) shows the count of cells with at least one piracy event, ranging from a minimum of 6–82.

Fig. 3. Yearly average vessel traffic in Indonesian EEZ
structure. We choose a GEE estimator rather than a simple logistic model because it allows for a population-averaged approach to correct for correlation in time-series cross-sectional data, meaning that coefficients show whether covariates influence piracy on average. But as a robustness check, we also run separately logistic regression models that control for temporal and spatial autocorrelation (Beck et al., 1998).

We choose a GEE estimator rather than a simple logistic model because it allows for a population-averaged approach to correct for correlation in time-series cross-sectional data, meaning that coefficients show whether covariates influence piracy on average. But as a robustness check, we also run separately logistic regression models that control for temporal and spatial autocorrelation (Beck et al., 1998).

The opportunity presented by higher reported vessel traffic also appears to increase the likelihood of piracy. How will the results change if we alter the cut point? As noted earlier, we expect that including smaller increment will only dilute the effect of the two variables on piracy, as shown in model (3). But the interaction term in the model is not statistically significant. To fully understand the association, we plot the interaction term from the model in Fig. 5 (Brambor et al., 2006).

Table 2
Decrease in IUU Fishing and the onset of Piracy in Indonesian grid cells.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IUU decrease</td>
<td>1.852***</td>
<td>1.618***</td>
<td>0.858</td>
</tr>
<tr>
<td>(0.731)</td>
<td>(0.503)</td>
<td>(0.616)</td>
<td></td>
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<tr>
<td>Vessel Traffic log (yearly mean)</td>
<td>1.003***</td>
<td>0.979***</td>
<td>0.977***</td>
</tr>
<tr>
<td>(0.046)</td>
<td>(0.044)</td>
<td>(0.045)</td>
<td></td>
</tr>
<tr>
<td>Near nightlife</td>
<td>5.402***</td>
<td>5.405***</td>
<td>5.405***</td>
</tr>
<tr>
<td>(1.183)</td>
<td>(1.183)</td>
<td>(1.183)</td>
<td></td>
</tr>
<tr>
<td>Port count</td>
<td>1.379***</td>
<td>1.379***</td>
<td>1.379***</td>
</tr>
<tr>
<td>(0.160)</td>
<td>(0.161)</td>
<td>(0.161)</td>
<td></td>
</tr>
<tr>
<td>PSDKP bases</td>
<td>0.265</td>
<td>0.262</td>
<td>0.262</td>
</tr>
<tr>
<td>(0.352)</td>
<td>(0.353)</td>
<td>(0.353)</td>
<td></td>
</tr>
<tr>
<td>IUU decrease X Traffic</td>
<td>0.166</td>
<td>0.150</td>
<td>0.150</td>
</tr>
</tbody>
</table>

*p < 0.1*<sup>23</sup> **p < 0.05*<sup>23</sup> ***p < 0.01.*

Note: The Dependent variable in all models is the presence/absence of piracy incident(s) in a grid cell.

and the estimates are robust to model specifications with or without the control variables.<sup>23</sup> Our third hypothesis (H3) expects an interaction effect of the two variables on piracy, as shown in model (3). But the interaction term in the model is not statistically significant. To fully understand the association, we plot the interaction term from the model in Fig. 5 (Brambor et al., 2006).

The interaction plot in Fig. 5 reveals an interesting pattern. The y-axis in the figure represents the predicted probability of piracy in a grid cell, and the x-axis represents the mean annual vessel traffic on a log scale. The two lines in the figure represent grid cells (1) with 10% or more decline in IUU fishing compared to the preceding year and (2) other grid cells where no such decline was observed. It shows that the decline in IUU catch is more impactful on the likelihood of piracy, mainly for grid cells with mean annual vessel traffic of more than 1097 vessels (log scale of 7), and the result is statistically significant at p < 0.05. Note that the data on yearly mean traffic is derived from the monthly vessel traffic in grid-cells, and its maximum value in the Indonesian dataset is 9457.5 (log scale of 9.15). Compared to grid cells that do not experience IUU decline, grid cells that experience a decrease in IUU catch are, on average, two times more likely to experience piracy attacks in higher vessel traffic regions. As expected, the finding supports the hypothesis that pirate attacks are more likely to occur in areas with a decline in IUU fishing and high vessel traffic (H3).

7. Changing the cut point level for IUU decline

Hypothesis 3 expects that piracy is more likely to occur in grid-cell years with higher vessel traffic and decreasing IUU fishing compared to the previous year. But a small-unit decrease in IUU fishing may not produce a discernible impact on pirate activity. In other words, decreases in IUU fishing may not affect piracy linearly. Therefore, we chose an arbitrary cut point of 10% decrease in IUU fish catch compared to the preceding year, which we found to have the expected impact on piracy. How will the results change if we alter the cut point? As noted earlier, we expect that including smaller increment will only dilute the difference between grid cells with or without a decline. In contrast, increasing the cut point value should show a stronger effect on piracy. To examine this pattern, we re-run model (3) in Table 1 varying the cutpoints: 2% decline, 6% decline, and 15% decline. Of the 66,248 Indonesian grid-cell years, 12.61% have a 2% or more decline in IUU

---

Table 1
Summary statistics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>2003.5</td>
<td>8.08</td>
<td>1990</td>
<td>2017</td>
</tr>
<tr>
<td>Piracy</td>
<td>0.01</td>
<td>0.12</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Yearly Mean Vessel Traffic</td>
<td>130.92</td>
<td>462.11</td>
<td>0</td>
<td>9457.54</td>
</tr>
<tr>
<td>Near Nightlight (Mean)</td>
<td>0.14</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>PSDKP Bases</td>
<td>0.02</td>
<td>0.1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Port Counts</td>
<td>0.04</td>
<td>0.2</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Reported Industrial catch</td>
<td>1407.5</td>
<td>1637.64</td>
<td>0.02</td>
<td>24437.02</td>
</tr>
<tr>
<td>Reported (log)</td>
<td>6.48</td>
<td>1.65</td>
<td>-2.66</td>
<td>10.1</td>
</tr>
<tr>
<td>IUU Industrial catch</td>
<td>1388.73</td>
<td>1563.98</td>
<td>0.01</td>
<td>20513.43</td>
</tr>
<tr>
<td>IUU (log)</td>
<td>6.41</td>
<td>1.73</td>
<td>-2.87</td>
<td>9.93</td>
</tr>
<tr>
<td>IUU Decrease</td>
<td>0.02</td>
<td>0.13</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: The Dependent variable in all models is the presence/absence of piracy incident(s) in a grid cell.

20 The results, included in the supplementary information, are similar to the main results.

21 Realizing the sensitivity of results to how we code the data, we show in the following section the results when using various other cutpoint levels.

22 Exp(1.618) = 5.043, and exp(0.979) = 2.66.

23 These results are unaffected when we change the modelling technique to logistic regression, results from which are included in the supplementary information.
fishing, 2.45% experience a 6% or more decline IUU fishing, 1.47% have a 10% or more decline, and only 1.07% of grid-cell years see a 15% or more decline in IUU fishing.

Fig. 6 shows the estimates of the interaction term from model (3) in Table 1, but with the four new cutpoints indicated in its legend. As expected, the top left panel in the figure shows that the impact of the IUU fishing decline on piracy is not distinct when we include the smaller (2%) change. However, we start to see the effect when the decrease

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**Fig. 5.** Decrease in IUU compared to last year, opportunity targets and piracy likelihood.

**Fig. 6.** Comparing different cutpoints of IUU decline

Note: Figures above show the predicted probability of piracy (y-axis) in Indonesian grid-cell years as explained by the interaction of vessel traffic and decrease in IUU fishing.
cutpoint is larger than 6%. For instance, for grid cells with 10% or more decline in IUU fishing, the marginal probability of piracy at a log value of 7 yearly mean traffic is 0.436, approximately four times more than in other grid cells with no such decrease (0.092). As we increase the IUU fishing decline to 15% or more, this distinction only widens to a marginal probability of piracy at a log value of 7 yearly mean traffic of 0.745, approximately eight times more than in other grid cells with no such decrease (0.093). The difference, however, tends to narrow towards the high traffic density areas, but continues to remain statistically significant at p < 0.05, as shown in the figure.

8. Does a decline in reported (legal) fishing also cause an increase in piracy?

We argue that a decline in illegal fishing increases the likelihood of piracy incidents mainly because it is easier for individuals engaging in one form of illegal activity to perpetrate another, a more risky criminal offense in this case. The evidence lends credence to the geography of crime research, which suggests that criminal events are more likely in areas with increases incidents of pirate attacks in its vicinity. But, we do not expect this mechanism to hold true for legal offense in this case. The evidence lends credence to the geography of piracy incidents mainly because it is easier for individuals engaging in illegal fishing to compensate for their inability to fish illegally by shifting to another more lucrative crime. But we do not foresee a decline in legal fishing, due to fish migration or other reasons, having a similar effect on economic grievance among fishers as a generator for maritime piracy, more than the hypothesis about the geography of crime.

The correlation between legal and illegal fish catch in all Indonesian grid cell years is positive and strong (correlation coefficient of 0.8, p < 0.01) when disregarding the temporal dynamics. However, visualizing the yearly trend tells a different story. Fig. 7 shows smoothed curves of the two events in Indonesian grid cells from 1990 to 2017, where the shade represents 95% confidence interval. The yearly trend of the two events, in fact, seem inversely related.

The figure suggests that the decline in illegal fishing seems to be compensated by increased legal fishing. Illegal fishing in Indonesia started to decline around 2000, and the rate of decrease tended to slow after 2009. This quantitative visualization of the data matches insights from qualitative studies describing how the government’s policies to address IUU fishing led to a decline in such activities. According to Sodik (2009), the Indonesian government implemented strict measures against IUU fishing in the 2000s, following the FAO’s 2001 International Plan of Action-IUU fishing. The government started to maintain a fishing logbook. In 2004, The Law of the Republic of Indonesia no. 31 established the rule of installing the vessel monitoring system (VMS) in ships to address illegal fishing. The responsibility to oversee VMS and monitor vessel activities was shared among three fisheries management authorities; (i) the Directorate General of Surveillance and Control of Marine Resources and Fisheries; (ii) the Directorate General of Capture Fisheries; and (iii) the Agency of Marine Affairs and Fisheries Research. According to Muawanah et al. (2021), Article 7 of Law No. 45/2009 further expanded the role of the Minister of Marine Affairs and Fisheries in implementing measures to control fishing activities by: (i) specifying regulations about the fishing method or gear; (ii) determining the maximum sustainable yield (MSY) or total allowable catch (TAC) for domestic and foreign fishing; (iii) specifying fishing and aquaculture activities; (iv) preventing activities such as pollution and destructive fishing of the resource and its ecosystems; and (v) rehabilitation of the resources and its habitat. Furthermore, in 2012, Indonesia formulated a National Plan of Action to Prevent and Combat IUU Fishing 2012–2016 (Satria et al., 2018).

Reported industrial fishing catch in the country increased steadily since 1990, slowing somewhat around 2007. Government efforts to regulate illegal and unreported fishery likely helped legalize and log the previously unreported practices, thus increasing the reported catch. But most importantly, we believe that one unintended consequence of curbing illegal fishing was the increase in maritime piracy, as local perpetrators compensated for their inability to fish illegally by shifting to another more lucrative crime. But we do not foresee a decline in legal fishing, due to fish migration or other reasons, having a similar effect on increasing piracy.

To test our conjecture on legal fishing, we replace the variable decrease in IUU fishing in Table 2 models with the variable decrease in legal fishing, which is a dichotomous variable coded as 1 if a grid cell year had 10% or more decline in the legal fish catch (in log scale). Unlike the results with illegal fish catch, we do not find a reduction in legal fishing to be a significant explanatory factor for piracy. The interaction term, decrease in legal fishing X Vessel traffic, in the table is statistically significant, but when visualizing, we do not find any substantive difference between grid cell years with or without decline in legal fishing. Fig. 8 depicts the visualization of the interaction term, where we also include results from a slightly higher cutpoint for comparison. The left and right panels show the predicted probability of piracy occurrence, as influenced by 10% and 15% decreases in legal fishing and varying levels of vessel traffic. As shown in the figure, the probability of a pirate attack is not significantly different in such grid-cell years compared to others. As expected, we do not find that the decline in legal fishing affects piracy similarly to the decline in illegal fishing. The contrasting results between legal and illegal fishing support our argument on crime displacement. It demonstrates that an increase in the probability of a pirate attack is directly linked to perpetrators within a specific local area who possess the willingness and capability to carry out such attacks when illegal fishing is restricted.

9. Conclusion

Like many other archipelagic and littoral countries, Indonesia depends on aquatic resources. There are millions of fishers in Indonesia, and issues that affect them directly, such as food insecurity, poverty, and joblessness, can all be tied to the health and security of Indonesia’s maritime space. The Indonesian government and President Joko Widodo have recently prioritized combatting IUU fishing and other criminal activities, such as corruption, human trafficking, and narcotics trade,
which seem to flow from, or are associated with, illegal fishing. Despite regulatory progress in addressing maritime crime, capacity limitations inhibit effective surveillance of Indonesia’s sprawling maritime space. Consequently, local perpetrators can easily shift from one illicit maritime activity to another.

In this paper, we discussed how illegal fishing influences piracy occurrences. More specifically, we found that piracy is more likely to occur in areas where illegal fishing has declined. This study is the first to establish the negative association between maritime piracy incidents at the local level and illegal fishing. It builds on recent studies that argue for looking at maritime crime holistically (Jacobsen, 2019). Our study indicates that rather than piracy and IUU fishing being complementary, the two practices are substitutive, at least in Indonesia. But incidents of piracy tend to occur at a much lower rate than illegal fishing, and the study does not fully evaluate and compare costs incurred from these two events to understand if policy measures to curb illegal fishing are still worth pursuing despite the increase in piracy. Future research can assess whether or how government measures to check illegal fishing may offset the cost because of piracy. Still, piracy is a high-cost, high-reward event for the perpetrator. Our study informs policymakers of the unintended consequence of increasing piracy incidents. Future studies should focus on sustainable policy approaches that address the underlying causes of these criminal activities (Battista et al., 2018; Belhabib, Le Billon, & Bennett, 2022; Belhabib, Le Billon, & Wrathall, 2020) and further explore how they might be associated with other forms of organized crime, like drug trafficking.

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CRediT authorship contribution statement
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Maria Lourdes D. Palomares: Resources.
Daniel Pauly: Resources, Writing – review & editing.
Brandon Prins: Writing – original draft, Writing – review & editing.
Sayed Riyadi: Resources.

Declaration of competing interest
None.

Data availability
Data will be made available on request.

References