Tasmanian School of Business and Economics
University of Tasmania

Discussion Paper Series N 2022-02

Fish to fight: does catching more fish increase conflicts in Indonesia?

Yifan Lu
University of Tasmania, Australia

Satoshi Yamazaki
University of Tasmania, Australia

ISBN 978-1-922708-30-4

UNIVERSITY of TASMANIA

Fish to fight: does catching more fish increase conflicts in Indonesia?

Yifan Lu[1*] Satoshi Yamazaki[1,2]

1. Tasmanian School of Business and Economics, University of Tasmania, TAS, Australia
2. Centre for Marine Socioecology, University of Tasmania, TAS, Australia

*Corresponding Author

Yifan Lu

Tasmanian School of Business and Economics

University of Tasmania

Private Bag 84, Hobart

Tasmania, 7001

Australia

Email: yifan.lu@utas.edu.au

Abstract

To what extent do marine-based economic activities influence the onset of violent conflict? Despite ongoing debate over several decades around the relationship between natural resources and violent conflict, little of the relevant research has addressed the marine environment. Based on satellite data in Indonesia, this paper provides new evidence on the relationship between fisheries and violent conflict. From a sample of 757 cells representing the spatial interaction of conflict and catch landings in 2015 and employing ocean productivity as an exogenous instrument, both industrial and non-industrial catches were found to have a statistically significant positive effect on the number of conflict events. Additionally, increased illegal, unreported and unregulated (IUU) catches are more likely than legal catches to cause violent conflict. An increase in fish catches in Indonesian waters fuels conflict of every kind, among which protests and riots are most sensitive to fisheries while fighting and terrorism are least sensitive. Overall, these empirical findings support the hypothesis that increased competition for common-pool resources contributes to the onset of violent conflict.

JEL Classification: D74, O13, Q22

Keywords: conflict, illegal fishing, marine resources, ocean productivity, satellite data, Indonesia

1. Introduction

Failures of natural resource management are increasingly recognized as a major source of social instability and civil conflict. For example, weak state capacity to manage lucrative resource rents from diamonds has deepened ethnic fractionalization in Africa (Lujala et al. 2005). Similarly, windfalls from oilfield discovery have increased the risk of political violence and armed conflict in oil-producing countries (Lei & Michaels 2014). In conflict-prone regions, the undesirable consequences of civil conflict extend beyond direct casualties and economic loss to broader issues such as poverty and changes in victims' social behaviours (Abadie & Gardeazabal 2003, Blattman & Miguel 2010, Voors et al. 2012). To formulate effective development and resource management policies, it is imperative to understand the causal link between natural resources and conflict. However, the nature of this relationship is not well understood, and whether natural resources are beneficial or harmful to regional peace remains unresolved in the literature (Ploeg 2011, Cotet & Tsui 2013, Bhattacharyya & Mamo 2021).

Previous studies have suggested that natural resources contribute to the increased incidence of conflict in three distinct ways. First, the presence of valuable natural resources is likely to motivate resource wars by incentivizing fighting and the elimination of competitors (Collier 2004, Caselli et al. 2015, Koren 2018, Schollaert & van de gaer 2009). Second, rich natural resources make armed conflict more feasible by providing the financial resources to develop insurgent capacity (Collier et al. 2008, Nunn & Qian 2014, Dube & Naidu 2015). Third, scarcity of natural resources and resultant inequalities in resource allocation generate social tensions and provoke conflict among competing groups (Hodler 2006, Caselli & Coleman

2013). On the other hand, these issues may not arise when natural resources drive income shocks that sufficiently increase the opportunity cost of fighting (Miguel et al. 2004). There is recent evidence of this effect in Colombia (Dube & Vargas 2013) and in Africa (McGuirk & Burke 2020a), where an increase in the price of agricultural products has deterred violent conflict.

Building on the available evidence, this paper uses detailed information about the geographical location of conflict events and associated levels of violence in Indonesia to explore the mechanisms through which fisheries affect conflict. While the global prevalence of such conflicts has been widely reported (Hendrix & Glaser 2011, Spijkers et al. 2019, Bulte et al. 1995, Parker & Vadheim 2017), the relevant literature has until now focused largely on high-value non-renewable resources, such as oil, diamonds and other mineral resources. As a common-pool resource, stock depletion and increased competition are seen as major catalysts for fisheries-related conflict (Pomeroy et al. 2007, Costello 2012, Smith & Wills 2018).[1] The level of resource competition in fisheries is further escalated by illegal, unreported and unregulated (IUU) fishing, which not only threatens resource sustainability but poses a risk to maritime security (Agnew et al. 2009, Cabral et al. 2018). Recent empirical studies have shown that fishers are more likely to engage in sea piracy when their legal income opportunities are adversely affected by oceanographic conditions (Flückiger & Ludwig 2015, Axbard 2016). However, an empirical understanding of the relationship between fisheries and conflict that takes place on land remains limited.

[1] In relation to renewable resources, previous studies have investigated water-related conflict (Gleick 1993, Dimitrov 2002, Zeitoun et al. 2020). As a fundamental resource for most human activities, competition and disputes over freshwater are recognized as a national security issue in water-scarce countries. In addition, conflict over forest resources has been studied (Bazzi et al. 2021, Hares 2009, Rustad et al. 2008).

As the sixth largest exclusive economic zone (EEZ) in the world, Indonesia is a pertinent case for present purposes. Ocean-based activities are central to national and regional economic development (FAO 2021), and the fisheries sector also plays a crucial role as an essential source of food and employment for vast coastal communities (Béné et al. 2016, George et al. 2020). The current situation in Indonesia highlights the importance of understanding conflict patterns and their causal relation to fisheries. Since the end of the 1990s, Indonesia has experienced major conflicts involving violence, civilian causalities and the destruction of infrastructure at community and national levels (Barron et al. 2009). The causes and consequences of these conflicts are complex and multifaceted (Brambilla & Jones 2020), but anecdotal evidence suggests that many are fisheries-related (Aragon 2001, Thorburn 2001, Muawanah et al. 2012).

Assessing the impact of fisheries on conflict events is not a trivial task for at least two reasons. First, while fisheries are marine-based, most of the conflict events are recorded on land territory. As the two activities are by construction not observed at the same location, and thus their relationship needs to be considered at a geographical scale. However, it is inadvisable to use institutional boundaries such as country, district or village for this purpose, as conflict patterns are highly correlated with unobservable characteristics of institutional boundaries (de Ree & Nillesen 2009, Martin-Shields & Stojetz 2019) and so confound the fishery-conflict relationship. For example, while there are many cross-country panel studies of conflict and natural resources (Cotet & Tsui 2013, Bazzi & Blattman 2014), these nation-level analyses may aggregate too much information at the expense of regional nuances

(Berman et al. 2017).[2] Second, while our primary concern here is the impact of fisheries on conflict, the adverse impact of conflict on fishing activities is also clear (Gleditsch 1998, Schwartz et al. 2018), and this feedback effect may bias estimates of how fisheries impact conflict. This problem of endogeneity is a long-standing issue in the relevant literature (Miguel et al. 2004).

To address these issues, we performed a geographically disaggregated analysis based on grid cell data at 1 × 1 degree resolution, enabling us to assess how fisheries influence the number of conflicts within a given cell and in neighbouring areas. To identify the causal relationship, we adopted an instrumental-variables approach exploiting geographical variations in ocean productivity as an instrument. Ocean productivity is determined solely by exogenous environmental factors that include chlorophyll concentration and sea surface temperature (SST) (Nelson & Smith 1991, Henson et al. 2010). As ocean productivity is known to be a key driver of fisheries productivity (Piroddi et al. 2010, Stock et al. 2017), the geographical variations in ocean productivity facilitate investigation of how exogenously determined fishery shocks affect conflict.

The rest of the paper is structured as follows. Section 2 provides an overview of Indonesian fisheries and the potential channels through which fisheries might affect conflict. Section 3 describes the data and the grid cell sample construction. Section 4 outlines the empirical strategy for assessing the causal effect of fisheries on conflict. Section 5 presents the main findings and assesses the robustness of those results. This section also explores possible mechanisms through which fisheries affect conflict. Section 6 discusses the findings and their

[2] Berman et al. (2017) noted that country-level aggregation may result in noisy estimates and attenuation bias because of the unobserved heterogeneity within as well as across countries. The present study differs from previous studies by relying on geocoded information for the case country that includes geographical variations in oceanographic conditions to assess the relationship between fisheries and conflict.

implications for policy, followed by conclusions in Section 7.

2 Background

As the world's largest archipelagic state, Indonesia has one of the richest marine habitats and the second largest capture fishery production sector globally. The country’s fisheries sector accounts for 21% of its agricultural economy, providing direct employment for six million people in 2012 (FAO 2021). The importance of fish as an essential source of animal protein has driven a fourfold increase in per capita annual consumption of fish products over the last four decades (FAO 2021). Fishery activities in Indonesia fall into two broad categories: an industrial sector operated by commercially oriented entrepreneurs with large fishing boats, and a non-industrial sector involving subsistence and commercial fishers with motorized or non-motorized fishing boats (Halim et al. 2019). As compared to other major fishing countries, one distinguishing feature of Indonesia’s fisheries sector is that marine capture is dominated by small-scale operators. According to FAO (2021), about 95% of total fish production comes from small-scale fisheries, and small unpowered or outboard-engine boats account for 67% of the country’s fishing vessels.

As the competent national authority, Indonesia’s Ministry of Marine Affairs and Fisheries (MMAF) is responsible for managing fishing licenses, monitoring fishing activities, preventing illegal fishing and conserving fisheries resources (Muawanah et al. 2012). The government’s top-down management approach focuses mainly on the enforcement of fishing licensing and vessel registration for large-scale industrial producers (Halim et al. 2019), typically for vessels larger than 30 GT. In contrast, non-industrial fisheries are managed by provincial governments or local community-based resource management systems (Satria & Matsuda 2004, Yamazaki et al. 2018). However, despite current management efforts at national and local levels (Muawanah et al. 2018), Indonesia's fisheries sector is experiencing increasing pressure from overexploitation, and the prevalence of IUU fishing has further complicated the management of marine areas, posing additional risks to sustainability (Cabral et al. 2018).

Previous studies provide anecdotal evidence that three possible channels through which fisheries might affect conflict. The first of these relates to disputes that directly involve fishing operators (i.e., "fish wars"). These conflicts have long been the subject of theoretical studies (Levhari & Mirman 1980) and have also been documented widely in Indonesia and elsewhere (Muawanah et al. 2012, Yamazaki et al. 2018). The main causes of fish wars in Indonesian waters include vague claims related to sea territory and excessive resource competition. In Papua, for example, migration from highland to coastal regions aggravated competition between migrants and traditional resource user groups. This dispute later escalated into violent conflict, fuelled by opposing claims regarding territorial user rights (Koczberski & Curry 2004).

The second channel from fisheries to conflicts is related to contentious development that adversely impacts the welfare of coastal communities. In a region where communities are highly dependent on fisheries for their food and livelihood, public protests and demonstrations against development authorities are commonplace. While these may begin peacefully, they can quickly escalate into violent confrontation with police and government actors (Haryadi & Wahyudin 2018). Finally, the increasing pressure on fishing and the resulting resource depletion can have spillover effects in other sectors. In particular, an increasing number of studies across various disciplines have noted the link between fisheries and maritime crimes such as piracy, trafficking and smuggling (Axbard 2016, Mackay et al. 2020, Halim et al. 2019).

3. Data

3.1 Conflict

The conflict data were sourced from the Armed Conflict Location and Event Data (ACLED) project (Raleigh et al. 2010) for two reasons. First, ACLED records geolocation data for each conflict event. National Violence Monitoring System (NVMS) and Village Potential Statistics (PODES) are the other two widely used conflict datasets that are also publicly available for Indonesia. However, the geographical location of conflict events is not recorded in these datasets. For the current research design that uses spatial interaction of conflict and catch landings, the ACLED dataset is the only source of the conflict variables. Our sample includes the 599 events recorded for Indonesia in 2015.[3] Of these, 90% (540 cases) relate to village or town level while 9% (53 cases) relate to regional level, with only 1% (6 cases) recorded at province level.

Second, ACLED provides detailed information about conflict participants and types (Table 1).[4] In 2015, Indonesia's most common conflicts were protests (63%) that did not typically involve severe violence. Along with civilian conflicts that included protests, riots and strategic developments, accounting for more than 80% of all such events, 33 armed conflicts

[3] The year 2015 was chosen because the first recorded conflict in ACLED is January 1, 2015; as our fisheries data (Global Fisheries Landings v4.0) only cover the years 1950–2015, our conflict and fisheries data intersect only for 2015, and our analysis was necessarily based on cross-sectional data.

[4] On December 2, 2015, for instance, fishermen and local people mounted a theatrical demonstration in Muara Angke, North Jakarta, opposing the ongoing coastal reclamation project to create 17 manmade islands (Event-ID 402 from ACLED).

(battles and explosions) were also recorded in 2015.

[Table 1 about here]

3.2 Fisheries

Indonesian fisheries data were collected from Global Fisheries Landings v4.0 (Watson 2017). The database was developed using multiple sources supplied by international and fisheries science agencies, including the Food and Agriculture Organization (FAO), the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR), the Northwest Atlantic Fisheries Organization (NAFO) and the International Council for the Exploration of the Sea (ICES). Spatial information from regional fisheries management organisations (RFMOs) and satellite-based vessel Automatic Identification System (AIS) is also used to improve the precision of data. The data include landings of industrial and non-industrial catch in tonnes for grid cell intervals of 0.5 degrees (latitude and longitude). The database usefully separates industrial and non-industrial fishing according to catch taxonomic composition (Pauly and Zeller, 2016), reported type of fishing gear and fishing location. For example, non-industrial fishing typically involves a relatively large number of small-scale fishing boats in inshore coastal areas while industrial fishing predominates in offshore wasters and uses large boats and technologically sophisticated gear (Muawanah et al. 2018).

To the best of our knowledge, Global Fisheries Landings v4.0 (Watson 2017) is the only publicly available geocoded catch data, which has been widely used in previous studies (e.g., Miller et al. 2019, Boyce et al. 2020). There are two other datasets that include geocoded fisheries information — the Global Fishing Watch (GFW) and Visible Infrared Imaging Radiometer Suite (VIIRS). However, these datasets only provide information about the fishing effort (e.g., location of fishing vessels and the time spent for fishing) and no catch information is included.

From the database, we retrieved catch data on industrial and non-industrial fishing within 200 nautical miles (nmi) of Indonesia. The database also contains separate information about estimated IUU fishing catches, based on a combination of surveillance, trade and stock assessment data. In terms of geographical coverage, we included all data recorded within 200 nmi of shore, as some offshore fishing by Indonesian vessels occurs (legally or illegally) outside the EEZ, exacerbating overfishing and resource degradation (Arias & Pressey 2016).[5]

3.3 Ocean productivity

To identify the causal relationship between fisheries and conflict in Indonesia, spatial variation in the chlorophyll-based ocean productivity (OP) index, which is known to determine geographical differences in catch, was used as an instrumental variable (Stock et al. 2017). We retrieved monthly data for that index at a spatial resolution of 1 × 1 degree cells from the Oregon State University website (http://www.science.oregonstate.edu/ocean.productivity/). The ocean productivity index is based on the Vertically Generalized Production Model (VGPM), which estimates net primary production from chlorophyll using a temperature-dependent description of chlorophyll-specific photosynthetic efficiency (Behrenfeld & Falkowski 1997a, Behrenfeld & Falkowski 1997b). This is calculated as:

$$OP_{c,m} = chl_{c,m} \times SST_{c,m} \times daylight_{c,m} \times v_{c,m} \qquad (1),$$

where $chl_{c,m}$ is chlorophyll concentration; $SST_{c,m}$ is sea surface temperature; $daylight_{c,m}$ is hours of daylight (i.e. potential duration of photosynthesis); and $v_{c,m}$ is the volume function in cell c and month m. The volume function represents primary production from the surface to a depth of 1% of surface light (euphotic depth); this was included to account for the effects of

[5] For example, the Strait of Malacca is less than 200 nautical miles wide, and we therefore included all observations in the Strait.

light on water column production at different depths. We aggregated the monthly data for ocean productivity ($OP_{i,m}$), to calculate ocean productivity for 2015 in each *c*, where $OP_c = \sum_m OP_{c,m}$.

3.4 Sample construction

The unit of observation is a 1 × 1 degree cell within 200 nmi of the Indonesian shore. This is determined by the original resolution of ocean productivity data, and thus the finest spatial scale achievable with the data available for the present analysis. The choice of this cell size also means that provinces are the level above the cell. For present purposes, a larger cell size is therefore not advisable because we control unobserved regional heterogeneity in economic, social, and climatic conditions using province fixed effects (see Section 4).[6] Data with the same spatial resolution have been commonly used in previous studies examining the relationship between conflict and potential causes (Hunziker & Cederman 2022, Harari & Ferrara 2018), whereas other studies, including Axbard (2016) and Berman et al. (2017), have also used a broader (2 × 2 degree) or finer (0.5 × 0.5 degree) spatial scale.

Cells that included other countries' land territory (i.e., Malaysia, Singapore, Philippines) and those that did not contain any sea area were dropped from the sample, which meant that 757 cells were included in the analysis (see Appendix, Figure A1). The catch variable was constructed by matching catch data to ocean productivity data for each 1 × 1 degree cell in terms of the spatial resolution. Rather than matching conflict data with other sea-based data (i.e., fisheries and ocean productivity) within each cell, we constructed the conflict variable by using a "search-by-radius" approach to count the number of conflict events or fatalities around each cell (Figure 1). This is because the fisheries and conflict data were recorded on

[6] A smaller cell size may allow us to control regional heterogeneity at a lower geographical level (e.g., districts). However, this poses a risk of spillovers between cells; e.g., fishers catch fish in areas far from home.

sea and land, respectively. As no conflict observations were recorded in about 52% of the cells in our sample that contained no land area, the use of the search-by-radius approach to link land- and sea-based data enabled us to determine whether increasing fishing intensity in a given sea area altered conflict patterns in adjacent land areas. For the baseline case, we used a search radius of 100 nmi from cell edges to construct the conflict variable. We also performed a sensitivity analysis to assess how the baseline results would respond to different search ranges (0, 50, 150 and 200 nmi) as well as possible spatial correlation between cells.

[Figure 1 about here]

3.5 Sample characteristics

Table 2 shows summary statistics for the variables used in the analysis (conflicts, fisheries and ocean productivity), and Figure 2 shows the geographical distribution of the 599 conflict events and total fisheries catch. The distribution of conflicts is highly skewed; for example, while the mean number of conflicts in each cell is less than 1 (0.724), the maximum number of conflicts within a cell (around the national capital Jakarta) is 133, accounting for about 22% of all conflicts in 2015.[7] Although the probability of observing a conflict in a given cell is relatively low (9%), there were 12 conflicts on average within 100 nmi of each cell. By construction, the mean number of conflicts generally increases with search radius, as some conflicts are matched to multiple cells.

[Table 2 about here]

[Figure 2 about here]

The geographical distribution of fisheries catches is also highly skewed towards western regions, where fisheries have developed faster than in other areas. The overexploitation of

[7] A simple log-transformation of the conflict variable is not advisable to reduce the skewness because of zero values in many observations. Alternatively, we transformed the conflict variable by taking $\ln(conflict_{c,p}+1\times epsilon)$, where *epsilon* is the machine epsilon (i.e., 1.11e-16). We estimated our models (Section 4) with the transformed variable and found no changes in the conclusions.

marine resources is of particular concern in these regions (Heazle & Butcher 2007, FAO 2021). There is a moderate positive correlation between conflicts and fisheries catches (see Appendix, Table C1), and Figure 2 shows that adjacent areas of high fishing intensity are also likely to experience some conflict events. For example, the area of highest fishing intensity is the Strait of Malacca, which coincides with the highest concentration of conflicts in Sumatra Island's western coastal provinces (Aceh, North Sumatra, Riau, Jambi and South Sumatra).

4. Empirical Strategy

To evaluate the impact of fisheries on conflict, we employed the following structural equation:

$$conflict_{c,p} = \beta catch_c + \gamma_p + \varepsilon_{c,p} \qquad (2).$$

The dependent variable $conflict_{c,p}$ refers to the number of conflicts or fatalities in cell c and province p. Our primary interest is the coefficient of $catch_c$, which denotes the quantity of fish caught in cell c. The equation also includes province fixed effects γ_p to control for factors potentially associated with regional differences in conflict patterns, including economic, social, and climatic conditions.[8]

The omission of province fixed effects may bias the estimated effect of fisheries on conflict in either a positive or negative direction. However, the overall consequence of omitting province fixed effects is ambiguous because the direction of the bias that arises from these factors depends on the way in which they are associated with conflict and fisheries catches. For example, fish catches are expected to be high in regions with a large population of fishers. At the same time, the number of conflicts is expected to increase with the increasing density of human settlements (Acemoglu et al. 2020). In such a case, the omission of regional differences in population may lead to an upward bias in the estimated effect of fisheries on

[8] Provinces are the level above the cells in our sample, meaning that we are exploiting variation within provinces in the empirical strategy.

conflict.[9] By contrast, the failure to control for regional differences in climatic conditions may bias the estimates downward. Previous research suggests that severe climatic conditions in terms of temperature, rainfall, and drought intensity increase the risk of violent conflict (Maystadt & Ecker 2014, Burke et al. 2015), whereas severe climatic conditions such as increasing rainfall during the monsoon season and strong ocean winds are known to negatively impact on fisheries productivity (Lam et al. 2020, Allison et al. 2009). We therefore included province fixed effects to control for inter-regional differences in economic, social, and climatic conditions.

Moreover, OLS estimation of equation (2) is likely to suffer from endogeneity arising from reverse causality. More particularly, fisheries in a given cell may be adversely affected in at least two ways by conflict in adjacent areas. First, conflicts in coastal areas may hinder fishing activities by posing a threat to the safety of fishing operators, preventing the use of harbour or sea areas and limiting access to input or output markets (Pomeroy et al. 2007, Hendrix & Glaser 2011). Second, the fishermen themselves might seek to affect catch landings by participating in protests or riots. The parameter β in (2) is likely to be underestimated neglecting the significant negative feedback effect of fisheries on conflict.

To address the endogeneity problem, we exploited the exogenous variation of the chlorophyll-based ocean productivity index OP_c for two-stage least squares (2SLS). For present purposes, this variable is the ideal instrument that satisfies the two assumptions necessary to identify the causal impact of fisheries on conflict. First, the chlorophyll-based ocean productivity index does not directly affect land-based conflicts but only through fisheries activities since the concentration of chlorophyll in the sea or SST does not directly influence household behaviours or economic activities of other sectors. Second, the

[9] It is also possible that the population size is positively correlated with ocean productivity. For example, people may be more likely to migrate to places with historically good fishing conditions, and this may also result in higher fish catches and a greater likelihood of conflict onset. Province fixed effects are thus included in the first-stage regression to block this back-door path.

chlorophyll-based ocean productivity index captures regional differences in marine fisheries catches. In the biology literature, this index is widely used to estimate the abundance, growth and production patterns of fisheries resources (Hendiarti et al. 2005, Semedi & Dewanti Dimyati 2010, Nurdin et al. 2017). The first-stage regression also confirmed that, as the literature suggests, ocean productivity has a positive impact on all catch variables at the 1% significance level (Table 3). The Kleibergen-Paap Lagrange Multiplier test rejected the null hypothesis of under-identification (Kleibergen & Paap 2006), and Stock and Yogo's F-statistics for the excluded instrument of ocean productivity also suggest that ocean productivity is a relevant instrument for the fisheries variable (Stock & Yogo 2002).

[Table 3 about here]

Despite the first-stage regression, the violation of exclusion restriction through omitted variables could still be a concern. For example, other climatic conditions may have a direct relationship with ocean productivity and conflict (Bazzi & Clemens 2013, Sarsons 2015). To address this concern, we estimated the correlation coefficient between conflict and ocean productivity with a subsample of observations that have low fisheries catches (i.e., the bottom 10 percentile). Theoretically, if the exclusion restriction is fulfilled, we should observe no correlation between conflict and ocean productivity in this subsample because ocean productivity only affects the conflict through fisheries. Consistent with this prediction, the correlation coefficient in the subsample of low catch areas is near zero (0.003) and statistically insignificant at any conventional significance level. In comparison, the correlation coefficient between conflict and ocean productivity with the full sample is 0.233 (see Table C1 in Appendix), which is statistically significant and larger in size. These results suggest that fisheries are the major channel through which ocean productivity affects conflict.

5. Results

5.1 Baseline results

Table 4 shows the OLS and 2SLS estimation results with and without province fixed effects. Industrial catch, non-industrial catch and their combined total respectively serve as the fisheries variable. Across all model specifications, there is consistent evidence of a statistically significant positive impact of fisheries on conflict within a range of 100 nmi. As expected (see Section 4), the magnitude of impact estimated by 2SLS is consistently higher than OLS estimates. The omission of province fixed effects also results in an underestimation of the impact, suggesting the presence of unobserved regional heterogeneity in conflict patterns. On that basis, we used the fixed effects 2SLS outcome to interpret the results.

The fixed effects 2SLS model indicates that an increase of one thousand tonnes in overall annual catch increases the number of conflicts within an area of 100 nmi around the cell by 1.501 cases. Comparing the impacts of industrial and non-industrial fishing, the number of conflicts associated with an increase in industrial catch is greater than for a non-industrial catch by roughly a factor of four (i.e., 7.945 cases for an additional thousand tonnes versus 1.851 cases for an additional thousand tonnes of non-industrial catch).[10] The analysis also confirms the positive impact of fisheries on both the number of conflicts and the number of fatalities; an additional thousand tonnes of annual catch increase the number of conflict-related deaths within 100 nmi of the cell by an average of 0.223.

[Table 4 about here]

[10] The exclusion restriction of the instrumental variable requires the condition Γ=0 to be satisfied in the equation $conflict_{c,p} = \beta catch_c + \Gamma OP_c + \gamma_p + \varepsilon_{c,p}$. To further assess the sensitivity of our results to this assumption, we applied a plausible exogeneity test (Conley et al. 2012) that allows Γ to take a non-zero value. The test reports a confidence interval of β while relaxing the exclusion restriction. The 95% confidence interval of β is estimated at [1.83, 19.75] for the industrial catch; [0.58, 3.50] for the non-industrial catch; and [0.48, 2.92] for the overall catch. These results suggest that our baseline results in Table 4 are robust to possible violation of the exclusion restriction assumption.

5.2 *Conflicts in alternative search radius*

To assess the sensitivity of the fixed effects 2SLS results in Table 4 for a 100 nmi search radius, we ran regressions with search radiuses of 0, 50, 150 and 200 nmi. Estimated coefficients of the catch variable (β) with 95% confidence intervals (Figure 4) show that the positive impact of fisheries on conflict remains the same regardless of the search radius value. For example, the estimated coefficient from the regression with a search radius of 0 nmi is positive and statistically significant, suggesting that an increase in fish catches in a cell leads to an increase in the number of conflicts within the same cell. The estimated coefficient and confidence interval generally increase with search radius, especially from 0 to 100 nmi. This increase in the estimated coefficient is expected because each cell is linked to a greater number of conflicts as the search radius increases. For example, for a search radius of 0 nmi, offshore cells are not linked to any conflict event, and the estimate considers only the relationship between conflicts and nearshore fishing. However, when the search radius exceeds 100 nmi, the impact of offshore fishing is included. For a search radius of 100 to 200 nmi, the estimate of β remains relatively constant at around 1.5 while the standard error (and hence the confidence interval) increases moderately.

[Figure 3 about here]

5.3 Spatial autoregressive analysis

A concern with the data is spatial correlation between cells that might be present because of the way in which the grid cell sample was constructed based on the search-by-radius approach. To assess how sensitive the fixed effects 2SLS results in Table 4 are to the issue of spatial correlation, we estimated the spatial autoregressive (SAR) 2SLS model (Kelejian & Prucha 2010, Drukker et al. 2013), in which the structural equation in (2) is replaced by the following equation:

$$conflict_{c,p} = \beta catch_c + \gamma_p + \lambda W\, conflict_{c,p} + u_{c,p} \qquad (3)$$

$$u_{c,p} = \rho W u_{c,p} + \varepsilon_{c,p} \tag{4}$$

where W is a 742×742 spectral-normalized spatial weight matrix based on the haversine distance for the longitude and latitude of sample cells.[11] The spatial autoregressive parameters λ and ρ measure the extent of spatial interactions in the dependent variable $conflict_{c,p}$ and disturbance term $u_{c,p}$, respectively. The SAR-2SLS model shows that the positive impact of fisheries on conflict remains robust after accounting for spatial autocorrelation (Table 5). The magnitude of impact estimated by SAR-2SLS is smaller than the baseline estimates. We also estimated the SAR-2SLS model for the subsequent analyses in Sections 5.4 to 5.6, which confirmed that the conclusions are not sensitive to spatial autocorrelation (see Appendix D).

[Table 5 about here]

5.4 Level of violence

The analysis also examined whether fisheries have a consistent positive effect on conflicts involving different levels of violence. To that end, we first categorized each conflict event as one of three types according to level of violence as defined by ACLED. We then re-estimated equation (2) for fixed effects 2SLS, replacing the dependent variable with each conflict type in turn (Table 6). Using different levels of violence in conflicts, we intend to disentangle the mechanisms through which increased fish catches affect conflict. In theory, fish catches may be associated with conflict in all levels of violence; however, the magnitude of such a conflict-fisheries relationship would be sensitive to the level of violence involved in the conflict. The results indicate that the total catch coefficient is positive and statistically significant for all types of conflict, but the magnitude of this effect varies for the different types. Type I (protests, riots and strategic development) is the least violent and has the largest

[11] Each element in the spatial weight matrix W is expressed as $w_{i,j} = d_{i,j}^{-1}$, where $d_{i,j}$ is the haversine distance (in miles) from the centroid of cell i to the centroid of cell j. Each element of the spatial weight matrix was spectral normalized by dividing it by the moduli of the largest eigenvalues of the matrix W. The measured distance for the centroids of the two closest cells lie within approximately 68 miles of each other, and the two most distant cells are 3,783 miles apart.

estimated coefficient; specifically, there were 1.2 additional cases of Type I conflict for each additional thousand tonnes of catch. In contrast, the most violent conflicts (Type III) returned the lowest magnitude (0.079).

[Table 6 about here]

5.5 Regional differences

To investigate whether the impact of fisheries on conflict differed by region, we re-estimated the model with a subsample of four development regions as classified by the National Development Planning Agency of Indonesia. These regions are different in terms of the exploitation status of important commercial stocks and the way coastal resources are managed (MMAF 2017; Muawanah et al. 2018; Halim et al. 2020). For example, fishing intensity is generally higher in western regions where fisheries are more industrialised than eastern regions where small-scale fisheries account for a significant share of total production (Figure 2). The subsample analysis thus allows us to assess how these regional differences in resource status and management systems are associated with the way in which fisheries influence conflict patterns. The results confirm the positive impact of fisheries on the number of conflicts for all regions (Table 7). However, the magnitude of that impact was about 20% higher in western regions than in the east; the greatest impact was in Region B, where the national capital region returned the highest concentration of conflicts.

[Table 7 about here]

5.6 Illegal, unreported and unregulated (IUU) fishing

We also assessed the impact of IUU fishing by replacing catch variables with IUU catch variables. IUU fishing is a major contributor to overfishing in Indonesian waters, posing a serious threat to the sustainable use of fisheries resources (Resosudarmo & Kosadi 2019). This means that if overfishing and increased competition over declining resources were an important driver of the fisheries-conflict relationship, we would expect to see a greater impact of IUU fishing on conflict than non-IUU fishing. The regressions with IUU catch variables show that all types of IUU fishing have a positive impact on the number of conflicts at the 1% significance level (Table 8). As shown in the baseline estimation of non-IUU fishing, a unit increase in industrial IUU fishing in a given cell also had a greater impact than non-industrial IUU fishing on the number of conflicts in adjacent areas. However, the relative impact of industrial and non-industrial IUU fishing differed from the baseline estimation; that is, the impact of industrial IUU fishing increased moderately when compared to the baseline estimate while the impact of non-industrial fishing was almost four times greater than that of its non-IUU counterpart.

[Table 8 about here]

6. Discussion

These results show that oceanographic conditions directly affect fisheries production in Indonesia and that the resulting higher fish catches fuel violent conflict in coastal areas. According to our estimates, the number of conflict events in Indonesia increases by 15% with every 10% increase in total catch. This positive relationship between conflict occurrence and fish catch is apparent both in nearshore and in offshore fisheries as far as 100 nmi from the coast. Our results also show that, although Indonesian fisheries are dominated by non-industrial small-scale fishing boats (FAO 2021), industrial fisheries are associated with four times more conflict events than non-industrial fisheries, possibly because industrial fishing boats are larger and are equipped with more modern gear (e.g., trawl, purse-seine). While these technological advances have increased the productive capacity of fishing industries, they have also raised concerns about detrimental impacts on marine ecosystems (Thurstan et al. 2010, Pauly et al. n.d., Pichegru et al. 2012).

The same pattern is evident in regional differences in the fishery-conflict relationship; an increase in fish catches in western regions affects the conflict occurrence 20% more than that in eastern regions. Fisheries in Indonesia's western regions are more industrialized and more intensively exploited, with less scope for further development (FAO 2021). Additionally, fisheries management in Indonesia focuses mainly on industrial fisheries, but individual catches are not restricted by total allowable catches or quota systems. Similarly, small-scale fisheries are only weakly regulated (Halim et al. 2019). However, the impact of non-industrial fisheries and those in eastern regions is generally weaker, possibly because they provide food and livelihood security directly to the country's vast coastal communities.

Our results also show an association between favourable oceanographic conditions and increased IUU fishing, which results in a greater number of conflict events in surrounding areas. Importantly, IUU fishing has a greater impact on conflict occurrence (by a factor of about 2.4) than non-IUU fishing, further reinforcing the link between fisheries conditions and conflict, as IUU fishing is considered a major threat to resource sustainability and maritime security in Indonesian waters (Resosudarmo & Kosadi 2019). Recent studies (Flückiger & Ludwig 2015, Axbard 2016) have shown that incidence of sea piracy increases with decreased fishing returns, and our results also align with existing observations that conflict patterns in coastal areas reflect increases in environmental degradation and resource competition (Muawanah et al. 2012).

Civil conflicts in Indonesia involve different levels of violence, ranging from relatively peaceful public protests to armed battles (Raleigh et al. 2010). Our results show the causal impact of fishing on all types of conflict, which suggests that no single factor predominantly explains the underlying mechanisms. Previous theoretical and empirical studies have identified multiple ways in which natural resources affect conflict. However, contrary to some earlier studies (Miguel et al. 2004, Maystadt & Ecker 2014, McGuirk & Burke 2020b) we found no evidence that Indonesian fisheries prevent conflict by providing sufficient rewards to increase the opportunity cost of fighting; instead, our results suggest that increasing fish catches fuel conflict in surrounding areas. This may reflect the current overexploitation of important species in Indonesian waters (MMAF 2017) and the fact that the non-exclusivity of fisheries resources serves to diminish their long-term benefits.

In the present context, there are at least two other channels that may be at play in the relationship between fisheries and conflict in Indonesia. First, increased fish catches in a given location may be associated with increased inequality of access to the benefits of natural resources. In light of the state's weak fisheries management capacity, frustrations around inequitable access to resource rents may fuel violence in local communities. Grievances of this kind have triggered civil conflicts in Indonesia, exacerbated by inequalities related to income, employment and political opportunity (Barron et al. 2009). Previous studies have also reported cases of local disputes around territorial claims and resource allocation that eventually escalated into violent communal conflict (Aragon 2001). Second, an increase in fish catches supported by favourable oceanographic conditions may enhance the financial feasibility of insurgency in the short term; in a related context in Africa, lucrative rents from a mining site improved the financial capacity of fighting groups to fuel violent conflict (Berman et al. 2017).

7. Conclusions

Inappropriate resource management potentially poses a major threat to the social and political stability of resource-dependent states and regions. Previous studies have uncovered a causal relationship between violent conflict and non-renewable resources such as oil and diamonds, but little is known about this issue in marine contexts. To bridge this gap, the present study provided a geographically disaggregated analysis to assess the impact of fisheries exploitation on the onset of violent conflict in Indonesia. To that end, we constructed a unique sample of grid cell data at 1 × 1 degree resolution for the year 2015. Exploiting the exogenous variation in oceanographic conditions, our results confirmed a quantitatively relevant positive relationship between fish catches and conflict. According to our analysis, offshore fishing up to 100 nautical miles from the coast effectively explains conflict patterns in Indonesia's coastal areas. Our results further show that the fisheries-conflict relationship is especially strong in the case of industrial and illegal fishing, which is a significant source of socio-ecological concern in Indonesia. Possible channels through which increased fish catches may fuel conflict include mounting competition for declining fish stocks, conflicting claims regarding territorial user rights, socioeconomic inequality and empowerment of armed insurgents.

We draw three possible policy implications based on our empirical analysis. First, we show that changes in fisheries conditions impact the wider community beyond those directly involved in fishing. It has long been accepted that economic performance in the fishing sector is affected by inherent variations in the marine environment (Hjort 1914) and by incentives for overfishing (Warming 1911). By implication, improved fisheries management that curb overfishing and prevents stock depletion offers benefits that extend beyond resource user groups to society as a whole. Second, our analysis suggests that the Indonesian government's current regulatory focus on large fishing vessels above 30 GT is sensible in terms of conflict mitigation, as adequate management of these vessels is imperative to break the link between fisheries and conflict. Finally, this study bolsters the case for monitoring and reducing illegal fishing in Indonesian waters, whether by industrial or small-scale operators. This aligns with recent evidence of a link between illegal fishing and maritime crimes that lead to social unrest, including piracy, trafficking and smuggling (Mackay et al. 2020, Vince et al. 2021).

Our study is not without limitations, and some caveats need to be considered. First, we used cross-sectional data for 2015 due to the availability of conflict, catch, and ocean productivity data for the same year. One avenue for further research is to address the current research questions using panel data when such data become available. We found that the estimated effect of fisheries is consistently higher in regressions with province fixed effects than without them, suggesting that the omission of unobserved regional differences was controlled in the model. We additionally provided a plausible exogeneity test (Conley et al. 2012) to show that our results are robust to potential violation of the exclusion restriction assumption. However, panel data allow researchers to exploit cross-sectional and time series variations in conflict and fisheries catches, and this may enable a stronger identification of the causal link between fisheries and conflict. Second, there are potential measurement errors in catch data that were constructed based on multiple sources, including information provided by governments, international organisations, and AIS. The use of alternative fisheries data may be a possible way to reduce the problem of potential measurement errors. For example, Indonesia's Vessel Monitoring System (VMS) tracks vessel locations. Although VMS date do not contain catch information or are publicly available (Global Fishing Watch 2017), they would provide accurate locations of fishing activities, enabling one to study the relationship between the movement of fishing vessels and conflict.

References:

Abadie, A & Gardeazabal, J 2003, "The Economic Costs of Conflict: A Case Study of the Basque Country," American Economic Review, vol. 93, no. 1, pp. 113–132.

Acemoglu, D, Fergusson, L, & Johnson, S 2020, "Population and Conflict," The Review of Economic Studies, vol. 87, no. 4, pp. 1565–1604.

Agnew, DJ et al. 2009, "Estimating the Worldwide Extent of Illegal Fishing," PLoS ONE, vol. 4, no. 2, p. e4570.

Allison, EH et al. 2009, "Vulnerability of national economies to the impacts of climate change on fisheries," Fish and Fisheries, vol. 10, no. 2, pp. 173–196.

Aragon, L v. 2001, "Communal Violence in Poso, Central Sulawesi: Where People Eat Fish and Fish Eat People," Indonesia, vol. 72, p. 45.

Arias, A & Pressey, RL 2016, "Combatting Illegal, Unreported, and Unregulated Fishing with Information: A Case of Probable Illegal Fishing in the Tropical Eastern Pacific," Frontiers in Marine Science, vol. 3.

Axbard, S 2016, "Income Opportunities and Sea Piracy in Indonesia: Evidence from Satellite Data," American Economic Journal: Applied Economics, vol. 8, no. 2, pp. 154–194.

Barron, P, Kaiser, K, & Pradhan, M 2009, "Understanding Variations in Local Conflict: Evidence and Implications from Indonesia," World Development, vol. 37, no. 3, pp. 698–713.

Bazzi, S et al. 2021, "The Promise and Pitfalls of Conflict Prediction: Evidence from Colombia and Indonesia," The Review of Economics and Statistics, pp. 1–45.

Bazzi, S & Blattman, C 2014, "Economic Shocks and Conflict: Evidence from Commodity Prices," American Economic Journal: Macroeconomics, vol. 6, no. 4, pp. 1–38.

Bazzi, S & Clemens, MA 2013, "Blunt Instruments: Avoiding Common Pitfalls in Identifying the Causes of Economic Growth," American Economic Journal: Macroeconomics, vol. 5, no. 2, pp. 152–186.

Behrenfeld, MJ & Falkowski, PG 1997a, "Photosynthetic rates derived from satellite-based chlorophyll concentration," Limnology and Oceanography, vol. 42, no. 1, pp. 1–20.

Behrenfeld, MJ & Falkowski, PG 1997b, "A consumer's guide to phytoplankton primary productivity models," Limnology and Oceanography, vol. 42, no. 7, pp. 1479–1491.

Béné, C et al. 2016, "Contribution of Fisheries and Aquaculture to Food Security and Poverty Reduction: Assessing the Current Evidence," World Development, vol. 79, pp. 177–196.

Berman, N et al. 2017, "This Mine is Mine! How Minerals Fuel Conflicts in Africa," American Economic Review, vol. 107, no. 6, pp. 1564–1610.

Bhattacharyya, S & Mamo, N 2021, "Natural Resources and Conflict in Africa: What Do the Data Show?," Economic Development and Cultural Change, vol. 69, no. 3, pp. 903–950.

Blattman, C & Miguel, E 2010, "Civil War," Journal of Economic Literature, vol. 48, no. 1, pp. 3–57.

Boyce, DG et al. 2020, "Future ocean biomass losses may widen socioeconomic equity gaps," Nature Communications, vol. 11, no. 1, p. 2235.

Brambilla, C & Jones, R 2020, "Rethinking borders, violence, and conflict: From sovereign power to borderscapes as sites of struggles," Environment and Planning D: Society and Space, vol. 38, no. 2, pp. 287–305.

Bulte, E, Folmer, H, & Heijman, W 1995, “Open access, common property and scarcity rent in fisheries,” Environmental & Resource Economics, vol. 6, no. 4, pp. 309–320.

Burke, M, Hsiang, SM, & Miguel, E 2015, “Climate and Conflict,” Annual Review of Economics, vol. 7, no. 1, pp. 577–617.

Cabral, RB et al. 2018, “Rapid and lasting gains from solving illegal fishing,” Nature Ecology & Evolution, vol. 2, no. 4, pp. 650–658.

Caselli, F & Coleman, WJ 2013, “ON THE THEORY OF ETHNIC CONFLICT,” Journal of the European Economic Association, vol. 11, pp. 161–192.

Caselli, F, Morelli, M, & Rohner, D 2015, “The Geography of Interstate Resource Wars *,” The Quarterly Journal of Economics, vol. 130, no. 1, pp. 267–315.

Collier, P 2004, “Greed and grievance in civil war,” Oxford Economic Papers, vol. 56, no. 4, pp. 563–595.

Collier, P, Hoeffler, A, & Rohner, D 2008, “Beyond greed and grievance: feasibility and civil war,” Oxford Economic Papers, vol. 61, no. 1, pp. 1–27.

Conley, TG, Hansen, CB, & Rossi, PE 2012, “Plausibly Exogenous,” Review of Economics and Statistics, vol. 94, no. 1, pp. 260–272.

Costello, C 2012, “Introduction to the Symposium on Rights-Based Fisheries Management,” Review of Environmental Economics and Policy, vol. 6, no. 2, pp. 212–216.

Cotet, AM & Tsui, KK 2013, “Oil and Conflict: What Does the Cross Country Evidence Really Show?,” American Economic Journal: Macroeconomics, vol. 5, no. 1, pp. 49–80.

Dimitrov, RS 2002, “Water, Conflict, and Security: A Conceptual Minefield,” Society & Natural Resources, vol. 15, no. 8, pp. 677–691.

Drukker, DM, Prucha, IR, & Raciborski, R 2013, “A Command for Estimating Spatial-Autoregressive Models with Spatial-Autoregressive Disturbances and Additional Endogenous Variables,” The Stata Journal: Promoting communications on statistics and Stata, vol. 13, no. 2, pp. 287–301.

Dube, O & Naidu, S 2015, “Bases, Bullets, and Ballots: The Effect of US Military Aid on Political Conflict in Colombia,” The Journal of Politics, vol. 77, no. 1, pp. 249–267.

Dube, O & Vargas, JF 2013, “Commodity Price Shocks and Civil Conflict: Evidence from Colombia,” The Review of Economic Studies, vol. 80, no. 4, pp. 1384–1421.

FAO 2021, Indonesia Country Profile Fact Sheets, Rome, viewed 9 December 2021, <https://www.fao.org/fishery/en/facp/idn?lang=en>.

Flückiger, M & Ludwig, M 2015, “Economic shocks in the fisheries sector and maritime piracy,” Journal of Development Economics, vol. 114, pp. 107–125.

George, J, Adelaja, A, & Weatherspoon, D 2020, “Armed Conflicts and Food Insecurity: Evidence from Boko Haram’s Attacks,” American Journal of Agricultural Economics, vol. 102, no. 1, pp. 114–131.

Gleditsch, NP 1998, “Armed Conflict and The Environment: A Critique of the Literature,” Journal of Peace Research, vol. 35, no. 3, pp. 381–400.

Gleick, PH 1993, “Water and Conflict: Fresh Water Resources and International Security ,” International Security , vol. 18, no. 1, pp. 79–112.

Global Fishing Watch 2017, Indonesia VMS Joint Statement, viewed 26 May 2022, <https://globalfishingwatch.org/news-views/republic-of-indonesia-vms-joint-statement/>.

Halim, A et al. 2019, “Developing a functional definition of small-scale fisheries in support of marine capture fisheries management in Indonesia,” Marine Policy, vol. 100, pp. 238–248.

Harari, M & Ferrara, E la 2018, “Conflict, Climate, and Cells: A Disaggregated Analysis,” The Review of Economics and Statistics, vol. 100, no. 4, pp. 594–608.

Hares, M 2009, “Forest Conflict in Thailand: Northern Minorities in Focus,” Environmental Management, vol. 43, no. 3, pp. 381–395.

Haryadi, D & Wahyudin, N 2018, “FROM CHARM TO SORROW: THE DARK PORTRAIT OF TIN MINING IN BANGKA BELITUNG, INDONESIA,” PEOPLE: International Journal of Social Sciences, vol. 4, no. 1, pp. 360–382.

Heazle, M & Butcher, JG 2007, “Fisheries depletion and the state in Indonesia: Towards a regional regulatory regime,” Marine Policy, vol. 31, no. 3, pp. 276–286.

Hendiarti, N et al. 2005, “Seasonal Variation of Pelagic Fish Catch Around Java,” Oceanography, vol. 18, no. 4, pp. 112–123.

Hendrix, CS & Glaser, SM 2011, “Civil conflict and world fisheries, 1952–2004,” Journal of Peace Research, vol. 48, no. 4, pp. 481–495.

Henson, SA et al. 2010, “Detection of anthropogenic climate change in satellite records of ocean chlorophyll and productivity,” Biogeosciences, vol. 7, no. 2, pp. 621–640.

Hjort, J 1914, Fluctuations in the Great Fisheries of Northern Europe, Viewed in the Light of Biological Research, ICES.

Hodler, R 2006, “The curse of natural resources in fractionalized countries,” European Economic Review, vol. 50, no. 6, pp. 1367–1386.

Hunziker, P & Cederman, L-E 2022, Natural Resources, Inequality and Conflict, HE Ali & L-E Cederman (eds.), Springer International Publishing, Cham.

Kelejian, HH & Prucha, IR 2010, “Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances,” Journal of Econometrics, vol. 157, no. 1, pp. 53–67.

Kleibergen, F & Paap, R 2006, “Generalized reduced rank tests using the singular value decomposition,” Journal of Econometrics, vol. 133, no. 1, pp. 97–126.

Koczberski, G & Curry, GN 2004, “Divided communities and contested landscapes: Mobility, development and shifting identities in migrant destination sites in Papua New Guinea,” Asia Pacific Viewpoint, vol. 45, no. 3, pp. 357–371.

Koren, O 2018, “Food Abundance and Violent Conflict in Africa,” American Journal of Agricultural Economics, vol. 100, no. 4, pp. 981–1006.

Lam, VWY et al. 2020, “Climate change, tropical fisheries and prospects for sustainable development,” Nature Reviews Earth & Environment, vol. 1, no. 9, pp. 440–454.

Lei, Y-H & Michaels, G 2014, “Do giant oilfield discoveries fuel internal armed conflicts?,” Journal of Development Economics, vol. 110, pp. 139–157.

Levhari, D & Mirman, LJ 1980, “The Great Fish War: An Example Using a Dynamic Cournot-Nash Solution,” The Bell Journal of Economics, vol. 11, no. 1, pp. 322–334.

Lujala, P, Gleditsch, NP, & Gilmore, E 2005, “A Diamond Curse?: Civil War and a Lootable Resource,” Journal of Conflict Resolution, vol. 49, no. 4, pp. 538–562.

Mackay, M, Hardesty, BD, & Wilcox, C 2020, “The Intersection Between Illegal Fishing, Crimes at Sea, and Social Well-Being,” Frontiers in Marine Science, vol. 7.

Martin-Shields, CP & Stojetz, W 2019, “Food security and conflict: Empirical challenges and future opportunities for research and policy making on food security and conflict,” World Development, vol. 119, pp. 150–164.

Maystadt, J-F & Ecker, O 2014, “Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks?,” American Journal of Agricultural Economics, vol. 96, no. 4, pp. 1157–1182.

McGuirk, E & Burke, M 2020a, “The Economic Origins of Conflict in Africa,” Journal of Political Economy, vol. 128, no. 10, pp. 3940–3997.

McGuirk, E & Burke, M 2020b, “The Economic Origins of Conflict in Africa,” Journal of Political Economy, vol. 128, no. 10, pp. 3940–3997.

Miguel, E, Satyanath, S, & Sergenti, E 2004, “Economic Shocks and Civil Conflict: An Instrumental Variables Approach,” Journal of Political Economy, vol. 112, no. 4, pp. 725–753.

Miller, EA et al. 2019, “The historical development of complex global trafficking networks for marine wildlife,” Science Advances, vol. 5, no. 3.

MMAF 2017, Regulation of the Minister of Marine and Fisheries No. 6/Permen-Kp/2017 on the Organization of the Ministry of Marine Affairs and Fisheries.

Muawanah, U et al. 2018, “Review of national laws and regulation in Indonesia in relation to an ecosystem approach to fisheries management,” Marine Policy, vol. 91, pp. 150–160.

Muawanah, U, Pomeroy, RS, & Marlessy, C 2012, “Revisiting Fish Wars: Conflict and Collaboration over Fisheries in Indonesia,” Coastal Management, vol. 40, no. 3, pp. 279–288.

Nelson, DM & Smith, W. 1991, “Sverdrup revisited: Critical depths, maximum chlorophyll levels, and the control of Southern Ocean productivity by the irradiance-mixing regime,” Limnology and Oceanography, vol. 36, no. 8, pp. 1650–1661.

Nunn, N & Qian, N 2014, “US Food Aid and Civil Conflict,” American Economic Review, vol. 104, no. 6, pp. 1630–1666.

Nurdin, S et al. 2017, “Applicability of remote sensing oceanographic data in the detection of potential fishing grounds of Rastrelliger kanagurta in the archipelagic waters of Spermonde, Indonesia,” Fisheries Research, vol. 196, pp. 1–12.

Parker, DP & Vadheim, B 2017, “Resource Cursed or Policy Cursed? US Regulation of Conflict Minerals and Violence in the Congo,” Journal of the Association of Environmental and Resource Economists, vol. 4, no. 1, pp. 1–49.

Pauly, D, Froese, R, & Palomares, ML n.d., “Fishing Down Aquatic Food Webs: Industrial fishing over the past half-century has noticeably depleted the topmost links in aquatic food chains.”

Pauly, D & Zeller, D 2016, “Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining,” Nature Communications, vol. 7, no. 1, p. 10244.

Pichegru, L et al. 2012, “Industrial fishing, no-take zones and endangered penguins,” Biological Conservation, vol. 156, pp. 117–125.

Piroddi, C, Giovanni, B, & Villy, C 2010, “Effects of local fisheries and ocean productivity on the northeastern Ionian Sea ecosystem,” Ecological Modelling, vol. 221, no. 11, pp. 1526–1544.

Ploeg, F van der 2011, “Natural Resources: Curse or Blessing?,” Journal of Economic Literature, vol. 49, no. 2, pp. 366–420.

Pomeroy, R et al. 2007, “Fish wars: Conflict and collaboration in fisheries management in Southeast Asia,” Marine Policy, vol. 31, no. 6, pp. 645–656.

Raleigh, C et al. 2010, “Introducing ACLED: An Armed Conflict Location and Event Dataset,” Journal of Peace Research, vol. 47, no. 5, pp. 651–660.

de Ree, J & Nillesen, E 2009, “Aiding violence or peace? The impact of foreign aid on the risk of civil conflict in sub-Saharan Africa,” Journal of Development Economics, vol. 88, no. 2, pp. 301–313.

Resosudarmo, B & Kosadi, E 2019,“Illegal Fishing War: An Environmental Policy during the Jokowi Era?,” in, The Indonesian Economy in Transition, ISEAS Publishing, pp.414–440.

Rustad, SCA et al. 2008, “Foliage and fighting: Forest resources and the onset, duration, and location of civil war,” Political Geography, vol. 27, no. 7, pp. 761–782.

Sarsons, H 2015, “Rainfall and conflict: A cautionary tale,” Journal of Development Economics, vol. 115, pp. 62–72.

Satria, A & Matsuda, Y 2004, “Decentralization of fisheries management in Indonesia,” Marine Policy, vol. 28, no. 5, pp. 437–450.

Schollaert, A & van de gaer, D 2009, “Natural Resources and Internal Conflict,” Environmental and Resource Economics, vol. 44, no. 2, pp. 145–165.

Schwartz, DM, Deligiannis, T, & Homer-Dixon, T 2018, The Environment and Violent Conflict, 1st edn, Routledge.

Semedi, B & Dewanti Dimyati, R 2010, “STUDY OF SHORT MACKEREL CATH, SEA SURFACE TEMPERATURE, AND CHLOROPHYLL -A IN THE MAKASSAR STRAIT,” International Journal of Remote Sensing and Earth Sciences (IJReSES), vol. 6, no. 1.

Smith, B & Wills, S 2018, “Left in the Dark? Oil and Rural Poverty,” Journal of the Association of Environmental and Resource Economists, vol. 5, no. 4, pp. 865–904.

Spijkers, J et al. 2019, “Global patterns of fisheries conflict: Forty years of data,” Global Environmental Change, vol. 57, p. 101921.

Stock, CA et al. 2017, “Reconciling fisheries catch and ocean productivity,” Proceedings of the National Academy of Sciences, vol. 114, no. 8, pp. E1441–E1449.

Stock, J & Yogo, M 2002, Testing for Weak Instruments in Linear IV Regression, Cambridge, MA.

Thorburn, C 2001, “The House that Poison Built: Customary Marine Property Rights and the Live Food Fish Trade in the Kei Islands, Southeast Maluku,” Development and Change, vol. 32, no. 1, pp. 151–180.

Thurstan, RH, Brockington, S, & Roberts, CM 2010, “The effects of 118 years of industrial fishing on UK bottom trawl fisheries,” Nature Communications, vol. 1, no. 1, p. 15.

Vince, J, Hardesty, BD, & Wilcox, C 2021, “Progress and challenges in eliminating illegal fishing,” Fish and Fisheries, vol. 22, no. 3, pp. 518–531.

Voors, MJ et al. 2012, “Violent Conflict and Behavior: A Field Experiment in Burundi,” American Economic Review, vol. 102, no. 2, pp. 941–964.

Warming, J 1911, “Om grundrente af fiskegrunde.”

Watson, RA 2017, “A database of global marine commercial, small-scale, illegal and unreported fisheries catch 1950–2014,” Scientific Data, vol. 4, no. 1, p. 170039.

Yamazaki, S et al. 2018, “Productivity, Social Capital and Perceived Environmental Threats in Small-Island Fisheries: Insights from Indonesia,” Ecological Economics, vol. 152, pp. 62–75.

Zeitoun, M et al. 2020, “Analysis for water conflict transformation,” Water International, vol. 45, no. 4, pp. 365–384.

Table 1. ACLED types and number of conflicts in Indonesia for 2015

Type	Description	Number
Battles	A battle between two violent armed groups.	33
Remote violence	Events were engaging in conflict did not require the physical presence of the perpetrator. For example, bombings, IED attacks and missile attacks.	5
Protests	Protests are public demonstrations that participants do not engage in violence, though violence may be used against them. Often – though not always – protests are against a government institution.	380
Riots	Riots are violent form of public demonstrations. The participants engage in violent acts, including but not limited to rock throwing and property destruction.	99
Strategic development	Important activities of violent groups, but they are not violent in themselves. The inclusion of such events is limited, as its purpose is to capture pivotal events within campaigns of political violence.	17
Violence against civilians	Violence against civilians is violent groups commit violence against civilians who are not armed. Insurgents, governments, militias, external forces and rioters can all commit violence against civilians. Protesters are also civilians, and severe violence against protesters falls into this category.	65

Note: Total number of conflicts is 599.

Table 2. Summary statistics

	Obs.	Mean	S.D.	Min	Max
(a) Conflict variable with different search ranges ($conflict_{c,p}$)					
Number of conflicts (0 nmi)	757	0.703	5.537	0	133
Number of conflicts (50 nmi)	757	4.548	15.911	0	167
Number of conflicts (100 nmi)	757	11.337	26.269	0	195
Number of conflicts (150 nmi)	757	21.338	37.742	0	214
Number of conflicts (200 nmi)	757	34.894	50.229	0	264
Fatalities (100 nmi)	757	1.823	4.046	0	32
(b) Fisheries variable ($catch_c$)					
Total catch (000 tonnes)	757	9.402	11.341	0.0003	95.188
Industrial catch (000 tonnes)	757	3.566	4.001	0.0003	30.564
Non-industrial catch (000 tonnes)	757	5.836	8.169	0	67.585
IUU catch (000 tonnes)	757	3.999	5.663	0.00002	61.298
Industrial IUU catch (000 tonnes)	757	2.155	3.933	0.00002	44.369
Non-industrial IUU catch (000 tonnes)	757	1.844	2.558	0	23.208
(c) Instrumental variable (OP_c)					
Ocean productivity index	742	575.025	474.746	161.996	3216.1

Table 3. First-stage regressions

	Dependent variable		
	(1) Industrial catch	(2) Non-industrial catch	(3) Total catch
Ocean productivity	0.0012***	0.0052***	0.0064***
	(0.0003)	(0.0008)	(0.0011)
Observations	742	742	742
Province fixed effects	Yes	Yes	Yes
Kleibergen-Paap LM statistic	14.46	41.79	37.36
for under-identification (*p*-value)	(0.000)	(0.000)	(0.000)
F statistics of excluded	11.68	37.92	32.42
instruments (*p*-value)	(0.001)	(0.000)	(0.000)

Notes: The regressions are estimated by OLS with province fixed effects. The heteroskedasticity-robust standard errors are reported in the parentheses. We report Kleibergen-Paap Lagrange Multiplier (LM) statistics and F-statistics of excluded instruments to test for under-identification and weak instrument, respectively. The null hypotheses of these diagnostics tests are that the IV models are under-identified and that ocean productivity is a weak instrument. Significance at the 10%, 5% and 1% levels are indicated by *, ** and ***.

Table 4. Effects of industrial and non-industrial fisheries on the number of conflicts and fatalities within 100 nautical miles

	OLS			Pooled 2SLS			Fixed effects 2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(7)	(8)
Dependent variable	*Conflict*	*Conflict*	*Conflict*	*Conflict*	*Conflict*	*Conflict*	*Conflict*	*Conflict*	*Conflict*	*Fatality*
Industrial catch	1.962***			3.273***			7.945***			
	(0.211)			(0.272)			(1.901)			
Non-industrial catch		1.163***			1.777***			1.851***		
		(0.138)			(0.195)			(0.395)		
Total catch			0.800***			1.152***			1.501***	0.223***
			(0.089)			(0.092)			(0.292)	(0.076)
Observations	757	757	757	742	742	742	742	742	742	742
Province fixed effects	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Instrumented	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	86.58	70.95	80.22	144.44	82.95	155.72	8.07	10.89	23.03	9.62
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes**:** The regressions are estimated by OLS and 2SLS. For 2SLS estimation. The catch variable is instrumented with the chlorophyll-based ocean productivity index (Table 3). The search radius is set at 100 nmi. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Table 5. Spatial autoregressive regressions

Dependent variable	(1) *Conflict*	(2) *Conflict*	(3) *Conflict*	(4) *Fatality*
Industrial catch	1.413***			
	(0.364)			
Non-industrial catch		0.984***		
		(0.183)		
Total catch			0.694***	0.102***
			(0.132)	(0.022)
λ (spatial lag)	1.308***	1.332***	1.250***	2.429***
	(0.322)	(0.284)	(0.292)	(0.249)
ρ (spatial error)	1.854***	2.147***	2.031***	1.481***
	(0.194)	(0.288)	(0.251)	(0.078)
Province fixed effects	Yes	Yes	Yes	Yes
Instrumented	Yes	Yes	Yes	Yes
Observations	742	742	742	742

Notes**:** The regressions are estimated by spatial autoregressive 2SLS. The catch variable is instrumented with the chlorophyll-based ocean productivity index (Table 3). The search radius is set at 100 nmi. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Table 6. Catch landings and conflict by conflict types

	Type I: Protests, riots and strategic development	Type II: Violence against citizens	Type III: Battles, explosions and remote violence
Total catch	1.203*** (0.276)	0.219*** (0.065)	0.079*** (0.026)
Observations	742	742	742
Fixed effects	Yes	Yes	Yes
Instrumented	Yes	Yes	Yes
F-statistics (*p*-value)	9.72 (0.000)	7.52 (0.000)	8.57 (0.000)

Notes: The regressions are estimated by 2SLS with the province fixed effects. The catch variable is instrumented with the chlorophyll-based ocean productivity index. The dependent variable is reported in the column head. The search radius is set at 100 nmi. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Table 7. Regional differences in the impact of fisheries on the number of conflicts

		Western Indonesia		Eastern Indonesia	
		Region A	Region B	Region C	Region D
		(1)	(2)	(3)	(4)
Panel A: Regression results					
Total catch		2.037***	2.148***	1.782***	1.672***
		(0.490)	(0.492)	(0.378)	(0.331)
Observations		273	474	500	526
Fixed effects		Yes	Yes	Yes	Yes
Instrumented		Yes	Yes	Yes	Yes
F-statistics		15.09	13.76	20.15	18.04
(p-value)		(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Development region					
Region	Central city	Province			
Development Region A	Medan	Aceh, North Sumatra, West Sumatra, Riau, Riau Islands			
Development Region B	Jakarta	Jambi, South Sumatra, Bengkulu, Bangka Belitung Islands, Lampung, Banten, Special Capital Region of Jakarta, West Java, Central Java, Special Region of Yogyakarta, West Kalimantan			
Development Region C	Surabaya	East Java, Bali, Central Kalimantan, North Kalimantan, East Kalimantan, South Kalimantan			
Development Region D	Makassar	West Nusa Tenggara, East Nusa Tenggara, West Sulawesi, South Sulawesi, Southeast Sulawesi, Central Sulawesi, Gorontalo, North Sulawesi, Maluku, North Maluku, Papua, West Papua			

Notes: The regressions are estimated by 2SLS with the province fixed effects for the sub-sample of each development region. The four development regions are categorised based on the National Development Planning Agency of Indonesia. The catch variable is instrumented with the chlorophyll-based ocean productivity index. The dependent variable is the number of conflicts. The search radius is set at 100 nmi. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Table 8. Impact of IUU fishing

	(1)	(2)	(3)
Industrial IUU catch	8.336***		
	(2.638)		
Non-industrial IUU catch		6.397***	
		(1.335)	
Total IUU catch			3.620***
			(0.852)
Observations	742	742	742
Fixed effects	Yes	Yes	Yes
Instrumented	Yes	Yes	Yes
F-statistics	8.73	10.59	8.89
(*p*-value)	(0.000)	(0.000)	(0.000)

Notes**:** The regressions are estimated by 2SLS with the province fixed effects. The catch variable is instrumented with the chlorophyll-based ocean productivity index. The heteroskedasticity-robust standard errors are reported in parentheses. The dependent variable is the number of conflicts. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Figure 1. An example of the search-by-radius approach to link fisheries data (solid black cell) with conflict data (red coloured dot). The dotted line shows the boundary within a search radius of 100 nmi.

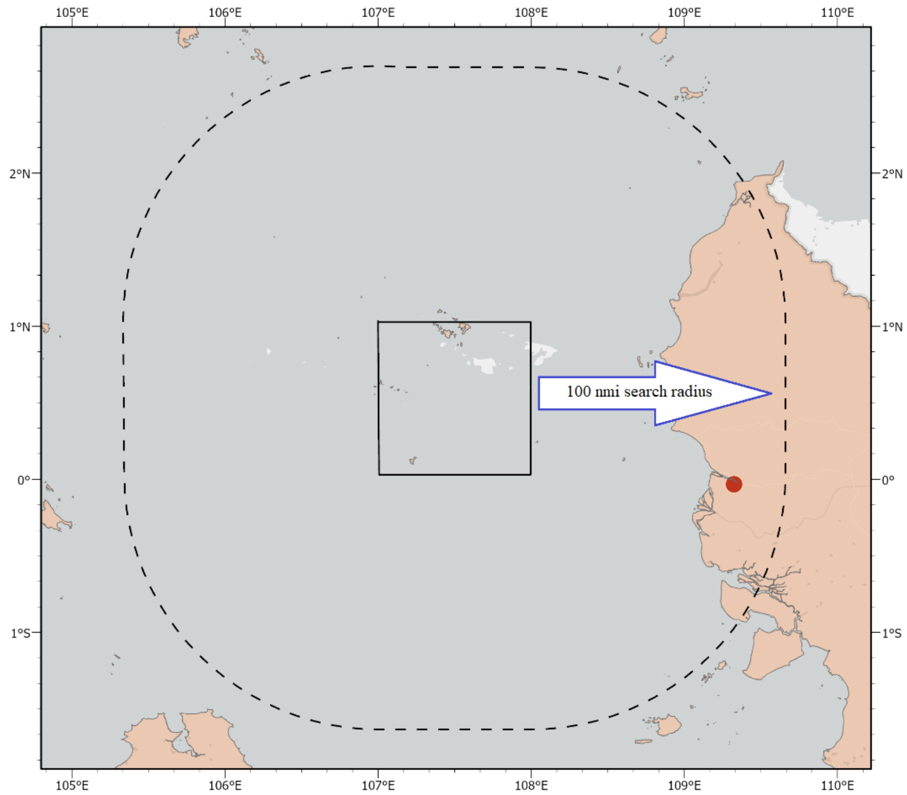


Figure 2. Geographical distribution of total catch and conflict events at a 1 × 1 degree cell in Indonesia for 2015. The geographical distributions of industrial and non-industrial catches are presented in Appendix B.

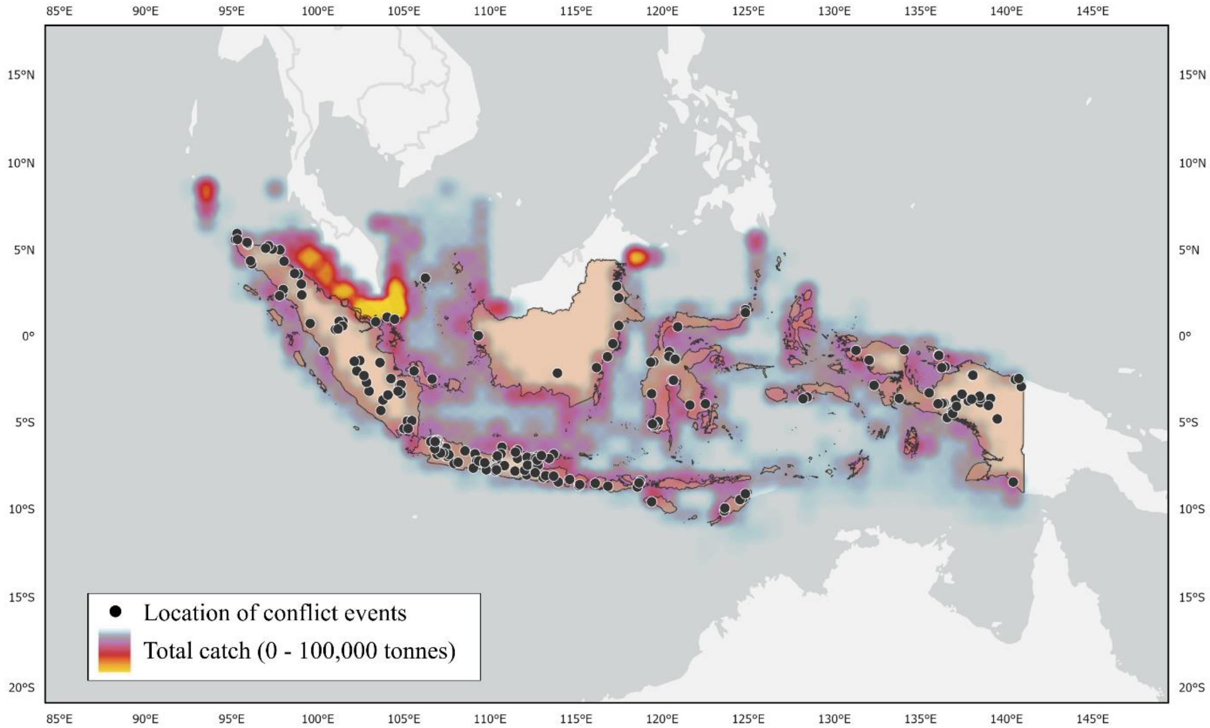
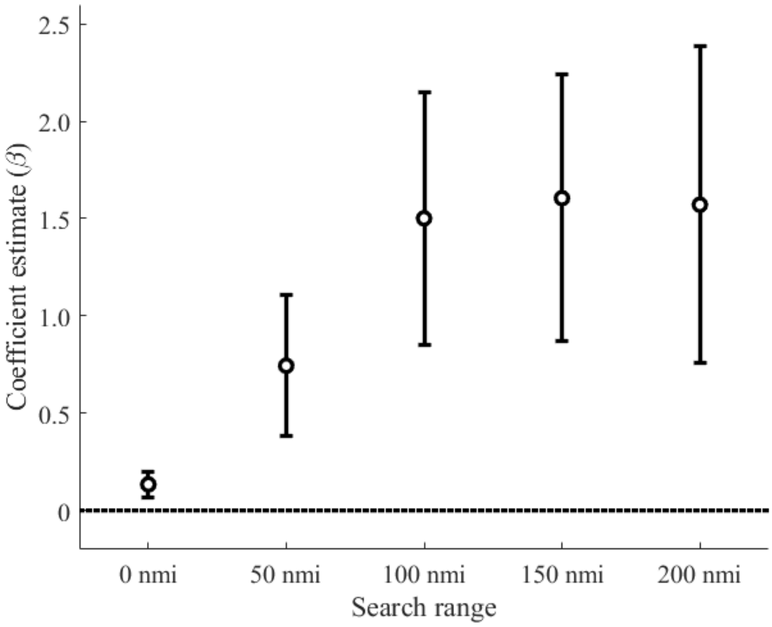
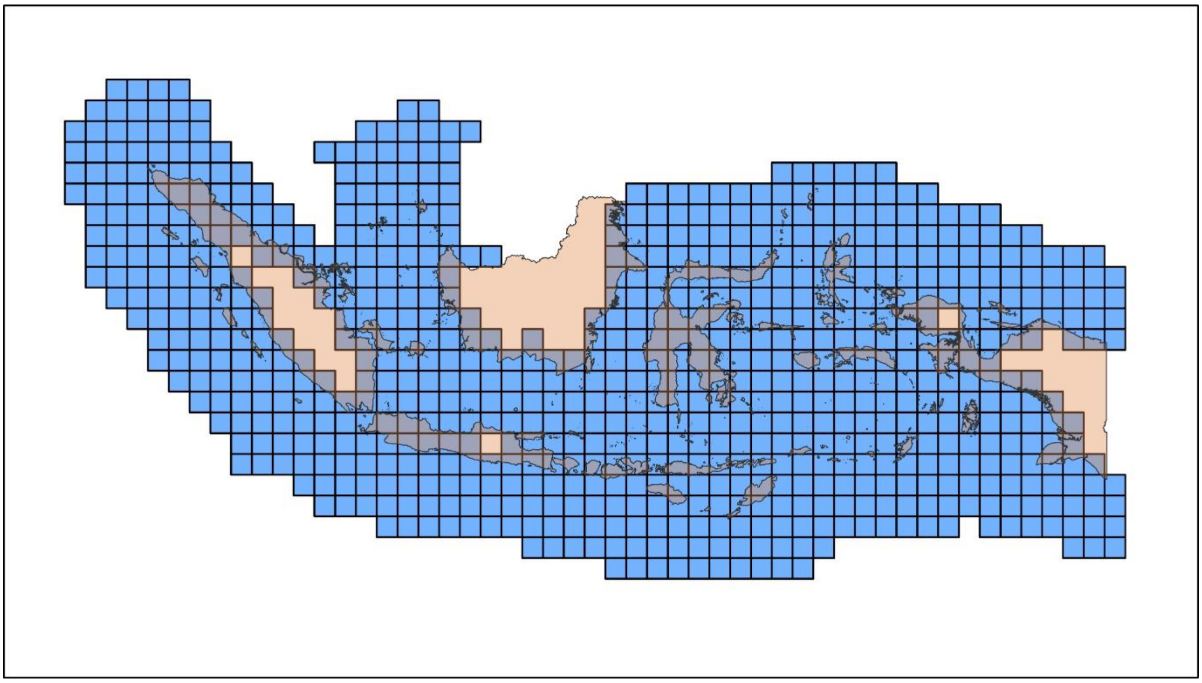


Figure 3. Estimates of the coefficient β in equation (2) with 95% confidence intervals with different search radiuses. The regressions are estimated by 2SLS with province fixed effects where the dependent variable is the number of conflicts. The explanatory variable is the total catch in tonnes.



Appendix A

Figure A1. Cell sample



Appendix B

Figure B1. Geographical distribution of non-industrial catch and conflict events at a 1 × 1 degree cell in Indonesia for 2015

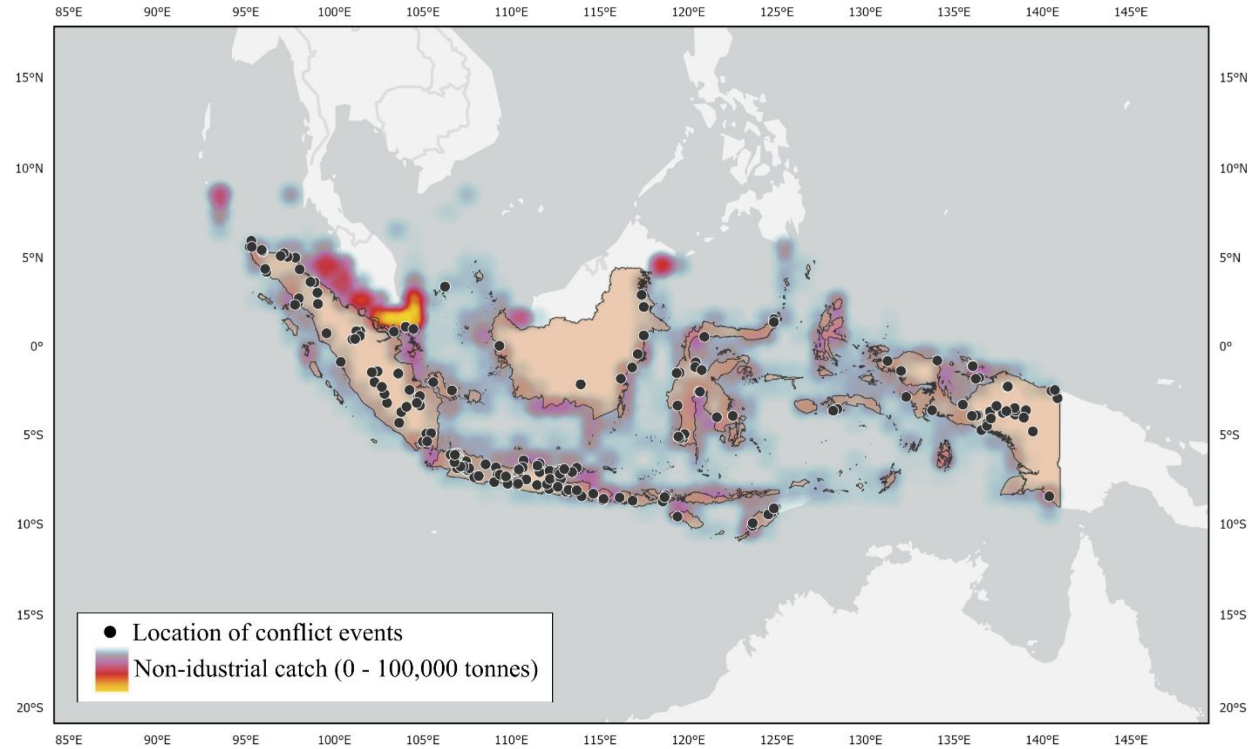
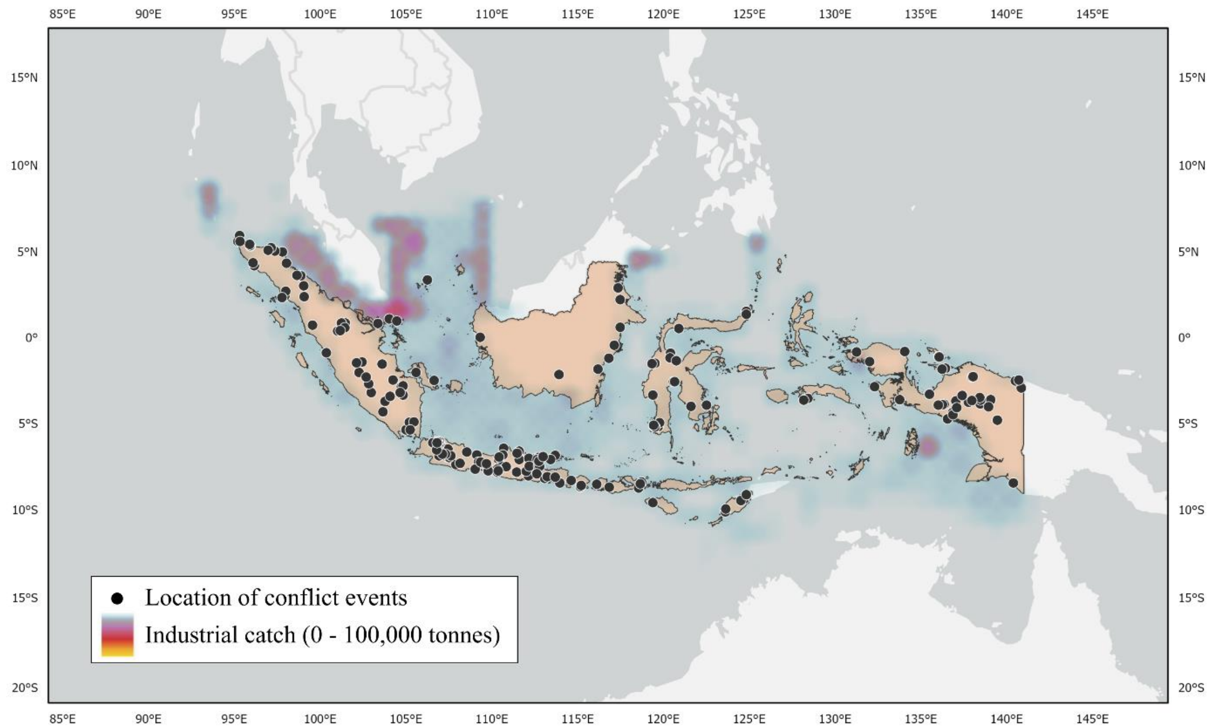


Figure B2. Geographical distribution of industrial catch and conflict events at a 1 × 1 degree cell in Indonesia for 2015



Appendix C

Table C1. Correlation of variables

	Conflict	Conflict (50nmi)	Conflict (100nmi)	Conflict (150nmi)	Conflict (200nmi)	Fatalities (100nmi)	Catch	IND-catch	NID-catch	IUU	IND-IUU	NID-IUU	OP
Conflict	1.0000												
Conflict (50nmi)	0.4054	1.0000											
Conflict (100nmi)	0.2995	0.7503	1.0000										
Conflict (150nmi)	0.2488	0.5620	0.8241	1.0000									
Conflict (200nmi)	0.2372	0.4484	0.6553	0.8671	1.0000								
Fatalities (100nmi)	0.2189	0.2698	0.3735	0.3300	0.2738	1.0000							
Catch (‘000)	0.1845	0.1943	0.2329	0.2010	0.1779	0.1840	1.0000						
IND-catch	0.0957	0.1183	0.1587	0.1471	0.1303	0.0958	0.8590	1.0000					
NID-catch	0.2094	0.2119	0.2457	0.2072	0.1833	0.2086	0.9680	0.7030	1.0000				
IUU	0.1857	0.1812	0.2233	0.1952	0.2013	0.1504	0.8216	0.7090	0.7937	1.0000			
IND-IUU	0.1358	0.1259	0.1676	0.1520	0.1767	0.0790	0.5966	0.6011	0.5340	0.9206	1.0000		
NID-IUU	0.2026	0.2077	0.2370	0.1988	0.1742	0.2117	0.9026	0.6461	0.9371	0.7991	0.5009	1.0000	
OP	0.1543	0.1595	0.2163	0.1993	0.1917	0.1405	0.3999	0.3170	0.4001	0.3582	0.2765	0.3683	1.0000

Appendix D

Table D1. Spatial autoregressive regressions: catch landings and conflict by conflict types

	Type I: Protests, riots and strategic development	Type II: Violence against citizens	Type III: Battles, explosions and remote violence
Total catch	0.562***	0.092***	0.032**
	(0.114)	(0.016)	(0.010)
λ (spatial lag)	1.559***	0.925**	3.625***
	(0.343)	(0.279)	(0.363)
ρ (spatial error)	1.939***	2.297***	1.209***
	(0.225)	(0.301)	(0.042)
Fixed effects	Yes	Yes	Yes
Instrumented	Yes	Yes	Yes
Observations	742	742	742

Notes: The regressions are estimated by spatial autoregressive 2SLS. The catch variable is instrumented with the chlorophyll-based ocean productivity index (Table 3). The search radius is set at 100 nmi. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Table D2. Spatial autoregressive regressions: regional differences in the impact of fisheries on the number of conflicts

	Western Indonesia		Eastern Indonesia	
	Region A	Region B	Region C	Region D
	(1)	(2)	(3)	(4)
Total catch	1.420***	0.500***	0.465***	0.306**
	(0.344)	(0.159)	(0.144)	(0.118)
λ (spatial lag)	1.586***	7.793***	2.623***	2.521***
	(0.442)	(0.618)	(0.552)	(0.448)
ρ (spatial error)	2.903***	4.224**	1.800***	2.014***
	(0.563)	(1.667)	(0.280)	(0.300)
Fixed effects	Yes	Yes	Yes	Yes
Instrumented	Yes	Yes	Yes	Yes
Observations	273	474	500	526

Notes**:** The regressions are estimated by spatial autoregressive 2SLS. The catch variable is instrumented with the chlorophyll-based ocean productivity index (Table 3). The search radius is set at 100 nmi. The definition of development regions can be found in Panel B of Table 7. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.

Table D3. Spatial autoregressive regressions: IUU catch

	(1)	(2)	(3)
Industrial IUU catch	0.878*		
	(0.489)		
Non-industrial IUU catch		4.157***	
		(0.677)	
Total IUU catch			1.204***
			(0.348)
λ (spatial lag)	1.569***	1.202***	1.410***
	(0.299)	(0.297)	(0.301)
ρ (spatial error)	1.975***	2.318***	2.056***
	(0.222)	(0.349)	(0.255)
Province fixed effects	Yes	Yes	Yes
Instrumented	Yes	Yes	Yes
Observations	742	742	742

Notes**:** The regressions are estimated by spatial autoregressive 2SLS. The catch variable is instrumented with the chlorophyll-based ocean productivity index (Table 3). The search radius is set at 100 nmi. The heteroskedasticity-robust standard errors are reported in parentheses. Significance at 10%, 5% and 1% levels are indicated by *, **and ***.