**Agricultural Shocks and Social Conflict in Southeast Asia**

**Abstract**

Conflicts are common and, to an extent, inevitable. Theories have linked forms of conflict to changes in income, and specifically of one group relative to another within a society. To that end, the harvest season in agrarian societies presents an interesting empirical setting, as farmers in this period experience a short-term increase in income. We study thirteen years of data across eight Southeast Asian countries and focus on changes in different forms of social conflict during the rice harvest season. In this period, compared to the rest of the year, we estimate an increase in political violence in the croplands. This estimate, which is statistically significant, accords with the rapacity effect. In the same period, we estimate a decrease in protests and riots, which would conform with the opportunity cost effect, but the estimates are not statistically significant. A possible explanation of this may be the presence of the offsetting resentment effect. We validate the mechanisms by incorporating plausible changes in harvest due to growing season rainfall. Our findings, which contribute to the research on the agroclimatic and economic roots of conflict, offer valuable insights to policymakers by suggesting temporal and geographic displacements of conflict associated with locations where a crop is produced and times when it is harvested.

**Keywords**: Agriculture, Conflict, Seasonality, Southeast Asia

**1. Introduction**

In low– and middle low–income countries, a small change in people’s well-being may trigger a range of behavioral responses, some of which may be unlawful and possibly violent. While protests, riots, and violence against civilians often happen in cities that not only are populous areas but also where the state administration—the key target of protesters—is located (e.g., Smith, 2014; Hendrix and Haggard, 2015), social conflict is not just an urban phenomenon. In rural areas, which often constitute the larger share of territories where the state capacity is limited, changes in income and employment can result in conflict and violence (e.g., McGuirk and Burke, 2020; Ubilava et al, 2022; Guardado and Pennings, 2023). Indeed, mounting empirical evidence points to a linkage between crop yields and conflict (Wischnath and Buhaug, 2014; Buhaug et al. 2015; Koren, 2018; Vestby, 2019)—which is a likely mechanism and a manifestation of climate shocks on conflict (e.g., Burke et al., 2009; Hsiang et al., 2013; Dell et al., 2014; Crost et al., 2018; Koubi, 2019)—and, somewhat less unequivocally, between commodity price shocks and conflict (Dube and Vargas, 2013; Maystadt and Ecker, 2014; Raleigh et al. 2015; Berman and Couttenier, 2015; Crost and Felter, 2020).

This paper addresses the question of whether harvest-time agricultural shocks lead to changes in conflict. The potential relationship between agriculture and conflict can be reduced to a couple of theories. One theory is *grievance*, which suggests that people protest the deterioration of their well-being, relative to others or to their own past (e.g., Hendrix and Haggard, 2015; de Winne and Peersman, 2021). The other theory is *greed*, which suggests that perpetrators are more likely to engage in conflict when there is more at stake. Both theories explain the conflict that happens not only because there are opportunities to extort wealth or incur damage and thus improve one’s own relative standing, but also because the opportunity costs of engaging in such activities are not very high (Mitra and Ray, 2014). The latter, in particular, has been primarily portrayed in the literature as a person’s choice of the less peaceful ways of generating income, when the lawful alternatives such as farming do not pay enough (e.g., after a bad crop year, or a drop in commodity prices). To that end, the opportunity cost of fighting is seen as an increasing function of income—a negative income shock leading to more violence (Collier and Hoeffler, 1998; Fjelde, 2015). This mechanism typically alludes to a relatively long-term commitment to a conflict, however. A shorter-term manifestation of the opportunity cost mechanism would be instances when people engage in a social conflict, such as protests and riots, when their value of time is relatively low. In the agricultural sector, this would be the period during the year when people are not actively farming (Guardado and Pennings, 2023).

At the heart of the question of the link between agricultural output and conflict is not only the mechanism but also the form of conflict. Moreover, different forms of conflict are likely to manifest one mechanism more so than the other, thus offering a chance to disentangle the otherwise potentially ambiguous relationship between agricultural shocks and conflict. On the one hand, violence aimed at civilians can be linked to the harvest-time positive income shocks, and the relationship is expected to be positive. After a good harvest season, for example, the transitory increase in the spoils to be appropriated make farmers a lucrative target, which can amplify violence in croplands relative to non-agricultural areas (Mitra and Ray, 2014; Koren, 2018; McGuirk and Burke, 2020). Such a relationship can also be seasonal. In crop-producing parts of Africa, for example, attacks on civilians increase during harvest months (Ubilava et al. 2022), which aligns with the theory of greed manifested through the rapacity mechanism.

On the other hand, social unrest, often triggered by negative income shocks, may be linked to agricultural harvest in rural areas. The relationship can be negative or positive, however. The opportunity cost mechanism would lead to less protests at harvest time. This can happen for at least two reasons. First, when people—potential protesters—are busy harvesting, they are unlikely to take part in protests as the opportunity cost of this type of conflict is high. Second, if there is a short period of time, during the calendar year, when people in rural areas are relatively better off, compared to other times of the year or to people in urban areas, it is during or shortly after the harvest season, when the years’ worth of income has been realized. So, the harvest-time increase in income can mitigate social unrest in croplands relative to the urban, non-agricultural areas. Within agricultural areas, however, the harvest time increase in income inequality—between farmers and non-farmers—may amplify social unrest (e.g., Panza and Swee, 2023). The net effect, manifested through opportunity cost and resentment mechanisms, can be ambiguous.

Finally, incidents linked to larger-scale conflicts, such as battles between incumbents and insurgents to take control of a territory, are unlikely to be driven by or related to agricultural employment and income (e.g., Mampilly and Stewart, 2021; Ubilava et al., 2022). And even if they were, the direction of the effect may very well go in the opposite direction. That is, in times of a civil war, for example, people willingly or unwillingly may be involved in the process, at the expense of their usual employment, which in rural societies is often agricultural production.

We study the relationship between agricultural shocks and different forms of conflict by examining over 70 thousand incidents across eight countries of Southeast Asia during the 2010–2022 period. We find that violent attacks increase in crop-producing areas during the harvest months of rice—the key cereal crop in the region. This suggests that for conflict *against* civilians, harvest season presents rapacious violent groups with an opportunity to appropriate or destroy agricultural surplus. For conflict *by* civilians, we find that protests decrease at harvest time, which would suggest the opportunity cost dominating the resentment. But there is a caveat.

A series of sensitivity checks suggest the elevated levels of conflict in Myanmar from 2021 onward drive the results. Absent the 2021-2022 data from Myanmar, the estimated increase in harvest-time violence remains, but the harvest-time increase in battles or reduction of protests vanish, at least statistically. Notably, the omitted subset of the data contains a third of observed conflict incidents in the sample. And to the extent that we can only estimate the causes and consequences of conflict where and when conflict happens, these data may contain valuable information. So, while we are more confident about, and in the main analysis rely on estimates from the data subset that excludes Myanmar 2021-2022 observations, we also present estimates from the full sample in the appendix.

We contribute and help advance knowledge in three strands of literature. First, we contribute to the literature on climate shocks and conflict (e.g., Burke et al., 2009; Hsiang et al., 2013; Dell et al., 2014; Crost, et al., 2018). We present empirical evidence that emphasizes the effect of growing-season precipitation on harvest-time conflict. Second, we contribute to the literature on the economic roots of conflict (Berman et al, 2011; Crost and Felter, 2020; McGuirk and Burke, 2020; Grasse, 2022). We present empirical evidence for the potentially diverging effects that agricultural windfalls have on different forms of conflict, thus emphasizing benefits and the need of nuanced data analysis. Third, we contribute to the emerging literature on the seasonality of conflict (Harari and La Ferrara, 2018; Ubilava et al., 2022; McGuirk and Nunn, 2023; Guardado and Pennings, 2023). We present suggestive evidence of harvest-time increase in violence (with high confidence) and a harvest-time reduction of protests (with low confidence), and link these effects to the existing theories of conflict.

**2. Agricultural Origins of Conflict in Southeast Asia**

The geographic focus— Southeast Asia—is suitable for the present analysis for several reasons. First, most of the countries in the region fall into the lower-middle-income economies, with a considerable proportion of people living at or below the national poverty line (World Bank, 2022a, 2022b). The region also has large across-country and within-country variation in governance and institutional capacity levels, as the Philippines, Myanmar, and Indonesia in particular struggle to control their geographic peripheries.

Second, agriculture is a crucial sector for employment and income generation, across much of the region (World Bank, 2022c). While subsistence farming exists in Southeast Asia as in many regions with less developed economies, Southeast Asian countries are often food exporters (unlike many African countries). Thailand, Vietnam, Myanmar, and Cambodia are all in the top ten rice exporting countries globally (FAO, 2023). This means that violence associated with rice-producing areas are especially relevant to income generation for both farmers and the state.

Finally, civil conflict and social unrest have been defining features of the region’s politics (e.g., Crost and Felter, 2020; Crost et al., 2020; Gatti et al., 2021). The Philippines and Myanmar, for example, have seen multiple insurgencies—ideology- or ethnicity-based—for nearly their entire independent existences. The protests and conflicts that were sparked by the Myanmar military’s coup in 2021 have evolved into a full-scale civil war, while the Philippines has high levels of civil conflict. Thailand struggled with a communist insurgency from the 1960s until the early 1980s, and spillover from Myanmar’s insurgencies, while the Thai government continues to fight a low-level ethnic insurgency in southern Thailand. Since Suharto’s fall in 1998, Indonesia has dealt with widespread protests, riots, civil conflict, and Islamist terrorism, as well as ethnic insurgencies in Aceh and West Papua.

We can imagine a number of different actors in Southeast Asian conflict, all of whom could instigate conflict, including civilians, armed rebel groups, state actors, and militias operating on behalf of competing elites. Civilians may instigate protests against government policies, and these protests may turn into riots. Armed rebel groups, state actors, and militias may engage in violence against civilians, either through armed attacks, battles, or explosions. The logic of conflict, agricultural shocks, and seasonality is likely to be different, and in some ways, diametrically opposed, depending on the type of actor (and thus the type of conflict).

Previous work on the connection between conflict and agricultural output in Southeast Asia has come to nuanced conclusions about the types of conflict pursued by different actors, and the potential relationship with agricultural outputs. Gatti et al. (2021) find that decreased agricultural output is associated with an increase in civil conflict in Indonesia, but that irrigation infrastructure specifically mitigates this link. They divide conflict into that over natural resources, issues of popular justice, conflicts triggered by government policy, those triggered by group identity, as well as separatist incidents. Their findings suggest that this effect is particularly strong for natural resource conflicts, popular justice, law enforcement actions, and less strong for conflicts driven by ethnic separatism and group identity. While their categorizations do not specifically differentiate civilian protest and rioting from state- and rebel-initiated conflict, in broad strokes, it appears that conflicts that would lead to protests against government policy and over natural resources are more amenable to mitigation through decreasing the effects of negative agricultural shocks than ethnic separatist conflicts, which are more likely to be associated with insurgent activities, particularly in Indonesia, where rebel groups generally have religious or ethnic goals.

*2.1. Harvest-Time Increase in Violence Against Civilians*

In Southeast Asia, both the opportunity cost and rapacity mechanisms may be at play, depending on the actor type (Table 1). For attacks on civilians, insurgencies may increase their activities during the harvest season to maximize the damage they do through a number of pathways. First, they may want to expropriate farmers’ income, which is realized during harvest season. Second, for farmers who do not support the insurgency or who are on the sidelines, insurgents may want to harm the farmers’ earning potential to minimize threats to the insurgency, or to intimidate the farmers into joining them (Raleigh, 2012; Raleigh and Choi 2017). Third, the insurgents may time their attacks to have maximum negative effect on the state, inasmuch as the state is also likely deriving revenues during the harvest season, and state revenue is related to the ability of the state to attack the insurgents (Fearon and Laitin 2003).

**Table 1. Actors and conflict seasonality: Theoretical expectations**

|  |  |  |  |
| --- | --- | --- | --- |
| **Form of conflict** | **Type of actor** | **Likely mechanism** | **Harvest-time effect** |
| Battles | Armed actors (State forces, rebel groups, militias) | Opportunity cost, Rapacity | Ambiguous |
| Violence | Armed actors (State forces, rebel groups, militias) | Rapacity | Increase |
| Riots | Civilians | Opportunity cost, resentment, rapacity | Ambiguous |
| Protests | Civilians | Opportunity cost, resentment | Ambiguous |

By this logic, violence against civilians is likely to be focused on the destruction or appropriation of agricultural outputs. Significant numbers of attacks on civilians in Southeast Asia revolve around the theft of rice or the destruction of rice fields, rice storage units, or rice milling facilities. In December 2013, for instance, the Myanmar military attacked civilian rice paddies in Kachin state during the harvest season.[[1]](#footnote-1)

State forces, political militias, and insurgent groups might choose the harvest season as the time to attack because it would maximize the destruction of their enemies’ resources, or allow them to appropriate that agricultural surplus. In November 2022, a Myanmar military force shot dead three villagers in a raid in Myanmar’s Magway region, two of who were engaged in harvesting rice in paddy fields.[[2]](#footnote-2) During the harvest season, the state may also attack villages that may be aiding rebel groups. In November 2021, for instance, in a clash between the Myanmar military and various People Defense Forces (the armed groups associated with the anti-junta civilian government in internal exile), the military burned harvested rice fields in a village that it (obviously) suspected was loyal to the anti-state groups.[[3]](#footnote-3)

Insurgent groups fighting against the state also have an incentive to attack civilians who are providing agricultural outputs to the state, both to intimidate the civilians against supporting the state, and to deny the state food. In November 2022, rebel groups ambushed a military convoy carrying rice in Myanmar in Mon state and killed a soldier.[[4]](#footnote-4) Pro-government militias can engage in similar behavior to degrade the resources available to their enemies and to appropriate resources for themselves. In June 2022, the pro-military junta militia group Pyu Saw Htee killed a rice mill owner in Sagaing and stole large amounts of money (which had been intended to buy more rice milling equipment) as well as mobile phones and a motorcycle.[[5]](#footnote-5)

*2.2. Harvest-Time Decrease in Protests by Civilians*

While riots and protests may be initiated by insurgencies or organized anti-government groups, they may also more generally be indicative of dissatisfaction by civilians, whether organized or not. A decrease in protests and riots during harvest season may come through several pathways. First, those who are directly involved in agriculture may decrease their protest activities during harvest time because they are busy harvesting. This relates to a second pathway, that of a direct opportunity cost mechanism, in which the opportunity cost of protesting increases during harvest time because there is more income to be derived from harvesting. Put another way, the infusion of income from the harvest makes protesting relatively less attractive. This may be because there are actually fewer grievances against the government when would-be protesters are realizing income. It may also be because the ‘income’ from protesting relative to other activities becomes less competitive. In Indonesia, for instance, paid protesting is a longstanding means for political parties and civil society groups to pressure the government or send a message. In many cases, protesters are provided with a packed lunch (‘nasi bungkus’ in Indonesian) and a cash payment (hence the term, the ‘nasi bungkus brigade’), and often have only a tenuous interest in the issue at the center of the protest (Andrews, 2017). Thus, protest campaigns may find fewer supporters (paid or not) during the harvest season.

Protests by farmers in Southeast Asia are often designed to pressure the government to increase (or maintain) the prices they receive for their products. Both Indonesia and the Philippines have seen pressure campaigns from farmers to maintain or increase the price of rice (through price guarantees), or to prevent rice imports (to minimize competition that can undercut the domestic price).[[6]](#footnote-6) In a logic where protests increase as grievances against the state increase, or as the opportunity cost of protesting decreases relative to harvesting, we would expect higher prices or better harvests to be associated with fewer protests and riots.

We would also expect protest and riots to decrease during the harvest season relative to the non-harvest season. In the case of Thailand, for instance, there was a spate of protests against the Thai government by farmers throughout the country in 2014 because of a rice purchasing scheme in which the Thai government was supposed to have paid farmers subsidies for their rice production, but payments were either delayed or non-existent (Mohanty 2012). These protests were largely *not* during rice harvest season (which is December in Thailand), but several months later, when farmer’s grievances increased, and the opportunity cost of protesting was lower relative to harvesting. Of interest here is that the Thai farmers’ grievances were against both the government (for not paying the subsidies) and anti-government groups (for supposedly blocking the government from paying the subsidies).[[7]](#footnote-7) The protests were ultimately followed by a military coup against the civilian government in May 2014.

Finally, fewer protests around the time of harvest, relative to other periods of the crop year, to some extent could be an effect of higher likelihood of civilians’ protest during the growing season (which is also often a season of hunger as supplies from the previous harvest dwindle) as a means of extracting concessions from the government. In Thailand in July 2019, for example, hundreds of farmers blocked a road to force the government to release irrigation water for their rice paddies during a drought.[[8]](#footnote-8)

**3. Data**

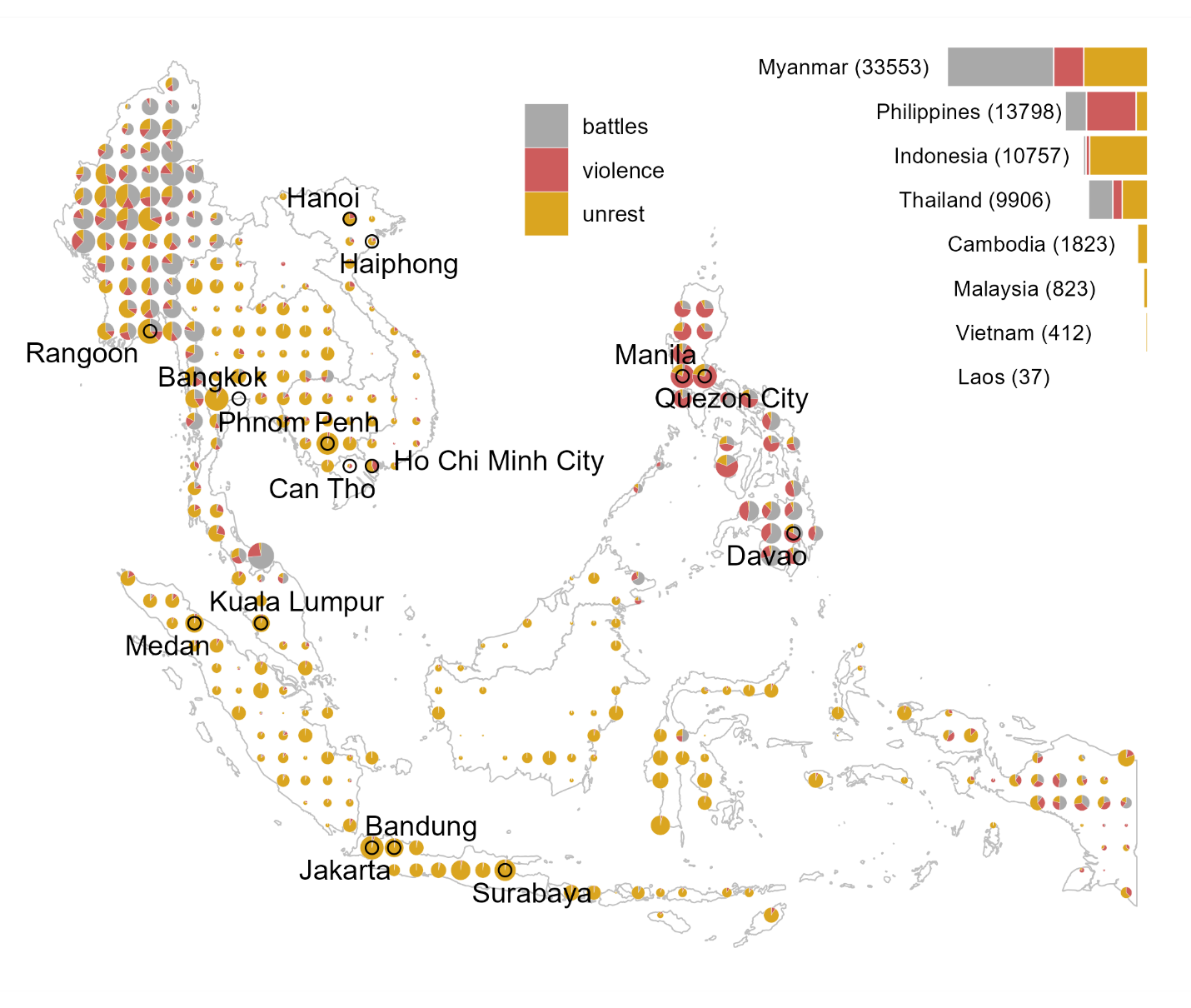
We use data from multiple sources. For social conflict, we use the Armed Conflict Location & Event Data (ACLED) compiled by Raleigh et al. (2010). For rice land cover, including the irrigation status, we use the data from IFPRI (2019), and for harvest calendars we use data from Monfreda et al. (2008). For precipitation we sourced data from the ERA5 Copernicus project. In what follows, we describe each dataset in more detail.

*3.1. Conflict*

The ACLED Project (Raleigh et al., 2010) presents highly granular data in the sense that: (i) it features any reported conflict regardless of whether the altercation resulted in any casualty; (ii) it groups incidents into six categories, which include *battles*, *explosions/remote violence*, and *strategic developments* that feature two actors, typically the state or state-affiliated militias and the rebels who dispute the control of a territory; *violence against civilians* perpetrated by any of the paramilitary groups, as well as *protests* and *riots* that represent manifestations of public disorder of sorts. In our analysis, we combine *battles* and *explosions/remote violence* into a single type of event, and drop *strategic developments* as they are not likely to be comparable across countries and over time as other ACLED event types are (Raleigh et al., 2010).

The main caveat of this dataset is that it covers a relatively short period of time, from 2010 onward for most Southeast Asian countries except for Indonesia (from 2015 onward), Philippines (from 2016 onward), and Malaysia (from 2018 onward). The countries included in the analysis are Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Timor-Leste, Thailand, and Vietnam. We exclude from the analysis Brunei, Singapore, and Timor-Leste because they are small and/or not agriculturally dependent countries, and because the ACLED coverage for these three countries is from 2020 onward only.

Our study period, which ranges from 2010 to 2022, covers a total of more than 70 thousand unique incidents observed across the eight countries. This excludes incidents for which exact locations are unknown and they are thus arbitrarily attributed to the nearest known site, typically a provincial capital (such locations are recorded with the geo-precision code 3 in the database). Figure 1 illustrates the geographical distribution of incidents across three distinct conflict categories (for illustration purposes, we combined protests and riots into a single *unrest* category) aggregated at the level of one-degree cells. The map also features a selected set of large cities in the region.[[9]](#footnote-9) From this map, it becomes apparent that: (i) conflict, broadly defined, occurs across much of the Southeast Asian region; (ii) within the region, some countries are more prone to conflict than others; (iii) there is a fair bit of spatial dependence in the prevalence of different types of conflict; and (iv) while generally observed in the cities, where most people reside, conflict not necessarily or exclusively a city phenomenon.



**Figure 1: Geographic distribution of social conflict (2010–2022)**

Note: The data are for Cambodia, Indonesia (2015 – 2022), Laos, Malaysia (2018 – 2022), Myanmar, Philippines (2016 – 2022), Thailand, and Vietnam. The size of the dots is proportional to the combined number of incidents in a cell. The featured cities are the largest, in terms of population, of those with geographic centroid within a one-degree cell. When multiple cities fall within a cell, the largest of these cities is selected. Specifically, featured are the cities with populations of more than 0.5 million that fall in the grid cell with aggregated city population of more than 2 million. This rule is arbitrary, and is only used for illustrative purposes, that is, to ensure that a manageable number of cities are presented on the map.

Figure 2 presents the time series of the four considered types of conflict over the study period. Additional features become apparent. First, there is no apparent trend across conflict types, but there is a notable increase in almost all types of conflict from 2021 onward, largely due to the Myanmar civil war. Second, despite a general co-movement among conflict types, there are periods when a rise in one type of conflict is not accompanied by other types of conflict. This is suggestive that root causes and mechanisms of different forms of conflict vary.

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**Figure 2: Dynamics of social conflict by event type**

Note: The time series are monthly rates of conflict incidents per cell, across available cells for a given period. The number of cells (the bottom panel) increased progressively as Indonesia (2015), Philippines (2016), and Malaysia (2018) were added to the dataset.

*3.2. Production*

We focus on rice which is, by far, the most dominant cereal—both in terms of production as well as consumption— across Southeast Asia. The harvest may extend multiple months. We define the period from the month when the harvest starts to the month when the harvest ends as the *harvest season*. We define the midpoint of the harvest season as the *harvest month*. In instances where a crop is grown over two seasons, we use the main season to identify the crop year. Within a cell, we maintain the area of cropland and the months of the harvest fixed over the study period. We do so not only due to the data limitations, but also to ensure that there is no reverse causality from conflict to the size and the timing of the harvest. We discuss this in more detail in the next section of the paper.

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**Figure 3: Geographic distribution of rice harvest months**

Note: The size of the dots is proportional to the area devoted for rice production; the radial bars indicate the count of cells that fall within a given harvest month. The data on the crop area and irrigation are from IFPRI (2019). The data on harvest calendar are from Monfreda et al. (2008).

Figure 3 aggregates at the level of one-degree cells the geographical distribution of relative cropland area fraction and the harvest months. The map also features locations where more than 50 percent of croplands are irrigated (indicated by empty circles). The data on irrigation status are from IFPRI (2019). Appendix Figure A1 presents the histogram of the proportion of irrigated rice across the considered locations in the region.

From this map, it becomes apparent that: (i) there is a fair bit of variation in the timing of the main harvest season, albeit March being the most dominant month in that regard; (ii) there is a considerable within-country variation in cropland area fractions, but hardly any within-country variation in the harvest month; and (iii) locations with larger cropland area fractions are more likely to be irrigated, although the irrigation prevalence can also be viewed as a country-specific phenomenon. Appendix Figure A2 presents the scatterplot of the proportion of irrigated rice against the (natural log of) rice cropland area.

*3.3. Rainfall*

Rainfall is one of the most crucial factors in rice production. So, we use it to test the mechanism related to year-to-year change in relative abundance of rice, at harvest time, in rice-producing cells. We obtain ERA5 reanalysis data on gridded total precipitation from the Copernicus Project (Hersbach et al., 2018). Specifically, we obtain monthly average total precipitation, which we aggregate to the one-degree grid cell level—the spatial unit of measurement in the present study. Next, we calculate the measure of total precipitation during the months between the planting and harvesting seasons. For each cell, to obtain the standardized measure of precipitation, we divide the mean-centered precipitation by its standard deviation. Thus, we can interpret the magnitude of the effect as that of a one standard deviation change in precipitation.

*3.4. Descriptive Statistics*

In Table 2 we summarize some of the key features of the data. Violence and protests represent the two most prevalent forms of conflict that typically involve civilians who either are directly targeted (e.g., violent attacks or abduction) or become targets (e.g., intervention against protesters). Battles combined with explosions/remote violence, labeled as ‘Battles’ emerge as another important conflict category. The least prevalent event type is riots, which is a violent version of protests that shares elements of other, more violent types of social conflict. The table also presents cell-specific details about croplands. Across the covered 376 cells, the average size of the land used in rice production is approximately 78 thousand hectares, which is approximately 6.5 percent of the cell (as measured near the equator).

**Table 2: Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Sum | Mean | S.D. | Min | Max | Incidence |
|  | *Unit of observation: cell-year-months (44,724)* | | | | | |
| All events | 71,109 | 1.590 | 7.480 | 0 | 350 | 0.253 |
| Battles | 26,030 | 0.582 | 3.759 | 0 | 106 | 0.092 |
| Violence | 15,803 | 0.353 | 2.748 | 0 | 164 | 0.088 |
| Riots | 2,254 | 0.050 | 0.441 | 0 | 42 | 0.032 |
| Protests | 27,022 | 0.604 | 3.743 | 0 | 268 | 0.155 |
|  | *Unit of observation: cells (376)* | | | | | |
| Rice cropland area (100,000 ha) |  | 0.781 | 1.255 | 0 | 9.087 |  |
| Irrigated |  | 0.348 | 0.738 | 0 | 7.786 |  |
| Rainfed |  | 0.433 | 0.858 | 0 | 5.759 |  |

Note: The conflict data are from ACLED Project (Raleigh et al., 2010), and covers eight countries over the period of thirteen years from *2010 to 2022,* except for Indonesia (2015–2022), Malaysia (2018–2022), and the Philippines (2016–2022); the other countries are Cambodia, Laos, Myanmar, Thailand, and Vietnam. *All events* contain the four presented categories of conflict wherein *Battles* combine battles and explosions/remote violence (as defined by ACLED Project). *Incidence* denotes the proportion of units with at least one conflict incident. The data on rice croplands, which are fixed at levels circa 2010, are from IFPRI (2019).

To gauge a better understanding about cross-sectional relationship between the size of croplands and conflict prevalence, we plot the latter against the former, both log-transformed for visual convenience (Figure 4). A positive relationship is apparent between the two variables. There also appears slightly more conflict in predominantly rainfed vis-à-vis irrigated croplands.

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**Figure 4: Cross-sectional relationship between cropland area and conflict prevalence**

Note: The conflict data are from ACLED Project (Raleigh et al., 2010), and covers eight countries over the period of thirteen years from 2010 to 2022, except for Indonesia (2015–2022), Malaysia (2018–2022), and the Philippines (2016–2022); the other countries are Cambodia, Laos, Myanmar, Thailand, and Vietnam. The rice cropland data are from IFPRI (2019). Each point represents a cell. Four of the cells have the cropland area equal to zero, and 43 of the cells have the average number of conflict incidents equal to zero. These respective points appear at the bottom and left edges of the plot.

**4. Estimation, Identification, and Interpretation**

We denote *location*, a one-degree cell, with subscript *i*, *country* with subscript *c*, *year* with subscript *t*, and *month* with subscript *m*. Henceforth, we also refer to year-month as *period*. The unit of analysis, thus, is a location–period covering 376 unique grid cells and, in most cases, 156 year-months from January 2010 to December 2022. The level of spatial aggregation—one-degree cells that measure approximately 110×110 km near the equator—is coarse enough to ensure that there are enough units with at least one conflict incident (Table 2). This level of aggregation, moreover, is granular enough to not sabotage the within-country variation in conflict incidents.

Our main econometric specification is given in a fixed effects setting as follows:

, (1)

where the outcome variable, , is a binary variable that takes the value of one if the number of conflict incidents in cell *i* in month *m* of year *t*, , exceeds zero, and zero otherwise. That is, the outcome variable measures the incidence of conflict. The treatment variable, , is the product of the cropland binary variable and the harvest binary variable. *cropland*, which is fixed over time, takes the value of one if more than 10 thousand hectares of land is used for rice production in the cell (IFPRI, 2019), and zero otherwise. *harvest*, which is cell-specific, takes the value of one when the period of observation is the harvest month, and zero otherwise. is a cell fixed effect, is a country-year fixed effect, and is a year–month fixed effect. is a set of controls—in most specifications just the contemporaneous rainfall—that vary across locations and over time. is the error term.

The identifying assumption in Equation (1) is that the treatment variable is exogenous to conflict. This assumption may seem tenuous, because conflict may affect production via abandoned plots and missed or mistimed harvests and planting seasons. So, a lower agricultural output may be the consequence, rather than the cause, of the change in conflict. But in the present study, we do not apply production data that would vary yearly. Instead, we use cropland area and harvest months, which are location-specific and fixed over time. Such an approach, admittedly driven by data limitations, mitigates the issue of reverse causality.

To address other threats to identification, we include the fixed effects and control variables in the regression. Specifically, cell fixed effects capture any time-invariant determinants of conflict (e.g., distance to roads, cities, or state borders), country-year fixed effects control for any country-specific trends in the data (e.g., large-scale political turmoil in election years), and year–month fixed effects capture common time-varying events observed in the region (e.g., global financial crises, large-scale climatic shocks, possible changes in the quality of data collection/reporting). We also include contemporaneous rainfall, which varies over time and across space, in the regression in an attempt to address, at least to an extent, remaining endogeneity issues. Specifically, this allows us to control for the direct impact of weather on conflict, for example, if excessive rainfall reduces the mobility of troops or makes protests and demonstrations somewhat untenable. Finally, in the robustness checks, we vary the fixed effects to get a better sense of potential threats to our identification strategy.

Under the outlined assumptions, the estimated coefficient, , reflects the harvest-time change in the probability of conflict in the cropland. A positive value of the coefficient, for example, would imply that in croplands, there is higher probability of conflict during the months of harvest, compared to the other months of the year. To aid with the interpretation of the estimated effect, we divide the estimated effect by the expected number of incidents and multiply by 100, to express the impact in percentage terms.

**5. Results and Discussion**

In Table 3 we summarize the baseline results of the study using all available data. During the harvest season, we estimate increase in battles and violence against civilians. These effects, which are statistically significantly different from zero, are of meaningful magnitude. The estimated harvest-time reduction in riots and protests are indistinguishable from zero. These effects are for locations that are deemed as croplands relative to other locations.

We obtain the magnitude of the effect by evaluating the estimated parameters relative to the baseline conflict incidence. So, we estimate a 7.4 increase in the probability of battles, and a 12.6 percent increase in the probability of violence against civilians during the harvest season. The estimated 2.6 and 3.3 percent reductions in the probabilities of riots and protests are not statistically significant.

**Table 3: Harvest-time change in conflict incidence in the croplands of Southeast Asia**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Cropland×Harvest | 0.005 | 0.008\*\* | 0.013\*\*\* | -0.001 | -0.006 |
|  | (0.005) | (0.003) | (0.003) | (0.002) | (0.005) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.503 | 0.463 | 0.183 | 0.359 |
| *Baseline conflict incidence:* | 0.29 | 0.11 | 0.10 | 0.03 | 0.17 |
| *Magnitude of the estimated effect relative to the baseline conflict incidence:* | | | | | |
| Cropland×Harvest (%) | 1.7 | 7.4\*\* | 12.6\*\*\* | -2.6 | -3.3 |
|  | (1.8) | (2.9) | (3.1) | (6.8) | (2.7) |

Note: The outcome variable is the indicator for the presence of conflict in a cell in a year-month; the treatment variable is the cropland indicator interacted with the harvest-season binary variable; the column headed by ‘All events’ combines all forms of conflict, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects, and control for contemporaneous rainfall; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as: , where is the parameter estimate, and is the baseline conflict incidence—the unconditional mean of the outcome variable.

Different mechanisms are presumably at play here. The rapacity mechanism may explain the harvest-time increase in conflict and violence against civilians, which likely combines a direct effect of perpetrators targeting areas where there are spoils to be appropriated, and an indirect effect of a collateral damage associated with explosions or other battle-related incidents, for example, as more people are out and about during the harvest season. The opportunity cost mechanism may explain the decrease in social unrest when people are busy harvesting. If a farmer—and especially a subsistence farer for whom rice harvest time may be the main and only payday of the year—were to choose one month when they would rather not participate in protests, that would likely be the month of the harvest. The presence of the offsetting resentment mechanism—linked with the harvest-time change in relative incomes of farmers and non-farmers—may explain why this decrease is small and statistically indistinguishable from zero.

Before we proceed with tests for the mechanisms—because the study covers a relatively small and geographically concentrated area, as well as a relatively short period—we check that the results are not sensitive to data subsetting or model variations.

*5.1 Robustness to data subsetting and alternative specifications*

First, we re-estimate the baseline model using balanced panels that (i) cover all eight countries but only include years from 2018 to 2022, and (ii) cover all thirteen years but not include Indonesia, Malaysia and Philippines. Appendix Tables B1 and B2 present the results of these regressions. The estimates for the harvest-time change in the probability of battles and violence are comparable with those of the main results of this study. The estimates for the harvest-time change in the probability of social unrest is somewhat sensitive to data subsetting, insomuch as when we analyze the panel of countries over the 2018-2022 period, we estimate statistically significant decrease in protests.

Next, we re-estimate the baseline model by omitting (i) one country at a time, and (ii) one year at a time. Appendix Figures A3 and A4 present the estimated parameters, which appear to be largely robust to omitting subsets of data from the analysis. A notable exception is when we omit Myanmar from the data, but that is not surprising—the country accounts for nearly half of all observed conflict incidents.

To ensure that our main results are not driven by our choice of the fixed effects, or that the inference is not affected by our choice of error clustering, we re-estimate the parameters using a set of alternative model specifications. We summarize these results in the specification chart presented in Appendix Figure A5. The results are not sensitive to different combinations of the fixed effects. The key finding that violence against civilians increases at harvest time, while all other forms of conflict either do not change or the change is not statistically significant, stands in most instances, except when we cluster the standard errors at country level.

To ensure that the estimated results are not a mere happenstance, we perform a sample randomization exercise. Specifically, we shuffle and randomly re-assign the observed harvest seasons to different locations and re-estimated the baseline regression. We repeat this 100 times. On average, we would expect no significant effect here. Appendix Figure A6 confirms this. Apart from just a few statistically significant estimates of the impact, we observe no substantial impact when the “wrong” harvest seasons are randomly assigned to the croplands.

*5.2 Testing for the Mechanisms*

To examine the mechanisms alluded above, we compare the changes in conflict incidence across years with crop growing seasons that experiences scarce or excessive rain, both plausibly damaging for crop yields. So, we interact the treatment variable with the cell-specific categorical variable that divides the growing seasons into dry (less than one standard deviation of the average rainfall in the cell), normal (within one standard deviation of the average rainfall in the cell), and wet (greater than one standard deviation of the average rainfall in the cell) years. If our proposed rapacity mechanism is valid, we would expect a smaller (or no) increase in harvest-time violence in presumably bad crop years compared to the presumably good crop years. Moreover, if our conjecture about the offsetting effects of the opportunity cost and resentment mechanisms is valid, we would expect a reduction in social unrest in presumably bad crop years. This is because regardless of how good or bad the crop year looks, farmers will harvest the crop. So, the opportunity cost of protesting during the harvest season would remain largely intact. But low yield will result in smaller change in within-cell income inequality between farmers and non-farmers. This will mitigate the possibility of social unrest attributed to resentment.

Table 4 presents the harvest-time effects of growing season rainfall on forms of conflict. The inverted U-shaped effect of growing season rainfall on violence well aligns with our expectation regarding the rapacity effect. The no effect in riots and protests cast a shadow over our expectation regarding the offsetting effects of the opportunity cost and resentment—it may very well be the case that neither of the effects are present.

We also observe a negative relationship between growing season rainfall and harvest battles. This could be pointing at the direct—unrelated to harvest—channel that the weather, and rainfall in particular, has on conflict: actors engage in large scale military campaigns with ease when roads are dry. So, the observed change in harvest-time battles can be due to intensified civil conflict due to the relatively dry conditions during the usually wet season. This effect then lingers into the harvest period, which in turn, presents an additional motivation for conflict (perhaps some citations).

**Table 4: Harvest-time change in conflict incidence in dry, normal, and wet growing seasons**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Cropland×Harvest×Dry | 0.024\*\* | 0.015\*\* | 0.014\* | 0.001 | -0.004 |
|  | (0.011) | (0.008) | (0.008) | (0.004) | (0.010) |
| Cropland×Harvest×Normal | 0.005 | 0.008\*\* | 0.016\*\*\* | -0.001 | -0.006 |
|  | (0.006) | (0.003) | (0.004) | (0.003) | (0.006) |
| Cropland×Harvest×Wet | -0.010 | 0.003 | 0.004 | -0.002 | -0.007 |
|  | (0.009) | (0.007) | (0.005) | (0.004) | (0.008) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.503 | 0.463 | 0.183 | 0.359 |
| *Baseline conflict incidence:* | 0.29 | 0.11 | 0.10 | 0.03 | 0.17 |
| *Magnitude of the estimated effect relative to the baseline conflict incidence (%):* | | | | | |
| Cropland×Harvest×Dry | 8.5\*\* | 13.7\*\* | 13.8\* | 2.3 | -2.2 |
|  | (3.7) | (6.9) | (7.8) | (12.2) | (5.8) |
| Cropland×Harvest×Normal | 1.8 | 7.3\*\* | 14.9\*\*\* | -2.9 | -3.3 |
|  | (2.1) | (3.5) | (3.5) | (8.6) | (3.2) |
| Cropland×Harvest×Wet | -3.6 | 2.8 | 4.3 | -5.1 | -4.0 |
|  | (3.3) | (6.1) | (5.1) | (12.3) | (4.8) |

Note: The outcome variable is the incidence of conflict in a cell during a year-month; the treatment variable is the cropland binary variable interacted with the harvest-season binary variable; the column headed by ‘All events’ combines all forms of conflict, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects, and control for contemporaneous rainfall; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as: , where is the parameter estimate, and is the baseline conflict incidence—the unconditional mean of the outcome variable.

To validate that we pick up the agricultural production link through our growing season rainfall, we interact the treatment variable with an irrigation binary variable. We denote cells *irrigated* if at least 50 percent of rice is produced on irrigated land, and *rainfed* otherwise (as illustrated in Figure 3). In general, irrigated rice is the higher-yield and, often, commercially produced, as opposed to rainfed rice, which is lower-yield and produced at subsistence levels. So, very different types of farmers are likely involved in these two production practices. As before, to test the mechanisms we interact the right-hand-side variables with the categorical variable depicting growing season rainfall. Table 5 presents these regression results.

**Table 5: Harvest-time change in conflict incidence in rainfed vs irrigated lands**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Cropland×Harvest×Dry | 0.020 | 0.018\* | 0.015 | -0.004 | -0.006 |
|  | (0.014) | (0.010) | (0.010) | (0.005) | (0.013) |
| Cropland×Harvest×Normal | -0.002 | 0.009\* | 0.019\*\*\* | -0.004 | -0.015\*\* |
|  | (0.008) | (0.005) | (0.005) | (0.004) | (0.007) |
| Cropland×Harvest×Wet | -0.006 | -0.001 | 0.007 | -0.002 | 0.002 |
|  | (0.012) | (0.009) | (0.007) | (0.005) | (0.011) |
| Cropland×Harvest×Dry | 0.012 | -0.008 | -0.001 | 0.014 | 0.008 |
| ×Irrigated | (0.018) | (0.014) | (0.016) | (0.009) | (0.019) |
| Cropland×Harvest×Normal | 0.016 | -0.002 | -0.008 | 0.007 | 0.021 |
| ×Irrigated | (0.011) | (0.007) | (0.006) | (0.004) | (0.010) |
| Cropland×Harvest×Wet | -0.010 | 0.008 | -0.007 | 0.000 | -0.020 |
| ×Irrigated | (0.017) | (0.013) | (0.010) | (0.009) | (0.014) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.503 | 0.463 | 0.183 | 0.359 |
| *Magnitude of the estimated effect relative to the baseline conflict incidence (%):* | | | | | |
| **Rainfed** | | | | | |
| *Baseline conflict incidence:* | *0.31* | *0.14* | *0.11* | *0.04* | *0.19* |
| Cropland×Harvest×Dry | 6.5 | 13.1\*\* | 13.0 | -10.4 | -3.4 |
|  | (4.6) | (7.1) | (9.1) | (13.8) | (7.0) |
| Cropland×Harvest×Normal | -0.5 | 6.5\* | 16.7\*\*\* | -10.3 | -7.9\*\* |
|  | (2.5) | (3.9) | (4.1) | (10.8) | (3.9) |
| Cropland×Harvest×Wet | -1.8 | -0.4 | 6.3 | -4.8 | 0.9 |
|  | (4.0) | (6.7) | (6.4) | (13.6) | (6.1) |
| **Irrigated** | | | | | |
| *Baseline conflict incidence:* | *0.24* | *0.07* | *0.09* | *0.03* | *0.16* |
| Cropland×Harvest×Dry | 13.5\*\*\* | 14.1 | 15.1 | 32.1 | 1.0 |
|  | (5.0) | (16.3) | (14.3) | (24.2) | (9.2) |
| Cropland×Harvest×Normal | 6.0\* | 10.4 | 12.2\*\* | 9.5 | 3.8 |
|  | (3.4) | (6.9) | (5.4) | (10.6) | (4.8) |
| Cropland×Harvest×Wet | -6.7 | 11.3 | 0.6 | -4.2 | -11.4\* |
|  | (5.4) | (14.0) | (8.3) | (24.9) | (6.7) |

Note: The outcome variable is the incidence of conflict in a cell during a year-month; the treatment variable is the cropland binary variable interacted with the harvest-season binary variable; the column headed by ‘All events’ combines all forms of conflict, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects, and control for contemporaneous rainfall; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as: , where is the parameter estimate, and is the baseline conflict incidence—the unconditional mean of the outcome variable.

Additional features of interest emerge that help explain the suggested mechanisms and clarify some of the earlier findings. The inverted U-shaped effect of the growing season rainfall is more evident in rainfed locations, expectedly. Moreover, as irrigation likely serves as a buffer against drier than usual crop growing seasons, on irrigated lands we estimate the decrease in violence only during wet growing seasons.

The harvest-time reduction in protests, during relatively normal crop growing seasons, becomes evident in rainfed locations, while absent in irrigated locations. Such a difference in the estimated effects points to a possibility that opportunity cost effect dominates the resentment effect in rainfed areas where harvest-time windfall is not as large as in more commercial irrigated areas. We do observe a considerable drop in protests in irrigated areas in the wake of the rainier than usual crop growing season, which is a plausibly yield-reducing and, therefore, resentment-mitigating effect.

Finally, to investigate whether the changes in harvest-time conflict is in any way a byproduct of larger scale military activities in the region, we zoom in on two distinct types of conflict: violence against civilians, which necessarily involves a perpetrator and an unarmed civilian; and protests (and riots), which do not involve a military actor as such and is largely a manifestation of grievance against the state or the de facto government. So, we interact the treatment variable in the baseline equation with the combined number of battles and explosions as defined by the ACLED Project during the crop growing season, and re-estimate the regression equations with violence against civilians, riots, and protests as the dependent variables. Table 6 presents the results of this exercise.

These results offer an additional set of insights. First, both violence and protests are more likely when the background conflict level is elevated. This is to be expected—the battles and explosions usually involve, directly or indirectly, the state. As a result, there is less policing elsewhere, which among other things, results in more crime and less order in the region. In the same vein, albeit in different context, Ekhator-Mobayode et al., (2022) found the increasing effect of armed conflict on intimate partner violence in Nigeria. Second, harvest-time increase in violence is only present during the ongoing larger scale conflict, but not otherwise. That is, seasonal violence is squarely a byproduct of broader political conflict. This finding is consistent with the ‘living off the land’ theory (Koren and Bagozzi, 2017), insofar as in times of war, any co-optation between fighters and farmers breaks down, which leads to more violence.

**Table 6: Elevated levels of battles and harvest-time violence and unrest in the croplands**

|  | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | |
| Area × Harvest | 0.028\*\*\* | -0.003 | -0.058\*\* |
|  | (0.007) | (0.003) | (0.028) |
| Area × Harvest × Battles | 0.142\*\*\* | -0.003 | -0.017 |
|  | (0.050) | (0.002) | (0.079) |
| Obs. | 44,724 | 44,724 | 44,724 |
| R2 | 0.392 | 0.145 | 0.296 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | |
| Baseline conflict | 0.36 | 0.05 | 0.61 |
| Area harvested | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | |
| Harvest (%) | 7.5\*\*\* | -6.0 | -8.9\*\* |
|  | (1.8) | (5.3) | (4.2) |
| Harvest × Battles (%) | 44.7\*\*\* | -11.1 | -11.5 |
|  | (14.1) | (7.8) | (14.0) |

Note: the outcome variable is a count variable that depicts the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Battles is the standardized measure of the total number of battles and explosions/remote violence during the crop growing season preceding the harvest; all regressions include cell and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

*5.2 Alternative specifications and robustness checks*

**7. Conclusion**

Can the seasonal nature of employment and income in the agricultural sector lead to temporal changes in social conflict? We address this question by examining more than a decade of granular data on different types of conflict across ten countries in Southeast Asia. We find that violence against civilians increases but protests decrease during months of the rice harvest. Using additional data on weather and irrigation, we investigate mechanisms that help explain such seasonal dynamics and link those to the theories of conflict. After subjecting our main results to a set of robustness checks, we remain confident about the harvest-time increase in violence but find the harvest-time decrease in protests being sensitive to omitting subsets of data that are likely linked to the recent social unrest in Myanmar.

We make several contributions to the literature on conflict and agricultural shocks. To better understand the pathways between harvest-time violence and conflict, we disaggregate conflict into two types of conflict which are often carried out by different groups of people for different reasons – violence against civilians, as well as battles and explosions, usually carried out by the state, allied militias, or anti-state insurgent groups; and protests and riots, often against state policies, by civilians. Instead of resolving the debate over the mechanisms of resource-related conflict on one side or the other, we suggest that different types of conflict (usually instigated by different types of conflict actors) are related to seasonal agricultural output through different mechanisms: conflict *by* civilians is better understood through the opportunity cost mechanism, while conflict *against* civilians is better understood through the rapacity mechanism.

The findings of the study present important insights for conflict resolution and development policy. The knowledge that political violence and social unrest in rural Southeast Asia can be linked to the rice harvest months can aid the more effective planning by local governments and, particularly, international agencies that are concerned with rural development programs.

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APPENDICES

APPENDIX A. FIGURES

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**Figure A1: Distribution of the proportion of irrigated rice croplands**

Note: Data are from IFRPI (2019), and cover Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Thailand, and Vietnam.

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**Figure A2: The proportion of irrigated croplands and the size of cropland areas**

Note: Data are from IFRPI (2019), and cover Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Thailand, and Vietnam.

**A picture containing text, screenshot, number, parallel

Description automatically generated**

**Figure A3: Sensitivity of the estimates to omitting one country at a time from the dataset**

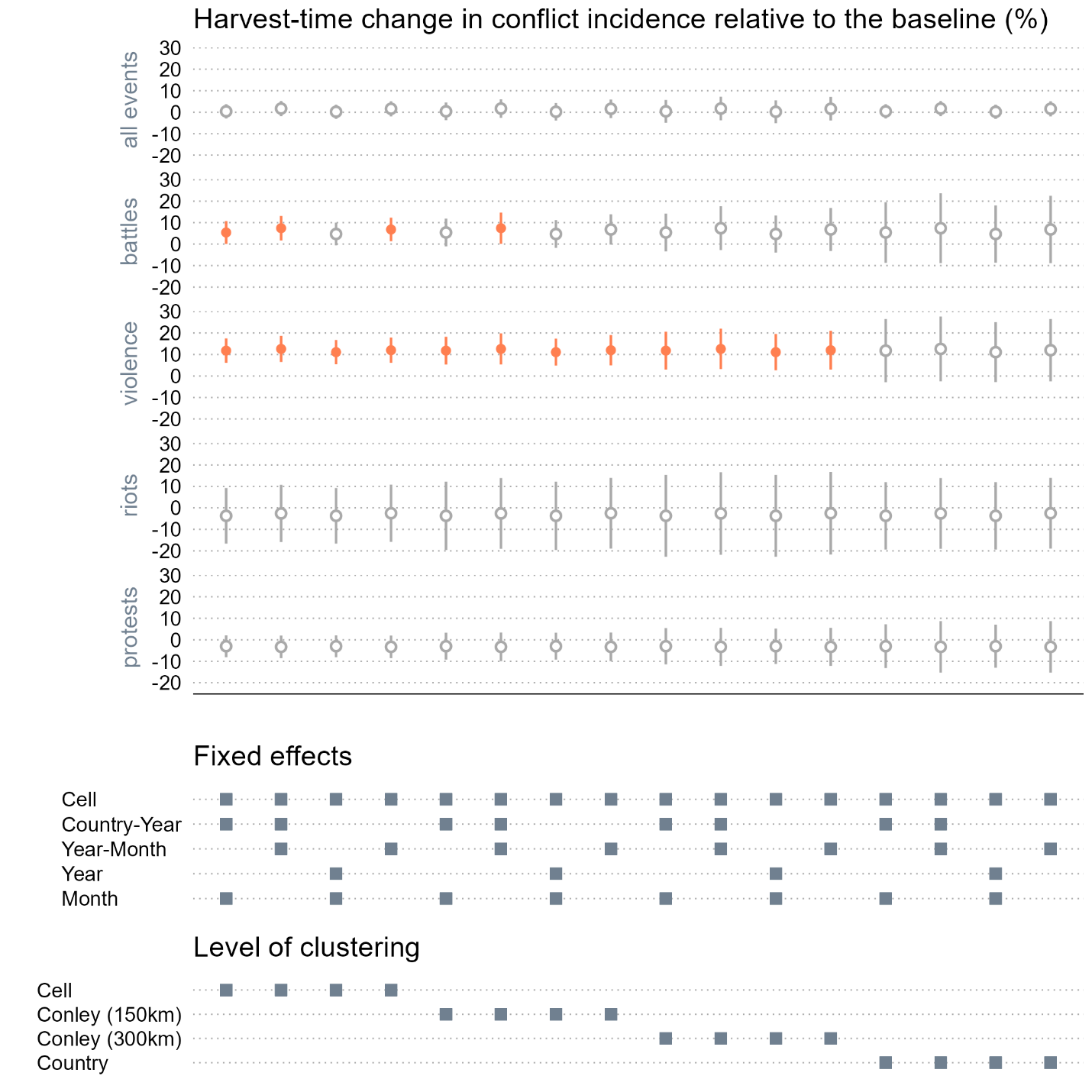
Note: The dots indicate point estimates, and the error bars show 95% confidence intervals around the point estimates; the confidence intervals are obtained using standard errors adjusted to clustering at the level of a cell. The colored dots and error bars show the impacts that are statistically significantly positive (orange) or negative (blue) at 5% level. The impact, presented in percentage terms, is calculated as: , where is the parameter estimate, and is the baseline conflict incidence.

**A picture containing text, screenshot, number, parallel

Description automatically generated**

**Figure A4: Sensitivity of the estimates to omitting one year at a time from the dataset**

Note: The dots indicate point estimates, and the error bars show 95% confidence intervals around the point estimates; the confidence intervals are obtained using standard errors adjusted to clustering at the level of a cell. The colored dots and error bars show the impacts that are statistically significantly positive (orange) or negative (blue) at 5% level. The impact, presented in percentage terms, is calculated as: , where is the parameter estimate, and is the baseline conflict incidence.

****

**Figure A5: Specification chart**

Note:

**A screenshot of a graph

Description automatically generated with low confidence**

**Figure A6: The estimated impacts using randomly assigned harvest seasons**

Note: In the top panel, the dots indicate point estimates, and the error bars show 95% confidence intervals around the point estimates; the confidence intervals are obtained using standard errors adjusted to clustering at the level of a cell. The colored dots and error bars show the impacts that are statistically significantly positive (orange) or negative (blue) at 5% level. In the bottom panel, the densities are those of the point estimates. The impact, presented in percentage terms, is calculated as: , where is the parameter estimate, and is the baseline conflict incidence.

APPENDIX B. TABLES

**Table B1: The harvest-time change in conflict incidence in the croplands of Southeast Asia**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Balanced panel: all countries, years 2018-2022* | | | | | |
| Cropland×Harvest | -0.002 | 0.016\*\*\* | 0.016\*\*\* | -0.005 | -0.018\*\*\* |
|  | (0.007) | (0.004) | (0.005) | (0.003) | (0.007) |
| Obs. | 22,560 | 22,560 | 22,560 | 22,560 | 22,560 |
| R2 | 0.506 | 0.575 | 0.508 | 0.227 | 0.413 |
| *Baseline conflict incidence:* | 0.37 | 0.15 | 0.15 | 0.05 | 0.24 |
| *Magnitude of the estimated effect relative to the baseline conflict incidence:* | | | | | |
| Cropland×Harvest (%) | -0.5 | 10.4\*\*\* | 10.6\*\*\* | -10.3 | -7.6\*\*\* |
|  | (1.9) | (2.9) | (3.4) | (6.8) | (2.7) |

Note: The outcome variable is the indicator for the presence of conflict in a cell in a year-month; the treatment variable is the cropland indicator interacted with the harvest-season binary variable; the column headed by ‘All events’ combines all forms of conflict, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects, and control for contemporaneous rainfall; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as: , where is the parameter estimate, and is the baseline conflict incidence—the unconditional mean of the outcome variable.

**Table B2: The harvest-time change in conflict incidence in the croplands of Southeast Asia**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries except Indonesia, Malaysia, and Philippines, all years* | | | | | |
| Cropland×Harvest | 0.019\*\* | 0.020\*\* | 0.022\*\*\* | 0.002 | 0.000 |
|  | (0.008) | (0.005) | (0.005) | (0.003) | (0.007) |
| Obs. | 26,052 | 26,052 | 26,052 | 26,052 | 26,052 |
| R2 | 0.399 | 0.485 | 0.389 | 0.125 | 0.309 |
| *Baseline conflict incidence:* | 0.23 | 0.10 | 0.08 | 0.02 | 0.14 |
| *Magnitude of the estimated effect relative to the baseline conflict incidence:* | | | | | |
| Cropland×Harvest (%) | 8.2\*\* | 20.7\*\*\* | 28.4\*\*\* | 10.8 | 0.0 |
|  | (3.3) | (4.8) | (6.0) | (16.1) | (4.9) |

Note: The outcome variable is the indicator for the presence of conflict in a cell in a year-month; the treatment variable is the cropland indicator interacted with the harvest-season binary variable; the column headed by ‘All events’ combines all forms of conflict, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects, and control for contemporaneous rainfall; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as: , where is the parameter estimate, and is the baseline conflict incidence—the unconditional mean of the outcome variable.

**Table B3: Harvest-time change in conflict after dry, normal, and wet crop growing seasons**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years, excluding Myanmar 2021-2022* | | | | | |
| Area × Harvest × Dry | -0.075 | -0.012 | 0.016 | -0.004 | -0.076 |
|  | (0.064) | (0.027) | (0.014) | (0.006) | (0.050) |
| Area × Harvest × Normal | 0.043\* | 0.002 | 0.021\*\*\* | -0.002 | 0.022 |
|  | (0.022) | (0.008) | (0.008) | (0.003) | (0.015) |
| Area × Harvest × Wet | -0.003 | -0.018 | 0.004 | 0.000 | 0.011 |
|  | (0.038) | (0.013) | (0.008) | (0.004) | (0.028) |
| Obs. | 43,308 | 43,308 | 43,308 | 43,308 | 43,308 |
| R2 | 0.506 | 0.459 | 0.408 | 0.181 | 0.458 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.11 | 0.33 | 0.28 | 0.05 | 0.45 |
| Area harvested | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | | | |
| Harvest × Dry (%) | -6.3 | -3.4 | 5.4 | -6.8 | -15.7 |
|  | (5.4) | (7.7) | (4.5) | (12.0) | (10.3) |
| Harvest × Normal (%) | 3.6\* | 0.5 | 6.9\*\*\* | -4.1 | 4.6 |
|  | (1.9) | (2.2) | (2.6) | (6.4) | (3.1) |
| Harvest × Wet (%) | -0.3 | 5.2 | 1.3 | 0.0 | 2.4 |
|  | (3.2) | (3.8) | (2.7) | (7.0) | (5.7) |

Note: the outcome variable is a count variable that depicts the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B4: Harvest-time conflict after dry, normal, and wet crop growing seasons**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest × Dry | -0.045 | 0.086 | 0.017 | -0.007 | -0.142\* |
|  | (0.168) | (0.098) | (0.021) | (0.007) | (0.077) |
| Area × Harvest × Normal | 0.049 | 0.069\*\* | 0.050\*\*\* | -0.005 | -0.065\* |
|  | (0.044) | (0.028) | (0.013) | (0.004) | (0.015) |
| Area × Harvest × Wet | -0.040 | -0.005 | 0.005 | -0.001 | -0.038 |
|  | (0.047) | (0.022) | (0.010) | (0.004) | (0.031) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.394 | 0.373 | 0.391 | 0.146 | 0.296 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.60 | 0.59 | 0.36 | 0.05 | 0.61 |
| Area harvested | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | | | |
| Harvest × Dry (%) | -2.6 | 13.7 | 4.6 | -12.1 | -21.7\* |
|  | (9.8) | (15.6) | (5.5) | (12.0) | (11.8) |
| Harvest × Normal (%) | 2.9 | 11.0\*\* | 13.1\*\*\* | -9.7 | -9.9\* |
|  | (2.6) | (4.5) | (3.3) | (7.5) | (5.1) |
| Harvest × Wet (%) | -2.3 | -0.8 | 1.2 | -2.8 | -5.9 |
|  | (2.8) | (3.4) | (2.5) | (6.8) | (4.8) |

Note: the outcome variable is the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects and control for contemporaneous rainfall in the cell; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B5: Harvest-time conflict incidence after dry, normal, and wet crop growing seasons**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest × Dry | 0.011\* | 0.007\*\* | 0.010\*\* | 0.002 | -0.004 |
|  | (0.007) | (0.003) | (0.004) | (0.003) | (0.006) |
| Area × Harvest × Normal | 0.004 | 0.004\*\*\* | 0.005\*\*\* | 0.000 | 0.000 |
|  | (0.003) | (0.002) | (0.002) | (0.001) | (0.003) |
| Area × Harvest × Wet | 0.000 | -0.001 | 0.002 | 0.000 | 0.001 |
|  | (0.004) | (0.002) | (0.002) | (0.002) | (0.003) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.503 | 0.463 | 0.183 | 0.359 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 0.25 | 0.09 | 0.09 | 0.03 | 0.16 |
| Area harvested | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | | | |
| Harvest × Dry (%) | 4.1\* | 7.5 | 10.0\*\* | 6.4 | -2.2 |
|  | (2.5) | (3.4) | (4.3) | (7.6) | (3.5) |
| Harvest × Normal (%) | 1.5 | 4.4\*\*\* | 5.0\*\*\* | -0.8 | 0.1 |
|  | (1.1) | (1.5) | (1.9) | (3.5) | (1.8) |
| Harvest × Wet (%) | -0.1 | -0.6 | 1.7 | -1.3 | 0.4 |
|  | (1.4) | (1.6) | (1.8) | (4.4) | (2.1) |

Note: the outcome variable is a binary variable that depicts the presence of any number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects and control for contemporaneous rainfall in the cell; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B4: Excess rain and harvest-time conflict in the croplands (subset of the data)**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years, excluding Myanmar 2021-2022* | | | | | |
| Area × Harvest | 0.023 | -0.001 | 0.015\*\*\* | 0.000 | 0.010 |
|  | (0.019) | (0.004) | (0.005) | (0.003) | (0.015) |
| Area × Harvest × Rain | -0.001 | 0.002 | -0.009 | -0.002 | 0.009 |
|  | (0.019) | (0.010) | (0.006) | (0.002) | (0.010) |
| Obs. | 43,308 | 43,308 | 43,308 | 43,308 | 43,308 |
| R2 | 0.506 | 0.459 | 0.408 | 0.180 | 0.458 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.11 | 0.33 | 0.28 | 0.05 | 0.45 |
| Area harvested | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | | | |
| Harvest (%) | 2.0 | -0.4 | 5.1\*\*\* | -0.9 | 2.1 |
|  | (1.6) | (1.2) | (1.7) | (5.0) | (3.0) |
| Harvest × Rain (%) | 2.0 | 0.2 | 2.1 | -4.0 | 3.9 |
|  | (1.9) | (2.5) | (1.7) | (4.4) | (3.5) |

Note: the outcome variable is a count variable that depicts the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B5: Excess rain, irrigation, and harvest-time conflict (subset of the data)**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years, excluding Myanmar 2021-2022* | | | | | |
| Area × Harvest | 0.075\*\*\* | 0.016 | 0.021\*\* | 0.004 | 0.033 |
|  | (0.028) | (0.010) | (0.008) | (0.004) | (0.020) |
| Area × Harvest × Rain | -0.023 | 0.008 | -0.004 | -0.007 | -0.019 |
|  | (0.050) | (0.021) | (0.011) | (0.006) | (0.035) |
| Area × Harvest | -0.116\*\* | -0.040\* | -0.014 | -0.011 | -0.051 |
| × Irrigated | (0.050) | (0.021) | (0.013) | (0.008) | (0.036) |
| Area × Harvest × Rain | 0.048 | -0.015 | -0.011 | 0.012 | 0.062 |
| × Irrigated | (0.099) | (0.027) | (0.018) | (0.012) | (0.076) |
| Obs. | 43,308 | 43,308 | 43,308 | 43,308 | 43,308 |
| R2 | 0.506 | 0.459 | 0.408 | 0.180 | 0.458 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.60 | 0.59 | 0.36 | 0.05 | 0.61 |
| Area harvested | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | | | |
| ***Rainfed*** | | | | | |
| Harvest (%) | 6.3\*\*\* | 4.6 | 7.0\*\* | 8.0 | 6.9 |
|  | (2.4) | (2.9) | (2.7) | (6.7) | (4.2) |
| Harvest × Rain (%) | 4.6 | 7.2 | 5.8\* | -4.6 | 2.9 |
|  | (4.2) | (6.8) | (3.1) | (8.2) | (7.5) |
| ***Irrigated*** |  |  |  |  |  |
| Harvest (%) | -3.4 | -6.8\* | 2.6 | -11.7 | -3.8 |
|  | (3.0) | (3.8) | (2.6) | (11.8) | (5.3) |
| Harvest × Rain (%) | -1.3 | -8.7 | -2.5 | -3.2 | 5.1 |
|  | (5.6) | (5.9) | (3.9) | (14.7) | (11.1) |

Note: the outcome variable is a count variable that depicts the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; Irrigated denotes the proportion of irrigated land in the cell; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B6: Battles and harvest-time violence and unrest in the croplands (subset of the data)**

|  | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years, excluding Myanmar 2021-2022* | | | |
| Area × Harvest | 0.015\*\*\* | -0.001 | 0.013 |
|  | (0.005) | (0.002) | (0.015) |
| Area × Harvest × Battles | 0.038\* | 0.000 | 0.011 |
|  | (0.023) | (0.002) | (0.011) |
| Obs. | 43,308 | 43,308 | 43,308 |
| R2 | 0.408 | 0.180 | 0.458 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | |
| Baseline conflict | 0.28 | 0.05 | 0.45 |
| Area harvested | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | |
| Harvest (%) | 4.9\*\*\* | -1.8 | 2.7 |
|  | (1.8) | (4.5) | (3.1) |
| Harvest × Battles (%) | 17.5\*\* | -1.5 | 4.9 |
|  | (8.8) | (5.8) | (4.6) |

Note: the outcome variable is a count variable that depicts the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Battles is the standardized measure of the total number of battles and explosions/remote violence during the crop growing season preceding the harvest; all regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B8: Excess rain and harvest-time conflict incidence in the croplands**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest | 0.005\* | 0.004\*\*\* | 0.005\*\*\* | 0.001 | 0.000 |
|  | (0.003) | (0.001) | (0.002) | (0.001) | (0.002) |
| Area × Harvest × Rain | -0.003 | -0.003\*\* | -0.002\*\* | -0.001 | 0.002 |
|  | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.503 | 0.463 | 0.183 | 0.359 |
| *Average cropland area (100,000 hectares) and the conflict incidence (baseline conflict):* | | | | | |
| Baseline conflict | 0.25 | 0.09 | 0.09 | 0.03 | 0.16 |
| Average cropland | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict incidence:* | | | | | |
| Harvest (%) | 1.8\* | 4.1\*\*\* | 5.1\*\*\* | 2.0 | 0.0 |
|  | (0.9) | (1.2) | (1.7) | (2.7) | (1.4) |
| Harvest × Rain (%) | 0.9 | 1.7 | 2.6\* | -1.4 | 1.3 |
|  | (0.9) | (1.3) | (1.4) | (2.6) | (1.4) |

Note: the outcome variable is a binary variable that depicts the presence of any number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B9: Excess rain, irrigation, and harvest-time conflict incidence**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest | 0.004 | 0.008\*\*\* | 0.007\*\*\* | 0.000 | -0.004 |
|  | (0.004) | (0.002) | (0.002) | (0.002) | (0.004) |
| Area × Harvest × Rain | -0.005 | -0.006\*\*\* | -0.003\* | -0.002 | 0.003 |
|  | (0.003) | (0.002) | (0.002) | (0.002) | (0.003) |
| Area × Harvest | 0.001 | -0.008\*\* | -0.006 | 0.002 | 0.008 |
| × Irrigated | (0.008) | (0.003) | (0.004) | (0.002) | (0.007) |
| Area × Harvest × Rain | 0.004 | 0.008\*\* | 0.002 | 0.001 | -0.002 |
| × Irrigated | (0.005) | (0.003) | (0.003) | (0.003) | (0.005) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.504 | 0.463 | 0.183 | 0.359 |
| *Average cropland area (100,000 hectares) and the conflict incidence (baseline conflict):* | | | | | |
| Baseline conflict | 0.25 | 0.09 | 0.09 | 0.03 | 0.16 |
| Average cropland | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict incidence:* | | | | | |
| ***Rainfed*** | | | | | |
| Harvest (%) | 1.6 | 7.5\*\*\* | 7.8\*\*\* | -1.0 | -2.1 |
|  | (1.4) | (2.0) | (2.3) | (4.6) | (2.4) |
| Harvest × Rain (%) | -0.1 | 2.0 | 4.6\*\* | -5.5 | -0.6 |
|  | (1.5) | (2.1) | (2.0) | (4.6) | (2.4) |
| ***Irrigated*** |  |  |  |  |  |
| Harvest (%) | 2.0 | -0.5 | 1.5 | 5.9 | -2.8 |
|  | (2.1) | (2.0) | (3.0) | (4.4) | (2.7) |
| Harvest × Rain (%) | 2.1 | 1.2 | 0.0 | 4.0 | 3.7 |
|  | (2.0) | (2.9) | (2.2) | (7.7) | (3.2) |

Note: the outcome variable is a count variable that depicts the presence of any number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Rain is the standardized measure of cumulative rainfall during the crop growing season preceding the harvest; Irrigated denotes the proportion of irrigated land in the cell; the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

**Table B10: Battles and harvest-time incidence of violence and unrest in the croplands**

|  | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | |
| Area × Harvest | 0.004\*\*\* | 0.000 | 0.001 |
|  | (0.001) | (0.001) | (0.002) |
| Area × Harvest × Battles | 0.017\*\*\* | -0.002 | -0.005 |
|  | (0.004) | (0.001) | (0.004) |
| Obs. | 44,724 | 44,724 | 44,724 |
| R2 | 0.465 | 0.183 | 0.359 |
| *Average cropland area harvested (100,000 hectares) and the baseline conflict incidence:* | | | |
| Baseline conflict | 0.09 | 0.03 | 0.16 |
| Area harvested | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | |
| Harvest (%) | 4.0\*\*\* | 1.1 | 0.4 |
|  | (1.5) | (2.4) | (1.3) |
| Harvest × Battles (%) | 22.1\*\*\* | -3.8 | -2.6 |
|  | (4.4) | (4.1) | (3.2) |

Note: the outcome variable is a count variable that depicts the presence of any number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); Battles is the standardized measure of the total number of battles and explosions/remote violence during the crop growing season preceding the harvest; all regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

We test the mechanisms by interacting our treatment variable with the growing season rainfall—one of the key factors in rice production. In so doing, we rely on empirical evidence that excessive rain during the rice growing season may be damaging for yields (e.g., Crost et al., 2018; Fu et al., 2023). So, if our proposed mechanisms are valid, we would expect the effects from our main specification to attenuate to zero in the wake of a rainier than usual growing season. Indeed, after a one-standard-deviation increase in the growing season rainfall, the harvest-time increase in violence is less pronounced, while both the harvest-time increase in battles and explosions/remote violence and the harvest-time decrease in protests largely vanish and become statistically indistinguishable from zero.

To further examine the potentially heterogeneous effect of agricultural shocks on conflict we introduce the cell–specific irrigation variable, bounded by zero and one, into the analysis. We find that much of the estimated effect happens in places where rainfed rice is cultivated. Irrigation, which likely also proxies the better infrastructure in general, mitigates much of the harvest-time conflict in Southeast Asia—a finding that echoes that of Gatti et al. (2021).

Finally, we entertain the idea that forms of conflict that involve civilians—i.e., violence against civilians and protests by civilians—can be related, directly or indirectly, to large-scale military events in the region. That is, incidents of violence against civilians and protests by civilians increase during periods of elevated levels of conflict that typically involves the state and insurgents. We find that armed conflicts that coincide with the crop growing season in the region amplify harvest-time increase in violence and mitigate harvest-time decrease in protests. The former, in particular, echoes the ‘living off the land’ theory (Koren and Bagozzi, 2017), which suggests that co-optation between fighters and farmers—observed in times of peace—breaks down during periods of conflict.

The outcome variable in our main specification is the count of conflict incidents in a given location at a given period. So, in this specification, the parameter associated with the treatment variable measures the harvest-time change in the number of incidents. Alternatively, we could define the outcome variable in terms of conflict incidence. Keeping all other elements of the model the same as before, this would result in the following model specification:

, (2)

where the outcome variable, , now is a binary variable that takes on value of one when any number of conflict incidents happen in cell *i* in month *m* of year *t*, and zero otherwise. This, of course, changes the interpretation of the estimated effect, which now measures the harvest time change in the conflict incidence.

**Table 4: Harvest-time change conflict in the croplands of Southeast Asia**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years, excluding Myanmar 2021-2022* | | | | | |
| Area × Harvest | 0.023 | -0.001 | 0.013\*\*\* | -0.001 | 0.012 |
|  | (0.019) | (0.004) | (0.004) | (0.002) | (0.015) |
| Obs. | 43,308 | 43,308 | 43,308 | 43,308 | 43,308 |
| R2 | 0.506 | 0.459 | 0.408 | 0.180 | 0.458 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.11 | 0.33 | 0.28 | 0.05 | 0.45 |
| Area harvested | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | | | |
| Harvest (%) | 1.9 | -0.3 | 4.2\*\*\* | -1.8 | 2.6 |
|  | (1.6) | (1.2) | (1.5) | (4.5) | (3.0) |

Note: the outcome variable is the number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects and control for contemporaneous rainfall; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

Using this alternative definition of the outcome variable, we re-estimate the baseline model. The results are presented in Table 5. These results—that are based on full sample, which includes the Myanmar 2021-2022 data—closely align with those when the outcome variable is the number of incidents, but the Myanmar 2021-2022 observations are excluded from the sample. Such comparable results are not entirely unexpected. By transforming the count variable (number of conflict incidents) to a binary variable (conflict incidence) we mitigate the effect of influential observations manifested through surges in forms of conflict incidents in the wake of the Myanmar civil conflict.

**Table 5: Harvest-time conflict incidence in the croplands of Southeast Asia**

|  | **All events** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest | 0.004 | 0.003\*\*\* | 0.004\*\*\* | 0.000 | 0.000 |
|  | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) |
| Obs. | 44,724 | 44,724 | 44,724 | 44,724 | 44,724 |
| R2 | 0.447 | 0.503 | 0.463 | 0.183 | 0.359 |
| *Average cropland area (100,000 hectares) and the conflict incidence (baseline conflict):* | | | | | |
| Baseline conflict | 0.25 | 0.09 | 0.09 | 0.03 | 0.16 |
| Average cropland | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict incidence:* | | | | | |
| Harvest (%) | 1.3 | 3.4\*\*\* | 4.6\*\*\* | -0.3 | 0.0 |
|  | (0.9) | (1.2) | (1.6) | (2.4) | (1.4) |

Note: the outcome variable is a binary variable that depicts the presence of any number of incidents in a cell during a year-month; the treatment variable is the cropland area (100,000 hectares) interacted with the harvest-season binary variables, which varies across locations (see Figure 2); the column headed by ‘All events’ combines all the considered events, the column headed by ‘Battles’ combines battles and explosions/remote violence, the remaining three columns represent the separate event types as labeled. All regressions include cell, country-year, and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

As another test, we examine the dose–response relationship between cropland intensity and harvest-time violence. If our conjecture is valid, we should expect a greater effect in cells where a higher share of land is dedicated to rice production. So, we introduce a step function that categorizes the croplands into very low agricultural intensity (locations with less than 5,000 hectares of total area dedicated to rice production, labeled as ‘tiny’), low agricultural intensity (more than 5,000 hectares but less than 20,000 hectares, labeled as ‘small’), medium agricultural intensity (more than 20,000 hectares but less than 50,000 hectares, labeled as ‘medium’), and high agricultural intensity (more than 50,000 hectares, labeled as ‘large’).

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**Figure 5: Harvest-time conflict after dry, normal, and wet crop growing seasons**

Note: The dots indicate point estimates, and the error bars show 95% confidence intervals around the point estimates. The point estimates depict impact presented in percentage terms and calculated as: , where is the estimated effect of the cropland area interacted with the harvest-season binary variables (treatment variable) on the number of incidents (outcome variable) after controlling for cell, country-year, and year-month fixed effects and the contemporaneous rainfall in the cell; is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type. The confidence intervals are obtained using standard errors adjusted to clustering at the level of a cell. The colored/filled dots and error bars show the impacts that are statistically significant at 5% level. ‘dry’, ‘normal’, and ‘wet’ depict years when the growing season rainfall was less than, within, and more than one standard deviation of the historically observed (over 1997-2022 period) average growing season rainfall in the cell.

Figure 6 presents the results of this exercise for the four forms of conflict. Appendix Table B6 presents the complete set of the regression results. Appendix Tables B7 and B8 present the same results using full sample (i.e., with Myanmar 2021-2022 data), and using incidence as the outcome variable. In the case of violence against civilians, we observe the expected pattern—bigger effect in larger croplands. In the case of the other forms of conflict, the patterns vary. In the largest cropland area size bands—which likely drive the main results presented in Table 4—we observe the harvest time decrease in battles and riots and increase in protests. These effects are measured with a considerable noise, however.

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**Figure 6: Dose-response relationship in the harvest-time changes in conflict**

Note: The dots indicate point estimates, and the error bars show 95% confidence intervals around the point estimates. The point estimates depict impact presented in percentage terms and calculated as: , where is the estimated effect of a binary variable that takes on one when cropland area is within a given size band interacted with the harvest-season binary variables (treatment variable) on the number of incidents (outcome variable) after controlling for cell, country-year, and year-month fixed effects and the contemporaneous rainfall in the cell; is the average cropland area within a given cropland area size band, and is the baseline conflict, which is the monthly average of incidents of a given conflict type, within the same cropland area size band. The confidence intervals are obtained using standard errors adjusted to clustering at the level of a cell. The colored/filled dots and error bars show the impacts that are statistically significant at 5% level. ‘tiny’, ‘small’, ‘medium’, and ‘large’ depict cropland area size bands that are, respectively, less than 5,000ha, 5,000ha to 20,000ha, 20,000ha to 50,000ha, and greater than 50,000ha.

1. ACLED # 9785083: “On 9 December 2013, in Mung Ding Pa, Kachin state, the Myanmar army shelled civilian rice fields.” [↑](#footnote-ref-1)
2. ACLED #9679246: “On 22 November 2022, in Zar Haw village (Gangaw township, Gangaw district, Magway region), the Myanmar military IB-50 shot dead a villager in the head during the raid. The military also shot dead two other villagers who were harvesting rice in the paddy fields for unknown reasons.” [↑](#footnote-ref-2)
3. ACLED #8807873: “On 4 November 2021, west of Pekon township (Taunggyi district, Shan-South), military troops clashed with the joint forces of Pekon PDF, Moebye PDF, Loikaw PDF, Demoso PDF, the KNDF and the Karenni Army. Military troops fired artillery and torched, looted a nearby village and burned harvested rice in paddy fields according to Pekon PDF. At least 20 military troops were killed and a resistance fighter was injured.” [↑](#footnote-ref-3)
4. ACLED #9641230: “On 11 November 2022, between Aye Ka Bar and Bay La Maing villages (coded as Aye Ka Bar) (Thanbyuzayat township, Mawlamyine district, Mon state), Mon State Mount Taungnyo People Guerrilla Force ambushed a convoy of three military vehicles carrying rice at about 7 am. One military solider was killed and two others were injured. [↑](#footnote-ref-4)
5. ACLED #9411619: “On 27 June 2022, in Kyunhla town (Kyunhla township, Kanbalu district, Sagaing region), Pyu Saw Htee members detained and killed a 40-year-old rice mill owner from Pi Tauk Pin village, Kanbalu township when he traveled to the Kyunhla town with a companion to buy equipment for his rice mill. The Pyu Saw Htee members seized 1.5 million Kyats, 2 mobile phones and 1 motorcycle from them. It was reported that the rice mill owner was shot dead as he tried to run away near a quarry outside the town. His companion escaped.” [↑](#footnote-ref-5)
6. ACLED # 7787765: “On 22 March 2021, dozens of students from the Agricultural Student Coalition (Komar) held a peaceful protest in front of their university in UPN Veteran, Yogyakarta city (Yogyakarta province). They opposed the government plan of importing rice. [size=dozens]”

   ACLED # 9103355: “On 24 September 2018, a group of students held a peaceful protest in Medan City, North Sumatra province, demanding the government to stop importing rice. [size=no report]”

   ACLED # 9225485: “On 22 January 2018, in Sukolilo, hundreds of farmers staged a rally to protest against the government's plan to import rice, stating that it will lower local rice prices.” [↑](#footnote-ref-6)
7. ACLED # 7908847: “Farmers in the province of Phichit staged a protest against the anti-government movement, blasting its attempt to block the government's efforts to secure funds for the rice pledging program. Hundreds of farmers gathered at a major intersection to express their opposition to the People's Democracy Reform Committee (PDRC), who they believed have been blocking the government's attempt to pay rice farmers for rice pledged under the pledging program.” [↑](#footnote-ref-7)
8. ACLED: “On 19 July 2019, approximately 150 farmers gathered at a dam in Moo 13, tambon Thep Nakhon, Mueang Kamphaeng Phet of Kamphaeng Phet province, Thailand. They demanded the Irrigation Department release some water into their rice field to ease the effect of the draught. After having waited for a long time to negotiate with an officer, they blocked the road. [size=150]” [↑](#footnote-ref-8)
9. The data on cities are from the World Cities Database available at <https://simplemaps.com/data/world-cities>. [↑](#footnote-ref-9)