INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

Australian Centre for International Agricultural Research

Australian Aid

IFPRI Discussion Paper 02418

June 2026

Conflict and Farmland Values

Spatial Panel Data Evidence from Rice Plots in Myanmar

Hiroyuki Takeshima

Bart Minten

Ian Masias

Zin Wai Aung

Hnin Ei Win

Agrifood Innovation and Resilience Unit

Development Strategies and Governance Unit

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

Hiroyuki Takeshima (h.takeshima@cgiar.org) is a Senior Research Fellow of the Agrifood Innovation and Resilience (AIR) Unit of the International Food Policy Research Institute (IFPRI), Washington, DC.

Bart Minten (b.minten@cgiar.org) is a Program Leader of IFPRI's Myanmar Strategy Support Program and a Senior Research Fellow in the Development Strategies and Governance (DSG) Unit, Vientiane, Laos.

Ian Masias (i.masias@cgiar.org) is a Program Head in IFPRI's DSG Unit, Washington, DC.

Zin Wai Aung (Z.W.Aung@cgiar.org) is a Research Analyst in IFPRI's DSG, Yangon, Myanmar.

Hnin Ei Win (H.Ei-Win@cgiar.org) is a Research Analyst in IFPRI's DSG Unit, Yangon, Myanmar.

Notices

[1]IFPRI Discussion Papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review via IFPRI's Publications Review Committee. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by IFPRI.
[2] The boundaries and names shown and the designations used on the map(s) herein do not imply official endorsement or acceptance by the International Food Policy Research Institute (IFPRI) or its partners and contributors.

Abstract

The significant economic implications of the value of farmland in developing countries is increasingly recognized, particularly in those countries where land scarcity is a growing problem. However, knowledge gaps remain about how farmland values can be affected by factors such as conflict and social instability. A knowledge gap also remains regarding how spatial transmission and feedback effects of land values among geographically proximate parcels may affect the relationship between conflict and farmland values. This impact has generally been overlooked in the literature, despite the well-established importance of clustering in agricultural economies. This paper addresses these gaps by utilizing unique, nationally representative panel data on farm households and spatial data on conflict intensity in Myanmar, with a focus on the period of significant conflict intensification following the 2021 political crisis, particularly in 2022 and 2023, when the country's conflict level largely shifted to a high-intensity state. We apply spatial econometric models and their extensions to a panel data framework, as well as models that allow for endogenous spatial weights, which enable conflicts to not only affect farmland values but also shape how changes in farmland values transmit across locations. Our results indicate that more local conflict during the prior 12 months, measured by the number of months with at least one fatal violent event within the township of respondents, significantly reduced the farmland values of the largest rice plot of these respondents. Specifically, in the monsoon and non-monsoon harvesting seasons of 2022 and 2023, an additional one month of fatal violence was associated with approximately 3 percent and 5 percent decline in land values, respectively, implying a potentially sizable decline for townships that experience more persistent conflicts over several months. Moreover, the effects of violent events are magnified by spatial spillover effects on land values across village tracts. These adverse effects are robust and consistent across a range of methodologies and hold across diverse agroecological conditions.

Keywords: farmland value; conflicts; spatial spillover; monsoon and non-monsoon seasons; panel data; Myanmar

Acknowledgments

This work was undertaken as part of the International Food Policy Research Institute (IFPRI) Myanmar Strategy Support Program. We would like to thank Isabel Lambrecht for providing constructive comments and suggestions. Funding support for this study was provided by the Australian Centre for International Agricultural Research. Authors are responsible for all remaining errors.

1 Introduction

The value of farmland in developing countries has various economic implications for farm households who possess use rights to these lands. An increase in land values can have effects similar to increases in household assets and wealth, which provide a greater safety net function (Rigg et al. 2016; Swift et al. 2024). When land tenure or access to land can serve as insurance against risks (e.g., Promsopha 2015) or as a source of status (World Bank 2007), an increase in its value can provide additional economic benefits to farm households. Where farmland use rights can be used as collateral and land values can be reasonably assessed by a third party, higher values can sometimes boost households' access to credit.. This is increasingly the case in developing countries, including those in Southeast Asia (e.g., Green 2019), although the enforcement of land tenurial rights in this context is still often limited.

There has been growing interest in which factors and types of shocks (environmental, hydrological) are associated with access to land in general and, in particular, with farmland values (e.g., Hossain et al. 2020; Caffera et al. 2024; Chaudhry et al. 2024). Among various factors, the literature has increasingly focused on the linkages between social risks, such as conflicts, and land values. The evidence generally suggests that local as well as regional conflicts are associated with reduced land values in the countries being studied, including both high-income countries such as the United States (Rajan & Ramcharan 2015) and Ireland (Besley & Mueller 2012) and low- and middle-income countries such as Ukraine (Deininger & Ali 2023), Colombia (e.g., Arias et al. 2019; Tellez 2022), and Nigeria (e.g., Adelaja & George 2019; George et al. 2021).

Nonetheless, knowledge gaps remain for many developing countries that have experienced intense conflicts in recent years, including Myanmar, which ranked second highest on the global conflict index in 2024 (second only to Palestine) based on the Armed Conflict Location & Event Data (ACLED) (2024). A knowledge gap also remains regarding how the relationship between conflict and farmland values may depend on spatial spillover effects of land values, which have generally not been considered in the literature, including many of the aforementioned studies. Such spillover effects might be particularly important in commercial agriculture, given the well-documented role of clustering in agricultural economies. Farmers located in close proximity to each other often rely on the same input markets (e.g., seeds, mechanization, chemicals, labor) and output markets (e.g., traders and processors), experience knowledge spillovers, benefit from economies of scale and scope, and share risks (e.g., Richards 2018; Sonobe & Otsuka 2010; Zhang 2023).

We narrow this knowledge gap by drawing on evidence from Myanmar during the period of significant conflict intensification that followed the 2021 political crisis, particularly in 2022 and 2023, when high conflict intensity had become the new norm for the country. Using unique nationally representative panel data on farm households and village-tract level data on conflict intensity (measured as the number of fatal violent incidents), we examine the effects of rising conflict intensity on year-on-year changes in farmland values during the monsoon harvesting season. In so doing, we also obtain robust results that accommodate potential spillover of farmland values across locations, through application of spatial econometric models and their extension to a panel data framework (Anselin & Florax 1995; Lee & Yu 2010) as well as models that allow endogenous spatial weights (Qu et al. 2016; Delgado et al. 2018).

Myanmar is a critical case for examining the conflict-land-value nexus. First, as mentioned, widespread prevalence of violent events has been common since 2021, making it urgent to investigate the effects of conflicts on the welfare of the population. Second, Myanmar has a relatively larger average farm size than other developing countries in South and Southeast Asia, albeit with significant variation in sizes of plots owned (Lambrecht et al. 2024b). The average holding size of 2.5 ha in 2010 is only exceeded in Thailand and Pakistan, and is larger than the typical range of 0.5–2 ha in other Asian countries (FAO 2024). Therefore, values of farmland may have relatively more important economic implications for farm households than they do in countries with smaller land sizes (where values of non-land factors like labor/human capital may be more important). Third, from a global perspective, Myanmar is still smallholder-dominated, with dense farmland spatial distribution, and thus, farmland markets may be spatially well integrated. Understanding the spatial transmission and feedback effects of land values, as we aim to do in this study, is therefore critical for Myanmar.

Our results indicate that more local conflict during the prior 12 months, measured by the number of months with at least one fatal violent event within the village tract of respondents, significantly reduced the farmland values of the largest rice plot of these respondents in the harvest seasons of 2022 and 2023. We find that an additional month of fatal violent events in the previous 12 months preceding the monsoon and non-monsoon harvests reduced land values by approximately 3% and 5%, respectively, with the larger effect in the non-monsoon period likely reflecting the greater disruption to more commercialized agricultural activities during that season. These effects can be sizable, particularly in townships that experience more persistent conflicts spanning multiple months, which is broadly consistent with, but in some cases exceeds, the magnitudes reported in recent studies in other contexts (e.g., Adelaja & George 2019; Deininger & Ali 2023). Moreover, these adverse effects of violent events are robust and generally magnified by spatial spillover effects on land values across village tracts.

This study contributes to various strands of the literature. The study expands the evidence base on the linkages between land values and various types of conflict (Besley & Mueller 2012; Rajan & Ramcharan 2015; Adelaja & George 2019; Deininger & Ali 2023; Takeshima et al. 2026) by providing new evidence from an Asian context. The paper also contributes to the emerging body of studies analyzing the linkages between conflicts and agrifood systems in low- and middle-income countries (George et al. 2021; Tellez 2022; Arias et al. 2019; Minten et al. 2023; Takeshima et al. 2024, 2025a) by offering additional insights into farmland outcomes. In addition, it adds to the literature on farmland values, their determinants, and their economic roles in Myanmar (Lau 2014; Mark 2016; Naing 2019; Lambrecht et al. 2024a, 2024b; Swift et al. 2024) by providing nationwide empirical insights on linkages between conflicts and land values. The paper also contributes to the agricultural clustering literature (Richards 2018; Sonobe & Otsuka 2010; Zhang 2023) by examining how violence in neighboring communities affects local farmland values and by comparing monsoon and non-monsoon seasons, which correspond to periods of relatively less and more commercialized agricultural activity, with the latter being more dependent on clustering and market integration. Lastly, the paper contributes to the literature on spatial econometrics with panel data structure and endogenous spatial weighting matrices (Qu & Lee 2015; Qu et al. 2016; Delgado et al. 2018) by extending the methodologies to the analysis of the conflict-land nexus in Myanmar.

The remainder of the paper is structured as follows. Section 2 briefly discusses the roles of farmland values in Myanmar. Section 3 discusses the empirical methods. Section 4 describes the data and descriptive statistics. Section 5 presents and interprets the results. Section 6 provides discussions on mechanisms and policy implications, and section 7 concludes.

2 Farmland values in the Myanmar context

Farmland values in Myanmar have both direct and indirect economic implications for farm households, although indirect pathways are more common. The direct benefits from higher farmland values materialize from sales or rental revenues of land, transfers that had been practiced informally before 2012 and were legalized in 2012 (Mark 2016; Boutry et al. 2017; Lambrecht et al. 2024b). However, only a small share of farm households in Myanmar engage in such transactions. For example, in the 2017 Myanmar Living Conditions Survey, 88% of agricultural parcels were owner-operated and had been acquired on average 21 years prior (indicating the infrequency of farmland sales), and only 4.7% of cultivated parcels are accessed through rental and 2.5% through sharecropping (Lambrecht et al. 2024b).[1] These patterns may have largely continued since 2017, including during the political crisis since 2021.

Indirect benefits of farmland values may arise through various channels, for example, (a) improved access to credit/loans not only at extensive margins but also at intensive margins (i.e., the amount of such credit/loans that can be taken) or (b) greater expected financial compensation in the event of future confiscation of the land by the government, among others. Most agricultural parcels in Myanmar, except in hilly/mountainous regions, are associated with formal documents, such as Form 7, Form 105, or a tax receipt, which are generally regarded as evidence of the right of the household to use the land parcel (Lambrecht et al. 2024b).

Regarding (a), in many Southeast Asian countries, including Cambodia (Yagura 2020), Viet Nam (Luan 2019), and Thailand (Pochanasomboon et al., 2020), the maximum value of the loan that can be obtained is often proportional to the total value of the land (i.e., land value per unit of area times the land size) used as collateral. Anecdotal evidence suggests that similar practices are also used in Myanmar (e.g., Lau 2014; Naing 2019; Aung et al. 2019).

Regarding (b), the 2012 Farmland Law allows the government to confiscate land through the Farmland Administration Body when in the interest of the state, providing compensation that is based on estimated land value (Mark 2016). Although how the value of confiscated land is actually estimated by the government is unclear, having such criteria stipulated in the law may encourage farm households to base their economic decision-making on perceived land values. More broadly, anecdotal evidence indicates that farmers in Myanmar continue to perceive farmland as a major asset (e.g., Swift et al. 2024) and that increases in its value may have beneficial effects, similar to those arising from overall household asset accumulation among low-income households in developing countries, such as increased productive investments (e.g., Carter & Barrett 2006).

3 Empirical methods

Our empirical approach is to assess the effects of change in conflict intensity within the village tracts by looking at the change in the values of farm plots reported by surveyed farm households residing in respective village tracts before and after the start of political crisis in Myanmar (section 4 describes our data in more detail). We first describe a simple model for this empirical approach, and then describe models that incorporate potential spatial dependence that further affect land values in different locations.

[1] Anecdotal evidence suggests that farmers often increase farmland values in their area by using land brokers who can find buyers with high willingness to pay (Boutry et al. 2015) and increasingly through digital platforms like Facebook in more urbanized areas (Wittekind & Faxon 2023).

3.1 Standard panel fixed-effects model without spatial spillover effects

We start with a simple, standard panel fixed-effects model that assumes no direct spatial spillover of land values across locations. Specifically, we estimate,

$$A_{ijt} = \beta + \beta_V V_{jt} + \beta_X X_{ijt} + c_{ij} + \varepsilon_{ijt} \quad (1)$$

in which A_{ijt} is the natural log of estimated land value per acre of the largest rice plot cultivated by respondent i during the harvesting season in year t, V_{it} is the measure of conflicts in the village tract where respondent i resides, and X_{it} is the set of exogenous control variables (explained in subsection 3.3). The notation c_i represents the unobserved respondent-specific effects that are time-invariant. β notations represent estimated parameters, and ε_{it} is the idiosyncratic error term.

Equation (1) is estimated separately for the land values during the harvesting period of the monsoon production season (*monsoon harvesting season* hereafter) and that of the non-monsoon production season (*non-monsoon harvesting season* hereafter). The former largely falls in December of year t, and the latter largely falls in June of year t.

3.2 Models accounting for potential spatial dependence and feedback effects of land values across locations

3.2.1 Empirical specifications

We then estimate a modified version of equation (1), which incorporates possible spatial dependence in land values across village tracts.[2] The values of immobile economic goods, such as land, can exhibit unique spatial dependence structures, and land values in different locations may be directly affected by each other, aside from any direct effects of other determinants. When such direct dependence is substantial, not incorporating it into the model (as in equation (1)) can lead to biased estimates of the overall effects of conflicts on land values.

Specifically, we estimate a spatial autoregressive (SAR) model and an SAR with autoregressive disturbances (SARAR) model (Anselin & Florax 1995) and their extension to panel data setting (Lee & Yu 2010). We estimate

$$\begin{gathered} A_{it} = \lambda_A \mathbf{W} A_{Nt} + \beta_V V_{it} + \lambda_V \mathbf{W} V_{Nt} + \beta_X X_{it} + c_i + \varepsilon_{it} \\ \varepsilon_{it} = \rho \mathbf{W} \varepsilon_{Nt} + \upsilon_{it} \end{gathered} \quad (2)$$

in which $\mathbf{W}$ is $N \times N$ spatial weighting matrix (with N being the number of households in the sample), which defines spatial lag of the dependent variable and idiosyncratic shocks, respectively, as described in more detail below.[3] Notations A_{Nt}, V_{Nt} and ε_{Nt} are $N \times N$ matrices that include A_{it}, V_{it} and ε_{it} as well as those of all the other observations in the sample. Notations λ and ρ are parameters estimated in addition to β. The term $\lambda_A \mathbf{W} A_{Nt}$ captures how land values A_{it} are affected by land values in neighboring village tracts. The terms $\lambda_V \mathbf{W} V_{Nt}$ and $\rho \mathbf{W} \varepsilon_{Nt}$ control for changes in A_{it} that are due to spillover effects of violent events and idiosyncratic shocks in neighboring village tracts, respectively.

---

[2] Typical village tracts in Myanmar are less than 5–10 km apart from each other, which is below the threshold assumed in some of the earlier studies (e.g., Feichtinger & Salhofer 2016). Considering the potential spatial dependence across village tracts, as we do in our analyses, is therefore important.

[3] In the literature, it is common to use the same matrices **W** for both spatial lag of the dependent variable and spatially lagged error (e.g., Fingleton 2008; Kelejian & Prucha 2010; Atreya et al. 2013; Hodge 2021).

Equation (2) focuses on identifying how an average increase in violent events across village tracts affects average land values in the sample, by taking into account not only the effects of violent events in respective village tracts but also how these effects potentially magnify (or, conversely, are offset) through spillover effects among land values across village tracts. Specifically, estimated parameters in (2) jointly identify three types of effects; average effects on land values within the same village tract (average *direct* impact), average effects on land values in the neighboring village tracts (average *indirect* impact), and average overall impacts, which are the sum of average *direct* and average *indirect* impacts. Following Lesage & Pace (2009), each of the aforementioned average impact measures are computed as:

$$\begin{aligned} \text{Average direct impact} &= \frac{1}{N}\sum_{i=1}^{N}\frac{\partial E(A_i|V,X,\mathbf{W})}{\partial V_i} \\ \text{Average indirect impact} &= \frac{1}{N}\sum_{i=1}^{N}\sum_{\substack{k=1 \\ (k\neq i)}}^{N}\frac{\partial E(A_i|V,X,\mathbf{W})}{\partial V_k} \\ \text{Average overall impact} &= \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{N}\frac{\partial E(A_i|V,X,\mathbf{W})}{\partial V_k} \end{aligned} \tag{3}$$

in which $E(A_i|V,X,\mathbf{W})$ is the i-th element of the reduced-form mean vector based on estimates from (2). Intuitively, the average overall impact is greater (smaller) than the average direct impact if there are positive (negative) spillover effects among land values, so that the average indirect impact has the same (opposite) sign as the average direct impact.

3.2.2 Spatial weight matrix *W*

3.2.2.1 Primary type of spatial matrix

We consider the following primary and supplementary spatial weight matrices for **W**. For our primary analyses, we use the inverse-distance between village tracts, which is commonly used in spatial economics literature. Specifically, **W** consists of element w_{ij}

$$w_{ij} = \frac{1}{d_{ij}} \tag{4}$$

in which d_{ij} is the Euclidean distance between the centroid of the village tracts of i and j. [4] The **W** defined in (4) is based on the premise that physical proximity between two farmlands and higher local physical mobility generally lead to greater spatial dependence between values of these lands. Farmers residing in close proximity rely on the same input and output markets, face comparable cost and price structures, and therefore experience similar effects on farm profitability, which in turn influences land valuation in similar ways. Land markets in two different locations may also be integrated because buyers/renters may face lower transaction costs by switching from one area to the other (conditional on all the determinants of land values), so that changes in the value of one landholding can cause changes in the value of the other landholdings more quickly. In addition, physical proximity to other farmlands may also lower the cost of

[4] When i and j are in the same village tracts, we computed average Euclidean distance to the centroid of the village tract, and use this value for d_{ij}.

learning the values of those lands, thus further integrating one's own farmland with markets for those other lands. For example, it is easier for potential buyers to travel and physically assess multiple plots that are located closer to each other, so that changes in the valuation of one plot can more easily affect the valuations of other plots than they would among plots that are located far apart.

3.2.2.2 Alternative types of spatial matrix

For robustness checks, we also consider two other types of **W**, both of which incorporate not only the distance d_{ij}, but also factors affecting mobility. The first type consists of element w_{ij}

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}}, & \text{if } i \text{ and } j \text{ are in the same township or state} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The **W** defined in (5) considers not only the distance between village tracts but also the significant restrictions in movement across townships or sometimes states imposed in various ways in Myanmar in recent years, initially in response to the COVID-19 pandemic in 2020 and later by the 2021 military coup (e.g., Boughton et al. 2021, 2024). If such township/state-based movement restrictions are effective enough to discourage movement (regardless of how they are enforced), they may significantly limit the spillover effects between values of lands located across township/state borders regardless of their proximity.

The second type of alternative **W** consists of element w_{ij}

$$w_{ij} = \frac{1}{d_{ij}} \cdot \frac{m_{i0} + m_{j0}}{2} \tag{6}$$

in which m_{i0} and m_{j0} are binary variables of mobility taking the value of 1 if household i and j perceived unrestricted mobility in their respective location in the initial survey round, and 0 otherwise (i.e., they perceived that their mobility was restricted due to government measures like curfews or overall security concerns).[5]

Importantly, even though (6) is based on the mobility perceptions in the initial survey round, these perceptions can still be affected by V_{it} in the initial round, potentially causing endogeneity issues. In the robustness check section, we address this potential endogeneity through additional methodology suggested by Qu et al. (2016) and Delgado et al. (2018) (described in Appendix B).

3.3 Variables

Outcome variables A_{it}

Our key outcome variable A_{it} is the natural log of perceived value reported by the respondent for the largest plot for rice at the end of the monsoon season. Self-reported perceived value of the land has often been used in the literature on hedonic land price (e.g., Chakraborty et al. 2023) and has been found to provide estimates generally similar to actual market values (Kiel & Zabel 1999; Gamper-Rabindran & Timmins 2013; Bigelow et al. 2020). Various studies have also emphasized the policy relevance of land-related research based on self-reported land values

[5] Both (5) and (6) are the Hadamard product (the element-by-element product of two matrices) of the inverse distance matrix and another matrix. Past literature (e.g., Skevas et al. 2022) used similar approaches.

(Choumert & Phélinas 2015; Joshi et al. 2017; Merry et al. 2008; Wineman & Jayne 2018). In our analyses, we also deflate this land value by the farmgate price of paddy, the major staple food, to assess land values in real terms accounting for spatiotemporal variations in inflation rates during the period.

Violent events V_{jt}

We proxy the intensity of conflicts V_{jt} as the total number of fatal violent events in the village tract reported in the ACLED data (further described in the data section).[6] The ACLED data have been used in numerous studies that assess the effects of conflicts on various outcomes (e.g., Takeshima et al. 2025). Specifically, we measure the total count of fatal violence over the previous 12 months, spanning the 6 months prior to the monsoon season (January–June) as well as the 6 months in the monsoon season (July–December). We choose this timeframe because land valuation tends to reflect perceptions of relatively longer-term economic returns, and conditions during the 12-month period may signal to farmers significant medium- to long-term shifts in the nature of conflicts in the area.

Control variables X_{it}

Control variables X_{it} are selected following related previous literature assessing the determinants of land values (e.g., Tione & Holden 2020; Deininger & Ali 2023; Chakraborty et al. 2023; Herrnstadt & Sweeney 2024). Specifically, X_{it} includes key household demographics, i.e., age, gender, education of the farm management decision-maker and household size (adult males, adult females, and children) that vary over time due to migration of household members. X_{it} also includes whether or not the plot for which the value is reported is irrigated.[7] X_{it} further include proxies related to access to inputs, i.e., size of farmland owned, types of livestock owned (principal component), machines owned (measured in aggregate horsepower),[8] and distances to the commonly used input-dealers, rice mills, and the center of the respondent's township (all measured as time of travel in hours). Lastly, X_{it} also includes the village-tract average of nighttime luminosity (proxy for overall economic activities), and 12-months rainfall shocks (measured as absolute percentile deviation from the historical 50th percentile).

4 Data and descriptive statistics

4.1 Data

Our primary data comes from the Myanmar Agricultural Performance Survey (MAPS). Specifically, we focus on two rounds of monsoon harvesting season data administered in January 2023 and January 2024, and two rounds of non-monsoon harvesting season data administered in

---

[6] These violent events consist of any of the following; battles (armed clashes, the government's regaining territories, and non-state actors' overtaking territories), explosions/remote violence (e.g., chemical weapons, air/drone strikes, suicide bombs, shelling/artillery/missile attacks, remote explosives/landmines/IED (improvised explosive devices), and grenades), and violence against civilians (e.g., sexual violence, attacks, and abduction/forced disappearances).

[7] Another potential variable would include whether the respondent has formal land title document. Unfortunately, the information is not available in all rounds and thus could not be included in our analysis. However, importantly, in the 2023 monsoon season, close to 90% had land certificates for their largest rice plot. Therefore, our analyses are generally not likely to be affected by the availability of land certificates.

[8] Following relevant literature of the typical horsepower in Asia, we apply the following: 40 hp for four-wheel tractors (Takeshima et al. 2013; Takeshima 2017; Diao et al. 2020), 15 hp for two-wheel tractors and Trawlarjee (Justice & Biggs 2020), and 5 hp for irrigation pump (Justice & Biggs 2020). We also assign 5 hp for other minor machines. We apply slightly different hp and find that our main results are largely robust.

July 2022 and July 2023, each of which captures key variables, including the land values (perceptions of market prices reported by farmers) of the largest rice plot that they cultivated during the 2022 and 2023 monsoon seasons (production seasons during July–December in 2022 and 2023) and during the 2022 and 2023 non-monsoon seasons (production seasons during January–June in 2022 and 2023). Each round of MAPS data is nationally representative, collected through multi-stage stratified sampling methods. A fraction of the 2023 monsoon season data was collected as panel samples of the 2022 monsoon season data, among which approximately 50% of respondents grew rice in both monsoon seasons and reported the value of their largest rice plots. Similarly, a fraction of the 2022 non-monsoon season data was collected as panel samples of the 2021 non-monsoon season data, among which approximately 10% of respondents grew rice in both non-monsoon seasons and reported the value of their largest rice plots.[9] Our final sample consists of a balanced panel of 2,173 monsoon-season rice farmers and 502 non-monsoon-season rice farmers (totals of 4,346 and 1,004 observations from two rounds, respectively). These samples are located across 1,280 and 341 village tracts, respectively, and measures of violent events at the village tract level (as described below) are used to assess effects on land values at the farmer level.

Data for the intensity of violent events within the village tracts of the respondents are from the ACLED data (Raleigh et al. 2010) and have been used in recent studies assessing the role of conflicts on various development outcomes across the world, including Myanmar (Boughton et al. 2024; Takeshima et al. 2024, 2025; Davis et al. 2025). The ACLED data compiles information on violent events from numerous sources, as well as their dates and approximate geographic coordinates or location information, which allow us to identify how many of these events took place in each village tract within a particular time period. These violent events include battles, explosions/remote violence, and violence against civilians. The ACLED data also reports whether each event directly involved any fatality.[10]

Other supplementary spatial data are extracted from various sources. Historical monthly rainfall data are from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk et al. 2015). Historical daily temperature data are from the AgERA5 data (Dee et al. 2011). Soil properties data are from FAO et al. (2012), and nighttime light data are from Elvidge et al. (2021), whose methodologies have also been applied to 2022 and 2023. All these data are extracted at the village-tract level, using the GIS shapefile of 14,600 village tracts in Myanmar from GeoNode (https://geonode.themimu.info/). The township level cumulative COVID-19 case count up to February 2021 is from the COVID Myanmar Dashboard (2022). Lastly, spatial land surface data are from Chen et al. (2020).

4.2 Descriptive statistics

[9] The nature of panel samples as described embeds certain sample attrition partly caused by violent events (e.g., some farmers discontinuing rice production due to increase in violent events). Nonetheless, given the adverse effects of violent events on land values as described in our results section, rigorously accounting for the sample attrition may rather magnify the adverse effects of local violence on land values. Therefore, our results are likely to provide more conservative estimates of the effects of local violence on land values.

[10] More detailed definitions of violent events are provided in https://acleddata.com/acleddatanew/wp-content/uploads/2021/11/ACLED_Codebook_v1_January-2021.pdf. Battles can include armed clashes, the government's regaining territories, and non-state actors' overtaking territories. Explosions/remote violence include chemical weapons, air/drone strikes, suicide bombs, shelling/artillery/missile attacks, remote explosives/landmines/IED (improvised explosive devices), and grenades. Violence against civilians includes sexual violence, attacks, and abduction/forced disappearances.

Land values

Table 1 summarizes the key descriptive statistics of the variables used for both the monsoon harvesting season and the non-monsoon harvesting season. The top row shows that the average land values per acre of the largest rice plot, measured in real terms, is equivalent to about 7.1 tons of paddy based on local paddy price, while exhibiting significant variations with standard deviations of about 7.6. The average values also declined significantly for both the monsoon harvesting season (from 7.9 in 2022 to 6.3 in 2023) and the non-monsoon harvesting season (from 11.0 in 2022 to 7.0). This could also be partly explained by a significant increase in rice prices in the global rice market during around the same period.[11]

[Table 1]

Violent events

The exposure to violent events is highly uneven. While the number of months with fatal violent events in the village tracts was around 0.2–0.25 in the monsoon harvesting season and around 0.35 in the non-monsoon harvesting season, the associated standard deviations are about 3–4 times larger. Violent events are concentrated in village tracts inhabited by 11–12% of respondents. These respondents, on average, experienced violent events in about 2–3 months out of 12 months (e.g., 2.25 = 0.252/0.112). On average, about 18% and 15% of respondents, in the monsoon season and the non-monsoon season respectively, experienced some changes in the number of months with violent events between years. Figure 1 further illustrates how the changes in violent event intensity, as measured above, vary across space. As shown, the changes in intensity exhibit spatial variations not only across regions but also within each region, in both the January–December and July–June periods. Furthermore, since the overall intensity of violent events in Myanmar somewhat plateaued (at a high level) after the summer of 2021 (Takeshima et al., 2025, Figure 5), a significant share of village tracts also saw a net decrease in violent events after July 2021 (the period which our study focuses on). These sufficient spatiotemporal variations, including both net increases and net decreases in violent event intensity, allow us to identify their effects on land values.

Other exogenous characteristics

Descriptive statistics on other variables in Table 1 suggest that sampled farm households to which these plots belong typically have male farm management decision-makers (of all farms including plots other than the largest rice plot) around ages 45–50 and having completed 8 years of education, consist of about 4–5 household members, own poultry and a few other livestock animals as wellas agricultural equipment that totals about 13–16 hp equivalent. They are typically located between 0.5 and 1 hours from agri-input retailers and the nearest township center, and about 0.4–0.5 hours from rice mill/hullers.

Descriptive statistics for time-invariant factors suggest that our sample farm households are typically in areas with soils that are slightly acidic, less fine (coarser), and have poor drainage capacity, with topography that is generally sloping southward (as indicated by negative average slope aspects).

5 Results

[11] For example, the FAO Rice Price Index increased by 21% between 2022 and 2023 (FAO 2026).

5.1 Models without accounting for potential spatial spillover effects

Table 2 summarizes the results of the simple model (1) (without accounting for potential spatial relations) for the values of the largest rice plot at the monsoon harvesting season (December 2022 and 2023) and the non-monsoon harvesting season (June 2022 and 2023), respectively (Table 12 in the Appendix A provides full results). For robustness-check purposes, we show results for the number of months with violent events over the previous 12 months (our primary measure of violent events), as well as for the previous 6 months.

[Table 2]

Results in Table 2 suggest that, for both the monsoon harvesting season and the non-monsoon harvesting season, a higher intensity of violent events in the respondent's village tract during the previous 12 months is significantly negatively associated with the land values. Specifically, an additional month of violent events is associated with a 2.6% decrease in land values during the monsoon harvesting season and a 5.3% decrease during the non-monsoon harvesting season. The results are qualitatively similar, even when we focus on violent events over the previous 6 months. Importantly, results in Table 2 hold after including year dummy variables so that we are not confounding other period-specific effects that are correlated with both violent events and land values.

The estimated effects in Table 2 can be translated into the actual effects based on the descriptive statistics of violent events in Table 1. On average, effects in Table 2 translate into reduced land values by about 0.6% (≈ 2.7% * 0.213) in the 2023 monsoon harvesting season, and by 2.0% (≈ 5.5% * 0.361) in the 2023 non-monsoon harvesting season, compared to what they would have been under the counterfactual scenarios of no violent events. Given the concentration of violent events (Table 1), these effects are in fact driven by village tracts that experienced at least one violent event (which constitute about 11–12% of all samples), where land values declined, on average, by 5.1% (≈ 2.7% * 0.213 / 0.112) and 16.3% (≈ 5.5% * 0.361 / 0.122) in each season, respectively. Put differently, in townships that experience more persistent conflicts across multiple months, the overall effects on land values can be sizable. In an extreme case, a township experiencing violent conflicts in 10 of 12 past months (the highest in our sample) would experience declines on the order of 27–55% in land values.

Associations with other control variables

Associations between land values and other control variables are of secondary importance in our analysis and are summarized in Appendix Table 12. Generally, land value per area during the monsoon harvesting season is higher if the largest rice plot is smaller, the farmer owns more livestock and machines, the plot is located in a more urban area (with a higher nighttime light index) (as predicted by von Thünen, 1966), and the plot is irrigated. Each of these factors can raise productivity per area of land. In the non-monsoon harvesting season, land value is statistically significantly associated with somewhat fewer factors, possibly because farmers without favorable conditions may simply not cultivate rice during the non-monsoon season. However, during the non-monsoon harvesting season, land value is perceived as lower by older farmers with more children. This may be because investments to maintain land quality for non-monsoon season rice cultivation, such as land leveling to improve irrigation efficiency, may be labor-intensive and undertaken less frequently by older farmers or those with higher dependency rates (with more children). In both seasons, land value per area is lower if the seasons experienced more than normal rainfall. This may be due to potentially adverse factors, such as floods, weeds, and pests, that are often associated with excessive rain.

5.2 Models accounting for potential spatial spillovers

We now turn to the results that account for potential spatial dependence among land values across village tracts, based on equations (2) through (6).

5.2.1 Primary results using spatial weight matrix based on standard inverse distance (equations (2) through (4))

Table 3 and Table 4 summarize the primary results of equations (2) through (4), which account for spatial weights based on standard inverse distance between village tracts, for the monsoon harvesting season and the non-monsoon harvesting season, respectively. In both tables, for robustness, multiple sets of results are shown to account for additional spatial dependence among idiosyncratic shocks and violent events as summarized in the Table footnotes. Table 3 and Table 4 show both the overall effects of violent events (in the upper parts of the tables), which are our main interest, as well as the raw coefficients and spatial spillover patterns (in the lower parts of the tables) that jointly determine these effects.

Results for the monsoon harvesting season in Table 3 are generally consistent with those in Table 2, suggesting that more local violence during the prior 12 months is associated with lower land values during the monsoon harvesting season. Specifically, in specifications (a) and (b), an additional month of at least one violent event during the previous 12-month period is associated with a 2.7% lower land value (in the row "Average overall impact"), which is statistically significant at the 5% level. When the term $\lambda_V \mathbf{W}$ is included (i.e., violent events can directly affect land values in other village tracts) (models (c) and (d)), estimated coefficients become less precise, potentially due to multicollinearity, but they are still statistically significant at the 10% level, with somewhat larger point estimates (3.0–3.5% reduction in land values). Results in Table 3 also suggest that there are some positive spatial spillover effects in land values across village tracts (although distinguishing them from spatial spillover of idiosyncratic shocks is somewhat difficult). Because of this, in certain models such as (d), while the average direct impact is statistically insignificant, the average overall impact (which also includes the average indirect impact) is larger and identified with greater statistical significance.

Similarly, results for the non-monsoon harvesting season in Table 4 are generally consistent with those in Table 2. An additional month with at least one violent event during the previous 12-month period is associated with a 5.1% to 5.8% lower land value on average, with statistical significance at the 5% level. Results also suggest positive spatial spillover effects of idiosyncratic shocks across village tracts. In models (c) and (d), while the average direct impacts are statistically insignificant, the average overall impacts are larger and statistically significant.

Overall, the results in Table 3 and Table 4 show that the results from Table 2 remain robust even when accounting for spatial spillover in land values across village tracts.

5.2.2 Robustness results using alternative spatial weight matrices (equations (2), (5), and (6))

As discussed in section 3.2.2, the spatial weight matrix based on the standard inverse distance (as in Table 3 and Table 4), an approach commonly used in the literature, may fail to account for other factors that affect spatial spillovers. Table 5 and Table 6 summarize the results similar to Table 3 and Table 4 but also account for additional factors affecting the mobility across village tracts and thus potential spillover effects, including limited mobility across township or state borders (equation (5)) and in specific village tracts due to government measures like curfews and local security concerns perceived by the respondent (equation (6)).

The results in Table 5 and Table 6 are generally consistent with those in Table 2 through Table 4. In Table 5, results in columns (a1) through (d2) suggest estimated average overall impacts of –0.035 to –0.027 (statistically significant at 10% or above), which are generally larger and associated with higher statistical significance than average direct impacts alone, due in part to some positive spillover in land values across village tracts. Similarly, results in (a1) through (d2) in Table 6 are largely consistent with those in Table 4. Our primary results are therefore robust even with added complexity in spillover potential across township and state borders.

Similarly, results in (a3) through (d3) in Table 5 and Table 6 are generally consistent with Table 2 through Table 4 as well, suggesting their robustness against additional location-specific mobility restrictions that can further affect spillover patterns. As discussed above, models (a3) through (d3) may be subject to endogeneity issues because the spatial weight matrix is partly based on respondents' perceptions and can be affected by both land values and violent events. In Appendix B, we show that the endogeneity is less of a concern, and our results in (a3)–(d3) are likely to be unbiased.

5.3 Further insights on heterogeneity

5.3.1 Robustness against potential heterogeneity

We also check whether the effects of violent events are heterogeneous enough to be significantly different across specific subgroups. We do so by re-estimating primary models in Table 2 (in which we use the number of months with violent events in the previous 12 months), adding interaction terms between violent events and various local characteristics, such as major agroecological zone dummies, as well as nighttime light intensity, irrigation, dominant soil characteristics, terrain ruggedness, and slope aspects.

Table 7 summarizes the results with various local characteristics, while Table 8 summarizes the results with agroecological zone dummies. In Table 7, heterogeneity factors are standardized so that the estimated coefficients of interaction terms measure the effects of a one-standard-change increase in each heterogeneity factor, while the coefficient for the violent event variable (non-interacted term) captures the average effect of violent events. Table 8 shows that, using Dry zone as the base, the interaction terms with Hills zone, Delta zone and Coastal zones are all statistically insignificant for both the monsoon harvesting season and the non-monsoon harvesting season, suggesting that our primary results are generally consistent across agroecological zones.

Similarly, Table 7 shows that interaction terms are generally statistically insignificant. Some results for the non-monsoon harvesting seasons are also insignificant, simply because the samples are generally homogeneous with respect to the particular heterogeneity factor, leading to multicollinearity between the violent event variable and the interaction term. An exception is nighttime light intensity during the non-monsoon harvesting season, for which a statistically significant positive coefficient for the interaction term suggests that the adverse effect of violent events on land value is somewhat milder in more urban/suburban areas than in rural areas. Nonetheless, the magnitude of the coefficient for the interaction term (0.019) is relatively smaller than the overall average effect of violent events (–0.085), suggesting that heterogeneity is relatively small. Overall, Table 7 likewise confirms that our primary results are broadly robust.

Heterogeneity based on rice areas per capita at the township level

The effects of conflict on the value of rice plots can also differ between relatively rice-surplus ("exporting") regions and rice-deficit ("importing") regions, due to potentially differential structures of local land markets and effects of conflict on real returns to land. We briefly check the robustness of our results by re-estimating Table 2 separately for sub-samples split at median values of rice area per capita at the township-level using high-resolution (30m × 30m) GIS data of seasonal rice areas (Li et al., 2025) and the latest population census in 2014 (Government of Myanmar 2014) (Table 9). Table 9 shows that in both types of townships, real land value is negatively associated with violent events over the past 12 months, and these associations are statistically significant, with magnitudes that are insignificantly different (last column). These results further suggest that our results are broadly robust.

5.3.2 Additional insights from decomposition based on nominal terms

While our primary analyses focus on land values in real terms (i.e., deflated by the farmgate rice price), it is informative to decompose the associations into those involving nominal land value and nominal farmgate rice price to see whether our results are due to spurious artifacts of the deflating method. To gain insights on this, we re-estimated Table 2 separately for each of the nominal land values and the nominal farmgate rice price as a dependent variable, and also differentiated by rice-surplus and rice-deficit regions as defined above. Table 10 presents regression results for key coefficients, while Table 11 summarizes key implications. Essentially, as is characterized in Table 11, we find somewhat differential patterns across seasons and types of townships based on surplus-deficit status.

In the monsoon season, nominal rice prices may be relatively unaffected by violent events. This is possibly because rice markets may be more integrated (due to greater production) and thus may not be affected by local violence in either rice-exporting or rice-importing townships. In contrast, nominal land value is negatively associated with violent events, possibly because reduced yield and thus revenue/profit can be generated from the land.

In the non-monsoon harvesting season, we observe some offsetting effects because rice plots in this season are relatively scarce. Nominal rice prices and effects of violent events can be more variable across surplus townships and deficit townships because rice quantity marketed is generally smaller, and the rice market is thinner in the non-monsoon season. Specifically, local violence may raise nominal rice prices in rice-importing townships (potentially due to a violence-induced rise in transportation costs from rice-exporting townships), although it may not affect the price in rice-exporting townships. At the same time, nominal land value is more negatively associated with violent events in rice-exporting townships, due to adverse effects on yield/revenue. In contrast, in rice-importing townships, this adverse effect on revenue due to lower yields may be offset by higher farmgate rice prices, as mentioned above, which explains the insignificant effects of local violence.

Altogether, the results in Table 10 and Table 11 offer richer insights into how potential mechanisms underlying our primary results based on real-term land values are somewhat heterogeneous across seasons and types of townships, even though they ultimately lead to generally consistent patterns of conflict-land-value nexus overall in real terms.

6 Discussions and policy implications

Potential mechanisms

Other studies investigating the effects of conflicts in Myanmar and elsewhere offer insights into the potential mechanisms behind our results. Reduced farmland values may be partly due to lower economic returns resulting from conflicts. As evidenced by recent studies in Myanmar, conflicts can suppress agricultural productivity and responses to yield-enhancing inputs like fertilizer partly due to reduced access to extension services (Takeshima et al., 2024, 2025a) and increase marketing costs (Minten et al., 2023; Goeb et al., 2025), potentially leading to reduced farmgate prices and lower profitability. A persistent conflict in the local area may shift farmers' perceptions of such profitability in the medium-to-long run, leading to reduced farmland values. Conflicts can also lead to an excess supply of land in the locality, further decreasing land values. For example, such excess supply of land may result from distress sales of productive assets, including land, during conflicts (e.g., van Asselt et al., 2024), and/or due to outmigration and abandonment of farmland by certain local farmers (Adelaja & George 2019). Conflicts can further lower farmland values by weakening perceptions of land property rights, although the share of households experiencing this remained relatively low as of 2022 in Myanmar (Boughton et al. 2024, Table 5.1). Lastly, conflicts can also lead to severe damage to farmland, reducing land quality and thus its value (Adelaja & George 2019). Our findings of adverse effects of conflicts on farmland values are broadly consistent with these hypotheses on underlying mechanisms.

Implications for household welfare

Identifying the welfare implications of reduced land values is beyond the scope of this study and requires a thorough investigation in future studies. Nonetheless, we can get some insights from additional qualitative analyses of available data to a limited extent. Appendix C briefly discusses partial insights from additional analyses based on subsamples of our MAPS data, which are also captured in a separate dataset (the Myanmar Household Welfare Survey (MHWS)) for the periods following those covered by the MAPS data. Using average land values of neighboring samples as instrumental variables (IV) and applying the IV-method to panel data, Appendix C suggests that lower land values are associated with a higher likelihood of distress sales of precious (non-land) assets, distress engagements in risky income-earning activities, distress borrowing of money (which is likely under unfavorable terms from the informal sector), and reduced dietary diversity of purchased food. These patterns are generally consistent with the roles of farmland values emphasized in the literature, such as its roles as assets and wealth, safety-net function and status, and access to more reasonable loans from the formal sector (World Bank 2007; Promsopha 2015; Rigg et al. 2016; Swift et al. 2024). Overall, the potentially adverse welfare implications add importance to our findings on the adverse effects of conflict on farmland values.

Policy implications

As the latest farmland policies in Myanmar do not explicitly address land value, the direct policy implications of our study are somewhat ambiguous. Nonetheless, other aspects of policies in Myanmar, including those of the agriculture sector, and experiences from other countries can be relevant.

Policies supporting more equitable and secure access to land in general (Lambrecht et al. 2024b) are likely to be critical, particularly for smallholders who own farmland, since one way to overcome the losses associated with declining land value per area is to expand the size of accessible land. In conflict settings characterized by fragmented governance, complex tenure arrangements, and uncertain property rights, the design and effectiveness of improved policies are highly dependent on local context.[12] While challenges remain, reducing transaction costs in land administration and the land sales/rental market can mitigate land value depreciation (or the perception thereof) and may be worth pursuing. While more direct evidence is needed through further research, exploring the increased use of modern technologies, such as information and communications technologies, for overall land administration and transactions, starting in regions where conflicts have relatively subsided, could be promising.[13]

Facilitating freer use of farmland may make farmland values more resilient to conflicts. For example, in Myanmar, converting paddy land to alternative crops often requires a lengthy, cumbersome approval process from local administrations (Boughton et al. 2024). Revising these policies can facilitate such processes. Doing so can potentially lower transaction costs for farmers switching to a more optimal use of farmland,[14] while also attracting renters with a higher willingness to pay, potentially mitigating farmland depreciation during local conflict. Similar policies of relaxing crop-choice restrictions are also found to have generally positive economic effects in relatively peaceful settings (e.g., relaxing rice production requirements in Viet Nam (Le 2020)). In the Myanmar context, recurring conflicts further enhance the importance of implementing such a policy. Importantly, such a policy should be implemented in ways that do not magnify inequality in farmland values between safe/stable areas and unsafe/conflict-affected areas.

Finally, declining land values and heightened uncertainty over property rights may reduce farmers' ability to access agricultural credit, given that land is often used as collateral. The substantial decline in the use of agricultural credit by farmers in Myanmar since the onset of the conflict may illustrate these dynamics (Minten & Win 2025). These findings suggest that exploring alternative forms of collateral could be an important policy response.

7 Conclusions

The value of farmland, including that in developing countries, has various economic implications for farm households who possess use-rights to these lands. Knowledge gaps remain regarding how farmland values can be affected by factors such as conflicts and social instability. A knowledge gap also remains regarding how the relationship between conflict and farmland values may depend on spatial transmission and feedback effects of conflict on land values on farmlands in proximity to each other, which has generally not been considered in the literature. This paper attempts to narrow these knowledge gaps by utilizing nationally representative panel data of rice producers in Myanmar, their perceptions of the values of their largest rice plots, and spatial data on conflict intensity, with a focus on the period of significant conflict intensification following the 2021 political crisis in Myanmar, particularly in 2022 and 2023.

[12] It is important to acknowledge that, while our findings have more direct relevance to farm households that own land, it is possible that landless farm households are generally even more vulnerable to adverse effects of violent events.

[13] Elsewhere, the use of ICTs and other emerging technologies has often benefited farmers. For example, computerization of land registration led to a modest increase in credit provision (Deininger & Goyal 2012), while advancing digitalization of land administration can foster farm productivity (Ali & Deininger 2022).

[14] For example, a recent study finds that allowing farmland use for cultivation of more diverse crops can also mitigate the loss in dietary diversity under conflict (Takeshima et al. 2025b).

We find that the average value of the largest rice plot per acre declined in real terms (relative to paddy prices) during both the monsoon harvesting season (December 2022 and December 2023) and the non-monsoon harvesting season (June 2022 and June 2023). During these periods, the country shifted to a high-conflict-intensity state, while exhibiting significant spatial variations. Our regression analyses find that more local conflict during the prior 12 months, measured by the number of months with at least one fatal violent event within the village tract of respondents, significantly reduced the farmland values of the largest rice plot of these respondents in the monsoon and non-monsoon harvesting seasons of 2022 and 2023. These results hold after controlling for a year dummy variable that accounts for any other year-specific potential confounders. Furthermore, these adverse effects of violent events are robust and sometimes magnified by spatial spillover effects on land values across village tracts. Results remain robust when limiting the relevant violent events to those during the prior 6 months, and considering various local, township or state level factors that affect the potential spatial spillover of land values. Supplementary analyses also suggest that our primary results hold broadly across different agroecologies and dominant local characteristics of soil and topography.

Our results are generally consistent with earlier studies investigating the impact of conflicts on land values outside Myanmar. Within the context of Myanmar, where studies have already shown that the recent surge in conflicts has adversely affected society, our results show yet another channel through which conflicts have inflicted potential economic losses on farmers, that is, reduced values of their farmland and the various associated economic functions it plays as an asset among others. As mentioned, the implications of our findings can be particularly substantial in areas that sometimes experience significantly persistent conflicts lasting over several months or longer.

Lastly, while we provided reasonably compelling arguments that our findings are robust (and conservative at worst) against potential sample attrition issues, it is important in future studies to formally accommodate the methods that incorporate the attrition issues within the context of panel spatial econometrics used in our analyses. Furthermore, our analyses, by construction, assume symmetric effects of violent events; in other words, the magnitude of the effects are the same whether the violent events increase or decrease, which implies that the cessation of conflicts could immediately lead to the recovery of land values. It is important for future studies to investigate longer-term, potentially dynamic effects of declined land values during the conflicts.

References

Ali DA & K Deininger. 2022. Institutional determinants of large land-based investments' performance in Zambia: Does title enhance productivity and structural transformation?. *World Development 157*:105932.

Anselin L & RJGM Florax. 1995. *Small Sample Properties of Tests for Spatial Dependence in Regression Models: Some Further Results*. In *New Directions in Spatial Econometrics*, edited by L Anselin & RJGM Florax, 21-74. Berlin: Springer-Verlag.

Arias MA, AM Ibáñez & A Zambrano. 2019. Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty. *World Development 119*:165-184.

Armed Conflict Location & Event Data (ACLED). 2024. *Conflict Index*. Available at https://acleddata.com/conflict-index/. Accessed December 17, 2024.

Atreya A, S Ferreira & W Kriesel. 2013. Forgetting the Flood? An Analysis of the Flood Risk Discount Over Time. *Land Economics 89*(4):577-96.

Aung N, HTM Nguyen & R. Sparrow. 2019. The impact of credit policy on rice production in Myanmar. *Journal of Agricultural Economics*, *70*(2), pp.426-451.

Besley T & H Mueller. 2012. Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland. *American Economic Review 102*:810-833

Bigelow DP, J Ifft & T Kuethe. 2020. Following the market? Hedonic farmland valuation using sales prices versus self-reported values. *Land Economics 96*(3):418-440.

Boughton D, J Goeb, I Lambrecht, D Headey, H Takeshima, K Mahrt, I Masias, S Goudet, C Ragasa, MK Maredia, B Minten & X Diao. 2021. Impacts of COVID-19 on agricultural production and food systems in late transforming Southeast Asia: The case of Myanmar. *Agricultural Systems 188*, 103026.

Boughton D, B. Belton, I Lambrecht, I Masias & B Minten. 2024. Myanmar's Agrifood Systems: Historical Development, Recent Shocks, Future Opportunities. IFPRI, Washington DC.

Boutry M, KP Sone, SC Par & TM Win. 2015. *Land dynamics and livelihoods in peri-urban Yangon.* Livelihoods and Food Security Trust Fund: Yangon, Myanmar.

Boutry M, C Allaverdian, M Mellac, S Huard, US Thein, TM Win & KP Sone. 2017. *Land Tenure in Rural Lowland Myanmar: From Historical Perspectives to Contemporary Realities in the Dry Zone and the Delta.* Of Lives and Land Myanmar Research Series. Yangon, Myanmar: GRET.

Bovkir R & AC Aydinoglu. 2018. Providing land value information from geographic data infrastructure by using fuzzy logic analysis approach. *Land Use Policy 78*:46-60.

Bruno E, R Castellano, G Punzo & L Salvati. 2024. Direct and spillover effects of short-and long-term land pricing drivers: Evidence from Italian districts, 1992−2019. *Journal of Regional Science*, in press.

Caffera M, FV Lavín, M Barrientos, DR Anza & L Carrasco-Letelier. 2024. The implicit market price of soil erosion: An estimation using a hedonic model with spatial spillovers. *Agricultural Economic 55*(6): 963-984.

Carter MR & CB Barrett. 2006. The economics of poverty traps and persistent poverty: An asset-based approach. *Journal of development studies 42*(2):178-199.

Chakraborty KS, A Chakraborty & RP Berrens. 2023. Valuing soil erosion control investments in Nigerian agricultural lands: A hedonic pricing model. *World Development 170*:106313.

Chaudhry AM, DH Fairbanks & C Nolte. 2024. Water Market Participation and Agricultural Land Values. *Land Economics*, *100*(1), 127-147.

Chen D, A Baer, J He, A Hoffman-Hall, V Shevade, Q Ying & TV Loboda. 2020. *Land cover land use map for Myanmar at 30-m resolution for 2016*. Pangaea, doi, 10.

Choumert J & P Phélinas. 2015. Determinants of agricultural land values in Argentina. *Ecological Economics 110*:134-140.

COVID Myanmar Dashboard. 2022. *COVID-19 Myanmar Surveillance dataset*. https://datastudio.google.com/u/0/reporting/445c1281-c6ea-45e4-9bc0-5d561c511354/page/I44CB.

Davis, C. A., Lopez-Pena, P., Mobarak, A. M., & Wen, J. Y. (2025). The economic drivers of state violence against civilians: Evidence from Myanmar. *Economic Journal*, in press.

Deininger K & A Goyal. 2012. Going digital: Credit effects of land registry computerization in India. *Journal of Development Economics 99*(2):236-243.

Deininger K & DA Ali. 2023. *Land and Mortgage Markets in Ukraine. Pre-War Performance, War Effects, and Implications for Recovery*. World Bank Policy Research Working Paper 10385.

Delgado FJ, S Lago-Peñas & M Mayor. 2018. Local tax interaction and endogenous spatial weights based on quality of life. *Spatial Economic Analysis 13*(3):296-318.

Diao X, H Takeshima & X Zhang. 2020. *An Evolving Paradigm of Agricultural Mechanization Development: How Much Can Africa Learn from Asia?* Washington DC. IFPRI.

Feichtinger P & K Salhofer. 2016. The Fischler reform of the common agricultural policy and agricultural land prices. *Land Economics 92*(3):411-432.

Food and Agriculture Organization (FAO). 2024. *World Census of Agriculture*. Rome, Italy.

FAO. 2026. *FAO Rice Price Update.* Available at https://www.fao.org/markets-and-trade/commodities/rice/fao-rice-price-update/en.

Fingleton B. 2008. A Generalized Method of Moments Estimator for a Spatial Model with Moving Average Errors, with Application to Real Estate Prices. *Empirical Economics* 34(1):35-57.

Gamper-Rabindran S & C Timmins. 2013. Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits. *Journal of Environmental Economics and Management 65*(3):345-360.

George J, A Adelaja & TO Awokuse. 2021. The agricultural impacts of armed conflicts: the case of Fulani militia. *European Review of Agricultural Economics 48*(3), 538-572.

Green WN. 2019. From rice fields to financial assets: Valuing land for microfinance in Cambodia. *Transactions of the Institute of British Geographers 44*(4):749-762.

Goeb J, B Minten, ZW Aung, MT Htar, M Sabai, NLK Synt, AM Zu & K Mahrt 2025. Disruptions to agrifood value chains in fragile and conflict-affected states: Evidence from Myanmar. *International Food and Agribusiness Management Review* 1(aop): 1-10.

Government of Myanmar. 2014. *The 2014 Myanmar Population and Housing Census.* Yangon, Myanmar.

Herrnstadt E & RL Sweeney. 2024. Housing Market Capitalization of Pipeline Risk: Evidence from a Shock to Salience and Awareness. *Land Economics*.

Hodge TR. 2021. Flooding and the Value of Agricultural Land. *Land Economics 97*(1):59-79.

Hossain MS, M Arshad, L Qian, H Kächele, I Khan, MDI Islam & MG Mahboob. 2020. Climate change impacts on farmland value in Bangladesh. *Ecological indicators 112*: 106181.

Joshi J, M Ali & RP Berrens. 2017. Valuing farm access to irrigation in Nepal: A hedonic pricing model. *Agricultural Water Management 181*:35-46.

Justice S & S Biggs. 2020. The spread of smaller engines and markets in machinery services in rural areas of South Asia. *Journal of Rural Studies 73*, 10-20.

Kelejian HH & IR Prucha. 2010. Specification and Estimation of Spatial Autoregressive Models with Autoregressive and Heteroskedastic Disturbances. *Journal of Econometrics 157*(1):53-67.

Kiel KA & JE Zabel. 1999. The accuracy of owner-provided house values: The 1978–1991 American Housing Survey. *Real Estate Economics 27*(2):263-298.

Lambrecht IB, NLK Synt, HE Win, K Mahrt & KZ Win. 2024a. "It doesn't matter at all—we are family": Titling and joint property rights in Myanmar. *Land Use Policy 139*:107089.

Lambrecht IB, B Belton, P Fang, B Minten & PT Naing. 2024b. *Agricultural land: Inequality and insecurity*. In *Myanmar's agrifood system: Historical development, recent shocks, future opportunities*. D Boughton, B Belton, IB Lambrecht, I Masias & B Minten (Eds.). Chapter 6, pp. 149-170. https://hdl.handle.net/10568/155256.

Lau S. 2014. *Land reform in Myanmar and lessons learned from Southeast Asia.* Arts Internship Report. Institute for International Development. University of Adelaide. Adelaide, Australia.

Le K. 2020. Land use restrictions, misallocation in agriculture, and aggregate productivity in Vietnam. *Journal of Development Economics 145*:102465.

Lee LF & J Yu. 2010. Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics 154*:165-185.

LeSage J & RK Pace. 2009. *Introduction to Spatial Econometrics.* Boca Raton, FL: Chapman and Hall/CRC. https://doi.org/10.1201/9781420064254.

Li S, R Shen, J Jiang, Q Peng, X Chen, J Dong, J Dong & W Yuan. 2025. A long-term paddy rice distribution dataset in Asia at a 30 m spatial resolution. *Scientific Data 12*(1), 1052.

Luan DX. 2019. Bridging the credit gap for sustainable medicinal plant value chain development in Northwestern Vietnam. *Agricultural Finance Review 79*(4):443-466.

Mark S. 2016. Are the odds of justice "stacked" against them? Challenges and opportunities for securing land claims by smallholder farmers in Myanmar. *Critical Asian Studies 48*(3):443-460.

Merry F, G Amacher & E Lima. 2008. Land values in frontier settlements of the Brazilian Amazon. *World Development 36*(11):2390-2401.

Minten B, J Goeb, KZ Win & PP Zone. 2023. Agricultural value chains in a fragile state: The case of rice in Myanmar. *World Development 167*:106244.

Minten B & HE Win. 2025. Farm commercialization and farm services: Myanmar Agricultural Performance Survey (Dry Season 2025). Myanmar Strategy Support Program Working Paper 73. IFPRI, Washington DC.

Naing CC. 2019. *Client satisfaction on corporate loan in selected private banks*. Doctoral dissertation, MERAL Portal.

Pochanasomboon A, W Attavanich & A Kidsom. 2020. Impacts of land ownership on the economic performance and viability of rice farming in Thailand. *Land 9*(3):71.

Promsopha G. 2015. Land ownership as insurance and the market for land: A study in rural Vietnam. *Land Economics 91*(3):460-478.

Rajan R & R Ramcharan. 2015. The Anatomy of a Credit Crisis: The Boom and Bust in Farm Land Prices in the United States in the 1920s. *American Economic Review 105*:1439-1477.

Richards P. 2018. It's not just where you farm; it's whether your neighbor does too. How agglomeration economies are shaping new agricultural landscapes. *Journal of Economic Geography*, 18(1):87–110.

Rigg J, A Salamanca & EC Thompson. 2016. The puzzle of East and Southeast Asia's persistent smallholder. *Journal of Rural Studies 43*:118-133.
Qu X, X Wang & LF Lee. 2016. Instrumental variable estimation of a spatial dynamic panel model with endogenous spatial weights when T is small. *Econometrics Journal 19*(3):261-290.
Skevas T, I Skevas & N Kalaitzandonakes. 2022. The role of peer effects on farmers' decision to adopt unmanned aerial vehicles: evidence from Missouri. *Applied Economics 54*(12):1366-1376.
Sonobe T. & K Otsuka. 2010. *Cluster-based industrial development: A comparative study of Asia and Africa*. Springer.
Swift P, SE Htoo, SM Klay & H Rueff. 2024. COVID-19 migrant returnees, access to land, and subsistence under uncertain times in Karen State, Myanmar. *Land Use Policy 146*:107293.
Takeshima H, A Nin Pratt & X Diao. 2013. Mechanization and agricultural technology evolution, agricultural intensification in sub-Saharan Africa: typology of agricultural mechanization in Nigeria. *American Journal of Agricultural Economics 95*(5), 1230–1236.
Takeshima H. 2017. Custom-hired tractor services and returns to scale in smallholder agriculture: A production function approach. *Agricultural Economics 48*(3), 363–372.
Takeshima H, I Masias, MT Win & PP Zone. 2023. Effects of COVID-19 restrictions on mechanization service providers and mechanization equipment retailers: Insights from phone surveys in Myanmar. *Review of Development Economics 27*(1):323-351.
Takeshima H, ZW Aung, I Masias & B Minten. 2024. Endogenous technologies and productivity in rice production: Roles of social instability in Myanmar since 2021. *Agricultural Economics 55*(6):925-942.
Takeshima H, B Minten, J van Asselt, I Lambrecht, I Masias, J Goeb, ZW Aung & MT Htar. 2025a. Fertilizer and conflict: Evidence from Myanmar. *Food Policy 133*:102786.
Takeshima H, I Masias, B Minten, J van Asselt, PT Naing & HE Win. 2025b. *Crop diversification and nutritional resilience amid conflicts: Evidence from farmers in Myanmar.* IFPRI MAPSA Working Paper.
Takeshima H, B Minten, J van Asselt, ZW Aung & J Goeb. 2026. Climate shocks, conflict, and agricultural change. *Global Food Security*, in press.
Tellez JF. 2022. Land, Opportunism, and Displacement in Civil Wars: Evidence from Colombia. *American Political Science Review 116*:403-418.
van Asselt J, IB Lambrecht & ZW Aung. 2024. *Vulnerability and welfare during multiple crises*. In *Myanmar's agrifood system: Historical development, recent shocks, future opportunities*. D Boughton, B Belton, IB Lambrecht, I Masias & B Minten (Eds.). pp. 121-148.
von Thünen JH. 1966. *Der Isolierte Staat in Beziehung auf Landwirtschaft und Nationalökonomie*. Wiss. Buchges.
Wineman A & TS Jayne. 2018. Land prices heading skyward? An analysis of farmland values across Tanzania. *Applied Economic Perspectives and Policy 40*(2):187-214.
Wittekind CT & HO Faxon. 2023. Networks of speculation: Making land markets on Myanmar Facebook. *Antipode 55*(2):643-665.
World Bank. 2007. *World Development Report 2008: Agriculture for Development*. Washington, DC: World Bank.
Yagura K. 2020. Rapid diffusion of combine harvesters in Cambodian Rice farming: a business analysis. *Asian Journal of Agriculture and Development 17*(1):71-87.

Zhang X. 2023. Cluster-based agricultural development: a comparison between China and Africa. *Agricultural Development in Asia and Africa: Essays in Honor of Keijiro Otsuka*, pp. 317-328.

Table 1. Descriptive statistics among farmer respondents

Variables		Monsoon harvesting season		Non-monsoon harvesting season	
		2022	2023	2022	2023
		Mean (std.dev)	Mean (std.dev)	Mean (std.dev)	Mean (std.dev)
Land value per acre (in 100 tons of paddy)		0.079 (0.079)	0.063 (0.072)	0.110 (0.117)	0.070 (0.060)
Land size of the largest rice plot (acre)		1.376 (1.299)	1.276 (1.297)	1.314 (1.019)	1.235 (0.783)
Characteristics of farm management decision maker					
	Age (100 years)	0.482 (0.114)	0.484 (0.115)	0.477 (0.115)	0.480 (0.116)
	Gender (female=1)	0.152 (0.334)	0.148 (0.355)	0.124 (0.329)	0.131 (0.338)
	Education (years)	7.848 (4.227)	7.952 (4.292)	7.960 (4.265)	7.908 (4.176)
Household-members (adult male)		1.697 (0.885)	1.685 (0.864)	1.725 (0.900)	1.713 (0.890)
Household-members (adult female)		1.901 (0.992)	1.902 (0.979)	1.896 (0.967)	1.884 (0.955)
Household-members (children)		0.909 (0.975)	0.886 (0.968)	0.869 (0.906)	0.876 (0.909)
Livestock ownership (yes=1)	Chicken	0.524 (0.500)	0.497 (0.500)	0.576 (0.495)	0.564 (0.496)
	Sheep	0.003 (0.052)	0.003 (0.057)	0.002 (0.045)	0.002 (0.045)
	Goat	0.027 (0.163)	0.022 (0.146)	0.014 (0.117)	0.014 (0.117)
	Pig	0.167 (0.373)	0.168 (0.374)	0.193 (0.395)	0.207 (0.406)
	Draft animal	0.295 (0.456)	0.153 (0.360)	0.253 (0.435)	0.187 (0.391)
	Others	0.275 (0.447)	0.380 (0.485)	0.171 (0.377)	0.211 (0.409)
Machines owned (100 horsepower)		0.128 (0.145)	0.127 (0.146)	0.163 (0.157)	0.165 (0.157)
Travel time: most commonly used agri-input retailer (hours)		0.642 (0.636)	0.658 (0.697)	0.629 (0.562)	0.575 (0.509)
Travel time: rice mill / hullers (hours)		0.456 (0.671)	0.487 (0.769)	0.437 (0.406)	0.440 (0.403)
Nighttime light (nanoWatt cm^{-2} per square radian)		0.593 (1.096)	0.440 (0.886)	0.728 (1.581)	0.693 (1.585)
Irrigation (yes = 1)		0.407 (0.491)	0.405 (0.491)	0.900 (0.300)	0.984 (0.125)
Rainfall (6 months production season – historical percentile/100)		0.434 (0.281)	0.400 (0.281)	0.379 (0.247)	0.320 (0.269)
Number of months with fatal violent events in the village tracts (out of 12 months)		0.233 (0.875)	0.213 (0.774)	0.345 (1.310)	0.361 (1.271)
At least 1 month with fatal violent events in the village tracts (yes=1)		0.113 (0.316)	0.112 (0.315)	0.112 (0.315)	0.122 (0.327)
Nonzero changes in the number of months with fatal violent events (yes=1)		0.183 (0.387)	0.183 (0.387)	0.147 (0.355)	0.147 (0.355)
Mobility is **not** restricted (yes = 1)		0.789 (0.408)	0.802 (0.398)	0.712 (0.454)	0.865 (0.343)
Time-invariant factors[a]					
Soil characteristics	Alkalinity (pH)	6.080 (0.775)		6.314 (0.769)	
	Organic contents (gram / kg of soil)	1.915 (1.476)		2.529 (1.779)	
	Fine texture (proportion of soil)	0.328 (0.169)		0.328 (0.184)	
	Salinity (deciSiemens per metre)	0.693 (0.959)		0.734 (1.052)	
	Sodicity (percent of soil)	4.918 (10.227)		7.079 (14.553)	
	Poor drainage (proportion of soil)	0.655 (0.412)		0.826 (0.331)	
Terrain ruggedness (index)		41.368 (70.796)		20.224 (34.413)	
Slope aspects (–90 = South; 90 = North)		–3.237 (29.978)		–5.548 (27.198)	
Confirmed COVID counts in the townships in 2020		390.933 (1725.130)		773.168 (3005.348)	
Sample-size		2,173	2,173	502	502

Source: Authors' computations based on MAPS data.

[a]Time invariant variables are used in robustness check analyses in Appendix B.

Table 2. Violent events and perceived land values (without spatial dependence)

Variables	Dependent variable = ln (land value per acre)			
	Monsoon harvesting season		Non-monsoon harvesting season	
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Number of months with violent events (previous 12 months)	–0.026*** (0.008)		–0.053*** (0.018)	
Number of months with violent events (previous 6 months)		–0.023* (0.013)		–0.074*** (0.023)
Other controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000
No. obs	4,346	4,346	1,004	1,004

Source: Authors. ***1% **5% *10%.

Table 3. Violent events and perceived land values in monsoon harvesting season, using spatial weights based on inverse distance between village tracts

Variables	Dependent variable = ln (land value per acre)			
	(a)	(b)	(c)	(d)
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Overall effects of violent events (previous 12 months)				
Average overall impact	**–0.027****	**–0.027****	**–0.030***	**–0.035***
	(0.013)	**(0.013)**	**(0.017)**	**(0.019)**
Average direct impact	–0.025**	–0.026**	–0.024*	–0.022
	(0.012)	(0.012)	(0.013)	(0.014)
Average indirect impact	–0.001	–0.001	–0.007	–0.013
	(0.001)	(0.001)	(0.019)	(0.021)
Raw coefficients				
Ln (Violent events)	–0.025***	–0.026**	–0.024*	–0.022
	(0.012)	(0.012)	(0.013)	(0.014)
Other controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Spatial lagged effects				
Ln (Violent events)			–0.027	–0.064
			(0.092)	(0.111)
Ln (Land value) (λ)	0.264**	0.165	0.256*	0.130
	(0.133)	(0.191)	(0.135)	(0.203)
ε_{it} (ρ)		0.230		0.267
		(0.228)		(0.235)
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000
No. obs	4,346	4,346	4,346	4,346

Source: Authors. ***1% **5% *10%.

Model (a): model assuming no spillover effects of violent events and idiosyncratic shocks ($\lambda_V \mathbf{W} = 0$, $\rho\mathbf{W} = 0$ in (2))

Model (b): model assuming $\lambda_V \mathbf{W} = 0$ in (2)

Model (c): model assuming $\rho\mathbf{W} = 0$ in (2)

Model (d): full model

Table 4. Violent events and perceived land values in non-monsoon harvesting season, using spatial weights based on inverse distance between village tracts[a]

Variables	Dependent variable = ln (land value per acre)			
	(a)	(b)	(c)	(d)
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Overall effects of violent events (previous 12 months)				
Average overall impact	**–0.055****	**–0.051****	**–0.058*****	**–0.058****
	(0.022)	**(0.023)**	**(0.022)**	**(0.026)**
Average direct impact	–0.053**	–0.051**	–0.043	–0.042
	(0.021)	(0.023)	(0.027)	(0.028)
Average indirect impact	–0.002	0.000	–0.015	–0.016
	(0.003)	(0.004)	(0.023)	(0.028)
Raw coefficients				
Ln (Violent events)	–0.053**	–0.051**	0.086***	–0.042
	(0.021)	(0.023)	(0.017)	(0.028)
Other controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Spatial lagged effects				
Ln (Violent events)			–0.030	–0.041
			(0.055)	(0.068)
Ln (Land value) (λ)	0.099	–0.009	0.093	–0.020
	(0.133)	(0.168)	(0.134)	(0.171)
ε_{it} (ρ)		0.303*		0.308*
		(0.185)		(0.187)
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000
No. obs	1,004	1,004	1,004	1,004

Source: Authors. ***1% **5% *10%.

[a]Models (a) through (d) are as defined as in Table 3 footnote.

Table 5. Same sets of results as Table 3 but adding local violence factors to the spatial weights

Variables	Dependent variable = ln (land value per acre)											
	Spatial weights = inverse distance * commonality of township[a]				Spatial weights = inverse distance * commonality of state[a]				Spatial weights = inverse distance * mobility perception[a]			
	(a1)	(b1)	(c1)	(d1)	(a2)	(b2)	(c2)	(d2)	(a3)	(b3)	(c3)	(d3)
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Overall effects of violent events (previous 12 months)												
Average overall impact	**–0.027****	**–0.027****	**–0.029****	**–0.031****	**–0.027****	**–0.027****	**–0.030***	**–0.035***	**–0.026****	**–0.026****	**–0.023***	**–0.025***
	(0.013)	**(0.013)**	**(0.014)**	**(0.015)**	**(0.013)**	**(0.013)**	**(0.017)**	**(0.019)**	**(0.011)**	**(0.011)**	**(0.014)**	**(0.015)**
Average direct impact	–0.026**	–0.026**	–0.024*	–0.022	–0.025***	–0.026**	–0.024*	–0.022	–0.025**	–0.025**	–0.026**	–0.026**
	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.011)	(0.011)	(0.012)	(0.012)
Average indirect impact	–0.001	–0.001	–0.005	–0.009	–0.001	–0.001	–0.007	–0.013	–0.001	–0.001	0.002	0.001
	(0.001)	(0.001)	(0.014)	(0.016)	(0.001)	(0.001)	(0.019)	(0.021)	(0.001)	(0.001)	(0.016)	(0.016)
Raw coefficients												
Ln (Violent events)	–0.025**	–0.026**	–0.024*	–0.022	–0.025**	–0.026**	–0.023*	–0.022	–0.025**	–0.025**	–0.026**	–0.026**
	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.011)	(0.011)	(0.012)	(0.012)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hhd. Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial lagged effects												
Ln (Violent events)			–0.023	–0.059			–0.027	–0.064			0.024	0.012
			(0.091)	(0.110)			(0.092)	(0.111)			(0.114)	(0.121)
Ln (Land value) (λ)	0.260*	0.163	0.253*	0.129	0.264**	0.165	0.256*	0.130	0.265**	0.182	0.268**	0.186
	(0.146)	(0.194)	(0.149)	(0.207)	(0.133)	(0.191)	(0.145)	(0.203)	(0.132)	(0.213)	(0.136)	(0.216)
ε_{it} (ρ)		0.216		0.252		0.230		0.267		0.155		0.150
		(0.230)		(0.237)		(0.228)		(0.235)		(0.256)		(0.260)
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
No. obs	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346

Source: Authors. ***1% **5% *10%.

[a]Spatial weights including "commonality of township" and "commonality of state" are as defined in equation (5), while the weights including "mobility perception" are defined in equation (6).

Table 6. Same sets of results as Table 4 but adding local violence factors to the spatial weights

Variables	Dependent variable = ln (land value per acre)											
	Spatial weights = inverse distance * commonality of township				Spatial weights = inverse distance * commonality of state				Spatial weights = inverse distance * mobility perception			
	(a1)	(b1)	(c1)	(d1)	(a2)	(b2)	(c2)	(d2)	(a3)	(b3)	(c3)	(d3)
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Overall effects of violent events (previous 12 months)												
Average overall impact	**–0.054** (0.022)**	**–0.051** (0.023)**	**–0.052** (0.022)**	**–0.052** (0.023)**	**–0.055** (0.022)**	**–0.051** (0.023)**	**–0.055*** (0.022)**	**–0.055** (0.024)**	**–0.057*** (0.022)**	**–0.051** (0.022)**	**–0.100** (0.046)**	**–0.101** (0.051)**
Average direct impact	–0.052** (0.021)	–0.051** (0.023)	–0.043 (0.027)	–0.043 (0.027)	–0.053** (0.021)	–0.051** (0.023)	–0.043 (0.027)	–0.042 (0.028)	–0.055*** (0.021)	–0.051** (0.022)	–0.042* (0.024)	–0.039* (0.023)
Average indirect impact	–0.002 (0.002)	–0.001 (0.002)	–0.009 (0.015)	–0.010 (0.017)	–0.002 (0.003)	0.000 (0.003)	–0.012 (0.018)	–0.012 (0.022)	–0.003 (0.005)	0.001 (0.005)	–0.058 (0.052)	–0.062 (0.060)
Raw coefficients												
Ln (Violent events)	–0.052** (0.021)	–0.051** (0.023)	–0.043 (0.027)	–0.043 (0.028)	–0.053** (0.021)	–0.051** (0.023)	–0.043 (0.027)	–0.042 (0.028)	–0.055*** (0.021)	–0.051** (0.022)	–0.042* (0.024)	–0.039* (0.024)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hhd. Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial lagged effects												
Ln (Violent events)			–0.027 (0.054)	–0.035 (0.067)			–0.030 (0.055)	–0.039 (0.068)			–0.101 (0.222)	–0.120 (0.116)
Ln (Land value) (λ)	0.147 (0.135)	0.048 (0.167)	0.143 (0.135)	0.039 (0.170)	0.106 (0.133)	0.002 (0.167)	0.101 (0.133)	–0.008 (0.170)	0.093 (0.141)	–0.004 (0.173)	0.080 (0.141)	–0.012 (0.173)
ε_{it} (ρ)		0.306* (0.183)		0.309* (0.184)		0.299* (0.180)		0.303* (0.186)		0.372** (0.184)		0.367** (0.184)
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
No. obs	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004

Source: Authors. ***1% **5% *10%.

Table 7. Relatively insignificant heterogeneity in the effects of violent events on land values

Variables	Dependent variable = ln (land value per acre)									
	Heterogeneity factors interacted with violent events									
	Nighttime light	Irrigation	Soil alkalinity	Soil organic contents	Fine soil texture	Soil salinity	Soil sodicity	Poor soil drainage	Terrain ruggedness	Slope aspects
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
<u>Monsoon harvesting season</u>										
Number of months with violent events	–0.025** (0.012)	–0.027* (0.014)	–0.028** (0.012)	–0.027* (0.016)	–0.026** (0.012)	–0.025** (0.012)	–0.031** (0.013)	–0.024* (0.014)	–0.028** (0.011)	–0.029** (0.013)
Violence × Heterogeneity factors[a]	–0.002 (0.006)	0.001 (0.011)	–0.005 (0.011)	0.002 (0.022)	–0.008 (0.012)	–0.009 (0.010)	–0.028 (0.045)	–0.006 (0.012)	0.006 (0.012)	–0.011 (0.011)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hhd. Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
No. obs	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346
<u>Non-monsoon harvesting season</u>										
Number of months with violent events	–0.085*** (0.023)	–0.056** (0.027)	–0.049 (0.043)	–0.041 (0.037)	–0.054* (0.029)	–0.066*** (0.022)	–0.049 (0.038)	–0.043 (0.036)	–0.046 (0.032)	–0.056** (0.027)
Violence × Heterogeneity factors[a]	0.019*** (0.003)	0.010 (0.006)	0.011 (0.040)	0.027 (0.047)	0.001 (0.060)	0.038 (0.026)	0.022 (0.085)	0.017 (0.018)	–0.014 (0.021)	–0.023 (0.017)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hhd. Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
No. obs	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004

Source: Authors. ***1% **5% *10%.

[a]"Heterogeneity factors" correspond to those listed at the top of each column.

Table 8. Insignificant heterogeneity across major agroecological zones in the effects of violent events on land values

Variables	Dependent variable = ln (land value per acre)	
	Coef. (std.err)	Coef. (std.err)
Number of months with violent events (previous 12 months)	–0.037***	–0.121**
	(0.013)	(0.050)
Violence × Hills Zone	0.025	0.089
	(0.032)	(0.058)
Violence × Delta Zone	0.015	0.014
	(0.044)	(0.082)
Violence × Coastal Zone	0.061	0.172
	(0.039)	(0.157)
Other controls	Yes	Yes
Household fixed effects	Yes	Yes
Constant	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000
No. obs	4,346	1,004

Source: Authors. ***1% **5% *10%.

Table 9. Results specific to sub-samples differentiated by township-level rice area per capita

Variables	Ln (Land value, real term)		
	(a) Importing townships[a]	(b) Exporting townships[a]	(b) – (a)
	Coef. (std.err)	Coef. (std.err)	
Monsoon season			
Violent events during the past 12 months	**–0.031****	**–0.018***	0.013
	(0.013)	**(0.010)**	(0.016)
Other controls	Yes	Yes	
Household fixed effects	Yes	Yes	
Constant	Yes	Yes	
p-value (H_0: variables jointly insignificant)	.000	.000	
No.obs.	2,194	2,152	
Non-monsoon season			
Violent events during the past 12 months	**–0.045****	**–0.090*****	–0.045
	(0.019)	**(0.019)**	(0.028)
Other controls	Yes	Yes	
Household fixed effects	Yes	Yes	
Constant	Yes	Yes	
p-value (H_0: variables jointly insignificant)	.000	.000	
No.obs.	488	516	

Source: Authors. ***1% **5% *10%.

[a]"Importing townships" and "Exporting townships" here are defined as townships above and below sample medians in terms of township-level rice area per population, constructed from high-resolution (30m × 30m) GIS data of seasonal rice areas (Li et al. 2025) and the latest population census in 2014 (Government of Myanmar 2014).

Table 10. Results differentiated by townships based on rice area per capita in each season

Variables	Ln (Land value, nominal term)	Ln (Rice price, nominal term)	Ln (Land value, nominal term)			Ln (Rice price, nominal term)		
	(a) All townships	(b) All townships	(c) Importing townships[a]	(d) Exporting townships[a]	(d) – (c)	(e) Importing townships[a]	(f) Exporting townships[a]	(f) – (e)
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)		Coef. (std.err)	Coef. (std.err)	
Monsoon season								
Violent events	**–0.023*****	0.003	**–0.032*****	**–0.014***	0.018	–0.001	0.004	0.005
	(0.007)	(0.006)	**(0.011)**	**(0.008)**	(0.014)	(0.009)	(0.007)	(0.012)
Other controls	Yes	Yes	Yes	Yes		Yes	Yes	
Household fixed effects	Yes	Yes	Yes	Yes		Yes	Yes	
Constant	Yes	Yes	Yes	Yes		Yes	Yes	
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000		.000	.000	
No.obs.	4,346	4,346	2,194	2,152		2,194	2,152	
Non-monsoon season								
Violent events	–0.015	**0.038*****	0.000	**–0.078*****	**–0.078****	**0.045*****	0.012	**–0.033****
	(0.017)	**(0.007)**	(0.017)	**(0.026)**	**(0.031)**	**(0.008)**	(0.011)	**(0.014)**
Other controls	Yes	Yes	Yes	Yes		Yes	Yes	
Household fixed effects	Yes	Yes	Yes	Yes		Yes	Yes	
Constant	Yes	Yes	Yes	Yes		Yes	Yes	
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000		.000	.000	
No.obs.	1,004	1,004	488	516		488	516	

Source: Authors. ***1% **5% *10%.

[a]"Importing townships" and "Exporting townships" here are defined as townships above and below sample medians in terms of township-level rice area per population, constructed from high-resolution (30m × 30m) GIS data of seasonal rice areas (Li et al. 2025) and the latest population census in 2014 (Government of Myanmar 2014).

Table 11. Summary of the estimated effects of violent events on land value and rice price in nominal terms based on Table 10 results

Type of effects	Monsoon season		Non-monsoon season	
	Exporting township	Importing township	Exporting township	Importing town-ship
Effects of violent events on land value (nominal)	–	–	–	Insignificant
Effects of violent events on rice price (nominal)	Insignificant	Insignificant	Insignificant	+

Source: Authors.

[a]"Importing townships" and "Exporting townships" here are defined as townships above and below sample medians in terms of township-level rice area per population, constructed from high-resolution (30m × 30m) GIS data of seasonal rice areas (Li et al. 2025) and the latest population census in 2014 (Government of Myanmar 2014).

January–December 2023 relative to January–December 2022 period (corresponding to the monsoon-season)

July 2022–June 2023 relative to July 2021–June 2022 (corresponding to the non-monsoon season)

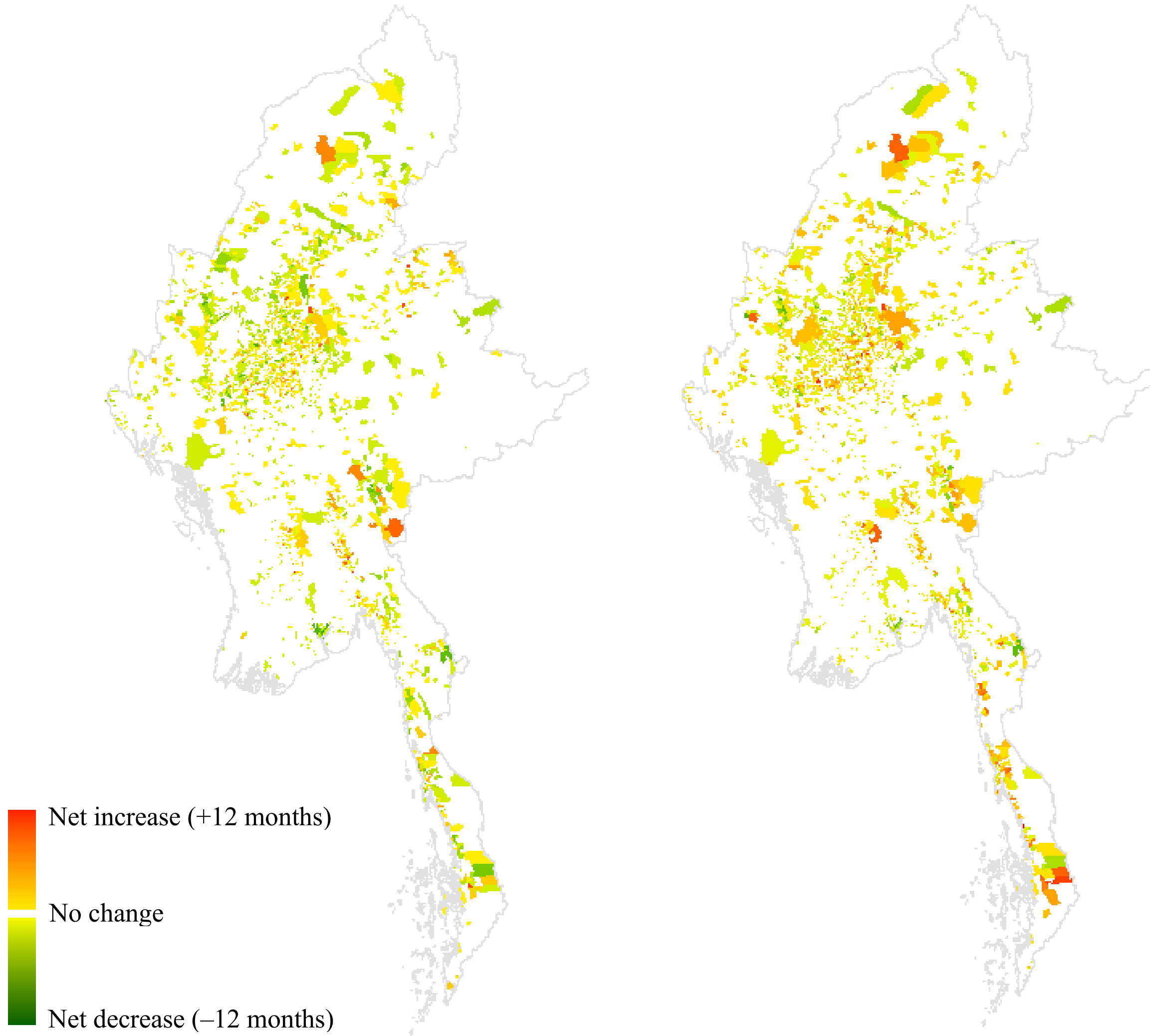

Figure 1. Net increase in the number of months with fatal violent events at village tract levels[a]

Source: Authors' compilations based on ACLED data.

[a] Blank areas without colors indicate no changes in violent events intensity during corresponding periods.

Appendix A: Additional results

Table 12. Full results of Table 2

Variables	Dependent variable = ln (land value per acre)			
	Monsoon harvesting season		Non-monsoon harvesting season	
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Number of months with violent events (previous 12 months)	–0.026***		–0.053***	
	(0.008)		(0.018)	
Number of months with violent events (previous 6 months)		–0.023*		–0.074***
		(0.013)		(0.023)
Size of the largest rice plot	–0.038**	–0.038**	0.010	0.011
	(0.015)	(0.015)	(0.021)	(0.021)
Age of farm management decision-maker	0.019	0.020	–0.076*	–0.075*
	(0.018)	(0.018)	(0.039)	(0.039)
Female farm management decision-maker	0.009	0.010	–0.023	–0.020
	(0.013)	(0.013)	(0.025)	(0.025)
Education of farm management decision-maker	0.011	0.009	0.039	0.038
	(0.019)	(0.019)	(0.029)	(0.029)
Household-members (adult male)	–0.004	–0.004	–0.025	–0.018
	(0.017)	(0.017)	(0.032)	(0.033)
Household-members (adult female)	–0.006	–0.006	–0.007	–0.005
	(0.023)	(0.023)	(0.031)	(0.032)
Household-members (children)	–0.016	–0.017	–0.084***	–0.083***
	(0.021)	(0.021)	(0.027)	(0.028)
Livestock ownership (principal component)	0.030*	0.030*	–0.001	–0.002
	(0.016)	(0.016)	(0.025)	(0.025)
Machines owned	0.052***	0.053***	0.013	0.017
	(0.016)	(0.016)	(0.030)	(0.031)
Time to agri-input retailer	0.009	0.009	0.000	–0.001
	(0.017)	(0.017)	(0.020)	(0.020)
Time to rice mill / hullers	0.017	0.017	0.021	0.020
	(0.014)	(0.014)	(0.017)	(0.017)
Nighttime light	0.026**	0.021*	0.099**	0.094**
	(0.012)	(0.012)	(0.045)	(0.045)
Irrigation	0.026**	0.026**		
	(0.013)	(0.013)		
Rainfall	–0.032***	–0.032***	–0.040**	–0.038**
	(0.006)	(0.006)	(0.016)	(0.016)
Year dummy (2^{nd} year)	–0.254***	–0.254***	–0.381***	–0.376***
	(0.010)	(0.010)	(0.017)	(0.017)
Household fixed effects	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000
No. obs	4,346	4,346	1,004	1,004

Source: Authors. ***1% **5% *10%.

Appendix B: Model with endogenous spatial weight matrix

To address the potential endogeneity in the spatial weight matrix with elements (6) (mentioned at the end of section 3.2), we estimate a modified version following the control function approach suggested by Qu et al. (2016) and Delgado et al. (2018). Specifically, we first estimate

$$m_{i0} = \alpha + \alpha_V V_{i0} + \alpha_X X_{i0} + \alpha_{\bar{X}} \bar{X}_i + \alpha_Z Z_{i,2020} + \varepsilon_i^d \tag{7}$$

in which V_{i0} and X_{i0} are the conflict level and values of X_{it} in the base year for the household i. In addition, $\bar{X}_i$ represents time-invariant exogenous variables. Notation $Z_{i,2020}$ is an instrumental variable (IV), which is expected to be correlated with mobility d_i but does not affect land value once d_i and other variables are controlled for. Specifically, for $Z_{i,2020}$, we use the cumulative count of reported COVID-19 cases per capita at township levels in 2020, which significantly affected the mobility of local population prior to the military-coup in February 2021 (Takeshima et al. 2023, 2025), and also likely had dynamic effects on mobility post military-coup. Notations α's are estimated parameters, and ε_i^d is a residual (control function term).

We then estimate

$$\begin{gathered}\Delta A_{it} = \lambda \mathbf{W} \Delta A_{it} + \beta_V \Delta V_{it} + \beta_X \Delta X_{it} + \beta_{\bar{X}} \bar{X}_i + \beta_\varepsilon \hat{\varepsilon}_i^d + \Delta \varepsilon_{it} \\ \Delta \varepsilon_{it} = \rho \mathbf{W} \Delta \varepsilon_{it} + \Delta v_{it}\end{gathered} \tag{8}$$

in which Δ represents first-difference operator of respective variables A_{it}, V_{it}, X_{it}. The notation $\hat{\varepsilon}_{it}^d$ is the predicted values of control function term ε_i^d obtained from equation (7). As is emphasized in Qu et al. (2016) and Delgado et al. (2018), inserting $\hat{\varepsilon}_i^d$ as additional variable corrects the potential endogeneity bias (8). Conversely, if the coefficient for $\hat{\varepsilon}_i^d$ is *not* statistically significant, this would imply that endogeneity is *not* an issue and no correction is needed.

Time-invariant variables $\bar{X}_i$ which enter in the model with endogenous spatial weight (7) and (8) include various agroecological conditions, such as village-tract level soil characteristics (first principal component score of six soil properties—alkalinity, organic contents, texture, salinity, sodicity, and drainage), terrain ruggedness, and average slope aspect.[15]

Table 13 summarizes the results of the main equation (8) applied to re-estimate the main models with spatial weight matrix elements (6) ((a3) through (d3) in Table 5 and Table 6). Results in Table 13 indicate that control function term ($\hat{\varepsilon}_i^d$) is not statistically significant in any models (row "Control function term ($\hat{\varepsilon}_i^d$)"), and estimated average overall impacts are largely consistent in signs and magnitudes with those of Table 5 and Table 6, suggesting that the potential endogeneity is less of a concern.

Table 14 summarizes the first stage regression (7). The coefficient for COVID count in 2020 (in 1,000) is statistically significant, suggesting its validity as an IV. Its negative sign indicates that the higher COVID count in 2020 continued to be negatively associated with respondents' mobility perception in July 2022 and January 2023, the initial rounds of the non-monsoon and monsoon harvesting seasons in our analyses, respectively.

[15] Average slope aspect (slope direction) captures, on average, how much the land within the village tract slopes down toward the north, as it captures the solar radiation patterns. Specifically, the variable ranges between 90 (all land sloping down toward the north) and –90 (all land sloping down toward the south). Related variables (sometimes called "aspect") have been used in the past literature (Bovkir & Aydinoglu 2018; Bruno et al. 2024).

Table 13. Control function approach applied to address potential endogeneity of spatial weight matrix

Variables	Monsoon harvesting season				Non-monsoon harvesting season			
	(a3)	(b3)	(c3)	(d3)	(a3)	(b3)	(c3)	(d3)
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Overall effects of violent events								
Average overall impact	–0.028** (0.013)	–0.027** (0.013)	–0.017 (0.080)	–0.021 (0.079)	–0.056** (0.024)	–0.053** (0.025)	–0.217** (0.085)	–0.213** (0.087)
Average direct impact	–0.026** (0.012)	–0.026** (0.012)	–0.027** (0.013)	–0.027** (0.013)	–0.050** (0.021)	–0.049** (0.022)	–0.025 (0.024)	–0.025 (0.024)
Average indirect impact	–0.001 (0.003)	–0.001 (0.004)	0.010 (0.085)	0.005 (0.084)	–0.006 (0.006)	–0.004 (0.008)	–0.191** (0.093)	–0.188** (0.094)
Raw coefficients								
Control function term ($\hat{\varepsilon}_i^d$)	**–0.005 (0.042)**	**–0.012 (0.046)**	**–0.004 (0.042)**	**–0.011 (0.047)**	**–0.053 (0.073)**	**–0.061 (0.077)**	**–0.060 (0.073)**	**–0.065 (0.076)**
Ln (Violent events)	–0.026** (0.012)	–0.026** (0.012)	–0.027** (0.013)	–0.027** (0.013)	–0.050** (0.021)	–0.049** (0.022)	–0.024 (0.025)	–0.024 (0.025)
Other time-invariant controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial lagged effects								
Ln (Violent events)			0.020 (0.149)	0.010 (0.156)			–0.275** (0.131)	–0.277** (0.134)
Ln (Land value) (λ)	0.099 (0.151)	0.028 (0.248)	0.100 (0.151)	0.029 (0.249)	0.166 (0.142)	0.122 (0.227)	0.166 (0.143)	0.141 (0.219)
ε_{it} (ρ)		0.164 (0.309)		0.161 (0.310)		0.159 (0.298)		0.089 (0.304)
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000
No. obs	2,173	2,173	2,173	2,173	502	502	502	502

Source: Authors. ***1% **5% *10%.

[a]Models (a) through (d) are as defined as in Table 3 footnote.

Table 14. Results of first-stage regression (7)

Variables	Dependent variable = Respondent perceives that mobility is not restricted in initial round (yes = 1)	
	Monsoon harvesting season	Non-monsoon harvesting season
	Coef. (std.err)	Coef. (std.err)
COVID count in 2020 (in 1,000)	–0.010**	–0.010*
	(0.005)	(0.006)
Violent events	–0.050***	–0.103***
	(0.011)	(0.020)
Other controls	Yes	Yes
Other time-invariant controls	Yes	Yes
Agroecological zone dummy	Yes	Yes
Constant	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000
No. obs	2,173	502

Source: Authors. ***1% **5% *10%.

Appendix C: Supplementary assessment of the roles of land values

The primary focus of this paper is the effect of conflict on farmland values, and the effects of changing farmland values, which are beyond the scope of this paper, need to be analyzed more thoroughly in future studies. Nonetheless, we provide partial evidence that, to the extent possible, shows short-term implications of declining farmland value on farm households. Specifically, depending on the suitability with outcomes, we estimate the following instrumental-variable (IV) fixed-effects regression,

$$Y_{it} = \gamma + \gamma_A A_{it} + \gamma_V V_{it} + \gamma_X X_{it} + c_i + \varepsilon_{it} \tag{9}$$

or IV probit regression with correlated random-effects (CRE),

$$Y_{it} = \gamma + \gamma_A A_{it} + \gamma_V V_{it} + \gamma_X X_{it} + \gamma_{\bar{X}} \bar{X}_i + \varepsilon_{it} \tag{10}$$

in which Y_{it} is a set of key binary outcomes, γ's are estimated parameters. $\bar{X}_i$ is a vector of variables consisting of averages of X_{it} over time, so that $\gamma_{\bar{X}} \bar{X}_i$ serves as CRE term that approximates unobserved fixed effects. Since variable A_{it} can be potentially endogenous to Y_{it}, we addressed it through IV method.

For IV, we use average values of A_{it} of all samples excluding i within the township or the state of i. Using township/state-level averages of A_{it} (excluding that of i itself) as an IV is consistent with both the spirit of spatial spillover effects examined in (2) through (6), and commonly used IV-based approaches in the literature (e.g., Dillon et al. 2019; Dolislager et al. 2021; Takeshima et al. 2025c). Further, we apply Lewbel's (2012) approach that expands the list of IVs to enhance the overall identification power of IVs, which was also used in various past studies (e.g., Takeshima et al., 2025). Where the number of township-level observations is few (e.g., fewer than 10 in total), we replaced the IV with state-level averages of A_{it} (excluding that of i itself) to minimize measurement errors.

We posit that equation (10) may be particularly relevant if farmland is treated as a key household asset. Since MAPS data focus primarily on agricultural production prior to the harvesting season, in which land value is measured, we instead turn to the Myanmar Household Welfare Survey (MHWS), which includes fewer samples that can be matched with the MAPS sample but captures relevant outcome variables for (10). Specifically, the MAPS samples of 2,173 farmers used for our analyses of the monsoon harvesting season can be matched with 1,216 farmers who provided additional information during the subsequent Spring 2023 and Spring 2024 (MHWS Round 5 and MHWS Round 7, respectively). Similarly, the MAPS samples of 502 farmers used for our analyses for the non-monsoon harvesting season can be matched with 221 farmers in MHWS Round 4 and Round 6, respectively.

Table 15 summarizes the descriptive statistics of key outcome variables that are found to be associated with decline in land values, including distress sales of precious assets, distress engagement in risky activities, distress borrowing of money, and dietary diversity of purchased food.

Table 16 and Table 17 summarize the results for IV regressions (9) and (10). Table 16 indicates that a 1% decrease in land value during the monsoon harvesting season is associated with about 0.1 percentage point increases in the likelihood of distress sales of precious assets or engagements in risky activities in the subsequent spring. Importantly, these associations hold after controlling for the direct effects of violent events. Similarly, Table 17 indicates that a 1% decrease in land value during the non-monsoon harvesting season is associated with about 0.3, 0.1, and 0.5 percentage points higher likelihood of distress sales of precious assets, engagement in risky activities, and distress borrowing of money, respectively, in the subsequent fall. It is also associated with a significant reduction in the dietary diversity score of purchased food. While these results should be investigated more thoroughly in future studies with fuller data, Table 16 and Table 17 still help to link our primary findings regarding the effects of conflicts on farmland value with the potential welfare implications for farmers.

Table 15. Descriptive statistics of key outcome variables from MHWS data

Outcome variables	Period			
	Spring 2023 (following 2022 monsoon harvesting season)	Spring 2024 (following 2023 monsoon harvesting season)	Fall 2022 (following 2022 non-monsoon harvesting season)	Fall 2023 (following 2023 non-monsoon harvesting season)
	Mean (std.dev)	Mean (std.dev)	Mean (std.dev)	Mean (std.dev)
Distress sales of precious assets (e.g., Gold, jewelry, US dollars) during the previous 30 days (yes = 1)	0.036 (0.187)	0.030 (0.170)	0.063 (0.244)	0.045 (0.208)
Distress engagement in risky activities[a] during the previous 30 days (yes = 1)	0.027 (0.163)	0.016 (0.124)	0.023 (0.149)	0.000 (0.000)
Distress borrowing of money[b] (yes = 1)			0.633 (0.483)	0.575 (0.496)
Dietary diversity: number of food groups (out of 8 groups) from purchased sources consumed by more than half of household members for all of the past 7 days			1.986 (1.170)	1.986 (1.134)
Number of observations	1216	1216	221	221

Source: Authors.

[a]These activities can include logging, risky migration, smuggling, selling wildlife products, artisanal mining.

[b]These types of borrowing are not likely to be loans taken from the formal sector for productive purposes (for which high land values can potentially serve as better collateral).

Table 16. Associations between <u>monsoon-harvesting season</u> land values and distress actions by farm households

Variables	Distress sales of precious assets (yes = 1)		Distress engagement in risky activity (yes = 1)	
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Ln (Land value per acre)	–0.107* (0.061)	–0.094* (0.056)	–0.104* (0.056)	–0.103* (0.057)
Number of months with violent events (12 months)	0.008* (0.004)		0.002 (0.002)	
Number of months with violent events (6 months)		0.015*** (0.005)		0.005 (0.003)
Other controls	Yes	Yes		
Correlated random effects	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000
No. obs	2,332	2,332	2,332	2,332

Source: Authors. ***1% **5% *10%.

Table 17. Associations between <u>non-monsoon-harvesting season</u> land values and key outcomes farm households

Variables	Distress sales of precious assets (yes = 1)	Risky activity (yes = 1)	Distress borrowing of money (yes = 1)	Dietary diversity from purchased food
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Ln (Land value per acre)	–0.272* (0.142)	–0.079** (0.040)	–0.499** (0.249)	1.193* (0.664)
Number of months with violent events (12 months)	–0.002 (0.004)	–0.002 (0.041)	–0.022 (0.021)	0.010 (0.090)
Other controls	Yes	Yes	Yes	Yes
Correlated random effects	Yes	Yes		
Household fixed effects			Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000
p-value (H_0: underidentified)			.001	.022
p-value (H_0: not overidentified)			.492	.250
No. obs	422	422	422	422

Source: Authors. ***1% **5% *10%.

Appendix references

Dillon B, P Brummund & G Mwabu. 2019. Asymmetric non-separation and rural labor markets. *Journal of Development Economics 139*:78-96.

Dolislager M, T Reardon, A Arslan, L Fox, S Liverpool-Tasie, C Sauer & DL Tschirley. 2021. Youth and adult agrifood system employment in developing regions: Rural (peri-urban to hinterland) vs. urban. *Journal of Development Studies 57*(4):571-593.

Lewbel A. 2012. Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics 30*(1):67-80.

Takeshima H, B Minten, J van Asselt, I Lambrecht, I Masias, J Goeb, ZW Aung & MT Htar. 2025a. Fertilizer and conflict: Evidence from Myanmar. *Food Policy 133*:102786.

Takeshima H, C Ragasa, T Bamiwuye, KS Andam, DJ Spielman, HO Edeh, A Fasoranti, B Haile, C Nwagboso, L Omoigui, T Abdoulaye, P. Lava Kumar & T Wossen. 2025c. Seed certification, certified seeds use and yield outcomes in Nigeria: Insights from nationally-representative farm panel data and seed company location data. *Agricultural Systems 224*:104268.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org