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

**Abstract**

Social conflicts are inevitable, but their occurrence and intensity have varied over time and across locations. In lower-income economies, where employment and income from agriculture are substantial, forms of political violence and social conflict may be linked with this sector. We investigate this linkage using granular conflict data covering a 13-year period across seven Southeast Asian countries. We focus on changes in conflict incidents during the rice harvest season, which is the most produced and consumed cereal crop in the region. We observe an increase in political violence but a decrease in social unrest in rice-producing areas during the harvest season. We investigate different plausible mechanisms that may lead to such effects, by incorporating shocks associated with rice prices and growing season rainfall, and by comparing regions with predominantly irrigated vs predominantly rainfed rice production practices. These findings offer important insights to policymakers as they point to possible temporal and geographic displacements of conflict, which can be linked 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 conflict. The linkage can be reduced to a couple of theories. One is that of *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). A food crisis caused by reduced availability or affordability of food items can be a factor in such conflict. Another theory is *greed*, which suggests that perpetrators are more likely to engage in conflict when there is more at stake. After a good harvest season, for example, the transitory increase in the spoils to be appropriated can amplify violence (Koren and Bagozzi, 2017; McGuirk and Burke, 2020).

Both theories, of grievance and greed, 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—the *predation* or *rapacity* mechanism—but also because the opportunity costs of engaging in such activities are not very high—the *opportunity cost* mechanism. The latter has been primarily portrayed 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 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. Political violence aimed at civilians can be linked to the harvest-time positive income shocks, and the relationship is expected to be positive (McGuirk and Burke, 2020). Such a relationship, moreover, can also be seasonal. In crop-producing parts of Africa, 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, protests and riots are often triggered by negative income shocks. In rural areas they may be linked to agricultural harvest, and if so, the relationship should be negative—i.e., negative agricultural income shocks can drive protests and riots (e.g., Panza and Swee, 2023)—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. In this context, the seasonal patterns in protests and riots in crop-producing regions can be linked with the theory of grievance and the opportunity cost mechanism.

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 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 conflict by examining over 70 thousand incidents in Southeast Asia at monthly frequency over a 13-year span from 2010 to 2022. We find that changes in conflict in crop-producing areas during the harvest months of rice—the key cereal crop in the region—depend on the type of conflict: battles and violence against civilians increase during rice harvest months, while protests and riots decrease during rice harvest months. This suggests that the mechanisms that primarily drive harvest-time conflict in Southeast Asia vary by their type. In the case of conflict *against* civilians, harvest time provides rapacious violent groups with an opportunity to appropriate or destroy agricultural surplus. In the case of conflict *by* civilians, the opportunity cost of conflict increases during harvest time, which leads to fewer protests and riots. The harvest-time estimated change in protests should be taken with some skepticism, as this result is sensitive to data subsetting.

To test the suggested mechanisms, we interact our treatment variable with the growing season rainfall—the key factor in rice production. In so doing, we rely on empirical evidence that excessive rain is damaging for rice yields (e.g., Crost et al., 2018; Fu et al., 2023). Thus, if our proposed mechanisms are valid, we would expect the effects of our main specification to attenuate to zero in times of the abundance of rain. Indeed, we find that the harvest-time violence vanishes after the rainy growing season. However, we also find that protests further decrease during the harvest months after the rainy growing season, which does not align with our priors.

To further examine the extent and scope of agricultural shocks on conflict, we introduce irrigation variable, bounded by zero and one, into the analysis. We find that much of the estimated effect happens at the rainfed rice locations. 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 while harvest-time reduction in protests happens in times of war and peace, harvest-time increase in violence is largely a war-time phenomenon. This 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.

We make contributions and advance knowledge in three strands of research. 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). We present empirical evidence that underlines the role of growing-season precipitation patterns on harvest-time conflict. Second, we contribute to the literature on the economic roots of conflict (Crost and Felter, 2020; McGuirk and Burke, 2020; Berman et al, 2011; 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; Guardado and Pennings, 2023). We present empirical evidence for a harvest time increase in violence and a harvest time reduction of protests, and link these effects to the existing theories of conflict that have been previously examined in temporally more aggregate (annual) setting.

**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 conflict 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 are 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 in order 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 so as 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**

|  |  |  |  |
| --- | --- | --- | --- |
| **Type of actor** | **Type of conflict** | **Seasonal effect** | **Mechanism** |
| Civilians | Protests, riots | Decrease during harvest times | Opportunity cost |
| Armed actors (State, armed rebel groups, militias) | Violence against civilians, battles and explosions | Increase during harvest times | Rapacity |

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.

A map of the world

Description automatically generated with low confidence

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

Note: The data are for Brunei (2020 – 2022), Cambodia, Indonesia (2015 – 2022), Laos, Malaysia (2018 – 2022), Myanmar, Philippines (2016 – 2022), Timor-Leste (2020 – 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: (i) there is no apparent trend across conflict types, but there is a notable increase in almost all types of conflict from 2021 onward; (ii) 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.

A picture containing text, screenshot, line, plot

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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.

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). See Appendix Figure A1 for 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. See Appendix Figure A2 for 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.

A map of asia with colorful dots

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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). The countries covered are Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Thailand, and Vietnam.

*3.4. Descriptive Statistics*

In Table 2 we summarize some of the key features of the data. Violence against civilians, labeled as ‘Violence’ and protests represent the two most prevalent types of violent events 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 category of social conflict is riots, which is a violent version of protests that shares elements of other, more involved types of conflict.

**Table 2: Descriptive Statistics**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Mean | S.D. | Min | Max | Prop |
|  | *Unit of observation: cell-year-months (44,796)* | | | | |
| All events | 1.830 | 8.964 | 0 | 417 | 0.261 |
| Battles | 0.578 | 3.746 | 0 | 106 | 0.092 |
| Violence | 0.351 | 2.739 | 0 | 164 | 0.088 |
| Riots | 0.050 | 0.439 | 0 | 42 | 0.032 |
| Protests | 0.600 | 3.731 | 0 | 268 | 0.154 |
|  | *Unit of observation: cells (378)* | | | | |
| Rice harvested area (100,000 ha) | 0.778 | 1.252 | 0 | 9.087 |  |
| Irrigated | 0.346 | 0.736 | 0 | 7.786 |  |
| Rainfed | 0.431 | 0.856 | 0 | 5.759 |  |

Note: The conflict data are from ACLED Project (Raleigh et al., 2010), and covers the thirteen-year period from *2010 to 2022,* except for Indonesia (2015–2022), Malaysia (2018–2022), and the Philippines (2016–2022). *All events* contain the four presented categories of conflict. *Prop* denotes the proportion of units with at least one conflict incident. The rice harvest data are from IFPRI (2019). Descriptive statistics are obtained across all units of observations.

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

We denote *location*, which is a one-degree cell, with subscript *i*, and *period*, which is a year–month, with subscript *t*. The units of analysis, thus, are location-period covering 378 unique grid cells and, in most instances, 156 periods 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 two-way fixed effect setting as follows:

, (1)

where is the dependent variable, which depicts the number of incidents in cell *i* in period *t*; is the treatment variable, which is the product of the time-invariant cropland area fraction in cell *i* and the cell-specific binary variable that takes the value of one when the period of observation is the harvest month, and zero otherwise. is a cell fixed effect, and is a year–month fixed effect. is the error term.

The identifying assumption in Equation (1) rests on the premise that the treatment variable, which is the product of the cropland area fraction and harvest month, is exogenous to conflict observed across locations. This assumption may seem tenuous, as 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 changes in conflict. But in this analysis, we do not apply production data that would vary yearly. Instead, we use cropland area fractions and harvest months, which are location-specific and do not vary over time. Such an approach, admittedly driven by data limitations, mitigates the issue of reverse causality.

To address other threats to identification, namely the confounders, we include the fixed effects in the regression. Specifically, cell fixed effects capture any time-invariant determinants of conflict (e.g., distance to roads, cities, or state borders) 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). In the robustness checks we vary fixed effects and introduce control variables, such as rainfall, that vary across space and over time to get a better sense of potential threats to our identification strategy.

Under the outlined assumptions, the estimated coefficient, , reflects the harvest-time effect on incidents of social conflict in a hypothetical location with the cropland area fraction of one (100 percent cropland). A positive value of the coefficient implies that there is more conflict during the harvest month, compared to other months of the crop year, and that this effect is more pronounced in cells with a higher fraction of cropland. No cell has the cropland area fraction of one. But there are cells with nearly half or more of the area devoted to rice production. To obtain the “representative” magnitude of the impact, we scale the estimated coefficient by the expected cropland area fraction.

**5. Results and Discussion**

In Table 3 we summarize the baseline results of the study. Overall, we observe an increase in conflict and violent attacks against civilians and a decrease in riots and, especially, protests during the harvest season. These effects are relative to the other months of the year, in the rice producing croplands of Southeast Asia.

We obtain the magnitude of the effect by evaluating the estimated parameters at the average size of the croplands (across all locations) relative to the baseline conflict (which is the average number of incidents of each form of conflict in consideration). So, we estimate approximately an eight-percent increase in battles and explosions as well as violence against civilians during the harvest season, and nine-percent decrease in protests during the harvest season. The estimated six-percent reduction in riots is not statistically significant.

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 mechanism may explain the decrease in protests as people are busy harvesting, meaning that the opportunity cost of participating in protests is high.

**Table 3: The harvest-time conflict in the croplands of Southeast Asia**

|  | **Conflict** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest | 0.046 | 0.054\*\* | 0.031\*\*\* | -0.003 | -0.059\*\* |
|  | (0.045) | (0.024) | (0.008) | (0.003) | (0.028) |
| Obs. | 44,796 | 44,796 | 44,796 | 44,796 | 44,796 |
| R2 | 0.288 | 0.271 | 0.340 | 0.138 | 0.244 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.85 | 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 (%) | 2.3 | 8.6\*\* | 8.2\*\*\* | -6.1 | -9.0\*\* |
|  | (2.2) | (3.8) | (2.1) | (5.3) | (4.3) |

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); the column headed by ‘Conflict’ combines the five event types (all but strategic developments), 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.

*5.1 Mechanism Checks*

To examine the mechanisms alluded above, we compare the intensity of conflict in years when the *volume* of the harvest is higher than expected due to the rainier crop growing season. We base this check on the documented positive relationship between wet growing season and rice productivity in the region (e.g., Lansigan et al., 2000). So, we interact the treatment variable, which is the product of the cropland area and the harvest season binary variable, with the growing season rainfall. If our proposed mechanisms are valid, then we would expect more violence and less protests during presumably more productive crop years. The results of this exercise are presented in Table 4.

**Table 4: The Effect of a Rainy Crop Growing Season on Harvest-Time Conflict**

|  | **Conflict** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest | 0.044 | 0.53\*\* | 0.031\*\*\* | -0.003 | -0.059\*\* |
|  | (0.044) | (0.023) | (0.008) | (0.003) | (0.028) |
| Area × Harvest × Rain | -0.204\*\* | -0.092\*\*\* | -0.034\*\*\* | -0.002 | -0.017 |
|  | (0.085) | (0.035) | (0.012) | (0.002) | (0.026) |
| Obs. | 45,036 | 45,036 | 45,036 | 45,036 | 45,036 |
| R2 | 0.289 | 0.272 | 0.340 | 0.138 | 0.244 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.84 | 0.58 | 0.35 | 0.05 | 0.60 |
| 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 (%) | 2.2 | 8.5\*\* | 8.1\*\*\* | -6.1 | -9.0\*\* |
|  | (2.2) | (3.7) | (2.4) | (5.3) | (4.5) |
| Harvest × Rain (%) | -8.0\*\*\* | -6.2\*\* | -0.7 | -9.4 | -11.5\*\* |
|  | (3.0) | (3.0) | (2.4) | (6.4) | (5.3) |

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 ‘Conflict’ combines the five event types (all but strategic developments), 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.

The key finding is that a presumably larger harvest decreases the intensity of all forms of conflict. For example, we observe a 2.5 percentage point (about 25 percent) further reduction in protests when a one-standard-deviation excess rain, relative to the historical average, is realized during the crop-growing season in a cell. Perhaps more drastically, we observe that the harvest-time violence against civilians pretty much vanishes after a one-standard-deviation excess rain.

To the extent that we consider rain a yield-improving factor, this finding supports the suggestive evidence that people do not protest when the opportunity cost of participating in protests is high. This also echoes the grievance theory, as people in rural regions protest less, at least relative to those who live in urban regions, when they receive a positive shock related to increase in agricultural output. That we observe no violence when the presumed volume of the harvest increases weakens the suggested rapacity mechanism but leaves room for a possibility of the opportunity cost mechanism dominating the effect. A decrease in violence in the cropland may be explained by less grievance in rural locations relative to urban locations. This suggests the relative spatial displacement of conflict, but the current modeling setting, which is akin to difference-in-differences, doesn’t allow us to further examine this hypothesis.

To validate that we pick up the agricultural production link through our rainfall variable, we further interact the treatment variables with the proportion of irrigated land in each cell (see Appendix Figure A1 for the histogram of the proportion of irrigated rice in the region). Irrigated rice is the higher-yield and, often, commercially produced rice, as opposed to the rainfed rice, which is lower-yield rice produced at subsistence levels. So, very different types of farmers are likely involved in these two production practices. As before, we assess harvest-time social conflict when the v volume of the harvest increases, by interacting the right-hand-side variables with the growing season rainfall. Results of this exercise are presented in Table 5.

Additional features of interest emerge that help clarify some of the earlier findings. Much of the estimated effect is due to changes in conflict and violence at the rainfed rice locations. Put differently, irrigation mitigates much of the harvest-time conflict in Southeast Asia, which accords with Gatti et al. (2021). There are no apparent harvest-time changes in social unrest in parts of the region where irrigated rice is produced, nor do any such changes emerge in the wake of a presumable yield increase.

**Table 5: The Harvest-Time Conflict in Irrigated/Rainfed Lands After a Rainy Season**

|  | **Conflict** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | | | |
| Area × Harvest | 0.083 | 0.122\*\*\* | 0.052\*\*\* | -0.003 | -0.123\*\* |
|  | (0.084) | (0.045) | (0.013) | (0.004) | (0.052) |
| Area × Harvest | -0.094 | -0.161\*\*\* | -0.048\*\*\* | -0.001 | 0.148\*\* |
| × Irrigated | (0.108) | (0.056) | (0.017) | (0.009) | (0.070) |
| Area × Harvest × Rain | -0.320\*\* | -0.145\*\* | -0.040\* | -0.006 | -0.041 |
|  | (0.151) | (0.061) | (0.021) | (0.005) | (0.046) |
| Area × Harvest × Rain | 0.268 | 0.123\* | 0.016 | 0.009 | 0.055 |
| × Irrigated | (0.180) | (0.067) | (0.028) | (0.012) | (0.079) |
| Obs. | 45,036 | 45,036 | 45,036 | 45,036 | 45,036 |
| R2 | 0.289 | 0.272 | 0.340 | 0.138 | 0.244 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.84 | 0.58 | 0.35 | 0.05 | 0.60 |
| 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 (%) | 4.2 | 19.5\*\*\* | 13.6\*\*\* | -5.2 | -18.9\*\* |
|  | (4.2) | (7.2) | (3.5) | (7.8) | (8.0) |
| Harvest × Rain (%) | -11.9\*\* | -3.6 | 3.0 | -15.7 | -25.2\*\*\* |
|  | (4.8) | (5.6) | (4.4) | (10.5) | (8.5) |
| ***Irrigated*** |  |  |  |  |  |
| Harvest (%) | -0.5 | -6.1\*\* | 1.0 | -7.4 | 3.8 |
|  | (2.1) | (2.9) | (2.2) | (11.2) | (4.8) |
| Harvest × Rain (%) | -3.1 | -9.8\*\* | -5.4 | -1.4 | 6.0 |
|  | (4.5) | (4.4) | (4.6) | (19.8) | (10.7) |

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; Irrigated denotes the proportion of irrigated land in the cell; the column headed by ‘Conflict’ combines the five event types (all but strategic developments), 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.

Finally, to investigate whether the change in lower scale conflict is in any way a byproduct of large-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, which neither involves a military actor as such not is violent per se, 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, and re-estimate the regression equations with violence against civilians and protests as the dependent variables. Table 6 presents the results of this exercise.

**Table 6: The Harvest-Time Violence and Protests Conditional on Battles and Explosions**

|  | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- |
| *Unbalanced panel: all countries, all years* | | | |
| Battles | 0.218\*\*\* | 0.000 | 0.240\*\*\* |
|  | (0.028) | (0.001) | (0.088) |
| Area × Harvest | 0.006 | -0.003 | -0.081\*\* |
|  | (0.007) | (0.003) | (0.034) |
| Area × Harvest × Battles | 0.030\*\*\* | -0.001 | 0.020 |
|  | (0.009) | (0.000) | (0.036) |
| Obs. | 45,036 | 45,036 | 45,036 |
| R2 | 0.416 | 0.138 | 0.291 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | |
| Baseline conflict | 0.35 | 0.05 | 0.60 |
| Area harvested | 0.93 | 0.93 | 0.93 |
| *Magnitude of the effect evaluated at the average cropland area relative to the baseline conflict:* | | | |
| ***In absence of battles*** | | | |
| Harvest (%) | 1.5 | -5.5 | -12.3\*\* |
|  | (1.7) | (5.2) | (5.2) |
| ***In presence of (historically average) battles*** | | | |
| Harvest (%) | 6.0\*\*\* | -6.2 | -10.6\*\* |
|  | (1.8) | (5.3) | (5.2) |

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 denotes the sum of incidents recorded as battles and explosions/remote violence; 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.

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.

*5.2 Robustness Checks*

The study covers a relatively small and geographically concentrated area (ten countries), as well as a relatively short period (eleven years). So, we performed several checks to ensure that the results are not sensitive to model specification or data subsetting.

First, we re-estimated the baseline model using balanced panels (i) covering all ten countries but only include years from 2018 to 2022, and (ii) covering all thirteen years but not include Indonesia, Malaysia and Philippines. These regression results, presented in Appendix Tables B1 and B2, are comparable with those of the main results of this study. We also re-estimated the baseline model using all available data covering the 2010-2019 period, i.e., excluding the years of the pandemic that, incidentally, has been associated with elevated violence of all forms as evidenced in Figure 2. The regression results, which appear in Appendix Table B3, suggest some discrepancy from the main results of the study. The estimated harvest-time increase violence against civilians remains largely intact. But the estimated harvest time reduction in protests reverses the sign. Notably, by omitting the last three years of data, we effectively discard more than 48 thousand (nearly 60 percent) of incidents in the sample.

Second, we re-estimated the baseline model by dropping one country at a time. The results of this exercise are presented in Appendix Figure A2. This sensitivity check provides some insights into the discrepancy between the results from the pre-pandemic dataset vis-à-vis the full dataset. The estimated harvest-time increase violence against civilians appears largely invariant to omitting any one of the countries. But the estimated harvest time reduction in protests pretty much vanishes when Myanmar is dropped from the sample. Taken together, the most recent social unrest in Myanmar appears to be driving part of the results of this study.

Finally, to ensure that the estimated results are not a mere happenstance, we performed a sample randomization exercise. Specifically, we shuffled and randomly re-assigned the observed harvest seasons to locations and re-estimated the baseline regression. We repeated this 100 times. On average, we would expect no significant effect here. Appendix Figure A3 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.

**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.

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**Figure A2: Sensitivity of the main results to dropping a country 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, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

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**Figure A3: 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, is the average cropland area harvested, and is the baseline conflict, which is the monthly average of incidents of a given conflict type.

APPENDIX B. TABLES

**Table B1: The harvest-time conflict in the croplands of Southeast Asia (subset of years)**

|  | **Conflict** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Balanced panel: all countries, years 2018-2022* | | | | | |
| Area × Harvest | 0.053 | 0.128\*\* | 0.041\*\*\* | -0.009\* | -0.158\*\* |
|  | (0.100) | (0.054) | (0.016) | (0.005) | (0.063) |
| Obs. | 22,680 | 22,680 | 22,680 | 22,680 | 22,680 |
| R2 | 0.380 | 0.322 | 0.443 | 0.172 | 0.327 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 2.64 | 0.80 | 0.42 | 0.07 | 0.94 |
| Area harvested | 0.79 | 0.79 | 0.79 | 0.79 | 0.79 |
| *Magnitude of the effect evaluated at the average cropland area fraction relative to the baseline conflict:* | | | | | |
| Harvest (%) | 1.6 | 12.6\*\* | 7.8\*\*\* | -10.4\* | -13.3\*\* |
|  | (3.0) | (5.3) | (3.0) | (6.2) | (5.3) |

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); the column headed by ‘Conflict’ combines the five event types (all but strategic developments), 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 B2: The harvest-time conflict in the croplands of Southeast Asia (subset of countries)**

|  | **Conflict** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Balanced panel: all countries excluding Indonesia, Malaysia, and Philippines, all years* | | | | | |
| Area × Harvest | 0.066 | 0.053\*\* | 0.028\*\*\* | -0.001 | -0.041 |
|  | (0.043) | (0.023) | (0.008) | (0.002) | (0.026) |
| Obs. | 26,364 | 26,364 | 26,364 | 26,364 | 26,364 |
| R2 | 0.279 | 0.284 | 0.260 | 0.074 | 0.220 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 2.12 | 0.83 | 0.26 | 0.03 | 0.61 |
| Area harvested | 1.33 | 1.33 | 1.33 | 1.33 | 1.33 |
| *Magnitude of the effect evaluated at the average cropland area fraction relative to the baseline conflict:* | | | | | |
| Harvest (%) | 4.1 | 8.4\*\* | 14.5\*\*\* | -4.2 | -8.9 |
|  | (2.7) | (3.7) | (4.0) | (8.0) | (5.5) |

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); the column headed by ‘Conflict’ combines the five event types (all but strategic developments), 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 B3: The harvest-time conflict in the croplands of Southeast Asia (pre-pandemic)**

|  | **Conflict** | **Battles** | **Violence** | **Riots** | **Protests** |
| --- | --- | --- | --- | --- | --- |
| *Balanced panel: all countries, years 2010-2019* | | | | | |
| Area × Harvest | 0.051\* | 0.002 | 0.022\*\*\* | 0.001 | 0.025\* |
|  | (0.021) | (0.007) | (0.008) | (0.002) | (0.014) |
| Obs. | 31,428 | 31,428 | 31,428 | 31,428 | 31,428 |
| R2 | 0.592 | 0.533 | 0.474 | 0.170 | 0.477 |
| *Average cropland area harvested (100,000 hectares) and the number of incidents (baseline conflict):* | | | | | |
| Baseline conflict | 1.09 | 0.36 | 0.30 | 0.04 | 0.31 |
| Area harvested | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| *Magnitude of the effect evaluated at the average cropland area fraction relative to the baseline conflict:* | | | | | |
| Harvest (%) | 4.6\*\* | 0.5 | 7.2\*\*\* | 2.4 | 7.9\* |
|  | (1.9) | (1.9) | (2.5) | (5.7) | (4.3) |

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); the column headed by ‘Conflict’ combines the five event types (all but strategic developments), 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.

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)