

# CAN IRRIGATION INFRASTRUCTURE MITIGATE THE EFFECT OF RAINFALL SHOCKS ON CONFLICT? EVIDENCE FROM INDONESIA

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This article provides evidence that rainfall shocks affect conflict through their effect on agricultural production and that irrigation infrastructure can mitigate this effect. Using data from Indonesia, we document that low rainfall during the agricultural season decreases agricultural production and increases civil conflict. We then show that the rainfall-conflict link is attenuated by the presence of irrigation infrastructure in a district. This attenuating effect is specific to irrigation infrastructure; we find no evidence for a similar effect of hydropower dams. Our results are stronger for small-scale conflicts over natural resources and popular justice than for conflicts over ethnic identity or ethnic separatism. These results are robust to controlling for interactions between rainfall and a wide range of socio-economic and geographic district characteristics. We conclude that adaptive policies that mitigate the negative effects of weather shocks on agriculture may also prevent conflict.

*Key words:* Civil conflict, economic conflict, ethnic conflict, irrigation, rainfall, weather shocks.

*JEL codes:* D74, H56, O13, Q15, Q54.

Climate change is projected to be a major source of civil conflict, threatening national security, global stability, and human welfare. While a growing body of evidence links rising temperatures and changing rainfall patterns to increased civil conflict and geopolitical instability (e.g., Miguel, Satyanath, & Sergenti, 2004; Miguel & Satyanath, 2011; Klomp and Bulte 2013; Fetzer, 2014a, b; Hsiang and Burke 2014; Maystadt and Ecker 2014; Wischnath and Buhaug 2014; Burke, Hsiang, and Miguel 2015; Axbard 2016), it is less clear what mechanisms underlie this relationship. Understanding the mechanisms that connect weather shocks to conflict is crucial can help identify

mitigating interventions that may break this link.<sup>1</sup>

Agriculture is critical for livelihoods in developing economies, and rainfall may affect conflict through shocks to agricultural production. Investments in irrigation infrastructure have been proposed as an adaptive response to sustain agricultural yields under higher temperatures and irregular rainfall (Duflo and Pande 2007; Asian Development Bank 2016a). If agricultural production links rainfall and conflict, irrigation infrastructure could have the added benefit of protecting societal stability against weather shocks.

We test whether agricultural production is part of the causal link between rainfall and conflict, and whether this link can be mitigated by irrigation. To do this, we use data from Indonesia, a country with a long history of conflict where agriculture is an important source of income. We begin by constructing data on irrigation capacity for all districts in the country, using a novel dataset on water resources from

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<sup>1</sup> We follow Dell et al. (2014) by using the distribution of rainfall outcomes through time and space to identify causal effects.

the Ministry of Public Works and Housing (MPWH) of Indonesia. We then document that lower rainfall leads to a decrease in agricultural production and that this effect is significantly weaker in districts with higher irrigation capacity.

Next, we use data from the Indonesian National Conflict Monitoring System (NVMS) to study the impact of rainfall and irrigation on conflict.<sup>2</sup> We find that lower rainfall leads to an increase in the number of conflict incidents and that this effect is mitigated by irrigation infrastructure: a one standard deviation decrease in rainfall increases conflict by 0.29 incidents per district year, and a one standard deviation increase in irrigation capacity reduces this effect by approximately 36%.

It is of course not certain that the lower effect of rainfall on conflict and agricultural production in districts with higher irrigation capacity is due to a causal effect. While some of the analyses presented below control for a wide range of observed and unobserved district characteristics, it is possible that irrigation capacity is correlated with remaining unobserved characteristics that attenuate the rainfall–agricultural–production and rainfall–conflict relationships. While we use causal language to improve the readability of the article, we urge readers to keep this caveat in mind.

We test several potential threats to our identification strategy. First, districts with different levels of irrigation capacity may also differ in characteristics that affect the relationship between rainfall and conflict, so that our estimates might not reflect a causal effect of irrigation. For instance, it is possible that irrigation facilities are built predominantly in districts that have lower conflict potential, perhaps because they are more developed or more ethnically homogeneous, and this might explain why rainfall affects conflict less strongly in these areas.

To address this concern, we control for interactions between rainfall and a wide range of demographic, socio-economic, and geographic district characteristics that might affect conflict. Demographic and socio-economic controls include percentage of urban households, population density, religious and language fractionalization, average household education and percentage of illiterate households, percentage

of total and skilled agricultural labor force, and housing conditions. Geographic controls include measures of terrain ruggedness and elevation. Including these controls does not substantially change our estimates, suggesting that the weaker rainfall–conflict link in districts with irrigation is not explained by differences in observable characteristics.

In addition, we conduct a placebo test that compares the effect of irrigation dams and hydropower dams. The placement of hydropower dams is likely to be affected by similar unobserved politico-economic characteristics as that of irrigation dams. If our estimates suffer from omitted variable bias from these characteristics, we would expect both types of dams to be associated with a weaker rainfall–conflict link. However, we find that the presence of irrigation dams strongly mitigates the rainfall–conflict link, while the presence of hydropower dams does not. This result increases our confidence that the effect of irrigation infrastructure on conflict comes from its effect on agricultural productivity and not from unobserved factors that affect the location of large infrastructure projects. In an additional placebo test, we find that the effects of rainfall and irrigation on conflict are specific to rainfall in the main agricultural growing season, which constitutes further evidence for the role of agriculture.

Further, one might be concerned that irrigation largely affects conflict by affecting property rights over agricultural land and that in times of economic stress, those property rights help mitigate conflict (Di Falco et al. 2020). To explore this possible mechanism, we interact rainfall with the number of households with land tenure and find that irrigation capacity continues to mitigate the negative effect of rainfall. On the other hand, we do find that the effects of irrigation capacity are largest in those regions with weaker tenure, suggesting that the interaction between tenure security and irrigation may be playing a role.

We then use detailed information on the nature of each conflict incident to explore whether certain types of conflict are more strongly affected by an agricultural mechanism. We find that the rainfall–conflict link, as well as the mitigating effect of irrigation, are substantially stronger for conflict incidents about natural resources, popular justice, and law enforcement, than for conflicts over ethnic identity or ethnic separatism.

Our article contributes to a nascent literature that explores whether weather shocks

<sup>2</sup> These data were previously used by several other studies of Indonesian conflict, e.g. Tovar-Garcia and Nugroho (2015), Bazzi and Gudgeon (2016), Bazzi et al. (2019).

increase conflict through their effect on agricultural production. Harari and La Ferrara (2018) find that weather shocks during the agricultural growing season affect conflict in sub-Saharan Africa, while shocks outside of the growing season do not. Crost et al. (2018) explore the role of variation in seasonal rainfall in the Philippines. They document that higher dry season rainfall leads to an increase in agricultural production, while higher wet-season rainfall lowers agricultural production. Consistent with an agriculture-based link between rainfall and conflict, they find that an increase in wet-season rainfall is associated with more conflict, while an increase in dry-season rainfall is associated with less conflict. Further evidence for an agricultural mechanism comes from Bellemare (2015), who finds that higher food prices are associated with increases in social unrest. In contrast to the studies by Harari and La Ferrara (2018), Crost et al. (2018) and Bellemare (2015), Koren (2018) finds that conflict in Africa is driven by higher agricultural yields rather than lower ones. This result is consistent with a variant on the agricultural mechanism in which armed groups fight over excess food production.

Evidence against an agricultural mechanism comes from Sarsons (2015), who finds that agricultural production in India is less sensitive to rainfall in districts located downstream versus upstream from irrigation dams but that irrigation does not change how rainfall shocks affect conflict. A possible explanation for this result is that Sarsons studies Hindu–Muslim riots, which primarily occur in urban settings and may, therefore, be less directly affected by agricultural conditions. The richness of our data allows us to add to this evidence by studying a variety of conflict types that occur across rural and urban settings. Like Sarsons (2015), we find no evidence that the presence of irrigation affects the link between rainfall and ethnic conflicts.

Our article makes four contributions to the literature. First, we provide additional evidence that weather shocks affect civil conflict through their effect on agricultural production. A small number of previous studies have found evidence for an agricultural mechanism (e.g. Bellemare 2015; Crost et al. 2018; Harari and La Ferrara 2018), and we add to this literature by providing evidence from a new context with a novel empirical approach. Our results strengthen the case that interventions that safeguard agricultural production against weather shocks may have the added benefit of reducing civil conflict.

Second, we provide the first evidence that irrigation infrastructure can mitigate the link between rainfall shocks and civil conflict. Third, we show that weather-induced shocks to agricultural production affect different types of conflicts differently. In particular, we find that negative agricultural shocks exacerbate conflict over natural resources, popular justice, and law enforcement, but have little or no effect on conflicts over ethnic identity. Finally, our results have important implications for cost–benefit analyses of irrigation projects in conflict-affected countries. Large infrastructure projects, such as irrigation dams, have been criticized for their substantial social costs in the form of environmental damages and displacement of people (McCully 1996; Shiva 2012). Although our results do not take away from these costs, they suggest that irrigation infrastructure may have previously unrecognized benefits in protecting societal stability against weather shocks.

The rest of the article is organized as follows. Section 2 introduces background information about agriculture, irrigation, and conflict in Indonesia. Section 3 describes the data used in the analysis. Section 4 presents the model, the main results, and robustness tests to our preferred specification. Section 5 concludes.

## Background

### *Agriculture and Irrigation in Indonesia*

Agriculture is an important sector of the Indonesian economy, directly employing almost a third (31.2%) of the labor force and representing approximately 14% of the GDP in 2016 (World Bank 2018). Rice is the main staple crop, representing half of the daily caloric intake of Indonesian households and using one-quarter of the planted land area (FAOSTAT 2019). Rice is primarily grown in lowland areas, which are concentrated on the islands of Java, Sumatra, Sulawesi, and Kalimantan. In 2015, these islands grew more than 90% of the national rice production, with half of the national production on Java (Badan Pusat Statistik 2017).

There are three rice crop seasons in Indonesia. The main growing season runs from October/November through April when average rainfall exceeds 1,600 mm (Aldrian and Dwi Susanto 2003; Funk et al. 2014; USDA-FAS 2016). Planting typically takes place in

October through January with harvest in March through April across the main productive areas of the different islands of Indonesia. The other two production seasons occur from May to August, but these seasons have both substantially lower production and smaller planted area (BPS-Statistics Indonesia 2015b, 2016). Almost three-quarters (73%) of the total rice production of Indonesia is grown during this season, whereas the other two seasons account for less than 20% and 7% of total production, respectively (USDA-FAS 2016).

Approximately 40% of the total rice area in Indonesia is irrigated, with the remaining 60% being rainfed (BPS-Statistics Indonesia 2015a). The vast majority of irrigation is supplied by 215 dams,<sup>3</sup> which have a total irrigation capacity of 811,000 hectares (ICOLD 2019). Groundwater irrigation plays a comparatively minor role, providing only 3,678 hectares of irrigation capacity (MPWH 2018). Irrigation systems were first developed in Java during the nineteenth century and expanded to the rest of the country after World War II, when intensification of rice production became a priority for public development. Since then, the Indonesian government has been the primary builder of irrigation dams, funded by subsidies and loans from the Japanese government and international organizations (Hirsch and Warren 1998). As a result, the majority of dams in Indonesia are state-owned (World Bank 2017). In 2017, 184 of the 215 dams were owned and operated by the Ministry of Public Works and Housing with the remaining ones owned and operated by private or state-owned firms.

While dams are regulated under the Ministry of Public Works and Housing, its policy related to water management is coordinated with provincial and district governments as well as other regional organizations (Mayangsari and Adji 2015; Asian Development Bank 2016b). The Indonesian Constitution (1945) and the Water Resources Development Act (1974) established that water use rights are assigned by the national government. In 2004, the New Water Law stated that the central government must respect individual basic needs and traditional irrigation rights in its water allocation decisions. In the case

of water rights for agriculture, the federal Ministry of Agriculture works in coordination with province/district/local agencies to allocate water supply (Asian Development Bank 2016a).

The placement of dams is largely determined by the geophysical requirements of building and operating them (Swenty 1989; Stephens 2010). Two main features that determine the siting of a potential dam are terrain elevation and slope. Higher elevation increases the dam's capacity to provide irrigation merely by gravity (Swenty 1989; Cech 2009). A moderate slope will allow irrigation without generating soil erosion, while locations with high slope are more favorable for hydropower dams (Duflo and Pande 2007; Lipscomb, Mobarak, and Barham 2013).

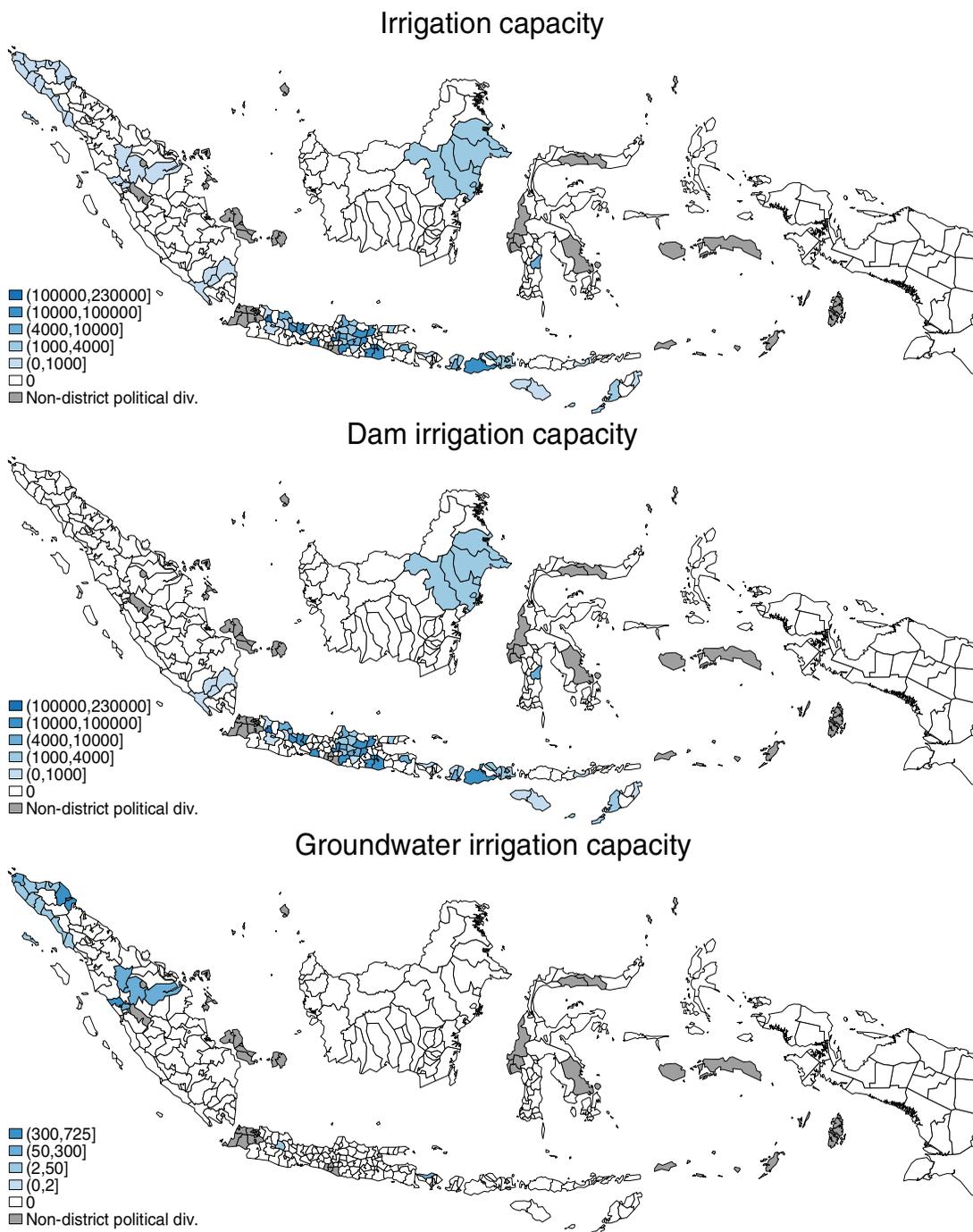
Figure 1 shows the geographical distribution of irrigation capacity in Indonesia. The majority of irrigation capacity is located in Java, with substantial geographic variation across the island. Central and East Java have districts with more than 10,000 hectares of irrigation, whereas irrigation is less abundant in Western Java. Groundwater irrigation, which plays a smaller role overall, is mainly concentrated in Sumatra, with a substantial within-island variation.

### *Civil Conflict in Indonesia*

Indonesia is the site of a number of long-running internal conflicts with a broad range of origins. Our analysis uses data from the National Violence Monitoring System (NVMS), which contains information on conflict incidents that occurred between 1998 and 2014. The NVMS dataset distinguishes between different types of conflict incidents based on their underlying cause: resources, popular justice, law enforcement, government programs, group identity, and separatism.

Resource incidents include conflicts over land and other natural resources, as well as environmental problems such as incidents resulting from pollution and environmental damage. The majority of resource conflicts in Indonesia is related to land disputes (The Asia Foundation 2017). Property rights over land tend to be insecure, as they are governed by contradictory laws and regulations, and recorded in low-quality cadastral maps. The resulting uncertainty over land rights leads to disputes that often turn violent. Furthermore, the government makes frequent use of its eminent domain to give land concessions to private companies to develop plantations, often against the will of local

<sup>3</sup> The International Commission on Large Dams (ICOLD) defines a large dam as the ones with "a height of 15 m or greater from lowest foundation to crest or a dam between 5 m and 15 m impounding more than 3 million cubic meters". Extracted from: [https://www.icold-cigb.org/GB/dams/definition\\_of\\_a\\_large\\_dam.asp](https://www.icold-cigb.org/GB/dams/definition_of_a_large_dam.asp)



**Figure 1. Irrigation by source in Indonesian districts, 1997 (hectares)***Note: Data come from the Ministry of Public Work and Housing (MPWH). Total irrigation is the sum of dam and groundwater irrigation capacity in hectares in 1997. The unit of analysis of this study is the district. Non-district political divisions, such as municipalities, cities, and small islands are excluded from our analysis.*

residents who believe they have customary rights to the land (The Asia Foundation 2017). This dynamic has led to some highly publicized

violent disputes between plantation owners and local populations, such as the Mesuji and Jambi conflicts (Jones 2013; Beckert, Dittrich,

and Adiwibowo 2014). Other land disputes arise between local native populations and migrants, some of which are resettled through the government's transmigration program (Dagur 2014).

Popular justice incidents are defined as retaliation over disputes that occur as a response to an act that is perceived as wrong. These incidents mostly consist of vigilante killings carried out in response to real or perceived crimes. The number of associated killings has increased substantially over the past decades, perhaps as a result of decreased confidence in the country's justice system. They often occur in poor communities in response to theft and other petty crimes (Emont 2017). Based on the NVMS data, the World Bank estimates that between 2005 and 2014, there were more than 33,000 vigilante attacks, resulting in over 1,600 deaths (Barron, Jaffrey, and Varshney 2016; The Asia Foundation 2017).

Conflict over law enforcement consists of violent incidents triggered by government security forces. Many of these incidents take the form of popular retaliation to police brutality that crime often triggers itself. In many poor communities, trust in law enforcement is low and police are seen as unaccountable and overly violent. The tensions between police and civilians sometimes escalate into violent confrontations. For example, in Buol, Central Sulawesi, police shot and killed seven men who protested the death of a teenager in police custody. In response, the local population destroyed police facilities (International Crisis Group 2012). In another incident in Bantaeng, South Sulawesi, villagers attacked a police station after police killed a man during a raid on gamblers during a wedding party. The International Crisis Group estimates that, since 2010, there have been at least forty attacks against police stations and personnel as a result of these tensions (*op cit.*).

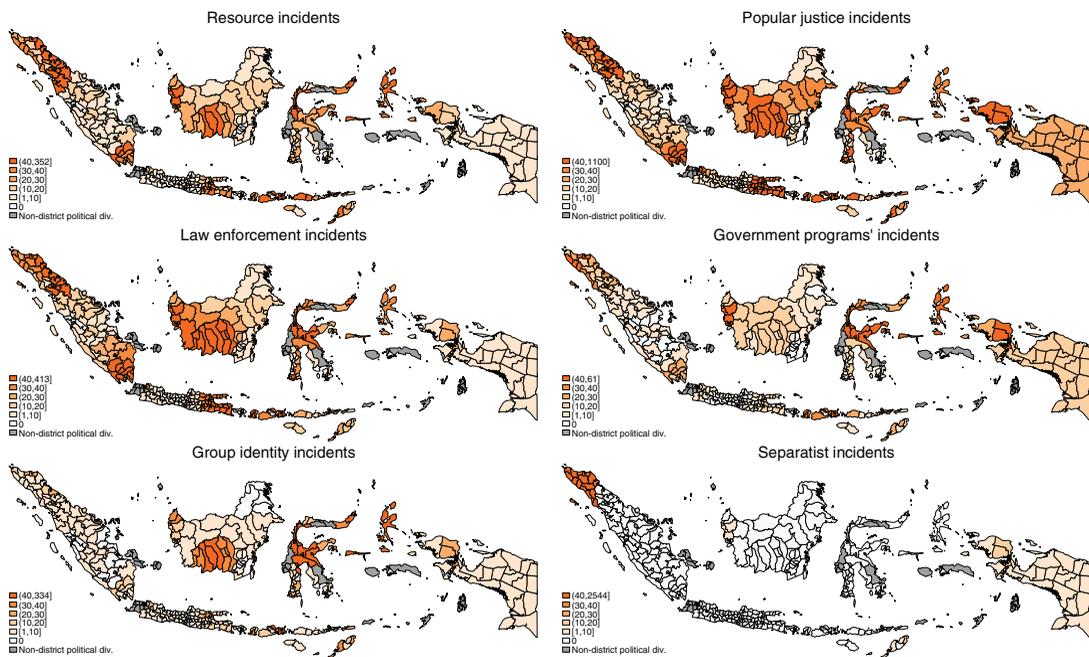
Conflict over government programs is defined as violent disputes over the implementation of public programs related to funding priorities and unmet needs. For instance, a substantial conflict resulted from the implementation of the cash transfer program Bantuan Langsung Tunai. Eligibility for this program was determined by a proxy means test, but many reports suggested some poor households, particularly in urban areas, were erroneously excluded, while wealthier households were included. The perception of mistargeting and political capture of the program led to social tensions that erupted in violence (Cameron and Shah 2014).

Group-identity conflict consists of incidents provoked by people who identify as part of a religion, tribe, or ethnic group against people who identify as part of another group. This category includes ethnic riots against Indonesians of Chinese descent, as well as religious riots between Muslim and Christian populations (Bonner 2006; Heijmans and Aditya 2019). Separatist incidents are attempts to separate from the central government of Indonesia. Examples of these conflicts are the Aceh insurgency between 1976 and 2005, and the ongoing conflict with the Free Papua Movement in West Papua. Figure 2 contains six maps with the spatial distribution of conflict by type of incidents in Indonesia. Most of the incident types are fairly widespread across different geographic regions of the country, with the exception of separatist conflict, which is concentrated in Aceh and West Papua.

The wide range of root causes of conflicts in Indonesia raises the possibility that different conflict types are differently affected by shocks to agricultural productivity. In principle, each type of conflict described above could be affected by agricultural productivity shocks, though the precise mechanisms and effect sizes are likely to differ.

In particular, we might expect agricultural shocks to affect natural resource conflicts, because they directly affect the productivity of the land and other resources that are being fought over. A temporary decrease in agricultural productivity makes land grabbing activities more lucrative, because it decreases the short-run return of agricultural labor but has a small effect on the long-run return to controlling the land.

Agricultural shocks might also affect popular justice incidents, because these often occur as retaliation over property crimes, such as petty theft. Shocks that decrease the incomes of individuals who are close to subsistence level will most likely increase property crime and may, therefore, increase retaliation (Gould, Mustard, and Weinberg 2002; Machin and Meghir 2004). Economic shocks may also increase the willingness to use violence in retaliation to imagined crimes, as suggested by previous evidence that rainfall shocks affect witch killings in Tanzania (Miguel 2005). Similar logic would cause us to expect that agricultural shocks affect law enforcement conflict. To the extent that shocks increase property crime, they are also likely to increase police activity, some of which will be seen as excessive or brutal, and provoke



**Figure 2. Spatial distribution of conflict in Indonesian districts, 1998–2014***Note: Data come from the Indonesia Conflict Monitoring System (NVMS), 1998–2014. The geographic unit of analysis of our study is the district. Non-district units, such as municipalities, cities, and small islands, are excluded.*

retaliation. For conflict over government programs, a link to agricultural shocks is perhaps less direct but nevertheless plausible. For instance, shocks may increase people’s reliance on government transfers and may, therefore, increase conflict over their allocation, or, as above, shocks may decrease the cost of violent retaliation to perceived unfairness.

Finally, agricultural shocks may cause a deterioration in wider economic conditions, which might lead to tensions between ethnic groups that erupt in violence, either in organized separatist conflicts or unorganized identity group riots.

**Data**

We conduct our analysis at the district-year level. We use the province and district boundaries that existed in 1997, just before the start of the period of study, before Indonesia began a decentralization process that split several provinces and districts. Two provinces, Jakarta and Yogyakarta, are not included in the analysis because they cover small, populous areas where agriculture is not relevant. Annual district-level

data on rice area and production come from the Ministry of Agriculture of Indonesia.<sup>4</sup>

Data on weather come from two different sources. Rainfall is extracted from the Weather Hazards Group InfraRed Precipitation with Station data (CHIRPS).<sup>5</sup> CHIRPS is a global dataset that contains high-resolution estimates of rainfall for 0.05-by-0.05-degree cells. This data source combines data from satellites and weather stations to help remove systematic bias in rainfall measures, a key problem from interpolating data from meteorological stations. Data on temperature are extracted from the Department of Geography of the University of Delaware (Matsuura and Willmott 2015). The temperature dataset consists of monthly gridded data interpolated to a 0.5° grid. Both datasets are overlaid onto district boundaries to obtain district-level monthly rainfall and temperature for Indonesia. We use these monthly data to obtain the sum of rainfall and the average temperature from November to April, which represents the weather conditions during the main rice growing season. This definition of growing season comes from USDA-FAS (2016), which

<sup>4</sup> Available at <https://aplikasi2.pertanian.go.id/bdsp/en>  
<sup>5</sup> Available at: <http://chg.geog.ucsb.edu/data/chirps/>

is coincident with the definition of the wet season in the literature (Aldrian and Dwi Susanto 2003; Asian Development Bank 2016a).<sup>6</sup>

Data on irrigation capacity are extracted from the Ministry of Public Works and Housing (MPWH) of Indonesia.<sup>7</sup> Each dam and groundwater facility is described by location, irrigation capacity in hectares, and the first year of operation. For our main measure of irrigation capacity, we calculate each district's irrigation capacity from all facilities listed in the MPWH data and express it as a share of the total district area. We also use irrigation capacity as a fraction of rice acreage and rice and corn acreage, and find our results effectively unchanged, available in the online supplementary appendix, table A1. To avoid reverse causality from rainfall and conflict to irrigation capacity, we use the total irrigation capacity built before 1998, the first year of our period of observation.

To validate our measure of irrigation capacity, we test whether it is correlated with the actual irrigated area, reported by the Historical Irrigation Dataset (HID) of Siebert et al. (2015), which contains surface irrigation estimates from satellite images for the years 1995, 2000, and 2005. Results reported in the online supplementary appendix, table A2, show that irrigation capacity in 1997 is strongly positively correlated with average surface irrigation at the district level. We also use data from the World Register of Dams (WRD), maintained by the International Commission on Large Dams (ICOLD), to obtain the electric power generation capacity from hydro-power dams, which we use in a placebo test.

Data on control variables come from the 1990 Indonesian National Census extracted from IPUMS-International (Minnesota Population Center 2018). The census includes socio-economic characteristics at the household level. We aggregate this information to the district level to build baseline variables that we use to test whether our results are driven by differences in socio-economic characteristics between districts with high and low irrigation capacity. Specifically, we use baseline district-level data on the percentage of urban households, population

density, household education and literacy, total and skilled agricultural labor force, religious and language fractionalization, and housing conditions. For the latter, we include the percentage of households with wood or grass roof, no floor, and cane or wood walls, respectively. To capture religious and ethnic diversity, we generate a Herfindahl-Hirshman Index (HHI), taking the sum of the square of the share of each religion/language in each district.

Data on terrain ruggedness come from the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA) (FAO/IIASA 2010). We overlay these data onto district boundaries to obtain the percentage of district area that has slope of  $0^{\circ}$ – $0.5^{\circ}$ ,  $0.5^{\circ}$ – $2^{\circ}$ ,  $2^{\circ}$ – $5^{\circ}$ ,  $5^{\circ}$ – $8^{\circ}$  and  $8^{\circ}$ – $16^{\circ}$ , respectively.

As noted above, we use data on conflict from the Indonesian NVMS dataset, maintained by the World Bank and the Government of Indonesia.<sup>8</sup> The dataset contains details on more than 235,000 conflict incidents that occurred between 1998 and 2014 derived from newspaper sources and checked with conflict reports, alternative media, and non-media sources (Barron, Jaffrey, and Varshney 2014). We follow Bazzi et al. (2019) and Tovar-Garcia and Nugroho (2015), who use the number of conflict incidents in a given district-year as the primary outcome of interest. We use the information contained in the NVMS on conflict categories to conduct a heterogeneity analysis that separately estimates effects for each of these six types of conflict.

### *Descriptive Statistics*

Table 1 provides descriptive statistics for rainfall, agricultural production, irrigation, and conflict-related incidents. In our sample, the main rice production season receives more rainfall than the rest of the year, getting an average of 1,680 mm of rainfall compared to 815 mm of rainfall for the rest of the year, a difference of approximately 50%.

On average, districts experienced 9.1 conflict-related incidents per year. The most common types of incidents are related to popular justice and separatist conflicts, which are responsible for approximately 38% and 24% of all incidents, respectively. Other common types of incidents are related to law enforcement (19% of incidents) and natural resources

<sup>6</sup> All regions of Indonesia receive substantially more rainfall during the rainy season with the possible exception of Papua and Maluku islands which contribute to only 2% of national rice production.

<sup>7</sup> The data comes from the General Directorate for Water Resources (Direktorat Jenderal Sumber Daya Air) of Indonesia (sda.pu.go.id).

<sup>8</sup> Available at: <http://www.worldbank.org/en/news/video/2015/08/17/indonesias-national-violence-monitoring-system>

**Table 1. Descriptive Statistics**

	Mean	Standard deviation
Annual rainfall (100 mm)	24.96	6.73
Growing-season rainfall (100 mm)	16.80	4.05
Off-season rainfall (100 mm)	8.15	4.95
Rice area (hectares)	54,715.89	43,033.87
Rice production (tons)	257,460.50	217,538.80
Irrigation capacity in 1997 (% of total district ha)	2.539%	17.413%
Total incidents	9.10	29.69
Resource incidents	1.11	3.00
Popular justice incidents	3.45	10.52
Law enforcement incidents	1.77	4.95
Government policy incidents	0.55	1.38
Separatist incidents	2.19	24.62
Group identity incidents	0.58	3.22
Urban households (% of total in the district)	0.15	0.13
Religion HHI (0 to 10,000)	8433.9	2132.34
Language HHI (0 to 10,000)	5555.4	1805.45
Agricultural labor force (% of total in the district)	0.26	0.082
Skilled agriculture (% of agricultural in the district)	0.25	0.083
Average education level (by HH in the district)	1.29	0.11
Illiterate households (% of total in the district)	0.19	0.08
Cane/wood wall (% of total in the district)	0.66	0.24
No floor (% of total in the district)	0.29	0.27
Wood/grass roof (% of total in the district)	0.20	0.25

Note: The unit of analysis is the district year. Rainfall is extracted from CHIRPS; irrigation capacity and groundwater are from MPWH; and conflict incidents is coming from NVMS dataset. Education level between 1 and 2 means that on average household are between primary level incomplete (1) and primary school complete (2).

(12%). The least common types of conflict are triggered by government policy and group identity (both approximately 6% of all incidents).

## Results

Our empirical strategy uses a fixed effects regression to estimate the interaction between a district's irrigation capacity (measured at baseline in 1997) and growing-season rainfall in the current year. In particular, we estimate the following regression:

$$(1) \quad Y_{ipt} = \alpha_0 + \beta_1 R_{it} + \beta_2 R_{it} \times Irr_i + X_{ipt} \beta + v_i + \eta_p t + \theta_t + \varepsilon_{ipt}$$

where  $Y_{ipt}$  denotes either the number of conflict incidents or the hyperbolic sine transformation<sup>9</sup> of total rice production in district  $i$  in

province  $p$  and year  $t$ ;<sup>10</sup>  $R_{it}$  is the total amount of rainfall in the main growing season, which starts in November of year  $t - 1$  and ends in April of year  $t$ ;  $Irr_i$  is the irrigation capacity per district area; and  $X_{ipt}$  is a vector of control variables that includes the growing-season average temperature. To address concerns about reverse causality from rainfall and conflict to irrigation, our preferred specification defines  $Irr_i$  as district  $i$ 's irrigation capacity in 1997, the year before the start of the period of observation. To control for unobservable variables, equation (1) includes district fixed effects ( $v_i$ ), province-specific time trends, ( $\eta_p t$ ) and year fixed effects ( $\theta_t$ ). Standard errors are clustered at the district level to allow for serial correlation of rainfall and conflict within districts.<sup>11</sup>

<sup>10</sup> We use the hyperbolic sine transformation of rice production which approximates the logarithmic function but is defined for zero-valued observations (Bellemare and Wichman 2019). There are only 34 zero-valued observations, out of a total 3,417 observations. Results of regressions that use the logarithm of rice production are presented in the online supplementary appendix, table A9 and are similar to those based on the hyperbolic sine transformation.

<sup>11</sup> To account for possible spatial correlation, we also estimate models with spatial autocorrelation robust standard errors (Conley 2010; Hsiang 2010; Fetzer 2014a), which allow errors to

<sup>9</sup> Total rice production includes low-land and up-land rice cultivation.

**Table 2. The Effect of Growing-Season Rainfall and Irrigation Capacity on Rice Production**

	<i>ih</i> (rice production)		
	OLS	OLS	OLS
	(1)	(2)	(3)
<i>GS rainfall</i>	0.0295*** (0.0102)	0.0316*** (0.0105)	0.0295*** (0.0102)
<i>GS Rainfall</i> × <i>Baseline Irrigation capacity</i>	-0.00298** (0.00126)	-0.00419** (0.00169)	
<i>GS Rainfall</i> × <i>Current Irrigation Capacity</i>			-0.00273** (0.00123)
Observations	3,417	3,417	3,417
R-squared	0.561	0.639	0.561
Number of districts	201	201	201

Note: Regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects; regression in column 2 contains district-specific linear time trends. Growing-season rainfall is the sum of rainfall from November in  $t - 1$  to April in year  $t$ . In columns 1 and 2, irrigation is defined as the district's irrigation capacity in 1997, the year before the start of the period of observation. In column 3, irrigation is defined as the district's irrigation capacity in the current year  $t$ . Both irrigation measures are expressed as a fraction of the total district area. Standard errors, clustered at the district level, are in parenthesis, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

All explanatory variables are converted to z-scores to allow for interpretation of the results in terms of standard deviations. We use within-district z-scores to measure rainfall shocks as deviations from the district's mean seasonal rainfall, but results are robust to using sample z-scores. The coefficient  $\beta_1$  reflects the additional effect of a standard deviation of rainfall on rice production or conflict in districts with zero irrigation capacity. We expect this estimate to be positive for agricultural production and negative for conflict, assuming that abundant rainfall decreases conflict at least partly through its beneficial effect on agricultural production.

The coefficient  $\beta_2$  reflects how the effect of rainfall differs between districts with varying levels of irrigation capacity. If irrigation capacity mitigates the effect of weather shocks, we would expect agricultural production to be less dependent on rainfall in districts with high irrigation capacity, leading to a negative value of  $\beta_2$  in regressions that use rice production as the outcome. When using conflict as the outcome, we would expect a positive value of  $\beta_2$ , because the conflict-reducing effect of rainfall is greater in districts with lower irrigation capacity.

be correlated across nearby districts within a certain spatial bandwidth. As an additional test for spatial correlation, we show that our results are robust to clustering standard errors at the province level (the average province contains on average 15 contiguous districts). Results of these regressions are presented in the online supplementary appendix, tables A6 and A7.

### *Rainfall and Irrigation Effects on Rice Production and Conflict*

Because one might be concerned that current irrigation is determined by local time-varying characteristics that may also affect conflict, we begin by estimating a reduced form regression using baseline irrigation capacity as the explanatory variable.<sup>12</sup>

Tables 2 and 3 provide estimates of the relationship among growing-season rainfall, irrigation capacity, and agricultural production as well as conflict incidents.<sup>13</sup> The first column shows the effect of baseline-year irrigation capacity interacted with rainfall on rice production and conflict including province-specific time trends. The second column presents the same specification with district-specific time trends. The third column presents results using baseline irrigation capacity.<sup>14</sup>

Table 2 shows estimates for the relationship among rainfall, irrigation, and agricultural production. To interpret the coefficients, note that the effect of rainfall on agricultural production

<sup>12</sup> In the online supplementary appendix, table A10 we present the results of an instrumental variables regression that instruments current irrigation capacity with baseline irrigation capacity in 1997.

<sup>13</sup> In our preferred specifications, irrigation capacity is expressed as a fraction of total district area. In the online supplementary appendix, table A1, we also show results for irrigation capacity per capita, and as a fraction of rice area and the sum of rice and corn area. Results are qualitatively similar to those in table 3.

<sup>14</sup> In table A10 of the online supplementary appendix, we present IV estimates of the current year irrigation instrumented by baseline irrigation on rice production and conflict jointly with the results of the first stage regressions. Our main results from tables 2 and 3 are robust to the latter specification.

**Table 3. The Effect of Growing-Season Rainfall and Irrigation Capacity on Conflict**

	Number of conflict incidents			
	OLS (1)	OLS (2)	OLS (3)	OLS (4)
<i>lns(rice production)</i>				-1.781** (0.871)
<i>GS rainfall</i>	-0.297 (0.291)	-0.170 (0.319)	-0.297 (0.291)	
<i>GS Rainfall × Baseline Irrigation capacity</i>	0.108** (0.0443)	0.101** (0.0446)		
<i>GS Rainfall × Current Irrigation Capacity</i>			0.0993** (0.0494)	
Observations	3,417	3,417	3,417	3,417
R-squared	0.208	0.386	0.208	0.203
Number of districts	201	201	201	201

Note: Regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects. The regression in column 2 contains district-specific linear time trends. Growing-season rainfall is the sum of rainfall from November in  $t - 1$  to April in year  $t$ . In columns 1 and 2, irrigation is defined as the district's irrigation capacity in 1997, the year before the start of the period of observation. In column 3, irrigation is defined as the district's irrigation capacity in the current year  $t$ . Both irrigation measures are expressed as a fraction of the total district area. In column 4, we regress the logarithm of rice production on conflict. Standard errors, clustered at the district level, are in parenthesis, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

in a given district is given by  $\frac{\partial Y_{ipt}}{\partial R_{it}} = \beta_1 + \beta_2 Irr_i$ , where  $\beta_1$  is the coefficient associated with rainfall and  $\beta_2$  is the coefficient associated with the interaction between rainfall and irrigation. Thus,  $\beta_1$  reflects the effect of rainfall on agricultural production in districts whose irrigation capacity is at the sample mean (note that the variable  $Irr_i$  is expressed in terms of simple standard deviations, so that a value of  $Irr_i = 0$  reflects an irrigation capacity at the simple mean). Using the results from Column 1, in districts with irrigation capacity at the sample mean, a one-standard-deviation increase in rainfall is associated with an increase in rice production of 3%, broadly consistent with previous estimates of the effect of rainfall on rice production in the Philippines (Crost et al. 2018). The negative coefficient associated with the interaction between irrigation capacity and rainfall suggests that irrigation mitigates the effect of rainfall on agricultural production. A one-standard-deviation increase in irrigation capacity reduces the effect of rainfall on rice production by approximately 0.3 percentage points or 10%. Note, however, that the rainfall-production relationship remains positive even in districts with very high levels of irrigation. For instance, in districts with an irrigation capacity that is two standard deviations above the mean, a one-standard-deviation increase in rainfall is associated with an increase in rice production of 2.3%. Column 2 shows that our results are robust to including district-specific linear time-trends in additions

to the province-specific trends included in column 1. Moreover, Column 3 shows that our results are robust to using current irrigation capacity (Column 3).

The results in table 2 are consistent with the hypothesis that irrigation protects yields against low rainfall shocks, so that irrigated districts have higher agricultural productivity in years with low rainfall. A limitation of our approach is that we can only estimate the coefficient associated with the interaction between irrigation capacity and rainfall but not the direct effect of an increase in irrigation capacity on agricultural production in years with zero rainfall.<sup>15</sup> We can, therefore, not rule out that the lower slope of the rainfall-production relationship in districts with high irrigation capacity is because irrigation leads to lower agricultural productivity at high rainfall levels, though this appears unlikely in practice.

Table 3 shows estimates for the relationship between rainfall, irrigation, and conflict. The results from column 1 show that, in districts with mean irrigation capacity, a one-standard-deviation decrease in growing-season rainfall is associated with approximately 0.3 more conflict-related incidents. As with the effect of rainfall on agricultural production, the effect on conflict

<sup>15</sup> This effect would be captured by the coefficient  $\beta_3$  in the regression  $Y_{ipt} = \alpha_0 + \beta_1 R_{it} + \beta_2 R_{it} \times Irr_i + \beta_3 R_{it} \times Irr_i + \epsilon_{ipt}$ . However, we cannot estimate this regression since we do not observe plausibly exogenous changes in irrigation capacity and the time-invariant irrigation levels in our regression are collinear with district fixed effects.

is mitigated by the presence of irrigation infrastructure. Specifically, a one-standard-deviation increase in irrigation capacity reduces the effect of rainfall on conflict incidents by approximately 0.11 incidents, decreasing the effect of rainfall on conflict by approximately 36%. Similar to the results in table 2, the effect of rainfall on conflict remains negative even for districts with high irrigation capacity. In districts with an irrigation capacity two standard deviations above the mean, a one-standard-deviation increase in rainfall is associated with a decrease in conflict of 0.08. As in table 2, our results are robust to including district-specific linear time trends (Column 2) and to using current irrigation capacity directly (Column 3).

Column 4 shows a simple descriptive regression of conflict on agricultural production. The results show that, controlling for district and year fixed effects, as well as province-specific time-trends, increases in agricultural production are associated with decreases in conflict. This is consistent with an agricultural mechanism in which higher agricultural production increases social stability, perhaps by supporting rural wages or by stabilizing food prices. A fundamental concern with this regression is that it may suffer from reverse causality, as increases in conflict from non-agricultural causes may depress agricultural production, which is why we focus on our results from the direct regression of rainfall on conflict.

The results in table 3 are consistent with the hypothesis that irrigation protects social stability against low rainfall shocks, so that irrigated districts experience less conflict in years with low rainfall. Taken together, the results in tables 2 and 3 are consistent with the hypothesis that irrigation increases agricultural productivity and decreases conflict in years with low rainfall, in keeping with an agricultural mechanism.<sup>16</sup>

### *Heterogeneous Effects by Type of Conflict*

Next, we test for heterogeneous effects across different types of conflict. If rainfall and irrigation affect conflict through an agricultural

mechanism, we would expect their effect to be largest for types of conflict directly affected by shortfalls in agricultural production. Results in table 4 suggest that the evidence for a conflict-increasing effect of rainfall and a mitigating effect of irrigation is strongest for conflicts over natural resources and popular justice. There is also some evidence that low rainfall increases conflict over law enforcement and government programs, but here we do not find a statistically significant effect of irrigation infrastructure. The evidence for an agricultural mechanism is weakest for separatist and group identity conflicts, which are higher in years with abundant rainfall and in places with more irrigation infrastructure.

One limitation of the estimates in table 4 is that they have large standard errors, because some conflict types are rare in our sample. To address this limitation, we conducted a factor analysis that groups types of conflict that tend to co-occur in the same district in the same year. The results of this analysis are presented in the online supplementary appendix, tables A3 and A4. They show that the effect of rainfall and irrigation is large and statistically significant for the first factor, which largely consists of conflicts over natural resources, popular justice and law enforcement, and small and statistically insignificant for all other factors.

These disaggregated estimates help reconcile our results with those of the previous study by Sarsons (2015). That study focused on religious riots in India, which are most similar to the separatist and group identity conflicts in our data. Like Sarsons (2015), we find no evidence that rainfall affects these types of conflict through an agricultural mechanism.

### *Nonlinear Effects*

We next explore possible non-linearities in the effect of rainfall and the mitigating effect of irrigation, following previous studies on non-linear effects of weather shocks on human capital and farmer behavior (Shah and Steinberg 2017; Garg, Jagnani, and Taraz 2018; Jagnani et al. 2018). For instance, one might expect that the effect of irrigation on agricultural production is particularly strong for years with very low rainfall when water constraints become binding in non-irrigated districts. If this is the case, we would also expect the conflict-mitigating effect of irrigation to be strongest at the low end of the rainfall distribution. To explore this possibility, we estimate the following equation:

<sup>16</sup> As noted above, our analysis is limited by the fact that we can only estimate the interaction between rainfall and irrigation but not the direct effect of irrigation. We can, therefore, not rule out that irrigation decreases agricultural production and increases conflict in years with high rainfall. We believe this to be unlikely in practice, though in principle it would still be consistent with an agricultural mechanism in which conflict is higher in years with low agricultural production.

**Table 4. Impact of Growing-Season Rainfall by Subcategories of Conflict**

	<i>Resources</i>	<i>Popular justice</i>	<i>Law enforcement</i>	<i>Government programs</i>	<i>Separatism</i>	<i>Group identity</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>GS rainfall</i>	−0.108*** (0.0397)	−0.317*** (0.105)	−0.292*** (0.0703)	−0.0580** (0.0258)	0.342 (0.228)	0.0776 (0.0479)
<i>GS Rainfall × Irrigation Capacity</i>	0.0176*** (0.00507)	0.0677* (0.0349)	0.0139 (0.00885)	−0.00434 (0.00350)	−0.0138 (0.0292)	0.0228** (0.00929)
Observations	3,417	3,417	3,417	3,417	3,417	3,417
R-squared	0.217	0.232	0.227	0.269	0.223	0.091
Districts	201	201	201	201	201	201

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects. Irrigation is defined as irrigation capacity in 1997, the year before the start of the period of observation. Growing-season rainfall is the sum of rainfall from November in  $t - 1$  to April in year  $t$ . The outcomes are the number of conflict incidents by type of conflict. Standard errors, clustered at the district level, are in parentheses, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

$$\begin{aligned}
 Y_{ipt} = & \alpha_0 + \beta_1 \text{negrain}_{it} + \beta_2 \text{posrain}_{it} + \beta_3 \text{negrain}_{it} \\
 & \times \text{Irr}_i + \beta_4 \text{posrain}_{it} \times \text{Irr}_i + X_{ipt} \beta + v_i \\
 & + \eta_p t + \theta_t + \varepsilon_{ipt}
 \end{aligned}
 \tag{2}$$

where  $\text{negrain}_{it}$  denotes rainfall levels below the sample mean (i.e. rainfall levels in district  $i$  in year  $t$ , with positive values replaced by zero), and  $\text{posrain}_{it}$  denotes rainfall levels above the sample mean (defined analogously). The coefficients  $\beta_1$  and  $\beta_2$  capture the slope of the relationship between rainfall and the outcome  $Y_{it}$  below and above the mean of rainfall, respectively. The coefficients  $\beta_3$  and  $\beta_4$  capture how these slopes differ in districts with higher versus lower irrigation.

Column 1 in table 5 shows results for the effect of rainfall on agricultural production. The point estimates of coefficients  $\beta_3$  and  $\beta_4$  suggest that the mitigating effect of irrigation is larger at low levels of rainfall, consistent with higher productivity of irrigation water during times of drought. However, the difference between the point estimates is relatively small and not statistically significant, so we cannot rule out that the two coefficients are equal. Column 2 shows similar results for the effect of rainfall on conflict. The point estimate of  $\beta_4$  is larger than that of  $\beta_3$ , suggesting a larger mitigating effect of irrigation at low rainfall levels, but the difference is not statistically significant.

We also conducted an analysis in which we split the rainfall variable into three terciles and included dummy variables for the terciles interacted with baseline irrigation capacity. The results of this analysis are presented in the online supplementary appendix, table A5.

The point estimates suggest that the conflict-reducing effect of irrigation is highest for rainfall in the lowest tercile and lowest for rainfall in the highest tercile, consistent with the results in table 5. However, the large standard errors associated with these estimates do not allow us to reject the hypothesis that the effects of irrigation are the same for rainfall in all three terciles, making the results of this analysis inconclusive.

**Table 5. Positive Versus Negative Growing-Season Rainfall Shocks on Rice Production and Conflict**

	<i>ih</i> (rice production)	<i>Conflict</i>
	(1)	(2)
<i>Positive shocks</i>	0.00781* (0.00457)	−0.823*** (0.250)
<i>Negative shocks</i>	0.0118** (0.00583)	−0.718*** (0.239)
<i>Positive Shocks × Irrigation Capacity</i>	−0.00171*** (0.000582)	0.0973** (0.0406)
<i>Negative Shocks × Irrigation Capacity</i>	−0.00279** (0.00115)	0.139** (0.0580)
Observations	3,417	3,417
R-squared	0.728	0.250
Number of districts	201	201

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and island-by-year fixed effects. Growing-season rainfall is the sum of rainfall from November in  $t - 1$  to April in year  $t$ . Negative shocks are defined as rainfall below the mean while positive shocks are defined as rainfall above the mean. Standard errors, clustered at the district level, are in parentheses, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 6. Robustness Tests: Heterogeneous Effects of Rainfall by Observable Characteristics and Rainfall by Geographic Location**

	Number of conflict incidents			
	(1)	(2)	(3)	(4)
<i>GS rainfall</i>	-0.297 (0.291)	-0.320 (0.300)	-0.311 (0.471)	0.885 (1.146)
<i>GS Rainfall × Irrigation Capacity</i>	0.108** (0.0443)	0.167*** (0.0540)	0.167*** (0.0558)	0.124** (0.0570)
Rainfall-by-baseline controls		x	x	X
Rainfall-by-outer/inner island			x	
Rainfall-by-island observations				X
observations	3,417	3,417	3,417	3,417
R-squared	0.208	0.210	0.210	0.211
Number of districts	201	201	201	201

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects, and the interaction between rainfall and baseline characteristics: percentage of urban households, religion and language fractionalization, average educational level by household, percentage of illiterate households total and skilled agricultural labor force, and housing conditions (roof, wall, and floor); the percentage of district area that has slope of 0°–0.5°, 0.5°–2°, 2°–5°, 5°–8°, and 8°–16°. Growing-season rainfall goes from November in  $t-1$  to April in year  $t$ . Irrigation is defined as the district's irrigation capacity in 1997, the year before the start of the period of observation. Standard errors, clustered at the district level, are in parentheses, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Overall the results discussed in this section are consistent with a larger mitigating effect of irrigation at times of drought but do not provide decisive evidence for it.

### Robustness Tests

A primary concern for our analysis is that irrigation capacity may be correlated with unobserved district characteristics that might mitigate the effect of rainfall shocks. For instance, it is

possible that irrigation facilities are built predominantly in districts that have lower conflict potential, perhaps because they are more developed or more ethnically homogeneous, and this might explain why rainfall affects conflict less strongly in these areas.

Table 6 presents several robustness tests to address this concern. First, we control for interactions between rainfall and a wide range of demographic, socio-economic, and geographic district characteristics that might affect conflict and/or the construction of irrigation dams.

**Table 7. Robustness Tests: Heterogeneous Effects of Rainfall by Observable Characteristics and Geographic Location**

	Number of conflict incidents			
	(1)	(2)	(3)	(4)
<i>GS rainfall</i>	-0.297 (0.291)	-1.450*** (0.504)	-1.170** (0.514)	-1.908*** (0.604)
<i>GS Rainfall × Irrigation Capacity</i>	0.108** (0.0443)	0.133 (0.102)	0.172** (0.0815)	0.175* (0.103)
Baseline controls-by-year FE		x	x	x
Outer/inner island FE			x	
Island-by-year FE				x
Observations	3,417	3,417	3,417	3,417
R-squared	0.208	0.306	0.348	0.371
Number of districts	201	201	201	201

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects, and the interaction between rainfall and baseline characteristics: percentage of urban households, religion and language fractionalization, average educational level by household, percentage of illiterate households total and skilled agricultural labor force, and housing conditions (roof, wall, and floor); the percentage of district area that has slope of 0°–0.5°, 0.5°–2°, 2°–5°, 5°–8°, and 8°–16°. Growing-season rainfall goes from November in  $t-1$  to April in year  $t$ . Irrigation is defined as the district's irrigation capacity in 1997, the year before the start of the period of observation. Standard errors, clustered at the district level, are in parentheses, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 8. Impact of Growing-Season Rainfall on Conflict in Rural versus Urban Areas**

	<i>Number of conflict incidents</i>			
	Agricultural (1)	Non-agricultural (2)	Agricultural (3)	Non-agricultural (4)
<i>GS rainfall</i>	-0.153 (0.260)	-0.563 (0.576)	-0.164 (0.257)	-0.565 (0.576)
<i>GS Rainfall × Irrigation capacity</i>			0.158*** (0.0207)	-0.0478 (0.325)
Observations	1,717	1,700	1,717	1,700
R-squared	0.209	0.267	0.209	0.267
Number of districts	101	100	101	100

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects. Growing-season rainfall is the sum of rainfall from November in  $t - 1$  to April in year  $t$ . We split the sample into agricultural and non-agricultural districts using the median area per capita planted to rice, corn, and cassava. In columns 1 and 2, we estimate the regression without the irrigation interaction. Columns 3 and 4 shows results corresponding to the same split but including the interaction between rainfall shocks and irrigation. Standard errors, clustered at the district level, are in parentheses, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Demographic and socio-economic controls include the percentage of urban households, population density, religious and language fractionalization, average household education and percentage of illiterate households, percentage of total and skilled agricultural labor force, and housing conditions. Geographic controls include measures of elevation and terrain ruggedness, specifically the percentage of district area whose slope falls into each of the following bins:  $0^\circ-0.5^\circ$ ,  $0.5^\circ-2^\circ$ ,  $2^\circ-5^\circ$ ,  $5^\circ-8^\circ$  and  $8^\circ-16^\circ$ . Column 2 of table 6 shows that our estimates are virtually unchanged by controlling for the interaction between rainfall and these characteristics, which suggests that differences in observable characteristics do not explain the weaker rainfall-conflict link in districts with irrigation.

A related concern is that differences in unobserved geographic characteristics might drive the results. Indonesia consists of several islands, which differ in political, socio-economic, and climate characteristics. This potential regional heterogeneity is particularly relevant because irrigation infrastructure is geographically concentrated in certain regions of the country. It is, therefore, possible that irrigation capacity is spuriously correlated with spatially correlated unobserved shocks that affect conflict. We address this concern by controlling for a set of interactions between rainfall and geographic fixed effects. Column 3 of table 6 shows results that control for interactions between rainfall and island-group fixed effects, where island-group is an indicator that divides districts based on whether they are on the inner islands (Java and Sumatra) or the outer islands (Bali, Kalimantan, Maluku,

Papua, Sulawesi, and Nusa Tenggara). This specification controls for spatially correlated unobservables that may affect the effect of rainfall on conflict in different geographic

**Table 9. Robustness Tests: Placebo Tests for Off-Season Rainfall and Hydropower Dams**

	<i>Number of conflict incidents</i>	
	(1)	(2)
<i>GS rainfall</i>	-0.480* (0.283)	-0.322 (0.301)
<i>GS Rainfall × Irrigation Capacity</i>	0.152** (0.0607)	0.173*** (0.0612)
<i>GS Rainfall × Hydropower Capacity</i>		-0.0185 (0.106)
<i>OS Rainfall</i>	3.102* (1.799)	
<i>OS Rainfall × Irrigation Capacity</i>	-0.0630 (0.154)	
Observations	3,417	3,417
R-squared	0.212	0.210
Number of districts	201	201

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects, and the interaction between rainfall and baseline characteristics: percentage of urban households, religion and language fractionalization, average educational level by household, percentage of illiterate households total and skilled agricultural labor force, and housing conditions (roof, wall, and floor); the percentage of district area that has slope of  $0^\circ-0.5^\circ$ ,  $0.5^\circ-2^\circ$ ,  $2^\circ-5^\circ$ ,  $5^\circ-8^\circ$  and  $8^\circ-16^\circ$ . Growing-season rainfall goes from November in  $t - 1$  to April in year  $t$ . Irrigation is defined as the district's irrigation capacity in 1997, the year before the start of the period of observation. Off-season rainfall goes from May to October in year  $t$ . Hydropower capacity is total megawatt capacity by district in 1997. In column 1, we include off-season rainfall and their interactions. In column 2, we test for the effect of hydropower capacity. Standard errors, clustered at the district level, are in parenthesis. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 10. Robustness Tests: Placebo Test for the Effect of Property Rights on Conflict**

	<i>Number of conflict incidents</i>		
	Full sample (1)	Ownership below the mean (2)	Ownership above the mean (3)
<i>GS rainfall</i>	-0.308 (0.299)	-2.218*** (0.823)	-0.458 (0.426)
<i>GS Rainfall × Irrigation Capacity</i>	0.178*** (0.0572)	0.342*** (0.0891)	-0.211 (0.180)
<i>GS Rainfall × Ownership</i>	0.552** (0.244)		
Observations	3,417	1,275	2,142
R-squared	0.210	0.224	0.306
Number of districts	201	75	126

Note: All regressions include temperature and temperature interacted with irrigation capacity, as well as district fixed effects, province-specific linear time trends, and year fixed effects, and the interaction between rainfall and baseline characteristics: percentage of urban households, religion and language fractionalization, average educational level by household, total and skilled agricultural labor force, and poverty; the percentage of district area that has slope of  $0^\circ$ – $0.5^\circ$ ,  $0.5^\circ$ – $2^\circ$ ,  $2^\circ$ – $5^\circ$ ,  $5^\circ$ – $8^\circ$  and  $8^\circ$ – $16^\circ$ . Growing-season rainfall goes from November in  $t-1$  to April in year  $t$ ; irrigation is defined as the district's irrigation capacity in 1997, the year before the start of the period of observation. Column 1 presents the results of the estimation of the full sample including the interaction between rainfall and the percentage of households that own their place of residence. In column 2, we use the districts where the percentage of ownership is below the sample mean. In column 3, we include the districts where the percentage of ownership is above the sample mean. Standard errors, clustered at the district level, are in parentheses, where \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

regions. Column 4 increases the spatial resolution of this approach by including interactions between rainfall and island fixed effects. Our results are robust to this specification, suggesting that they are not driven by spatially correlated unobserved determinants of the rainfall–conflict relationship.<sup>17</sup>

It is further possible that our estimates are biased by unobserved shocks to conflict in districts that have different baseline characteristics or that are located on different islands. This is of particular concern because irrigation is geographically concentrated on a small number of islands. Columns 2 to 4 of table 7 show results controlling for interactions between year fixed effects and both baseline characteristics and geographic fixed effects, using the same aggregation as in table 6. The results show that a one-standard-deviation increase in irrigation reduces conflict by 0.17, which is higher than the estimates from our main regressions in table 3.

Finally, table 8 shows a placebo test that separately estimates equation 1 for agricultural and non-agricultural districts. If our results are due to an agricultural mechanism, we would expect them to be strongest in districts where agriculture is an important sector of the economy and weak or nonexistent in districts with little

agriculture. We would, however, expect to see a less pronounced difference if our results are due to unobserved differences between irrigated and non-irrigated districts. For instance, if the lower effect of rainfall on conflict in irrigated districts is driven by their higher level of overall development, we would also expect to see a mitigating “effect” of irrigation there. Table 8 shows that this is not the case, and that our results are concentrated in agricultural districts. Columns 1 and 3 show results for districts where per capita agricultural area of the three major staple crops (rice, corn, and cassava) is above the median. For this subsample, we find strong evidence that conflict is attenuated by the presence of irrigation. For districts with agricultural area below the median, we find no significant evidence for an attenuating effect of irrigation (columns 2 and 4). This pattern increases our confidence that our results reflect an agricultural mechanism driven by the protective effect of irrigation rather than unobserved differences in overall economic development or other factors that affect conflict potential.

To provide further evidence for an agricultural mechanism, we present evidence from two placebo tests. Column 1 of table 9 shows that our results are specific to rainfall during the main agricultural growing season from November through April. We find no evidence that rainfall outside of the growing season affects conflict and no evidence that its effect is mediated by irrigation capacity. This result is consistent with that of Harari and La

<sup>17</sup> To further address this issue, the online supplementary appendix, tables A6 and A7 present Conley's spatial autocorrelation robust standard errors. Results are qualitatively similar to those presented here.

Ferrara (2018), who found that negative weather shocks during the growing season increase conflict in sub-Saharan Africa, whereas shocks outside of the growing season do not.

Column 2 of table 9 shows that our results are specific to irrigation dams. We find no evidence that the effect of rainfall is mitigated by the presence of hydropower capacity in the district. This result goes some way towards addressing the concern that our results are driven by unobserved characteristics that determine the placement of large infrastructure projects. For instance, if dams are built predominantly in districts that have lower conflict potential, it might explain why rainfall affects conflict less strongly in these districts. However, the placement of hydropower dams is likely to be affected by similar unobserved politico-economic characteristics as that of irrigation dams, such as political stability, economic development, or homogenous populations.<sup>18</sup> The fact that the presence of irrigation dams strongly mitigates the rainfall–conflict link, whereas the presence of hydropower dams does not, increases our confidence that our estimates reflect the effect of irrigation on conflict and is not due to unobserved factors that affect the location of large infrastructure projects.

Another potential concern is the possibility that irrigation capacity is capturing the effect of property rights of land, which in turn may help mitigate against conflict during periods of rain shortfall. To explore this possibility, we interact the percentage of household that are owners of their dwelling by district as a proxy for property rights. In column 1 of table 10, we show that irrigation capacity still mitigates the effect of rainfall shocks when including the tenure interaction, and that strength of tenure also appears to mitigate against the conflict effect of rainfall shocks. When we split the sample, we find that the effect of irrigation is coming from the districts where the percentage of ownership is lower than the average as opposed to places with a higher percentage of ownership. This finding suggests that the effect of irrigation may be in part through its effect of increasing land tenure security. At a minimum, we cannot rule out this linkage.

## Conclusions

Persistent conflict is a major impediment to global poverty reduction and economic development. A growing body of evidence has found evidence that weather shocks are an important driver of civil conflict, but the exact mechanism driving this link is unknown. To design policies that can protect society from the conflict effects of weather shocks, we need to understand this mechanism, including where and when it applies.

Our article contributes to this understanding by providing evidence that weather shocks affect conflict, at least in part, through an agricultural mechanism. Using district-level data from Indonesia, we show that negative rainfall shocks lead to a decrease in agricultural production and an increase in civil conflict, and that both effects are mitigated by the presence of irrigation infrastructure. Compared to a counterfactual of no irrigation, the country's current irrigation capacity decreases the effect of a one-standard deviation rainfall shock on conflict from sixty-two incidents to thirty-eight incidents country wide.<sup>19</sup> Our results are robust to controlling for interactions between district characteristics and rainfall, as well as to controlling for unobserved time-varying shocks at the island level. Placebo tests show that our results are specific to rainfall in the growing season and to the presence of irrigation infrastructure. Importantly, we find no evidence that the presence of hydropower dams reduced the effect of rainfall on conflict, which increases our confidence that our results are not explained by unobserved characteristics that determine the location of large infrastructure projects.

Importantly, our results suggest that the effect of rainfall on conflict varies substantially across locations and across types of conflict. Specifically, our evidence for an agricultural link between rainfall and conflict only holds for rural areas and for conflicts about natural resources, popular justice, and law enforcement. We find no evidence that rainfall affects urban conflicts, or conflicts about group identity and ethnic separatism through an agricultural mechanism. This reconciles our results with those of Sarsons (2015) who found no evidence that rainfall affects Hindu–Muslim riots,

<sup>18</sup> We explore the determinants of placement of hydropower and irrigation dams in the online supplementary appendix, table A8, and find no statistically significant differences with respect to observed district characteristics.

<sup>19</sup> We use the coefficients from equation 1 in table 3 to predict the effect of 1-sd deviation shock to rainfall when there is irrigation versus the counterfactual of no irrigation.

a largely urban conflict about ethnic identity, through an agricultural mechanism.

Our results suggest that irrigation can play a role in mitigating the effect of weather shocks on certain types of civil conflict. Large infrastructure projects, such as irrigation dams, have been criticized for their substantial social costs in the form of environmental damages and displacement of people (McCully 1996; Shiva 2012). Although our results do not take away from these costs, they suggest that irrigation infrastructure may have previously unrecognized benefits in protecting societal stability against weather shocks.

### Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

### References

- Aldrian, Edvin, and Raden Dwi Susanto. 2003. Identification of Three Dominant Rainfall Regions Within Indonesia and Their Relationship to Sea Surface Temperature. *International Journal of Climatology* 23(12): 1435–52. <https://doi.org/10.1002/joc.950>.
- Asian Development Bank. 2016a. Indonesia: Country Water Assessment. Available at: <https://www.adb.org/sites/default/files/institutional-document/183339/ino-water-assessment.pdf>. Accessed June 18, 2019.
- . 2016b. River Basin Management Planning in Indonesia: Policy and Practice. Available at: <https://www.adb.org/sites/default/files/publication/185758/river-basin-mgt-ino.pdf>. Accessed February 23, 2020.
- Axbard, Sebastian. 2016. Income Opportunities and Sea Piracy in Indonesia: Evidence from Satellite Data. *American Economic Journal: Applied Economics* 8(2): 154–94. <https://doi.org/10.1257/app.20140404>.
- Badan Pusat Statistik. 2017. BPS-Indonesia. Available at: <https://www.bps.go.id/>. Accessed January 9, 2017.
- Barron, Patrick John, Sana Jaffrey, and Ashutosh Varshney. 2014. How Large Conflicts Subside: Evidence from Indonesia (No. 18). Available at: <http://documents.worldbank.org/curated/en/127841478495882008/How-large-conflicts-subside-evidence-from-Indonesia>. Accessed June 18, 2019.
- . 2016. When Large Conflicts Subside: The Ebbs and Flows of Violence in Post-suharto Indonesia. *Journal of East Asian Studies* 16(2): 191–217. <https://doi.org/10.1017/jea.2016.6>.
- Bazzi, Samuel, Robert A. Blair, Christopher Blattman, Oeindrila Dube, Matthew Gudgeon, and Richard Merton Peck. 2019. The Promise and Pitfalls of Conflict Prediction: Evidence from Colombia and Indonesia. NBER Working Papers 25980. <https://doi.org/10.3386/w25980>
- Bazzi, Samuel, and Matthew Gudgeon. 2016. Local Government Proliferation, Diversity, and Conflict. ESOC Working Papers, 5. Available at: <https://esoc.princeton.edu/wp5>. Accessed February 23, 2020.
- Beckert, Barbara, Christoph Dittrich, and Soeryo Adiwibowo. 2014. Contested Land: An Analysis of Multi-Layered Conflicts in Jambi Province, Sumatra, Indonesia. *Austrian Journal of South-East Asian Studies* 7(1): 75–91. <https://doi.org/10.14764/10.ASEAS-2014.1-6>.
- Bellemare, Marc F. 2015. Rising Food Prices, Food Price Volatility, and Social Unrest. *American Journal of Agricultural Economics* 97(1): 1–21. <https://doi.org/10.1093/ajae/aa038>.
- Bellemare, Marc F, and Casey J Wichman. 2019. Elasticities and the Inverse Hyperbolic Sine Transformation. *Oxford Bulletin of Economics and Statistics* 82(1): 50–61. <https://doi.org/10.1111/obes.12325>.
- Bonner, Raymond. 2006. Indonesia to Execute 3 for Roles in Riots That Killed Hundreds. *New York Times*. Available at: <https://www.nytimes.com/2006/08/11/world/asia/11indo.html?mtrref=undefined>. Accessed February 23, 2020.
- BPS-Statistics Indonesia. 2015a. Land Area by Utilization, 2015. Available at: <https://www.bps.go.id/publication/2016/03/03/b1fde2b36ce16c983982405b/luas-lahan-menurut-penggunaan-2015.html>. Accessed February 23, 2020.
- . 2015b. Production of Food Crops, 2014. Available at: <https://www.bps.go.id/publication/2015/10/12/19ffec6f6cd8355469be2719/produksi-tanaman-pangan-2014.html>. Accessed February 23, 2020.
- . 2016. Production of Food Crops, 2015. Available at: <https://www.bps.go.id/publication/2016/09/26/b5a5f1072fea10fcf5>

- fa80c4/produksi-tanaman-pangan-2015.html. Accessed February 23, 2020.
- Burke, Marshall, Solomon M Hsiang, and Edward Miguel. 2015. Climate and Conflict. *Annual Review of Economics* 7(1): 577–617. <https://doi.org/10.1146/annurev-economics-080614-115430>.
- Cameron, Lisa A, and Manisha Shah. 2014. Can Mistargeting Destroy Social Capital and Stimulate Crime? Evidence from a Cash Transfer Program in Indonesia. *Economic Development and Cultural Change* 62(2): 381–415. <https://doi.org/10.1086/674102>.
- Cech, Thomas V. 2009. *Principles of Water Resources: History, Development, Management, and Policy*. Hoboken, NJ: John Wiley & Sons. The University of Michigan.
- Conley, Timothy G. 2010. Spatial Econometrics. In *The New Palgrave Dictionary of Economics*, ed. Palgrave Macmillan, 303–313. London: Macmillan.
- Crost, Benjamin, Claire Duquenois, Joseph H Felter, and Daniel I Rees. 2018. Climate Change, Agricultural Production and Civil Conflict: Evidence from The Philippines. *Journal of Environmental Economics and Management* 88: 379–95. <https://doi.org/10.1016/j.jeem.2018.01.005>.
- Dagur, Renee. 2014, November 6. Indonesia's Transmigration Program Threatens Papuans. LaCroix. Available at: <https://international.la-croix.com/news/transmigration-program-threatens-papuans/299#>. Accessed February 23, 2020.
- Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2014. What Do We Learn from the Weather ? The New Climate – Economy Literature. *Journal of Economic Literature* 52(3): 740–98. <https://doi.org/10.3386/w19578>.
- Di Falco, Salvatore, Jeremy Laurent-Lucchetti, Marcella Veronesi, and Gunnar Kohlin. 2020. Property Rights, Land Disputes and Water Scarcity: Empirical Evidence from Ethiopia. *American Journal of Agricultural Economics* 102(1): 54–71. <https://doi.org/10.1093/ajae/aaz036>.
- Duflo, Esther, and Rohini Pande. 2007. Dams. *Quarterly Journal of Economics* 122(2): 601–46. <https://doi.org/10.1162/qjec.122.2.601>.
- Emont, Jon. 2017. Indonesia's Sentencing of 'Son of God' Adds to Alarm Over Crackdown. *New York Times*. Available at: <https://www.nytimes.com/2017/03/09/world/asia/indonesia-blasphemy-laws.html>. Accessed February 23, 2020.
- FAO/IIASA. 2010. Global Agro-Ecological Zones (GAEZ v3.0). Available at: <http://www.fao.org/nr/gaez/en/>. Accessed February 23, 2020.
- FAOSTAT. 2019. Indonesia. Available at: <http://www.fao.org/faostat/en/#country/101>. Accessed July 20, 2019.
- Fetzer, Thimeo. 2014a. Can Warfare Programs Moderate Violence? Evidence from India. STICERD Working Papers, Working paper number 436. Available at: [https://warwick.ac.uk/fac/soc/economics/research/centres/cage/manage/publications/436-2019\\_fetzer.pdf](https://warwick.ac.uk/fac/soc/economics/research/centres/cage/manage/publications/436-2019_fetzer.pdf). Accessed March 16, 2020.
- Fetzer, Thimeo. 2014b. Social Insurance and Conflict: Evidence from India. EOPP Working Papers No. 53. Available at: <http://www.trfetzer.com/wp-content/uploads/JMP.pdf>. Accessed February 23, 2020.
- Funk, Chris C, Pete J Peterson, Martin F Landsfeld, Diego H Pedreros, James P Verdin, James D Rowland, Bo E Romero, Gregory John Husak, Joel C Michaelsen, and Andrew P Verdin. 2014. A Quasi-Global Precipitation Time Series for Drought Monitoring. *U.S. Geological Survey Data Series* 832: 4. <https://doi.org/10.3133/ds832>.
- Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2018. Human Capital Costs of Climate Change: Evidence from Test Scores in India. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2941049>.
- Gould, Eric D, David A Mustard, and Bruce A Weinberg. 2002. Crime Rates and Local Labor Market Opportunities in the United States: 1979-97. *Review of Economics and Statistics* 84(1): 45–61. Available at: [www.jstor.org/stable/3211738](http://www.jstor.org/stable/3211738). Accessed July 20, 2019.
- Harari, Mariaflavia, and Eliana La Ferrara. 2018. Conflict, Climate, and Cells: A Disaggregated Analysis. *Review of Economics and Statistics* 100(4): 594–608. [https://doi.org/10.1162/rest\\_a\\_00730](https://doi.org/10.1162/rest_a_00730).
- Heijmans, Philip J., and Arys Aditya. 2019. Deadly Jakarta Riots Revive Specter of Religion-Fueled Violence in Indonesia. *Bloomberg*. Available at: <https://www.japantimes.co.jp/news/2019/05/24/asia-pacific/deadly-jakarta-riots-revive-specter-religion-fueled-violence-indonesia/#.XTcxDehKg2x>. Accessed February 23, 2020.

- Hirsch, Philip, and Carol Warren. 1998. *The Politics of Environment in Southeast Asia: Resources and Resistance*. London and New York: Routledge.
- Hsiang, Solomon M. 2010. Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences of the United States of America* 107(35): 15367–72. <https://doi.org/10.1111/1471-0528.14569>.
- Hsiang, Solomon M, and Marshall Burke. 2014. Climate, Conflict, and Social Stability: What Does the Evidence Say? *Climatic Change* 123(1): 39–55. <https://doi.org/10.1007/s10584-013-0868-3>.
- ICOLD. 2019. The World Register of Dams. Available at: [https://www.icold-cigb.org/GB/world\\_register/world\\_register\\_of\\_dams.asp](https://www.icold-cigb.org/GB/world_register/world_register_of_dams.asp). Accessed February 23, 2020.
- International Crisis Group. 2012. Indonesia: The Deadly Cost of Poor Policing. Available at: <https://www.refworld.org/pdfid/4f3e4ed82.pdf>. Accessed July 20, 2019.
- Jagnani, Maulik, Christopher B Barrett, Yanyan Liu, and Liangzhi You. 2018. Within-Season Producer Response to Warmer Temperatures: Defensive Investments by Kenyan Farmers. *Economic Journal*, Forthcoming. <https://doi.org/10.2139/ssrn.3056840>. Accessed March 16, 2020.
- Jones, Sidney. 2013. The Growing Problem of Land Conflicts in Indonesia. CogitASIA. Available at: <https://www.cogitasia.com/the-growing-problem-of-land-conflicts-in-indonesia/>. Accessed February 23, 2020.
- Klomp, Jeroen, and Erwin Bulte. 2013. Climate Change, Weather Shocks, and Violent Conflict: A Critical Look at the Evidence. *Agricultural Economics* 44 (Suppl 1): 63–78. <https://doi.org/10.1111/agec.12051>.
- Koren, Ore. 2018. Food Abundance and Violent Conflict in Africa. *American Journal of Agricultural Economics* 100(4): 981–1006. <https://doi.org/10.1093/ajae/aax106>.
- Lipscomb, Molly, A Mushfiq Mobarak, and Tania Barham. 2013. Development Effects of Electrification: Evidence from the Topographic Placement of Hydro-power Plants in Brazil. *American Economic Journal: Applied Economics* 5(2): 200–31. [https://doi.org/10.1007/978-3-319-94289-6\\_18](https://doi.org/10.1007/978-3-319-94289-6_18).
- Machin, Stephen, and Costas Meghir. 2004. Crime and Economic Incentives. *Journal of Human Resources* XXXIX(4): 958–79. <https://doi.org/10.3368/jhr.xxxix.4.958>.
- Matsuura, Kenji, and Cort J. Willmott. 2015. Terrestrial Air Temperature: 1900–2014 Gridded Monthly Time Series. Available at: [http://climate.geog.udel.edu/~climate/html\\_pages/Global2014/README.GlobalTsT2014.html](http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsT2014.html). Accessed February 23, 2020.
- Mayangsari, Anissa, and Tri Bayu Adji. 2015. Implementation of Dam Safety in Indonesia. Available at: [https://www.ich.no/Oppplastet/Dokumenter/Hydropower15/Mayangsari\\_indonesia.pdf](https://www.ich.no/Oppplastet/Dokumenter/Hydropower15/Mayangsari_indonesia.pdf). Accessed February 23, 2020.
- Maystadt, Jean Francois, and Olivier Ecker. 2014. Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia Through Livestock Price Shocks? *American Journal of Agricultural Economics* 96 (4): 1157–82. <https://doi.org/10.1093/ajae/aau010>.
- McCully, Patrick. 1996. *Silenced Rivers: The Ecology and Politics of Large Dams*. London and Atlantic Highlands, NJ: Zed Books.
- Miguel, Edward. 2005. Poverty and Witch Killing. *Review of Economic Studies* 72 (4): 1153–72. <https://doi.org/10.1111/0034-6527.00365>.
- Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy* 112(4): 725–53. <https://doi.org/10.1086/421174> Accessed March 16, 2020.
- Miguel, Edward, and Shanker Satyanath. 2011. Re-examining Economic Shocks and Civil Conflict. *American Economic Journal: Applied Economics* 3(4): 228–32. <https://doi.org/10.1257/app.3.4.228> Accessed March 16, 2020.
- Minnesota Population Center. 2018. Integrated Public Use Microdata Series, International: Version 7.1. <https://doi.org/10.18128/D020.V7.1>
- MPWH. 2018. Water Resources. Ministry of Public Works and Housing of Indonesia website. Available at: <http://112.78.146.43/pdsdav6/>. Accessed April 5, 2018.
- Sarsons, Heather. 2015. Rainfall and Conflict: A Cautionary Tale. *Journal of Development Economics* 115: 62–72. <https://doi.org/10.1016/j.jdevec.2014.12.007>.

- Shah, Manisha, and Bryce Millett Steinberg. 2017. Drought of Opportunities: Contemporaneous and Long-term Impacts of Rainfall Shocks on Human Capital. *Journal of Political Economy* 125(2): 527–61. <https://doi.org/10.1086/690828>.
- Shiva, Vandana. 2012. Water Wars: Privatization, Pollution and Profit. In *Environmental Ethics: What Really Matters, What Really Works*, ed. John Thrasher, 217–219. New York: Oxford University Press. <https://doi.org/10.4296/cwrj2704485>.
- Siebert, Stefan, Matti Kummu, Miina Porkka, Petra Döll, Navin Ramankutty, and Bridget R. Scanlon. 2015. Historical Irrigation Dataset (HID). <https://doi.org/10.13019/M20599>
- Stephens, Tim. 2010. *Manual on Small Earth Dams: A Guide to Siting, Design and Construction (No. 64)*. Food and Agriculture Organization of the United Nations (FAO) Available at: <http://www.fao.org/3/i1531e/i1531e.pdf>. Accessed March 16, 2020.
- Swenty, Brian J. 1989. Engineering Analysis of Dams. Available at: <https://dnr.mo.gov/geology/wrc/docs/EngAnalysisDams.pdf>. Accessed February 23, 2020.
- The Asia Foundation. 2017. State of Conflict and Violence. Available at: <https://asiafoundation.org/wp-content/uploads/2017/10/Indonesia-StateofConflictandViolence.pdf>. Accessed February 23, 2020.
- Tovar-Garcia, Edgar D, and Indra Prasetya Adi Nugroho. 2015. Economic Determinants of Communal Conflict: Evidence from Indonesia. *Asia-Pacific Social Science Review* 15 (2): 19–32. Available at: [https://www.researchgate.net/publication/290456116\\_Economic\\_determinants\\_of\\_communal\\_conflict\\_Evidence\\_from\\_Indonesia](https://www.researchgate.net/publication/290456116_Economic_determinants_of_communal_conflict_Evidence_from_Indonesia). Accessed February 23, 2020.
- USDA-FAS. 2016. INDONESIA : Rice Production Prospects Reduced by El Nino. Commodity Intelligence Report website. Available at: <https://www.pecad.fas.usda.gov/highlights/2016/03/Indonesia/Index.htm>. Accessed August 20, 2017.
- Wischnath, Gerdis, and Halvard Buhaug. 2014. On Climate Variability and Civil War in Asia. *Climatic Change* 122(4): 709–21. <https://doi.org/10.1007/s10584-013-1004-0>.
- World Bank. 2017. Enhancing Dam Safety and Public Protection through InaSAFE-Based Emergency Action Plan and Contingency Planning. Available at: <http://documents.worldbank.org/curated/en/783681519225880487/Enhancing-dam-safety-and-public-protection-through-InaSAFE-based-emergency-action-plan-and-contingency-planning>. Accessed March 16, 2020.
- . 2017. *Enhancing Dam Safety and Public Protection through InaSAFE-based Emergency Action Plan and Contingency Planning (English)*. Washington, DC: World Bank Group Accessed March 16, 2020.
- . 2018. World Development Indicators Database. Agriculture, Forestry, and Fishing, Value Added (% of GDP). Available at: [https://databank.worldbank.org/views/reports/reportwidget.aspx?Report\\_Name=CountryProfile&Id=b450fd57&tbar=y&dd=y&inf=n&zm=n&country=IDN](https://databank.worldbank.org/views/reports/reportwidget.aspx?Report_Name=CountryProfile&Id=b450fd57&tbar=y&dd=y&inf=n&zm=n&country=IDN). Accessed July 20, 2019.