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Crop Diversification and Nutritional Resilience Amid Conflicts

Evidence from Farmers in Myanmar

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Abstract

Resilient food and nutrition systems that support dietary diversity are central to improving welfare outcomes and fostering the formation of human capital, with lasting implications for socioeconomic development. Historically, while smallholders in developing countries have accessed food both from diversified farms or kitchen gardens, markets have increasingly become the more dominant source of diet diversity as agrifood systems continue their transformation. Yet little is known regarding how intensifying conflicts and social instability affect these linkages between agrifood systems and households' dietary diversity. Addressing this knowledge gap is particularly relevant for countries like Myanmar, which is characterized not only by escalating conflicts in recent years but also by relatively lower levels of overall crop diversification and dietary diversity at the national level compared to many other countries in East and Southeast Asia. By using unique panel datasets from Myanmar that cover significant spatiotemporal variation in conflict intensity and addressing the potential endogeneity of crop diversification, we provide new evidence on the resilience of household dietary diversity in conflict-affected settings. We find that increased incidence of violent events at township levels (a proxy for conflict intensity) significantly lowers household dietary diversity during the post-monsoon season, particularly the diversity derived from purchased food items. These adverse effects are relatively more pronounced for healthier food items, such as pulses/legumes/nuts and vegetables/leaves. However, the negative impacts of conflicts on dietary diversity in the post-monsoon season are significantly mitigated by greater diversity in food crop production for farm households during the preceding monsoon season. Results are robust across different measurements of crop diversification and violent events. These findings suggest that in conflict-prone developing countries like Myanmar, household-level crop diversification remains an important strategy for farmers to safeguard household dietary diversity.

Keywords: Crop diversification, dietary diversity, conflicts, panel data, inverse-probability-weighting methods, Myanmar

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1 Introduction

Resilience in food and nutrition security is crucial for overall welfare improvement and formation of human capital, facilitating sustained socioeconomic development (e.g., Cole & Neumayer, 2006; World Bank, 2018; Marcus et al., 2021). Across various dimensions, dietary diversity and its stability are among the most crucial elements of food and nutrition security (e.g., Hatløy et al., 1998, 2000; Hoddinott & Yohannes, 2002; Korir et al., 2023). The ability to maintain a diverse diet can be hampered by disturbances in agrifood markets where diverse food items are traded and accessed by many low-income households. Social instability, such as intensifying conflict, can disrupt agrifood markets in developing countries (e.g., George et al., 2020; Kafando & Sakurai, 2024). Preserving resilient food/nutrition security, including dietary diversity, is therefore particularly crucial in conflict-prone countries like Myanmar. Increased incidence of violent events in the locality can disturb various functions of agrifood markets, including the transportation, processing, storage of and other value added to food items. Depending on the nature of violence, such disruptions can particularly affect certain types of food items, with the effects of reducing overall dietary diversity accessible from the markets.

A knowledge gap remains about how resilience in dietary diversity can be maintained in the face of conflict. The literature suggests that maintaining household-level crop diversification remains a viable means of sustaining household dietary diversity in face of agrifood market imperfections, particularly when semi-subsistence systems where households consume own-produced food items are still prevalent (e.g., Fan et al., 2019; Takeshima et al., 2020, 2025b; Meenakshi & Quisumbing 2025), including in South and Southeast Asia (e.g., Pandey et al., 2016; Zanello et al., 2019; Gupta et al., 2020; Shively & Evans 2021; Ahmed et al., 2024). Nonetheless, little empirical evidence exists regarding whether household-level crop diversification can, in fact, enhance resilience in dietary diversity during conflict. Expanding this evidence base is crucial because crop diversification can divert household resources away from other income-earning opportunities that might otherwise maintain dietary diversity.

We narrow this knowledge gap through empirical analyses of recent experiences in Myanmar. We utilize unique panel household data that span periods when spatiotemporal variations in violent events significantly increased following the 2021 military coup. Specifically, we first assess how the increase in violent events has affected household dietary diversity and then evaluate how crop diversification among commercial crops has mitigated these adverse effects. In doing so, we address the possibility that household crop diversification choices may be endogenous to both violent events and dietary diversity outcomes. We estimate various econometric models, including the multi-valued inverse-probability-weighted regression adjustment (MIPWRA) model and its extension to Poisson regression (MIPWRA-Poisson), to account for the fact that our measurements of crop diversification are continuous variables, and our outcome variable, the dietary diversity score, is a discrete variable. To the best of the authors' knowledge, ours is among the first studies to estimate MIPWRA-Poisson models.

Myanmar provides a compelling setting for this empirical analysis. Since 2021, Myanmar has experienced one of the highest levels of conflict intensity worldwide (ACLED, 2025), alongside significant spatiotemporal variations in violent events (Boughton et al., 2024), thereby creating conditions to empirically assess the effects of conflict. Furthermore, Myanmar has been characterized by a high degree of rice dominance in both production and consumption, with relatively lower production and dietary diversification compared to other countries in Southeast and East Asia (as described further in the subsequent section). Improving resilience in dietary diversity and assessing the role of crop diversification are, therefore, particularly critical in Myanmar.

Our results suggest that increases in violent events within localities significantly reduce household dietary diversity among farm households, particularly the diversity of purchased food items. These adverse effects are relatively more pronounced for healthier food items, including pulses/legumes/nuts and vegetables/leaves. However, in both the short- and medium-term, greater crop diversification at the farm household level significantly mitigates the adverse effects of conflict on dietary diversity. This supports the hypothesis that crop diversification enhances dietary diversity resilience in the face of conflict.

This paper contributes to several strands of the literature. First, we contribute to the literature on agriculture-nutrition linkages (Fan et al., 2019; Takeshima et al., 2020, 2025b; Meenakshi & Quisumbing, 2025), including studies that focus on developing countries in Asia (Pandey et al., 2016; Zanello et al., 2019; Gupta et al., 2020; Shively & Evans, 2021; Ahmed et al., 2024), by adding rare evidence from Myanmar. Second, we contribute to the literature on the effects of conflict on food and nutrition security (George et al., 2020; Kafando & Sakurai, 2024) as well as on agricultural diversification (e.g., Adelaja & George, 2019) by providing additional evidence from Myanmar. Third, we add to the growing literature on Myanmar's agrifood systems transformation in recent years, including during the conflict-intense period that began in 2021 (e.g., Minten et al., 2023; Boughton et al., 2024; Takeshima et al., 2024, 2025), by focusing on agricultural diversification and nutrition security. Lastly, from a methodological perspective, this paper contributes to the literature on inverse-probability weighting (IPW) in impact evaluations (Wooldridge, 2007) and on MIPWRA in particular (Cattaneo, 2010; Cattaneo et al., 2013; Takeshima, 2018) by extending its application to assess the role of crop diversification in promoting dietary diversity resilience amid conflict.

The remainder of this paper is structured as follows. Section 2 provides a brief historical context of rice and agricultural policy in Myanmar. Section 3 presents the data and methodology. Section 4 summarizes the descriptive statistics. Section 5 discusses the results. Section 6 concludes.

2 Historical context of rice and agricultural policy in Myanmar

Rice has long been central to agricultural policymaking in Myanmar and continues to be so today. In the 2020s, rice accounted for over 40 percent of total gross agricultural production value—the second-highest share in Southeast Asia after Cambodia. Unlike in most neighboring countries, where rice dominance waned amid growing diversification, its importance in Myanmar increased between the 2010s and 2020s (Figure 1).

According to the FAO's Food Balance Sheets, rice alone supplied 60 percent of all calories and 43 percent of all proteins available in Myanmar's food supply in 2022—among the highest shares globally. These levels surpassed the Southeast Asian (42 percent and 31 percent, respectively) and Asian (26 percent and 17 percent, respectively) averages (FAO, 2025). This heavy reliance on rice is reflected in limited dietary diversity: between 2021 and 2024, only 29 percent of the population (and 27 percent in rural areas) consumed all five primary food groups. On average, households consumed 5.3 out of 10 food groups daily—lower than most Southeast and East Asian countries (Figure 2).

Historically, Myanmar's socialist military regime enforced crop choices through production quotas, compulsory sales, export controls, land laws, and rice-focused irrigation investments. These policies entrenched rice's dominance (Boughton et al., 2024b; Minten et al.,

2024) but led to productivity stagnation and periodic rice shortages, which fueled social unrest. After the 1988 protests, a gradual liberalization of agricultural production and marketing began, including the dismantling of the rice export monopoly (Boughton et al., 2024b).

Reforms in the 2010s aimed to promote productivity growth and diversification. The establishment of the Ministry of Agriculture, Livestock, and Irrigation (MOALI) in 2016 and the launch of the Agriculture Development Strategy (ADS, 2018) emphasized diversification and sought to improve productivity and value chain efficiency (MOALI, 2018). Similarly, the Multi-sectoral National Plan of Action on Nutrition (MS-NPAN, 2018/19–2022/23) identified diversification as a core component of nutrition-sensitive agriculture (MOHS, 2018). However, implementation was limited by fragmented irrigation policies, weak local administrative capacity, and poor cross-ministerial coordination, diverting resources away from ADS priorities (Boughton et al., 2024).

These constraints were further compounded by disruptions from the COVID-19 pandemic, and even more so, following the 2021 military coup. The post-coup environment has seen widespread violence and deteriorating access to agricultural inputs, credit, and extension services (Boughton et al. 2024). Against this backdrop, understanding how crop diversification can improve dietary diversity—especially under conflict conditions—remains essential for advancing agrifood systems transformation and strengthening food and nutrition security in Myanmar.

3 Empirical analyses

Our empirical approach focuses on assessing how household-level crop diversification mitigates the effects of local violence on household dietary diversity scores (HDDS). We first describe our data. We then describe our measurements of the three key variables of crop diversification, violence, and HDDS. Subsequently, we describe the econometric approaches in later subsections.

3.1 Data

Our primary datasets on farm respondents come from multiple rounds of two series of surveys in Myanmar: the Myanmar Agricultural Performance Survey (MAPS) and the Myanmar Household Welfare Survey (MHWS). From MAPS, we use information on agricultural production from four monsoon seasons (July–December of 2020, 2021, 2022, and 2023). MAPS data capture the list of commercial crops cultivated as well as land areas cultivated for each crop.

We supplement MAPS-interviewed households' data with household dietary diversity data from the MHWS. Specifically, we use MHWS rounds that followed each monsoon season (Rounds 1 and 2 corresponding to post-2021 monsoon (early 2022), Round 5 post-2022 monsoon (early 2023), and Round 7 post-2023 monsoon (early 2024)).

Samples from each round of MHWS are nationally representative and comprise a mix of panel and repeated cross-sectional samples. The MHWS are phone surveys aimed at collecting data on a wide range of household welfare indicators, as well as whether the household engages in any crop production activities. MHWS samples are representatively selected from a large phone database (IFPRI, 2024). The MAPS samples are selected from these agricultural households identified in MHWS in ways that capture them in representative ways at the regional/state and urban/rural levels (IFPRI, 2024).

To properly control for unobserved household fixed effects in our analyses, we focus on panel samples with complete information on both monsoon season crop diversification and post-monsoon season dietary diversity for at least two survey rounds. Our final sample, therefore, consists of 5,988 observations from 2,648 farm households.[1]

Data on the intensity of violent events within respondents' township[2] are sourced from the Armed Conflict Location & Event Data (ACLED) (Raleigh et al., 2010), which has been used in recent studies on the impact of conflict on development outcomes globally, including Myanmar (Boughton et al., 2024; Takeshima et al., 2024, 2025). The ACLED database compiles reports from multiple sources, including event dates and approximate geographic coordinates, allowing us to identify the number of violent events occurring in each village tract over a specified time period. These events include battles, explosions/remote violence, and violence against civilians. The database also records whether each event directly involved any fatalities.[3]

We supplement these data with various spatial datasets. Historical monthly rainfall data come from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015) and historical daily temperatures are drawn from AgERA5 data (Dee et al., 2011). Soil property data are from FAO et al. (2012), while nighttime light data are from Elvidge et al. (2021) with methodologies extended to cover 2022 and 2023. All spatial data are extracted at the village tract[4] level, using GIS shapefiles for 14,600 village tracts in Myanmar from GeoNode (https://geonode.themimu.info/). Crop production suitability of rice and other key crops is taken from the Global Agro-Ecological Zones (GAEZ) (Fischer et al., 2012).

3.2 Construction of key variables

3.2.1 Household dietary diversity score (HDDS)

Our primary HDDS variables are the total number of food groups consumed by most of the household members, that is, more than 50 percent, during the seven days preceding the survey. The questions about food groups consumption patterns were administered to a respondent who was generally familiar with household members' food consumption patterns.[5] Respondents were given common examples of individual food items in each food group in the local context. Reponses provided were later categorized into food groups. Information on consumption both at home and away from home was collected.

Specifically, our main analyses consider a total of four primary food groups, namely (a) grains/root crops; (b) pulses/legumes/nuts/seeds; (c) vegetables/leaves; and (d) druits. We exclude other secondary[6] food groups (milk/dairy products, meat/fish/eggs, oil/fat/butter, and sugar/sweets) since the production of these other groups tends to be more specialized and often requires distinct resources such as skills and production capital (e.g., Masters et al., 2013), which

[1]About one–third of households are 3-round panels, while the rest are 2-round panels.
[2]Townships are the third-level administrative units in Myanmar, under states/regions.
[3]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.
[4]Village tracts are fourth-level administrative units, under the townships, in Myanmar, and there are approximately 14,600 village tracts in the country.
[5]Inferring household dietary diversity patterns from one representative respondent in the household has often been used as a low-cost way in several survey settings in developing countries, and HDDS derived from such an approach has been used to assess household-level agricultural-nutrition linkages in past studies (e.g., Takeshima et al., 2020).
[6]"Secondary" here simply refers to the level of focus in our analysis and does not refer to the dietary importance of these food groups.

may require separate analysis. Nonetheless, in the results section, we also provide some robustness results that, including these secondary food groups, do not significantly change our primary results.

Furthermore, we construct two separate measures of HDDS, depending on the regularity of consumption: (i) *regular* HDDS, which only counts the food group if it was consumed on all seven out of the previous seven days; and (ii) *occasional* HDDS, which counts the food group as long as it was consumed on at least four out of the previous seven days. Due to the more stringent criteria for counting consumption, the *regular* HDDS is always lower than the *occasional* HDDS.

3.2.2 Crop diversification indicators among commercial crops

In our analyses, we focus on crops that farm households grow for commercial purposes—that is, households sell at least some of the crops harvested—and thus exclude crops grown solely for home consumption purposes. We do so because these commercial crops tend to be cultivated on a more substantial scale and can be consumed more regularly, and diversification among them may have more meaningful nutritional implications for the household (e.g., Ogutu et al., 2020; Hazrana & Mishra, 2025).

Our first set of crop diversification indicators consists of (i) a simple count-based indicator (the number of crops grown). We then supplement the count-based indicators with more nuanced indicators that capture elements like richness and evenness. Specifically for the latter, following the literature on crop diversification (e.g., Meng et al., 1998; Smale et al., 1998; Benin et al., 2004; Di Falco & Chavas, 2009; Fabri et al., 2024), we use three measures: (ii) the *Margalef* (1958) index of richness; (iii) the *Simpson* index, and (iv) the *Shannon* index of evenness (Shannon & Weaver, 1949). Each index measures the following:

$$Margalef_{c,i} = \frac{N_{c,i} - 1}{\ln{(A_i)}}, Margalef_{g,i} = \frac{N_{g,i} - 1}{\ln{(A_i)}} \tag{1}$$

$$Simpson_{c,i} = 1 - \sum_c \left(\frac{a_{c,i}}{A_i}\right)^2, Simpson_{g,i} = 1 - \sum_g \left(\frac{a_{g,i}}{A_i}\right)^2 \tag{2}$$

$$Shannon_{c,i} = \sum_c \left[-\frac{a_{c,i}}{A_i} * \ln\left(\frac{a_{c,i}}{A_i}\right)\right], Shannon_{g,i} = \sum_c \left[-\frac{a_{g,i}}{A_i} * \ln\left(\frac{a_{g,i}}{A_i}\right)\right] \tag{3}$$

in which $N_{c,i}$ is the number of individual crops grown by farm household i in the monsoon season; $N_{g,i}$ is the number of the aforementioned crops-based food groups; A_i is the total cultivated area aggregated across all crop;, $a_{c,i}$ and $a_{g,i}$ are the cultivated area for individual crop c and food group g, respectively, so that $\frac{a_{c,i}}{A_i}$ and $\frac{a_{g,i}}{A_i}$ are the area shares for each crop and each food group, respectively.

These indicators each correspond to different aspects of diversity and allow us to assess the relationship between crop diversification and HDDS in multi-faceted ways. The Margalef index measures the richness (which focuses more on the number of crops). The Simpson index is synonymous with the Herfindahl index of concentration and puts more weight on relative abundance[7] than richness. For example, even when the Margalef index is the same, a more even distribution of crops across acres indicates greater diversity based on the Simpson index. The Shannon index focuses on balancing richness and relative abundance (Benin et al., 2004). In other words, the Shannon index not only emphasizes relative abundance as in the Simpson index but also captures some of the aspects of richness aspects as in the Margalef index.

We construct three crop diversification categories, $D^{*}_{ij,t=\tau}$, as shown in Table 1. For example, based on the count-based indicators (the number of crops grown by the household), categories are defined as "low" if only 1 crop is grown, "medium" if 2 crops are grown, and "high" if 3 or more crops are grown. Similarly, each of the Shannon, Simpson, and Margalef indexes are categorized as "low" if the index value = 0, "medium" if the index > 0 but below the median (among all positive values, excluding 0), and "high" if the index is above the median (again, among all positive values, excluding 0). While somewhat arbitrary, the categorization as described in Table 1 has various advantages; having three categories allows us to capture the effects of crop diversification more precisely along its intensive margins. Assigning the "low" category solely to households growing only 1 crop (and thus having Shannon/Simpson/Margalef scores of 0) ensures sufficient sample sizes for other categories, given that a significant share of sample households are already in the "low" category (as described in the later section). At the same time, splitting categories 2 and 3 using the thresholds described in Table 1 ensures sufficient sample sizes in each category and statistical power to detect differential effects between categories. Besides, using these categories makes the interpretations generally straightforward.

3.2.3 Violent events within the locality

Our indicator of local conflict is the incidence of violent events that occurred within the township of respondent household i, compiled from ACLED (Raleigh et al., 2010) and described in greater detail in the data section. Specifically, for the three months preceding the survey, we use (a) whether any violent events were reported in the township (separately for fatal events, and broader types including non-fatal events), and (b) the total number of such events per area of the township (again, separately for fatal- and non-fatal events).

In the robustness check section, we also show the results based on shorter durations (one month and two months preceding each survey round, respectively).

3.3 Econometric methods

We first assess how local violence affects HDDS. We then assess how farm household-level crop diversification is associated with the changes in local violence and HDDS (the conflict–HDDS nexus). As for the second analysis involving crop diversification, we focus on both short-term and medium-term associations. Each approach is based on different assumptions, including the exogeneity of crop diversification. Estimating both associations can improve the robustness of our results.

3.3.1 Effects of local violence on HDDS

To estimate how local violence affects HDDS, we estimate an ordinary least square (OLS) regression with panel fixed effects,

[7] "Relative abundance" refers to how common or rare a species is relative to other species in a defined location (Hubbell, 2001).

$$Y_{ijt} = \alpha + \alpha_V V_{jt} + \alpha_X X_{ijt} + c_{ij} + \varepsilon_{ijt}, \tag{4}$$

in which Y_{ijt} is the HDDS of farm household i in township j in survey round t. V_{jt} is the indicator of conflict intensity in township j, X_{ijt} is a vector of other time-variant exogenous variables (to be described in subsection 3.3). Notations of α represent estimated parameters, c_{ij} is the unobserved time-invariant fixed effects for i in j, and ε_{ijt} is an idiosyncratic shock.

As is described below, Y_{ijt} is a count variable. We therefore also estimate (4) through a Poisson regression:

$$\begin{gathered} \Pr(Y_{ijt} = y|\lambda_{ijt}) = \frac{\exp(-\lambda_{ijt}) \cdot \lambda_{ijt}{}^{y}}{y!} \\ \lambda_{ijt} = \alpha + \alpha_V V_{jt} + \alpha_X X_{ijt} + \alpha_{\bar{X}} \bar{X}_{ij} + \varepsilon_{ijt} \end{gathered} \tag{5}$$

in which $\Pr(Y_{ijt} = y)$ represents the probability that Y_{ijt} takes a count value of y, and $\exp(\cdot)$ is the exponential transformation operator. Equation (5) requires estimation through a maximum likelihood method in which directly controlling for unobserved time-invariant fixed effects leads to the incidental parameter problem. We instead use the correlated random effects (CRE) method (Mundlak, 1978; Chamberlain, 1984) to approximate unobserved farm household fixed effects through the inclusion of $\bar{X}_{ij}$, which is a vector of time-invariant variables as well as the farm household level average of X_{ijt}.

To understand the differential effects of violent events on consumption across food groups, we also estimate a CRE-probit regression,

$$\Pr(Y_{ijt,g} = 1|V_{jt}, X_{ijt}) = \alpha + \alpha_V V_{jt} + \alpha_X X_{ijt} + c_{ij} + \varepsilon_{ijt}, \tag{6}$$

in which $Y_{ijt,g}$ is a binary indicator of whether the consumption of each food group contributed to HDDS.

3.3.2 Associations between crop diversification and conflict–HDDS nexus: Short-term

To understand the relationship between crop diversification, HDDS, and the level of conflict, we first estimate models that focus on the short-term associations between these indicators. The short-term associations are identified by focusing on fluctuations in crop diversification levels across survey rounds, based on the assumption that crop diversification levels are exogenous to HDDS after controlling for household fixed effects Specifically, we estimate an ordinary least squares (OLS) model with panel fixed effects:

$$Y_{ijt} = \beta + \beta_D D_{ijt} + \beta_V V_{jt} + \beta_{DV} D_{ijt} V_{jt} + \beta_X X_{ijt} + c_{ij} + \varepsilon_{ijt}. \tag{7}$$

in which D_{ijt} represent crop diversification indicators, and all other variables are as previously defined. Notations of β are estimated parameters. Similar to (5), we also estimate the CRE-Poisson model to account for the count nature of the dependent variable.

$$\Pr(Y_{ijt} = y|\lambda_{ijt}) = \frac{\exp(-\lambda_{ijt}) \cdot \lambda_{ijt}{}^{y}}{y!} \tag{8}$$

$$\lambda_{ijt} = \beta + \beta_D D_{ijt} + \beta_V V_{jt} + \beta_{DV} D_{ijt} V_{jt} + \beta_X X_{ijt} + \beta_{\bar{X}} \bar{X}_{ij} + \varepsilon_{ijt}.$$

3.3.3 *Associations between crop diversification and conflict–HDDS nexus: Medium-term*

An important short-coming of the short-term associations between crop diversification and the conflict–-HDDS nexus, is that planting choices are likely endogenous with HDDS. The crops households decide to cultivate likely influence how diversely a household eats. At the same time, the desire to maintain dietary diversity, especially in the face of agrifood market imperfections, likely affects what a household plants. Because of this endogeneity issue, it is preferable to estimate a hypothetical medium-term effect that uses the initial level of crop diversification (which is predetermined and less likely to be endogenous to HDDS in subsequent survey rounds) as a proxy for crop diversification for the household. To assess the effect of a hypothetical change in this average tendency, the IPW approach is used to construct comparable samples that share similar characteristics and differ only in crop diversification patterns. Any differences in HDDS (and effects of conflict on HDDS) between these samples can then be attributed to crop diversification, enabling us to identify its effects.

This approach requires constructing comparable subsamples based on continuous variables, such as crop diversification indicators, rather than on clearly-defined, discrete, categorical variables. One workaround, which has been used in the literature, is to arbitrarily categorize crop diversification indicators into a few groups and apply MIPWRA.[8] Similar approaches have been used in past studies (Cattaneo et al., 2010, 2013; Takeshima, 2018; Takeshima et al., 2020).

The estimation proceeds as follows. We first estimate a CRE-multinomial logit model using the data from the initial survey round $t = \tau$ for each household i,

$$\begin{aligned}
\Pr\left(D^*_{ij,t=\tau} = 1\right) &= \frac{1}{1 + \exp\left(f_{2,ij}\right) + \exp\left(f_{3,ij}\right)} \\
\Pr\left(D^*_{ij,t=\tau} = 2\right) &= \frac{\exp\left(f_{2,ij}\right)}{1 + \exp\left(f_{2,ij}\right) + \exp\left(f_{3,ij}\right)} \\
\Pr\left(D^*_{ij,t=\tau} = 3\right) &= \frac{\exp\left(f_{3,ij}\right)}{1 + \exp\left(f_{2,ij}\right) + \exp\left(f_{3,ij}\right)} \\
f_{2,ij} &= \gamma_2 + \gamma_{2D} D_{ij,t=\tau} + \gamma_{2X} X_{ij,t=\tau} + \gamma_{2S} S_{ij,t=\tau} + \varepsilon_{2,ij,t=\tau} \\
f_{3,ij} &= \gamma_3 + \gamma_{3D} D_{ij,t=\tau} + \gamma_{3X} X_{ij,t=\tau} + \gamma_{3S} S_{ij,t=\tau} + \varepsilon_{3,ij,t=\tau}
\end{aligned} \tag{9}$$

in which $D^*_{ij,t=\tau}$ represent categories 1 through 3, as described in subsection 3.2.2. of the level of crop diversification by household i of township j in its initial survey round $t = \tau$ (τ varies across households i). $X_{ij,t=\tau}$ is the value of X_{ijt} in $t = \tau$. $S_{ij,t=\tau}$ is an exogenous variable that is

[8] We also tested alternative approaches for deriving IPW, such as ordered logit regressions. We find, based on likelihood-ratio tests, that the ordered logit is too restrictive to be incorporated in the IPWRA model. We therefore chose to proceed with a multinomial logit model. Nonetheless, if findings from MIPWRA show generally monotonic relations, they can still indicate that greater crop diversification is associated with greater resilience in dietary diversity against conflicts.

expected to have affected crop diversification decision $D^*_{ij,t=\tau}$ but not the HDDS in subsequent periods. $\Pr(\cdot)$ denotes the propensity score, that is, the probability that $D^*_{ij,t=\tau}$ is in category 1, 2, or 3, respectively. Notations γ_1 and γ_2 represent estimated parameters that are each associated with $D^*_{ij,t=\tau}$ categories 2 and 3, respectively (no parameters are estimated for $D^*_{ij,t=\tau} = 1$ since this is the base case). Equation (9) is a cross-section regression using only the information at the initial survey round $t = \tau$ for each household. From the CRE-multinomial logit, the probability that household i of township j in survey round t belong to each category of D^*_{ijt} is computed as predicted values of each $\Pr(\cdot)$ in (9). The inverse values of these predicted values of probability are then constructed for each i of j (denoted $\widehat{w}_{ij}$).

We then estimate the outcome regression separately for each $D^*_{ij,t=\tau}$ that a household belonged to by applying $\widehat{w}_{ij}$ as sample weights, through MIPWRA,

$$\begin{gathered} Y_{ijt} = \delta_d + \delta_{dV} V_{jt} + \delta_{dX} X_{ijt} + \delta_{d\bar{X}} \bar{X}_{ij} + \delta_{d\bar{X}} \bar{X}_{ij} + \varepsilon_{ijt} \\ \text{for household } i \text{ with } D^*_{ij,t=\tau} = d \ (d = 1,2,3) \end{gathered} \tag{10}$$

and MIPWRA-Poisson,

$$\begin{gathered} \Pr\left(Y_{ijt} = y\right) = \frac{\exp\left(-\lambda_{ijt,d}\right) \cdot \lambda_{ijt,d}^{y}}{y!}, \\ \lambda_{ijt,d} = \delta_d + \delta_{dV} V_{jt} + \delta_{dX} X_{ijt} + \delta_{d\bar{X}} \bar{X}_{ij} + \varepsilon_{ijt}, \\ \text{for household } i \text{ with } D^*_{ij,t=\tau} = d \ (d = 1,2,3) \end{gathered} \tag{11}$$

We then compare the estimated coefficients of interest, δ_{dV}, across different categories d, which allow us to identify crop diversification effects of violent events on HDDS. For example, a significantly more positive value of δ_{1V} relative to δ_{0V} (δ_{2V} relative to δ_{0V}, δ_{2V} relative to δ_{1V}) suggests that switching from lower crop diversification category 1 to higher category 2 (from category 1 to 3, from category 2 to 3) mitigates the adverse effects of violent event V_{jt} on HDDS.

Equations (9) and (10), or (9) and (11), are estimated simultaneously using STATA command `teeffects ipwra`. This enables us to obtain efficient, and still unbiased, estimators.

Importantly, as is the case for general classes of IPW regression adjustment (IPWRA) models (Robins & Rotnitzky, 1995; Imbens & Wooldridge, 2009), both MIPWRA and MIPWRA-Poisson are "doubly-robust", meaning that the overall model is consistent as long as either the regression (9), or the outcome regressions (10) and (11) are consistent, even when the other regression is misspecified.

3.4 Other control variables X_{ijt}

In regressions (4) through (11), control variables X_{ijt} include key household demographics, such as the age, gender, and education of the farm management decision maker and household size (adult males, adult females, and children), which vary over time due to migration of household members. X_{ijt} also includes proxies related to assets—size of farmland owned, the number of machines owned (measured in aggregate horsepower),[9] and the types of livestock owned (principal component), as well as access to markets proxied by distances to the commonly used input-dealers (time of travel in hours). X_{ijt} also includes the average annual nighttime light in j at t, as well as the village tract-level sample share of respondents who use irrigation at t (to proxy general access to irrigation given the local hydrological conditions and infrastructures).

X_{ijt} further include time-invariant variables, which enter into $\bar{X}_{ij}$ together with the household-level average of X_{ijt}. These time-invariant variables include various agroecological conditions, such as a dummy variable of agroecological zones (hills, dry, delta, and coastal zones), village tract-level soil characteristics (first principal component score of six soil properties—alkalinity, organic contents, texture, salinity, sodicity and drainage), historical average (1990 –2019) of total rainfall and average temperatures during the monsoon production season (six months total from July through December). The time-invariant variable also includes the suitability index of rice production as well as average suitability indexes of key non-rice crops (pulses, oil crops, fruits, and vegetables), which are scored between 0 and 100 to measure the suitability of each type of crop computed through a crop-model using various agroecological parameters (Fischer et al., 2012). Higher suitability for both rice and non-rice crops can increase the likelihood of crop diversification (particularly beyond rice).

For all time-variant variables in X_{ijt}, their initial-round values $X_{ij,t=\tau}$ affect crop diversification in (9), while their subsequent-round values are expected to affect dietary diversity once the crop diversification level is controlled for.

S_{ijt} in (9) is a set of exogenous variables expected to influence the crop diversification decision $D^*_{ij,t=\tau}$ but not HDDS in subsequent periods, that include daily farm wages for male workers and prices for hiring four-wheel tractors per acre of land preparation (both in real terms relative to the farmgate paddy price). S_{ijt} also includes whether the respondent received any advice related to crop agriculture from public extension services.[10]

Lastly, all estimated models include year dummy variables to capture any other year-specific factors affecting respective outcomes.

4 Descriptive statistics

4.1 Crop diversification

Table 2 summarizes various crop diversification indicators used in our analysis during the monsoon season. On average, our sample households grew 1.8 crops during the monsoon season, and 45 percent of them grew 2 crops or more, associated with Shannon, Margalef, and Simpson index scores of 0.357, 0.077, and 0.214, respectively. Crop diversification levels are generally higher in the dry zones and hills but lower in the delta zones (consistent with findings in Boughton et al. (2024)).

Figure 3 through Figure 5 illustrate additional key aspects of crop diversification. Figure 3 illustrates how the number (count) of crops grown by the farm households in the monsoon

[9]Following the past study in Myanmar (Takeshima et al., 2025), we apply the following: 40 horsepower (hp) for four-wheel tractors, 15 hp for two-wheel tractors and Trawlarjee, 5 hp for irrigation pump. We also assign 5 hp for other minor machines. We apply slightly different hp and find that our main results are largely robust.
[10]Past studies also used access to extension as one of the factors affecting crop investigating, while not directly affecting dietary diversity (e.g., Takeshima et al., 2020).

season is associated with diversification across food groups. The bar lengths indicate the relative frequency in proportion to the total sample size. Importantly, Figure 3 suggests that those who grow more than one crop in the monsoon season do so by adding other crops while maintaining rice production (as indicated by the persistent presence of the gray bars, which represent rice), instead of entirely switching away from rice production. For example, among those growing two crops, a majority grow rice and also grow one additional crop from a different food group (either legumes/nuts/seeds, or to a lesser extent, vegetables or fruits).[11] Similar patterns generally hold among those growing 3 crops or more, whereby many farm households grow rice, and also grow additional crops from different food groups. Complete diversification away from grain/root crops (those with "LGNS + VEG + FR" in Figure 3) is rare. Therefore, in general, an increase in the number (count) of crops grown is associated with diversification patterns in which rice (and more broadly grains/root crops) is the base crop on which crops from other food groups are added to the production.

Figure 4 illustrates the relations between the number (count) of crops grown and corresponding average values of the crop diversification indexes (with confidence intervals (CI) for each of the Shannon, Simpson, and Margalef indexes defined earlier). Not surprisingly, each of these indexes is positively correlated with the simple count of crops grown (horizontal axis). Nonetheless, relations are not strictly linear; an increase in the count-based indicator is associated with greater increases in the Shannon and Simpson indexes at lower count levels than at higher count levels. Representing crop diversification levels with both a simple count-based indicator and Shannon, Simpson, and Margalef indexes, as we do in our analyses, therefore enables robust inferences.

4.1.1 Relative consistency of crop diversification with respect to farm size

Figure 5 illustrates how crop diversification varies across farm size in the monsoon season. Notably, while there are positive relationships, particularly within the range of 2 to 10 acres (a range that contains most samples), the strength of these relations is generally modest. For example, when the total cultivated area is 10 acres, the typical numbers of crops grown are only about 25 percent higher (2.0 compared to 1.6). Similarly, between farm sizes of 2 acres and 10 acres, the Shannon, Simpson, and Margalef indexes differ by about 30 percent or less. These patterns suggest it is reasonable to estimate models (7) through (11) by combining all samples regardless of the farm size, instead of splitting samples by farm size.

4.2 Dietary diversity and sources

Table 3 summarizes HDDS. On average, *regular* HDDS and *occasional* HDDS are about 3.5 and 4.4, respectively, albeit with fluctuations across rounds. Under both measures, almost all households consumed grains/root crops, as well as oil/fat/butter. A majority of households also consumed vegetables/leaves. In contrast, only a fraction of households consumed fruits, meat/fish/eggs, sugar/sweets, and pulses/legumes/nuts, and a very small share of households consumed milk/dairy products. The rightmost columns indicate that, when households consumed food from each group, their own production is often the significant source of supply. Own production is a particularly important source of crops-based food items (accounting for 50 percent of more for fruits, grains/root crops, and pulses/legumes/nuts, and close to 40 percent for

[11]Importantly, some of them grow rice and another crop from the non-rice grains or root crop (GRRT) group, therefore still growing crops from a single food group (grains/root crops).

vegetables), and it is more so for food items that are constantly consumed (seven out of seven days) than those that are only occasionally consumed (at least four out of seven days).

4.3 Violent events at the township level

Table 4 summarizes the frequency of violent events at the township level, both at the extensive and intensive margins, and duration (1–3 months leading up to each of the relevant MHWS survey rounds). Overall, 73 percent of townships where our sample households resided experienced at least one incident of violent events during the three months leading up to each corresponding round of MHWS, with notably higher shares in early 2022 and early 2024 (81 percent in both periods). On average, 11.8 violent events per 1,000 km^2 were reported during the three-month period in townships where our sample households resided.

4.4 Other variables

Table 5 presents the descriptive statistics for the other explanatory variables. A majority of respondents are male, with about two adult males and two adult females in their households. Many are smallholders, typically owning 3 hectares of land, agricultural machines equivalent to a total of 11 horsepower, and certain livestock animals, such as chickens, draft animals, and pigs, among others. Approximately 13 to 15 percent of respondents received agricultural extension services from public organizations. Slightly below 30 percent of farmers use irrigation. Sampled respondents are typically located in areas that are 0.6 to 0.7 hours away from the most commonly used agri-input dealers. Many of these variables exhibited significant variations over time.

5 Results

5.1 Effects of local violence on HDDS

Table 6 summarizes the effects of local violence on *regular* HDDS, estimated from (4) and (5). The first 4 columns summarize the effects on HDDS based on food items obtained from all types of sources. Generally speaking, more local violence significantly reduced HDDS. For example, the estimated coefficient of –0.048 indicates that having at least one violent event in the township in the past 3 months led to a *regular* HDDS of 0.048 lower. Similarly, a one standard deviation higher number of violent events per township area led to a 0.021 to 0.031 decline in *regular* HDDS.

We further assess how local violence affects HDDS from two different sources: food items purchased and food items produced by the households themselves, by re-estimating (4) and (5) with these source-specific HDDS. Results are shown under the "purchased food" and "own-produced food" columns in Table 6. These results clearly show that local violence significantly reduces the HDDS among purchased food items, but it does not significantly affect the HDDS among own-produced food items. These patterns are consistent with the hypothesis that conflicts primarily affect households' access to diverse diets through agrifood markets, rather than diets accessible from households' own production.

To gain further insights into the implications for healthy diets, we also re-estimate (4) and (5) by separating HDDS into 2 subgroups; relatively "healthy" food groups (consisting of grains/oot crops, pulses/legumes/nuts, milk/dairy, meat/fish/eggs, vegetables/leaves, and fruits) and arguably "unhealthy" food groups (consisting of obesogenic foods like oil/fat/butter, and sugar/sweets). Table 7 shows the results.[12] We focus on results differentiated by sources (purchased vs. own-produced). Table 7 generally suggests that the local violence particularly hurts HDDS among purchased, healthier food groups, compared with HDDS among purchased unhealthier food groups.

Table 8 shows the results for food group-specific assessments (6). We again focus on results differentiated by sources (purchased vs. own-produced). Table 8 suggests that local violence has particularly adverse effects on consumption of purchased pulses/legumes/nuts and vegetables/leaves. Effects of conflict on the consumption of purchased food are statistically insignificant for other food groups, including, surprisingly, animal-based foods for which consumption is more commonly dependent on purchases (Table 3). Perhaps, consumers of these food groups are relatively well-off, and thus have the means to maintain the consumption through purchases (such as purchasing from alternative but pricier markets). As for consumption through own-production, effects of violent events are broadly insignificant across all food groups including pulses/legumes/nuts and vegetables/leaves.

Importantly, pulses/legumes/nuts and vegetables/leaves are among the key crop diversification options in the monsoon season (Figure 3). The seemingly pronounced effects of violent events on the reduced purchase of these food groups re-validate our motivation to examine the potential roles of crop diversification on HDDS among the four field-crops-based food groups.

5.2 Associations between crop diversification and conflict–HDDS nexus in the short-term (exogenous crop diversification conditional on household fixed effects)

We now show the results of short-term effects of crop diversification on HDDS from models (7) and (8), which are based on the restrictive assumption that the crop diversification choice in the monsoon season in each year is exogenous to HDDS in the subsequent post-monsoon season, once household fixed effects are controlled for.

Table 9 summarizes the results for both the linear fixed effects model (7) and the CRE-Poisson model (8), obtained using the aforementioned four indicators of crop diversification. Overall, Table 9 indicates that the incidence of violent events in the township during the three months prior is associated with a lower HDDS in the post-monsoon season, while the extent of such association is mitigated for households that had higher crop-diversification levels during the preceding monsoon season. For example, having at least one violent event reported in the township during the three months prior is associated with a HDDS of 0.088 lower at the lowest level of the crop diversification, as defined in Table 1, but this is mitigated by 0.054 if the household had a one standard deviation higher level of the crop diversification score (leftmost column). These patterns are consistently observed across models and various crop diversification indicators. Results in Table 9 are, therefore, robustly consistent with the hypothesis that greater crop diversification at the farm household level enhances resilience in dietary diversity against local conflicts.

[12] While it is debatable whether grains (including rice) and root crops can be considered "healthy", we keep them under "healthy" food groups, given that they can still be important sources of certain micronutrients like magnesium (in the case of rice (e.g., Fukagawa & Ziska, 2019)), and/or dietary fibers (often for root crops (e.g., Chandrasekara & Josheph Kumar, 2016)).

5.3 Associations between crop diversification and conflict–HDDS nexus in the medium-term (MIPWRA-CRE Linear/Poisson)

We then present the results of the analyses on the medium-term effects of crop diversification on HDDS based on equations (9) through (11).

5.3.1 Balancing properties

Table 10 summarizes the comparability of subsamples across three different levels of crop diversification when the count-based indicator (number of crops grown) is used as the crop diversification indicator (as defined in Table 1), for both raw samples as well as IPW-adjusted samples.

Under the "raw samples" columns, Table 10 shows that the original subsamples have considerably different characteristics across each crop diversification level, as indicated by statistically significant differences in averages for many variables. On the other hand, no variables exhibit statistically significant differences in averages across subsamples under the "IPW-adjusted samples" columns, validating that IPW-adjusted samples are sufficiently comparable. This allows for the remaining differences in outcomes (HDDS) to be reasonably attributed to the differences in crop diversification levels.

We also briefly interpret the multinomial logit regression results, which are used to construct the IPW-adjusted samples (these results are of secondary importance in our analysis and are presented in Appendix Table 14 as standardized marginal effects on the probability of each crop diversification level). Generally, higher crop diversification is associated with farm households with older primary farm decision-makers; with larger farm sizes owned (not rented) and livestock holdings; less local irrigation use (possibly because irrigation is mainly used for rice monocropping in the monsoon season); lower average temperature; and higher likelihood of being in coastal zone (which has suffered historically through relatively heightened levels of conflicts than other zones). Higher crop diversification is also associated with the receipt of public extension services, suggesting the potentially important roles of enhanced farming knowledge required for crop diversification (although this relation may be specific to our study context, as enhanced farming knowledge can instead help more specialization in other contexts).

5.3.2 Outcome model

Table 11 summarizes the key results on medium-term effects based on equations (9) through (11), for both MIPWRA and MIPWRA-Poisson models, as well as each of the 4 crop diversification indicators. Results for MIPWRA-Poisson are appropriately converted into marginal effects evaluated at sample means.

The results based on MIPWRA and crop diversification measured by the number of crops grown by the household in the monsoon season indicate the following: while the incidence of violent events within the township is associated with a 0.167 decline in HDDS for households with low crop-diversification with statistical significance, corresponding associations are less significant for households with higher crop diversification (–0.004 and 0.051 for medium and high crop diversification levels, respectively). Importantly, these estimated coefficients for medium and high crop diversification levels, are statistically significantly more positive than that for the low crop diversification level (0.163 and 0.219 higher for medium and high crop diversification levels, respectively). In other words, while households with low crop diversification levels incur a significant reduction in HDDS under local conflicts, households with higher crop diversification levels enjoy significantly greater resilience in their HDDS against local conflicts.

These patterns are generally robust and hold similarly under MIPWRA-Poisson models, as well as different crop diversification indicators. While differences between medium and low crop diversification are less significant when the Margalef, Simpson, and Shannon indexes are used as crop diversification indicators, differences between the high crop diversification and low crop diversification levels remain statistically significant at the 10 percent level or higher. Altogether, the results in Table 11 are consistent with the hypothesis that household-level crop diversification enhances resilience in household dietary diversity against conflicts.

5.4 Heterogeneity based on access to market

We further assess whether there is significant heterogeneity underlying our primary results in Table 9 and Table 11, particularly across areas with different levels of access to agrifood markets. To do so, we split the samples into two groups using nighttime light as a proxy for access to agrifood markets: samples are taken from areas where the nighttime light index is above the median (*connected areas*) and from areas where the nighttime light index is below the median (*remote areas*). We then re-estimate the same sets of models as in Table 9 and Table 11 separately for each subsample.

Table 12 and Table 13 summarize the results of key coefficients corresponding to those in Table 9 and Table 11. Our results generally suggest that the resilience-enhancing role of crop diversification on HDDS can be more clearly seen in the *connected areas* . For example, the upper rows in Table 12 suggest that in *connected areas*, HDDS are more significantly affected by violent events, but these effects are statistically significantly mitigated by higher crop diversification (as indicated by coefficients for "Violent events × CD"). Results are somewhat more ambiguous in *remote areas*. Similarly, in Table 13, the results for *connected areas* are relatively more consistent with those in Table 11, where the differences between medium/high crop diversification and low crop diversification are more statistically significant, compared to those in *remote areas*.

The heterogeneity shown in Table 12 and Table 13 is also consistent with the findings in Table 6 discussed in the previous subsection. Local violence tends to disrupt households' linkages with agrifood markets more than their linkages with their own food production, particularly for farm households that are captured in the MAPS data which we exclusively focus on. Therefore, HDDS may be more vulnerable to local violence for households that regularly rely on agrifood markets for their dietary diversity than for those that depend more on their own production. In turn, the former households may benefit more from higher crop diversification in enhancing the resilience of their HDDS against local violence.

Nonetheless, since the patterns in *remote areas* are not sufficiently distinct from those in *connected areas*, the observed effects of local violence and the impact of crop diversification on the resilience of household dietary diversity essentially hold for the entire sample, underscoring their broad implications.

5.5 Robustness checks

In this subsection we show the robustness of our primary results (Table 9 and Table 11). The appendix summarizes the results of these robustness checks.

5.5.1 Using occasional HDDS as the dependent variables instead of regular HDDS

Table 15, as well as Table 16, show the same sets of key results from Table 9 and Table 11, but using *occasional* HDDS as the dependent variable, instead of *regular* HDDS. The results in Table 15 and Table 16 are broadly consistent with our primary results, that is, *occasional* HDDS are negatively associated with violent events at a statistically significant level, while higher crop diversification levels significantly mitigate this negative association. These results suggest that our results hold for HDDS measured at different levels of regularity as a criterion.

5.5.2 Using violent events per area of township as a key violence variable

Similarly, the Table 15 as well as Table 17 show the same sets of key results from Table 9 and Table 11, but using the number of violent events per area of township during the prior three months as a key violence variable, instead of our original measures of whether there was any violent event in the township during the prior three months. The results in Table 15 and Table 17 are, again, largely consistent with our primary results, underscoring the robustness of our results across different measures of local violence.

5.5.3 Using average crop diversification across survey rounds instead of initial-period crop diversification, in medium-term model

Our medium-term results in Table 11 are based on the crop diversification level in the initial survey round for each household. However, it is possible that this indicator may not capture the representative tendency of crop diversification for some households if idiosyncratic shocks in this survey round led to significantly different crop diversification levels than this household would typically choose. We therefore re-estimate Table 11 by using the average crop diversification level across all survey rounds, rather than just the initial round alone. The results of these regressions are shown in Table 18. Again, we find that the results are generally consistent with those in Table 11.

5.5.4 Robustness against some violations of "selection-on-observables" assumptions

As described in the methodology section, MIPWRA relies on the assumption that IPW-adjusted samples are comparable across different crop diversification categories and all observable characteristics are comparable (as is shown in Table 10). This is a common assumption underlying IPW-based methods in general. However, there can still be significant differences in unobservable characteristics, and if there are, the differences in the effects of violent events on HDDS cannot be solely attributed to crop diversification. We therefore conduct sensitivity analyses to assess the robustness of our primary results against potential violations of the *selection-on-observables* assumption. Specifically, we follow the methodology by Li et al. (2011) developed for the IPW framework, which focuses on how these unobserved confounders lead to deviations of potential outcomes even with the same propensity score $\Pr(\cdot)$ in (9), and assesses the sensitivity of results against such deviations. Since this approach requires arbitrarily modifying the outcome values based on estimated $\Pr(\cdot)$, we use a two-step estimation method because it is more flexible, despite being less efficient than the simultaneous, one-step estimation method used for our primary model in Table 11.

Table 19 summarizes the results of sensitivity analyses for the key coefficients of interest for two hypothetical scenarios, one in which the HDDS conditional on the estimated $\Pr(\cdot)$ is 30 percent lower, and the other in which it is 30 percent higher, respectively, among those with the low crop diversification level relative to those in medium or high crop diversification levels. In both scenarios, results are largely consistent with our primary results, suggesting that our primary results in Table 11 are robust against modest violations of the selection-on-observables assumption underlying MIPWRA and MIPWRA-Poisson models.

5.5.5 Including livestock-based food and highly-processed food groups in HDDS

As mentioned above, our primary analyses focus on the four food groups due to their closer linkages with crop diversification options for smallholders in Myanmar. However, if increased consumption of the four primary food groups results from a substitution away from consumption of other secondary food groups, our primary results may be overstating the roles of crop diversification on the resilience of overall HDDS. We therefore conduct robustness checks of key results by expanding our HDDS measures to include other secondary food groups (milk/dairy products, meat/fish/eggs, oil/fat/butter, and sugar/sweets).

Table 20, Table 21, and Table 22 show the results that correspond to Table 6, Table 9, and Table 11, respectively. Results in Table 20 suggest that, although the levels of statistical significance are somewhat lower than in Table 6, violent events have adverse effects on overall HDDS, and particularly on HDDS from purchased food, while the effects are largely insignificant on HDDS from own-produced food. Similarly, in Table 21 and Table 22, although the levels of statistical significance are slightly lower, the results are generally consistent with the findings from Table 9 and Table 11, that is, higher crop diversification is associated with greater resilience in HDDS against violent events. These results suggest that higher crop diversification enhanced the resilience of HDDS among the four primary food groups, without incurring adverse substitution effects on the other secondary food groups.

6 Conclusions

Ensuring resilience in food and nutrition security, including adequate dietary diversity, plays a critical role in enhancing overall welfare and the formation of human capital, which are essential for long-term socioeconomic development. Literature has suggested that, for many smallholders in developing countries, household-level crop diversification and access to diverse foods from markets supplement each other, although the latter becomes an increasingly important source as agrifood systems continue to transform. A knowledge gap remains regarding how intensifying conflicts and social instability affect linkages between agrifood systems and households' dietary diversity. Addressing this knowledge gap is crucial, particularly for countries like Myanmar, which is characterized not only by intensifying conflict in recent years but also by relatively lower levels of overall crop diversification and dietary diversity at the national level compared to other countries in East and Southeast Asia.

We narrowed this knowledge gap using unique panel datasets from Myanmar, which cover periods of significant spatiotemporal variation in conflict intensity. We find that in the short term, increased township-level incidence of violent events in the post-monsoon season lowers household dietary diversity. However, such adverse effects are mitigated when the household exhibits a higher crop diversification level during the preceding monsoon season. We also find partial evidence that violent events reduce the dietary diversity from purchased food (including vegetables), suggesting that reduced market access and diminishing purchasing power of the households may contribute to lower dietary diversity scores. Similarly, in the medium term, a hypothetical increase in the initial level of crop diversification, conditional on household characteristics, enhances the resilience of household dietary diversity against local violence in subsequent periods. These results hold when addressing the potential endogeneity of the initial crop diversification level (with dietary diversity) through inverse probability weighting methods. The results are robust across a range of crop diversification measures (count-based indicators and Shannon, Simpson, and Margalef indexes) and alternative indicators of the intensity of township-level violent events. Overall, our findings support the hypothesis that in conflict-affected, fragile agrifood market contexts, the maintenance of diversified household-level food production—particularly beyond rice cultivation—remains a critical strategy for preserving dietary diversity among farm households.

Our findings have important policy implications, particularly for promoting household-level crop diversification as a means to enhance resilience in dietary diversity, where agroecological conditions are sufficiently favorable during the monsoon season (especially beyond rice). In the short- to medium-term, it is important to sustain and expand recent efforts on promoting homestead gardening and community gardening for promoting both dietary diversity and income earning.[13] NGOs can support crop diversification among farm households through targeted seed distribution, basic planting guidance, and the provision of simple irrigation technologies that enable diversification into vegetables—the crop group found to be most sensitive to conflict-induced market disruptions. While such interventions are likely to be particularly effective for commercially oriented farm households, further research is needed to assess their feasibility and impact among primarily non-commercial rural households and off-farm households. Our findings show that household dietary diversity declines with conflict and that diversification of crops grown for commercial purposes can help mitigate this effect; however, because the evidence pertains to already commercialized agricultural households, it remains unclear whether the skill, labor, and time requirements associated with vegetable cultivation would yield comparable benefits for households less engaged in farming. A lower-intensity alternative may therefore be the establishment of shared community gardens, allowing interested households to cultivate vegetables without requiring a full shift in livelihood strategies.

While this paper provides new evidence on the role of agricultural diversification in conflict-affected settings and its importance for supporting household dietary diversity, further research is required to assess the extent to which these findings generalize to less commercialized farm households. First, future studies should examine the impact of conflict on household dietary diversity among households that maintain kitchen gardens but do not engage in market-oriented agricultural production. Second, additional work is needed to understand whether diversification into non-commercial crops can meaningfully support diverse food consumption among primarily commercial farmers. Third, this study highlights differential effects of conflict on dietary diversity derived from purchased versus non-purchased foods More granular analysis at the individual food-item level, rather than at the food-group level, would help assess the robustness of these patterns. Finally, as our analysis focuses on four crop groups, extending this framework to animal-source foods is an important area for future research, particularly to better understand the relationship between livestock ownerships (also including poultry, fish) and derived products (e.g., eggs and milk) and their consumption in conflict-affected contexts.

This study makes an important and novel contribution to the literature by explicitly linking conflict exposure to household dietary diversity through distinct production- and market-

[13] For example, some recent projects helped smallholders expand home gardening through the provision of training and inputs, supplemented by complementary support on nutrition-knowledge enhancement, irrigation, and road infrastructure development, and financial training (e.g., Koster & Das, 2023).

based pathways in a fragile agrifood context. The analysis provides new evidence on how agricultural diversification can function as a resilience mechanism when markets are disrupted by conflict. The findings move beyond aggregate measures of food security to show which components of diets are most vulnerable and which forms of diversification matter in practice. In doing so, this paper advances understanding of the micro-level mechanisms through which conflict affects nutritional outcomes and offers empirically grounded insights that are directly relevant for both future research and programmatic interventions in conflict-affected rural settings.

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Tables

Table 1. Categorization of crop diversification levels

Crop diversification indicators	Crop diversification categories		
	Low	**Medium**	**High**
Count-based indicator (Number of crops grown)	1	2	≥ 3
Shannon / Simpson / Margalef	0	Greater than 0 but below the median among all positive values	Greater than or equal to the median among all positive values

Source: Authors.

Table 2. Crop diversification patterns in the monsoon season

Crop diversification indicators	**Survey rounds**			
	Monsoon season in all years	MAPS–1 (Monsoon season in 2021)	MAPS–3 (Monsoon season in 2022)	MAPS–5 (Monsoon season in 2023)
	Mean (std.dev)	Mean	Mean	Mean
Number of crops grown (count)	**1.837 (1.217)**	**2.008**	**1.825**	**1.733**
Hills	1.939 (1.197)			
Dry Zone	2.018 (1.277)			
Delta	1.527 (1.061)			
Coastal	1.833 (1.313)			
Number of crops grown >= 2 (yes = 1)	**0.449 (0.497)**	**0.507**	**0.431**	**0.431**
Hills	0.545 (0.498)			
Dry Zone	0.529 (0.499)			
Delta	0.287 (0.452)			
Coastal	0.404 (0.492)			
Shannon index (0 ~ Infinity)	**0.357 (0.457)**	**0.416**	**0.342**	**0.333**
Hills	0.416 (0.446)			
Dry Zone	0.458 (0.492)			
Delta	0.193 (0.362)			
Coastal	0.279 (0.425)			
Margalef index (0 ~ Infinity)	**0.077 (0.112)**	**0.091**	**0.076**	**0.068**
Hills	0.087 (0.112)			
Dry Zone	0.092 (0.114)			
Delta	0.049 (0.100)			
Coastal	0.079 (0.126)			
Simpson index (0 ~ 1)	**0.214 (0.265)**	**0.248**	**0.203**	**0.204**
Hills	0.254 (0.260)			
Dry Zone	0.275 (0.283)			
Delta	0.113 (0.210)			
Coastal	0.158 (0.239)			
Sample-size	5,988	1,423	2,507	2,058

Source: Authors' computations based on MAPS data.

Table 3. Descriptive statistics of dietary diversity

Variables	Consumption of each group of food				Share (percent) of major sources	
	All MHWS rounds	MHWS-2 (early 2022)	MHWS-5 (early 2023)	MHWS-7 (early 2024)	Own production	External sources[a]
	Mean (std.dev)	Mean	Mean	Mean	Share (percent)	Share (percent)
Whether most members consumed on all 7 out of the past 7 days						
Number of total food groups consumed	3.514 (1.223)	3.428	3.441	3.661		
Grains/Root crops (yes = 1)	0.995 (0.067)	0.989	0.999	0.996	56	44
Pulses/legumes/nuts (yes = 1)	0.142 (0.349)	0.145	0.139	0.143	50	50
Milk and other dairy products (yes = 1)	0.037 (0.190)	0.039	0.033	0.042	27	73
Meat/fish/eggs (yes = 1)	0.275 (0.447)	0.219	0.261	0.332	6	94
Vegetables/leaves (yes = 1)	0.644 (0.479)	0.633	0.641	0.657	39	61
Fruits (yes = 1)	0.249 (0.433)	0.292	0.242	0.228	69	31
Oil/fat/butter (yes = 1)	0.966 (0.182)	0.950	0.964	0.978	29	71
Sugar/sweets (yes = 1)	0.204 (0.403)	0.160	0.162	0.286	1	99
Whether most members consumed on **4 out of the past 7 days**						
Number of total food groups consumed	4.393 (1.330)	4.350	4.290	4.548		
Grains/Root crops (yes = 1)	0.997 (0.053)	0.992	1.000	0.997	56	44
Pulses/legumes/nuts (yes = 1)	0.292 (0.455)	0.309	0.280	0.295	45	55
Milk and other dairy products (yes = 1)	0.061 (0.239)	0.062	0.057	0.065	21	79
Meat/fish/eggs (yes = 1)	0.556 (0.497)	0.507	0.525	0.628	6	94
Vegetables/leaves (yes = 1)	0.813 (0.390)	0.801	0815	0.819	38	62
Fruits (yes = 1)	0.392 (0.488)	0.451	0.379	0.368	61	39
Oil/fat/butter (yes = 1)	0.985 (0.123)	0.979	0.984	0.989	28	72
Sugar/sweets (yes = 1)	0.297 (0.457)	0.248	0.250	0.387	0	>99

Source: Authors' computations based on MHWS data.

Note: [a]External sources are predominantly market purchases, while very small shares also include borrowing on credit, gift receipt, and payment for work.

Table 4. Descriptive statistics of violent events

Variables	Consumption of each group of food			
	All periods	Early 2022 (MHWS-2)	Early 2023 (MHWS-5)	Early 2024 (MHWS-7)
	Mean (std.dev)	Mean	Mean	Mean
Whether any violent events reported in the township (yes = 1) – all violent events				
3 months leading up to the MHWS survey	0.730 (0.444)	0.812	0.621	0.805
2 months leading up to the MHWS survey	0.652 (0.476)	0.745	0.543	0.720
1 month leading up to the MHWS survey	0.533 (0.499)	0.611	0.414	0.624
Number of violent events at township level (per 1000km^2) – all violent events				
3 months leading up to the MHWS survey	11.829 (96.860)	10.473	7.416	17.154
2 months leading up to the MHWS survey	7.983 (69.633)	7.039	4.781	11.820
1 month leading up to the MHWS survey	3.931 (38.629)	3.455	2.099	6.083

Source: Authors' computations based on ACLED, MAPS and MHWS data.

Table 5. Descriptive statistics of other control variables

Variables	All rounds	MAPS-1 /MHWS-2	MAPS-3 /MHWS-5	MAPS-5/ MHWS-7
	Mean (std.dev)	Mean	Mean	Mean
Time-variant variables				
Age of farm management decision maker (years)	47.799 (11.305)	44.382	48.743	49.012
Gender of farm management decision maker (female=1)	0.290 (0.454)	0.365	0.334	0.184
Education completed farm management decision maker (years)	7.917 (4.517)	8.167	7.789	7.901
Household-members (adult male)	1.693 (0.918)	1.800	1.679	1.635
Household-members (adult female)	1.930 (0.992)	2.006	1.916	1.895
Household-members (children)	0.918 (1.012)	0.944	0.929	0.887
Land owned (hectares)	3.223 (4.323)	3.409	3.295	3.008
Machines owned (total horsepower)	10.847 (13.978)	12.024	10.582	10.355
Livestock ownership (yes=1)				
Chicken	0.489 (0.500)	0.517	0.497	0.461
Sheep	0.002 (0.048)	0.004	0.001	0.002
Goat	0.024 (0.152)	0.025	0.024	0.022
Pig	0.158 (0.365)	0.160	0.158	0.157
Draft animal	0.283 (0.450)	0.408	0.315	0.157
Others	0.289 (0.454)	0.234	0.253	0.372
Male farm wage (per day, paddy-100kg equivalent)[a]	0.159 (0.600)	0.196	0.164	0.128
Four-wheel tractor hiring costs for land preparation (per acre, paddy-100kg equivalent)[a]	0.954 (0.316)	0.972	0.999	0.887
Received public extension services (yes=1)	0.141 (0.114)	0.153	0.144	0.129
Travel time to the most commonly used agri-input retailer (hours)	0.635 (0.657)	0.682	0.601	0.644
Irrigation access (township-level sample share using irrigation)	0.273 (0.229)	0.292	0.267	0.269
Nighttime light (index)	0.598 (1.203)	0.717	0.645	0.455
Time-invariant variables				
Historical average rainfall (total 1,000 mm, monsoon season)	1.264 (0.637)	1.263	1.275	1.250
Historical average temperature (average °C, monsoon season)	25.152 (2.203)	25.175	25.129	25.165
Soil characteristics				
Alkalinity (pH)	6.055 (0.785)	6.043	6.034	6.092
Organic contents (gram / kg of soil)	1.747 (1.356)	1.718	1.756	1.759
Fine texture (proportion of soil)	0.331 (0.160)	0.327	0.328	0.337
Salinity (deciSiemens per metre)	0.784 (0.989)	0.777	0.751	0.832
Sodicity (percent of soil)	4.569 (9.021)	4.337	4.423	4.937
Poor drainage (proportion of soil)	0.576 (0.420)	0.570	0.568	0.592
Suitability index (0-100)				
pulses, oil crops, fruits, vegetables (combined)	19.189 (10.980)	19.673	19.151	18.900
Sample-size	5,988	1,423	2,507	2,058

Source: Authors' computations based on MAPS data and various other data.
Note: [a]Based on farmgate paddy prices during the planting season.

Table 6. Short-term effects of local violence on household dietary diversity, by sources of food items (purchased, own-produced)[a]

Variables	Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days), differentiated by major sources of each food group											
	Food from all sources				Purchased food				Own-produced food			
	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson
	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)
At least one violent event in the township (yes = 1)	–0.048* (0.027)	–0.049 (0.047)			–0.054** (0.024)	–0.082* (0.046)			0.007 (0.022)	–0.035 (0.043)		
Number of violent events per area (standardized value)			–0.021* (0.012)	–0.031* (0.018)			–0.026** (0.011)	–0.041** (0.021)			0.007 (0.012)	0.021 (0.021)
Other controls	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
Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
CRE term		Yes		Yes		Yes		Yes		Yes		Yes
Constant	Yes	Yes	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	.000	.000
No. of obs.	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988

Source: Authors' estimations.

Note: [a]CRE = Correlated Random Effects. ***1 percent; **5 percent; and *10 percent.

Table 7. Similar results as Table 6, but disaggregated across healthy and unhealthy food groups[a]

Food group types	Measures of violent events	Dependent variable = number of food groups (healthy, unhealthy) consumed by more than half of household members in all of 7 previous days, by major source of food							
		Purchased food				Own-produced food			
		Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson
		Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Healthy foods[a]	At least one violent event in the township	–0.045 (0.030)	**–0.085*** **(0.047)**			0.022 (0.025)	0.023 (0.041)		
	Number of violent events per area			**–0.024*** **(0.014)**	**–0.042*** **(0.022)**			0.014 (0.012)	0.015 (0.020)
Un-healthy foods[b]	At least one violent event in the township	–0.016 (0.019)	–0.038 (0.027)			–0.018* (0.010)	–0.005 (0.015)		
	Number of violent events per area			–0.009 (0.009)	–0.019 (0.012)			–0.009* (0.005)	–0.002 (0.007)

Source: Authors.
Note: [a]CRE = Correlated Random Effects. [b]Healthy foods = Grains/Root crops, Pulses/legumes/nuts, Milk/dairy, Meat/fish/eggs, Vegetables/leaves, and Fruits. Unhealthy foods = Oil/fat/butter, and Sugar/sweets. ***1 percent; **5 percent; and *10 percent.

Table 8. Similar results for purchased food and own-produced food as Table 6, but disaggregated across each food group[a]

Food group	Measures of violent events	Dependent variable = 1 if the food group was consumed by more than half of household members in all of 7 previous days, by sources of food obtained							
		Purchased food				Own-produced food			
		Linear fixed effects model	CRE-Probit	Linear fixed effects model	CRE-Probit	Linear fixed effects model	CRE-Probit	Linear fixed effects model	CRE-Probit
		Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Grains / Root crops	At least one violent event in the township	–0.008	–0.056			0.015	0.113		
		(0.011)	(0.054)			(0.010)	(0.081)		
	Number of violent events per area			–0.005	–0.029			0.008	0.057
				(0.005)	(0.025)			(0.005)	(0.038)
Pulses / legumes / nuts	At least one violent event in the township	**–0.013***	**–0.028***			0.000	–0.006		
		(0.008)	**(0.015)**			(0.007)	(0.019)		
	Number of violent events per area			**–0.009****	**–0.018****			0.002	0.001
				(0.004)	**(0.009)**			(0.003)	(0.010)
Milk / dairy	At least one violent event in the township	–0.002	–0.001			0.003	–0.002		
		(0.005)	(0.016)			(0.003)	(0.013)		
	Number of violent events per area			–0.001	–0.002			0.001	0.000
				(0.002)	(0.008)			(0.001)	(0.006)
Meat / fish / eggs	At least one violent event in the township	0.016	0.005			0.006	0.014		
		(0.014)	(0.032)			(0.004)	(0.014)		
	Number of violent events per area			0.006	0.000			0.003	0.007
				(0.006)	(0.015)			(0.002)	(0.007)
Vegetables / leaves	At least one violent event in the township	**–0.038****	**–0.085****			0.015	0.009		
		(0.015)	**(0.043)**			(0.013)	(0.033)		
	Number of violent events per area			**–0.017****	**–0.034***			0.008	0.006
				(0.007)	**(0.020)**			(0.006)	(0.016)
Fruits	At least one violent event in the township	–0.001	–0.006			–0.017	–0.030		
		(0.008)	(0.019)			(0.014)	(0.026)		
	Number of violent events per area			0.003	0.001			–0.008	–0.015
				(0.004)	(0.009)			(0.007)	(0.012)
Oil / fat / butter	At least one violent event in the township	0.000	–0.060			–0.018	–0.014		
		(0.012)	(0.122)			(0.015)	(0.035)		
	Number of violent events per area			0.000	–0.029			–0.005	–0.005
				(0.006)	(0.057)			(0.009)	(0.016)
Sugar / sweets	At least one violent event in the township	–0.016	–0.044*			0.000	0.004		
		(0.013)	(0.027)			(0.002)	(0.007)		
	Number of violent events per area			–0.010	–0.023*			0.000	0.001
				(0.006)	(0.013)			(0.001)	(0.003)

Source: Authors.

Note: [a]CRE = Correlated Random Effects. ***1 percent; **5 percent; and *10 percent.

Table 9. Associations between violence, crop diversification and household dietary diversity among 4 crop-diversification-related food groups (short-term results)[a]

Variables	Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)							
	CD[b] = Number of crops		CD[b] = Margalef index		CD[b] = Simpson index		CD[b] = Shannon index	
	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Violent events[c]	–0.088*** (0.028)	–0.118** (0.053)	–0.090*** (0.028)	–0.119** (0.053)	–0.089*** (0.029)	–0.111** (0.053)	–0.082*** (0.029)	–0.110** (0.053)
CD	0.001 (0.011)	0.053*** (0.012)	0.003 (0.011)	0.054*** (0.012)	0.006 (0.011)	0.051*** (0.012)	0.001 (0.011)	0.051*** (0.012)
Violent events × CD	**0.054*** (0.020)**	**0.078*** (0.027)**	**0.056*** (0.021)**	**0.080*** (0.027)**	**0.054*** (0.021)**	**0.073*** (0.027)**	**0.047*** (0.021)**	**0.071*** (0.027)**
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes		Yes		Yes		Yes	
CRE term		Yes		Yes		Yes		Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000
No. of obs.	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988

Source: Authors' estimations.

Note: [a]CD = Crop diversification. CRE = Correlated Random Effects. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. ***1 percent; **5 percent; and *10 percent.

Table 10. Balancing properties of MIPWRA[a]

Variables	Raw samples			IPW-adjusted samples		
	Low CD	Medium CD	High CD	Low CD	Medium CD	High CD
Age	46.318	45.428	46.176	46.209	46.551	46.601
Gender	0.343	0.378	0.333	0.352	0.336	0.348
Education	7.884	7.880	8.096	7.948	7.895	8.389
Household-members (adult male)	1.700	1.690	1.822 **	1.715	1.704	1.730
Household-members (adult female)	1.907	1.998	2.003 *	1.938	1.948	1.885
Household-members (children)	0.961	0.930	0.949	0.952	0.957	0.949
Land owned (natural log)	1.740	1.850	2.028 ***	1.805	1.810	1.698
Machines owned	10.579	11.273	10.686	10.480	10.535	10.013
Livestock ownership (First principal component)	0.048	0.098	0.370 ***	0.102	0.091	0.040
Travel time	0.667	0.697	0.623	0.652	0.650	0.618
Nighttime light (natural log)	–0.795	–0.769	–0.748	–0.776	–0.788	–0.687
Soil characteristics (First principal component)	0.193	0.038	0.233 *	0.150	0.177	0.069
Irrigation access	0.275	0.286	0.287	0.280	0.280	0.258
Received public extension services	0.134	0.143	0.155 ***	0.140	0.138	0.135
Historical monsoon season rainfall	1384.032	1139.916	1093.602 ***	1285.904	1282.461	1407.745
Historical average temperature	25.328	24.670	24.999 ***	25.115	25.167	25.190
Suitability index	9.307	12.130	11.948 ***	10.332	10.355	9.691
Year 2021	0.474	0.638	0.636 ***	0.533	0.524	0.488
Year 2022	0.526	0.362	0.364 ***	0.467	0.476	0.512
Hills zone	0.173	0.284	0.193 ***	0.201	0.189	0.192
Dry zone	0.371	0.445	0.577 ***	0.421	0.435	0.378
Delta zone	0.403	0.236	0.186 ***	0.329	0.323	0.384
Coastal zone	0.053	0.035	0.044	0.049	0.053	0.046

Source: Authors' computations based on MAPS data and various other data.

Note: [a]CD = Crop diversification.

Table 11. Associations between violence, crop diversification and household dietary diversity among 4 crop-diversification-related food groups (medium-term results)[a]

Variables / Parameters	**Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)**					
	Model = MIPWRA			Model = MIPWRA-Poisson		
	Low CD[b]	Medium CD[b]	High CD[b]	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
(i) CD indicator = Number of crops						
Violent event (yes = 1)	–0.167***	–0.004	0.051	–0.171***	–0.001	0.050
	(0.050)	(0.088)	(0.088)	(0.051)	(0.090)	(0.088)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1240	1411	3337	1240	1411
Effects of violent events, relative to the lowest CD category		**0.163***	**0.219****		**0.170***	**0.220****
		(0.096)	**(0.101)**		**(0.103)**	**(0.102)**
(ii) CD indicator = Margalef index						
Violent event (yes = 1)	–0.167***	–0.017	0.063	–0.170***	–0.014	0.061
	(0.050)	(0.086)	(0.086)	(0.051)	(0.088)	(0.086)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1304	1347	3337	1304	1347
Effects of violent events, relative to the lowest CD category		**0.150**	**0.231****		**0.156**	**0.231****
		(0.100)	**(0.100)**		**(0.101)**	**(0.100)**
(iii) CD indicator = Simpson index						
Violent event (yes = 1)	–0.169***	–0.034	0.050	–0.172***	–0.035	0.050
	(0.050)	(0.090)	(0.090)	(0.051)	(0.091)	(0.092)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1261	1390	3337	1261	1390
Effects of violent events, relative to the lowest CD category		**0.135**	**0.219****		**0.138**	**0.222****
		(0.104)	**(0.103)**		**(0.104)**	**(0.105)**
(iv) CD indicator = Shannon index						
Violent event (yes = 1)	–0.168***	–0.022	0.016	–0.172***	–0.022	0.016
	(0.050)	(0.091)	(0.092)	(0.051)	(0.093)	(0.093)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1117	1534	3337	1117	1534
Effects of violent events, relative to the lowest CD category		**0.146**	**0.184***		**0.150**	**0.187***
		(0.103)	**(0.105)**		**(0.105)**	**(0.106)**

Source: Authors' estimations.

Note: [a]CD = Crop Diversification. MIPWRA = Multinomial-Logit Inverse Probability Weight Regression Adjustment. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. ***1 percent; **5 percent; and *10 percent.

Table 12. Same sets of key results from Table 9 differentiated by a proxy of food market access[a]

Variables	**Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)**							
	CD[b] = Number of crops		CD[b] = Margalef index		CD[b] = Simpson index		CD[b] = Shannon index	
	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Connected areas (above median night-time luminosity level)								
Violent events[b]	–0.126* (0.068)	–0.127* (0.068)	–0.128* (0.068)	–0.129* (0.068)	–0.113* (0.068)	–0.114* (0.068)	–0.115* (0.069)	–0.115* (0.069)
CD	0.064*** (0.017)	0.063*** (0.016)	0.066 (0.017)	0.065*** (0.016)	0.053** (0.017)	0.052*** (0.016)	0.055*** (0.017)	0.054*** (0.016)
Violent events × CD	**0.132*** (0.037)**	**0.131*** (0.036)**	**0.135*** (0.036)**	**0.133*** (0.036)**	**0.119*** (0.036)**	**0.118*** (0.035)**	**0.120*** (0.037)**	**0.119*** (0.036)**
Remote areas (below median night-time luminosity level)								
Violent events[b]	–0.109 (0.067)	–0.112 (0.069)	–0.111* (0.067)	–0.113 (0.069)	–0.108 (0.067)	–0.110 (0.069)	–0.107 (0.067)	–0.109 (0.069)
CD	0.032 (0.016)	0.031** (0.016)	0.033** (0.016)	0.033** (0.015)	0.036** (0.016)	0.036** (0.016)	0.035** (0.016)	0.034** (0.016)
Violent events × CD	**0.046 (0.035)**	**0.043 (0.036)**	**0.049 (0.035)**	**0.045 (0.036)**	**0.043 (0.036)**	**0.040 (0.036)**	**0.043 (0.036)**	**0.040 (0.036)**

Source: Authors' estimations.
Note: [a]CD = Crop diversification. CRE = Correlated Random Effects. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. ***1 percent; **5 percent; and *10 percent.

Table 13. Same sets of key results from Table 11 differentiated by a proxy of food market access[a]

Variables / Parameters	Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)					
	Model = MIPWRA			Model = MIPWRA-Poisson		
	Low CD[b]	Medium CD[b]	High CD[b]	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
Connected areas (above median night-time luminosity level)						
(i) CD indicator = Number of crops						
Violent event (yes = 1)[c]	–0.196** (0.080)	0.111 (0.116)	0.074 (0.120)	–0.193** (0.079)	0.114 (0.121)	0.070 (0.119)
Relative to the lowest CD category		**0.307** (0.140)**	**0.271* (0.142)**		**0.307** (0.143)**	**0.263* (0.140)**
(ii) CD indicator = Margalef index						
Violent event (yes = 1)[c]	–0.197** (0.080)	0.061 (0.116)	0.101 (0.116)	–0.193** (0.079)	0.064 (0.120)	0.096 (0.115)
Relative to the lowest CD category		**0.258* (0.140)**	**0.298** (0.138)**		**0.257* (0.143)**	**0.289** (0.137)**
(iii) CD indicator = Simpson index						
Violent event (yes = 1)[c]	–0.200** (0.080)	0.084 (0.120)	0.036 (0.120)	–0.196** (0.079)	0.082 (0.121)	0.037 (0.123)
Relative to the lowest CD category		**0.283** (0.143)**	**0.235* (0.141)**		**0.278* (0.144)**	**0.234* (0.141)**
(iv) CD indicator = Shannon index						
Violent event (yes = 1)[c]	–0.198** (0.080)	0.070 (0.127)	0.032 (0.118)	–0.195** (0.079)	0.071 (0.132)	0.033 (0.118)
Relative to the lowest CD category		**0.268* (0.149)**	**0.230* (0.139)**		**0.266* (0.153)**	**0.228* (0.139)**
Remote areas (below median night-time luminosity level)						
(i) CD indicator = Number of crops						
Violent event (yes = 1)[c]	–0.223 (0.141)	–0.103 (0.065)	0.023 (0.137)	–0.216 (0.137)	–0.110 (0.067)	0.017 (0.134)
Relative to the lowest CD category		**0.120 (0.157)**	**0.246 (0.188)**		**0.106 (0.154)**	**0.233 (0.183)**
(ii) CD indicator = Margalef index						
Violent event (yes = 1)[c]	–0.230* (0.139)	–0.101 (0.065)	0.026 (0.137)	–0.225* (0.136)	–0.108 (0.067)	0.017 (0.134)
Relative to the lowest CD category		**0.129 (0.155)**	**0.257 (0.186)**		**0.117 (0.153)**	**0.242 (0.181)**
(iii) CD indicator = Simpson index						
Violent event (yes = 1)[c]	–0.298** (0.134)	–0.102 (0.064)	0.068 (0.130)	–0.304** (0.132)	–0.108 (0.067)	0.060 (0.124)
Relative to the lowest CD category		**0.196 (0.151)**	**0.366* (0.188)**		**0.196 (0.150)**	**0.364** (0.183)**
(iv) CD indicator = Shannon index						
Violent event (yes = 1)[c]	–0.241* (0.131)	–0.102 (0.065)	0.008 (0.132)	–0.247* (0.132)	–0.109 (0.067)	–0.001 (0.127)
Relative to the lowest CD category		**0.139 (0.147)**	**0.249 (0.178)**		**0.138 (0.149)**	**0.245 (0.175)**

Source: Authors' estimations.
Note: [a]CD = Crop Diversification. MIPWRA = Multinomial-Logit Inverse Probability Weight Regression Adjustment. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. ***1 percent; **5 percent; and *10 percent.

Appendix: Supplementary results

Table 14. Multinomial logit regression results on correlates of crop diversification in the monsoon season (standardized marginal effects at sample means on probability of each crop diversification level)[a]

Variables	Dependent variables = Categorical CD levels in the initial survey round		
	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Age	–0.037** (0.017)	0.006 (0.013)	0.031** (0.014)
Gender	–0.022 (0.017)	0.003 (0.012)	0.018 (0.014)
Education	–0.007 (0.016)	0.005 (0.013)	0.002 (0.013)
Household-members (adult male)	0.015 (0.015)	–0.019 (0.013)	0.004 (0.013)
Household-members (adult female)	0.017 (0.017)	0.002 (0.014)	–0.019 (0.013)
Household-members (children)	–0.014 (0.016)	–0.010 (0.014)	0.024* (0.013)
Land owned (natural log)	–0.092*** (0.020)	0.011 (0.016)	0.081*** (0.016)
Machines owned	0.011 (0.017)	0.010 (0.014)	–0.021 (0.014)
Livestock ownership (First PC)	–0.063*** (0.017)	0.011 (0.014)	0.052*** (0.013)
Travel time	–0.028* (0.015)	0.030*** (0.010)	–0.002 (0.011)
Nighttime light (natural log)	0.001 (0.016)	–0.007 (0.013)	0.001 (0.016)
Soil characteristics (First PC)	–0.038 (0.026)	0.035* (0.019)	0.002 (0.023)
Irrigation access	0.059*** (0.020)	–0.015 (0.015)	–0.044*** (0.015)
Received public extension services	–0.053*** (0.020)	0.018 (0.015)	0.035** (0.015)
Historical monsoon season rainfall	0.058* (0.034)	–0.014 (0.023)	–0.045 (0.029)
Historical average temperature	0.113*** (0.036)	–0.037 (0.026)	–0.077** (0.031)
Suitability index	–0.053*** (0.020)	0.043*** (0.014)	0.010 (0.016)
Year 2021	–0.068*** (0.017)	0.035*** (0.013)	0.032** (0.014)
Year 2022	0.068*** (0.017)	–0.035*** (0.013)	–0.032** (0.014)
Dry zone	–0.008 (0.092)	0.078 (0.097)	–0.071 (0.066)
Delta zone	0.031 (0.072)	0.073 (0.083)	–0.103** (0.049)
Coastal zone	–0.023 (0.178)	–0.277 (0.190)	0.300** (0.128)

Source: Authors.

Note: [a]CD = Crop Diversification level; PC = Principal Component. [b]Based on categories defined in Table 1.

Table 15. Same results as Table 9 but with different measures of HDDS and violent events[a]

Dependent variables	Variables	CD[b] = Number of crops		CD[b] = Margalef index		CD[b] = Simpson index		CD[b] = Shannon index	
		Coef. (std.err)		Coef. (std.err)		Coef. (std.err)		Coef. (std.err)	
Regular HDDS	Violent events[c]	–0.088*** (0.028)	–0.118** (0.053)	–0.090*** (0.028)	–0.119** (0.053)	–0.089*** (0.029)	–0.111** (0.053)	–0.082*** (0.029)	–0.110** (0.053)
	CD	0.001 (0.011)	0.053*** (0.012)	0.003 (0.011)	0.054*** (0.012)	0.006 (0.011)	0.051*** (0.012)	0.001 (0.011)	0.051*** (0.012)
	Violent events[c] × CD	**0.054*** (0.020)**	**0.078*** (0.027)**	**0.056*** (0.021)**	**0.080*** (0.027)**	**0.054*** (0.021)**	**0.073*** (0.027)**	**0.047*** (0.021)**	**0.071*** (0.027)**
	Violent events[d]	–0.036*** (0.013)	–0.053** (0.024)	–0.036*** (0.013)	–0.053** (0.024)	–0.036*** (0.013)	–0.049** (0.024)	–0.034*** (0.013)	–0.049** (0.024)
	CD	0.001 (0.012)	0.054*** (0.012)	0.003 (0.011)	0.055*** (0.012)	0.006 (0.011)	0.051*** (0.012)	0.001 (0.011)	0.052*** (0.012)
	Violent events[d] × CD	**0.021** (0.009)**	**0.036*** (0.011)**	**0.022** (0.009)**	**0.036*** (0.011)**	**0.021** (0.009)**	**0.031*** (0.011)**	**0.018** (0.009)**	**0.031*** (0.011)**
Occasional HDDS	Violent events[c]	–0.117*** (0.032)	–0.128** (0.054)	–0.116*** (0.032)	–0.128** (0.054)	–0.121*** (0.031)	–0.127** (0.054)	–0.116*** (0.032)	–0.127** (0.054)
	CD	0.015 (0.013)	0.078*** (0.012)	0.017 (0.013)	0.078*** (0.012)	0.021* (0.012)	0.078*** (0.012)	0.015 (0.013)	0.077*** (0.012)
	Violent events[c] × CD	**0.060*** (0.022)**	**0.051** (0.026)**	**0.059*** (0.022)**	**0.051** (0.026)**	**0.066*** (0.023)**	**0.053** (0.027)**	**0.061*** (0.023)**	**0.052* (0.027)**
	Violent events[d]	–0.046*** (0.014)	–0.054** (0.025)	–0.046*** (0.014)	–0.053** (0.025)	–0.050*** (0.014)	–0.053** (0.024)	–0.048*** (0.014)	–0.053** (0.025)
	CD	0.015 (0.013)	0.078*** (0.012)	0.016 (0.013)	0.079*** (0.012)	0.021* (0.012)	0.078*** (0.012)	0.015 (0.013)	0.077*** (0.012)
	Violent events[d] × CD	**0.024** (0.010)**	**0.020* (0.011)**	**0.023** (0.010)**	**0.020* (0.011)**	**0.028*** (0.011)**	**0.020* (0.012)**	**0.027** (0.011)**	**0.020* (0.012)**

Source: Authors' estimations.

Note: [a]CD = Crop diversification. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. [d]Number of violent events per 1,000 km^2 within township area during the past 3 months. ***1 percent; **5 percent; and *10 percent.

Table 16. Same results as Table 11 but using *occasional* HDDS as the dependent variable[a]

Variables / Parameters	Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)					
	Model = MIPWRA			Model = MIPWRA-Poisson		
	Low CD[b]	Medium CD[b]	High CD[b]	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
(i) CD indicator = Number of crops						
Violent event (yes = 1)	–0.167***	–0.004	0.051	–0.171***	–0.001	0.050
	(0.050)	(0.088)	(0.088)	(0.051)	(0.090)	(0.088)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1240	1411	3337	1240	1411
Effects of violent events, relative to the lowest CD category		**0.163*** **(0.096)**	**0.219**** **(0.101)**		**0.170*** **(0.103)**	**0.220**** **(0.102)**
(ii) CD indicator = Margalef index						
Violent event (yes = 1)	–0.167***	–0.017	0.063	–0.170***	–0.014	0.061
	(0.050)	(0.086)	(0.086)	(0.051)	(0.088)	(0.086)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1304	1347	3337	1304	1347
Effects of violent events, relative to the lowest CD category		**0.150** **(0.100)**	**0.231**** **(0.100)**		**0.156** **(0.101)**	**0.231**** **(0.100)**
(iii) CD indicator = Simpson index						
Violent event (yes = 1)	–0.169***	–0.034	0.050	–0.172***	–0.035	0.050
	(0.050)	(0.090)	(0.090)	(0.051)	(0.091)	(0.092)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1261	1390	3337	1261	1390
Effects of violent events, relative to the lowest CD category		**0.135** **(0.104)**	**0.219**** **(0.103)**		**0.138** **(0.104)**	**0.222**** **(0.105)**
(iv) CD indicator = Shannon index						
Violent event (yes = 1)	–0.168***	–0.022	0.016	–0.172***	–0.022	0.016
	(0.050)	(0.091)	(0.092)	(0.051)	(0.093)	(0.093)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1117	1534	3337	1117	1534
Effects of violent events, relative to the lowest CD category		**0.146** **(0.103)**	**0.184*** **(0.105)**		**0.150** **(0.105)**	**0.187*** **(0.106)**

Source: Authors' estimations.

Note: [a]Same table footnotes as Table 11 applies to this table. [b]Based on categories defined in Table 1. ***1 percent; **5 percent; and *10 percent.

Table 17. Same results as Table 11 but using the number of violent events per area as the proxy for the intensity of local violence[a]

Variables / Parameters	Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)					
	Model = MIPWRA			Model = MIPWRA-Poisson		
	Low CD[b]	Medium CD[b]	High CD[b]	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
(i) CD indicator = Number of crops						
Violent events per area of township[c]	–0.064***	0.003	0.023	–0.065***	0.004	0.022
	(0.019)	(0.043)	(0.034)	(0.019)	(0.043)	(0.035)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1240	1411	3337	1240	1411
Effects of violent events, relative to the lowest CD category		**0.067**	**0.087****		**0.069**	**0.087****
		(0.047)	**(0.039)**		**(0.047)**	**(0.040)**
(ii) CD indicator = Margalef index						
Violent events per area of township[c]	–0.063***	–0.001	0.028	–0.065***	0.000	0.027
	(0.019)	(0.041)	(0.035)	(0.019)	(0.042)	(0.035)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1304	1347	3337	1304	1347
Effects of violent events, relative to the lowest CD category		**0.063**	**0.091****		**0.065**	**0.091****
		(0.046)	**(0.040)**		**(0.046)**	**(0.040)**
(iii) CD indicator = Simpson index						
Violent events per area of township[c]	–0.063***	0.001	0.020	–0.064***	0.000	0.020
	(0.019)	(0.038)	(0.039)	(0.020)	(0.039)	(0.039)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1261	1390	3337	1261	1390
Effects of violent events, relative to the lowest CD category		**0.064**	**0.083***		**0.064**	**0.084***
		(0.043)	**(0.043)**		**(0.043)**	**(0.044)**
(iv) CD indicator = Shannon index						
Violent events per area of township[c]	–0.063***	0.006	0.004	–0.064***	0.006	0.004
	(0.019)	(0.040)	(0.037)	(0.019)	(0.041)	(0.038)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1117	1534	3337	1117	1534
Effects of violent events, relative to the lowest CD category		**0.069**	**0.068***		**0.070**	**0.068***
		(0.045)	**(0.041)**		**(0.045)**	**(0.041)**

Source: Authors' estimations.

Note: [a]Same table footnotes as Table 11 applies to this table. [b]Based on categories defined in Table 1. [c]Standardized value of the number of violent events per area of township in the last 3 months. ***1 percent; **5 percent; and *10 percent.

Table 18. Same results as Table 11 but using average levels of crop diversification indices over time instead of those in the initial survey rounds[a]

Variables / Parameters	**Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)**					
	Model = MIPWRA			Model = MIPWRA-Poisson		
	Low CD[b]	Medium CD[b]	High CD[b]	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
(i) CD indicator = Number of crops						
Violent event (yes = 1)	–0.135***	0.061	0.004	–0.139***	0.063	0.000
	(0.042)	(0.077)	(0.071)	(0.043)	(0.078)	(0.070)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3229	1373	1386	3229	1373	1386
Effects of violent events, relative to the		**0.197****	**0.140***		**0.202****	**0.139***
lowest CD category		**(0.088)**	**(0.082)**		**(0.089)**	**(0.082)**
(ii) CD indicator = Margalef index						
Violent event (yes = 1)	–0.127***	0.027	–0.033	–0.131***	0.030	–0.035
	(0.044)	(0.066)	(0.078)	(0.045)	(0.066)	(0.076)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	2888	1550	1550	2888	1550	1550
Effects of violent events, relative to the		**0.154****	**0.094**		**0.160****	**0.096**
lowest CD category		**(0.079)**	**(0.089)**		**(0.080)**	**(0.088)**
(iii) CD indicator = Simpson index						
Violent event (yes = 1)	–0.128**	–0.082	0.050	–0.133**	–0.083	0.046
	(0.053)	(0.058)	(0.068)	(0.054)	(0.057)	(0.071)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	2326	1816	1846	2326	1816	1846
Effects of violent events, relative to the		**0.046**	**0.178****		**0.050**	**0.179****
lowest CD category		**(0.078)**	**(0.087)**		**(0.079)**	**(0.090)**
(iv) CD indicator = Shannon index						
Violent event (yes = 1)	–0.128**	–0.080	0.055	–0.134**	–0.082	0.048
	(0.053)	(0.057)	(0.070)	(0.054)	(0.057)	(0.072)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	2326	1817	1845	2326	1817	1845
Effects of violent events, relative to the		**0.048**	**0.183****		**0.052**	**0.181****
lowest CD category		**(0.078)**	**(0.088)**		**(0.079)**	**(0.090)**

Source: Authors' estimations.

Note: [a]Same table footnotes as Table 11 applies to this table. [b]Based on categories defined in Table 1. ***1 percent; **5 percent; and *10 percent.

Table 19. Robustness of estimated effects of violent events, relative to the lowest CD category from Table 11 against violations of selection-on-observables assumption[a]

Variables / Parameters	**Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)**			
	Model = MIPWRA		Model = MIPWRA-Poisson	
	Medium CD relative to low CD[b]	High CD relative to low CD[b]	Medium CD relative to low CD[b]	High CD relative to low CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
+ 30% biases in outcomes among low-CD households conditional on propensity scores				
(i) CD indicator = Number of crops	0.147*	0.194***	0.202**	0.231**
	(0.083)	(0.075)	(0.089)	(0.082)
(ii) CD indicator = Margalef index	0.135	0.207***	0.138	0.210**
	(0.087)	(0.079)	(0.090)	(0.084)
(iii) CD indicator = Simpson index	0.127**	0.185*	0.129**	0.190*
	(0.061)	(0.097)	(0.059)	(0.101)
(iv) CD indicator = Shannon index	0.144*	0.166*	0.148*	0.170*
	(0.084)	(0.095)	(0.083)	(0.098)
– 30% biases in outcomes among low-CD households conditional on propensity scores				
(i) CD indicator = Number of crops	0.150*	0.197**	0.172	0.233**
	(0.086)	(0.081)	(0.111)	(0.099)
(ii) CD indicator = Margalef index	0.154	0.248**	0.157	0.250**
	(0.112)	(0.097)	(0.116)	(0.102)
(iii) CD indicator = Simpson index	0.141*	0.218*	0.143*	0.223*
	(0.075)	(0.118)	(0.073)	(0.122)
(iv) CD indicator = Shannon index	0.162	0.194*	0.167	0.197*
	(0.106)	(0.115)	(0.106)	(0.119)

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

Note: [a]Same table footnotes as Table 11 applies to this table. [b]Based on categories defined in Table 1. [c]Standard errors are estimated through paired bootstrap methods (Efron & Tibshirani 1993) to account for the two-step estimation process. ***1 percent; **5 percent; and *10 percent.

Table 20. Same sets of results as Table 6 but using HDDS based on all 8 food groups including livestock products and highly processed food[a]

Variables	Dependent variable = regular HDDS (number of food groups, out of all 8 groups, consumed by more than half of household members in all of 7 previous days), differentiated by major sources of each food group											
	Food from all sources				Purchased food				Own-produced food			
	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson
	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)
At least one violent event in the township (yes = 1)	–0.041 (0.039)	–0.095* (0.057)			–0.055 (0.037)	–0.124** (0.059)			–0.005 (0.027)	0.015 (0.047)		
Number of violent events per area (standardized value)			–0.022 (0.018)	–0.045* (0.027)			–0.031* (0.018)	–0.062** (0.027)			0.001 (0.013)	0.012 (0.023)
Other controls	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
Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
CRE term		Yes		Yes		Yes		Yes		Yes		Yes
Constant	Yes	Yes	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	.000	.000
No. of obs.	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988

Source: Authors' estimations.
Note: [a]CRE = Correlated Random Effects. ***1 percent; **5 percent; and *10 percent.

Table 21. Same results as Table 9 but using HDDS based on all 8 food groups including livestock products and highly processed food[a]

Variables	Dependent variable = regular HDDS (number of food groups, out of all 8 groups, consumed by more than half of household members in all of 7 previous days)							
	CD[b] = Number of crops		CD[b] = Margalef index		CD[b] = Simpson index		CD[b] = Shannon index	
	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson	Linear fixed effects model	CRE-Poisson
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Violent events[c]	–0.080* (0.043)	–0.140* (0.075)	–0.084** (0.043)	–0.141* (0.075)	–0.081* (0.043)	–0.133* (0.075)	–0.082*** (0.029)	–0.136* (0.075)
CD	0.008 (0.017)	0.036** (0.017)	0.012 (0.017)	0.038** (0.017)	0.023 (0.016)	0.030* (0.017)	0.001 (0.011)	0.035** (0.017)
Violent events × CD	**0.051* (0.031)**	**0.094** (0.037)**	**0.056* (0.031)**	**0.095*** (0.037)**	**0.049* (0.030)**	**0.087** (0.037)**	**0.047*** (0.021)**	**0.090** (0.038)**
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes		Yes		Yes		Yes	
CRE term		Yes		Yes		Yes		Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000
No. of obs.	5,988	5,988	5,988	5,988	5,988	5,988	5,988	5,988

Source: Authors' estimations. ***1 percent **5 percent *10 percent.

Note: [a]CD = Crop diversification. CRE = Correlated Random Effects. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. ***1 percent; **5 percent; and *10 percent.

Table 22. Same results as Table 11 but using HDDS based on all 8 food groups including livestock products and highly processed food[a]

Variables / Parameters	Dependent variable = regular HDDS (number of food groups, out of 4 CD-related groups, consumed by more than half of household members in all of 7 previous days)					
	Model = MIPWRA			Model = MIPWRA-Poisson		
	Low CD[b]	Medium CD[b]	High CD[b]	Low CD[b]	Medium CD[b]	High CD[b]
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
(i) CD indicator = Number of crops						
Violent event (yes = 1)[c]	–0.159*	–0.028	–0.062	–0.160*	–0.022	–0.063
	(0.085)	(0.110)	(0.059)	(0.082)	(0.113)	(0.056)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1240	1411	3337	1240	1411
Effects of violent events, relative to the lowest CD category		**0.132** **(0.181)**	**0.097** **(0.094)**		**0.138** **(0.181)**	**0.098** **(0.092)**
(ii) CD indicator = Margalef index						
Violent event (yes = 1)[c]	–0.159*	–0.051	–0.017	–0.160*	–0.046	0.018
	(0.086)	(0.089)	(0.050)	(0.083)	(0.091)	(0.048)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1304	1347	3337	1304	1347
Effects of violent events, relative to the lowest CD category		**0.108** **(0.162)**	**0.142*** **(0.086)**		**0.114** **(0.161)**	**0.142*** **(0.085)**
(iii) CD indicator = Simpson index						
Violent event (yes = 1)[c]	–0.159***	–0.073	0.084	–0.160***	–0.069	0.086
	(0.060)	(0.104)	(0.112)	(0.060)	(0.105)	(0.124)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1261	1390	3337	1261	1390
Effects of violent events, relative to the lowest CD category		**0.087** **(0.120)**	**0.243*** **(0.127)**		**0.091** **(0.121)**	**0.246*** **(0.138)**
(iv) CD indicator = Shannon index						
Violent event (yes = 1)[c]	–0.177**	–0.103	0.162	–0.178**	–0.100	0.173
	(0.078)	(0.113)	(0.176)	(0.078)	(0.114)	(0.187)
Other controls, including CRE, year dummy	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 of obs. of each outcome regression	3337	1117	1534	3337	1117	1534
Effects of violent events, relative to the lowest CD category		**0.074** **(0.139)**	**0.339*** **(0.190)**		**0.078** **(0.139)**	**0.351*** **(0.201)**

Source: Authors' estimations.

Note: [a]CD = Crop Diversification. MIPWRA = Multinomial-Logit Inverse Probability Weight Regression Adjustment. [b]Based on categories defined in Table 1. [c]At least one violent event in the township during the past 3 months. ***1 percent; **5 percent; and *10 percent.

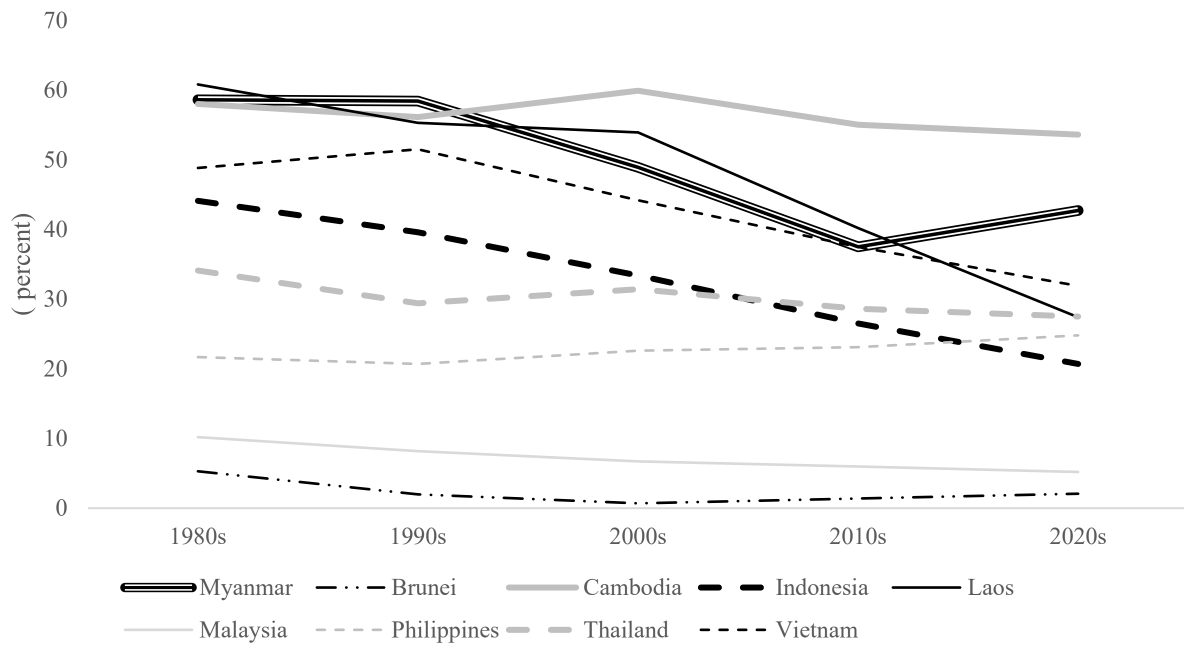

Figure 1. Historical shares (percent) of gross rice production values to total gross agricultural production values in selected Southeast Asian countries (decadal averages)
Source: FAO (2025); Takeshima & Joshi (2026).

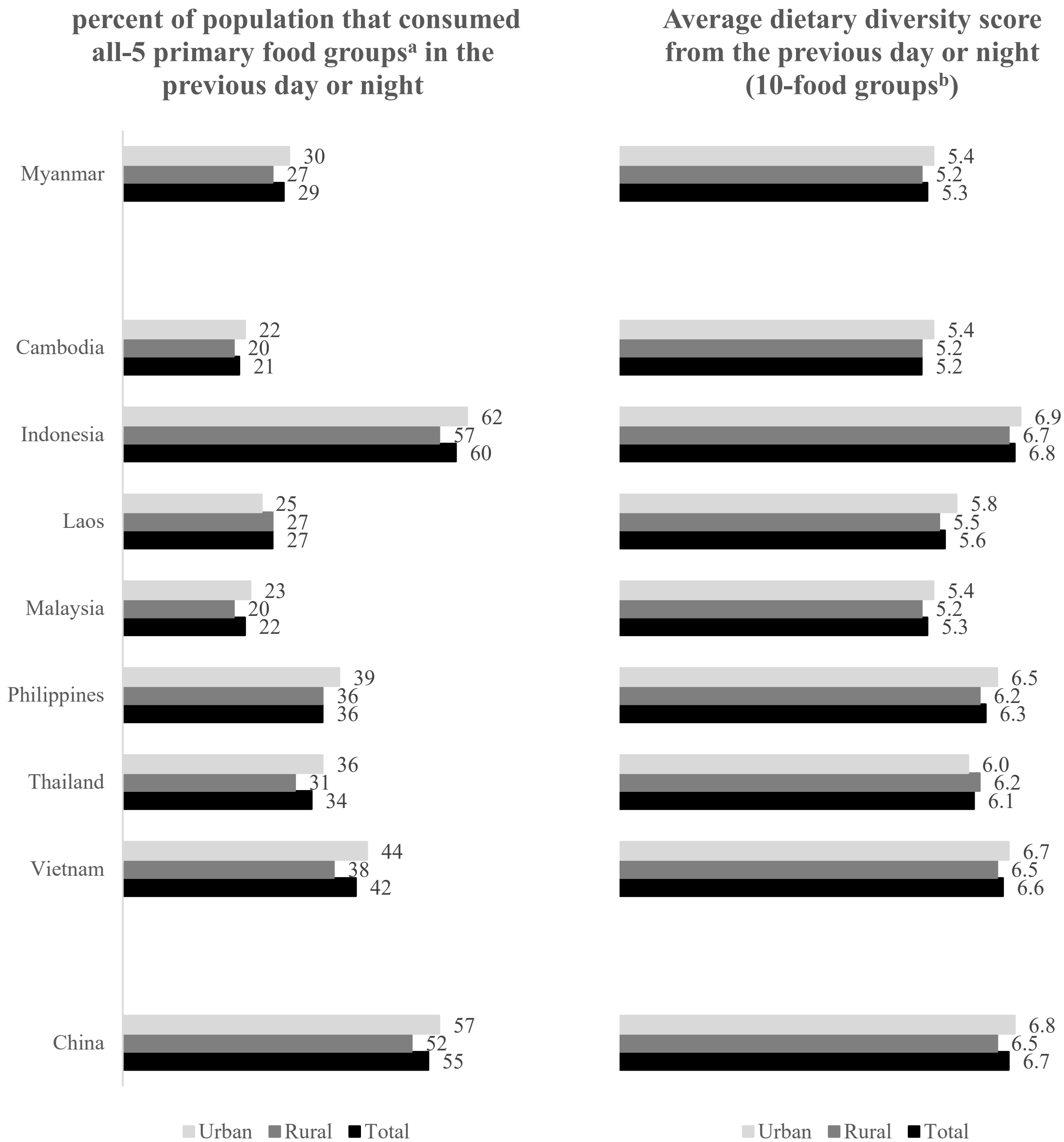

Figure 2. Dietary diversity patterns in Myanmar and other selected Asian countries

Source: Authors' compilations from Global Diet Quality Project (2024).

Note: [a]5-groups: vegetable, fruit, pulse/nut/seed, animal-source food, starchy staple. [b]Based on 10 groups used for DDS-Women but applied to all population; 1) grains, white roots and tubers, and plantains, 2) pulses (beans, peas and lentils), 3) nuts and seeds, 4) dairy, 5) meat, poultry, and fish, 6) eggs, 7) dark green leafy vegetables, 8) other vitamin A-rich fruits and vegetables, 9) other vegetables, and 10) other fruits.

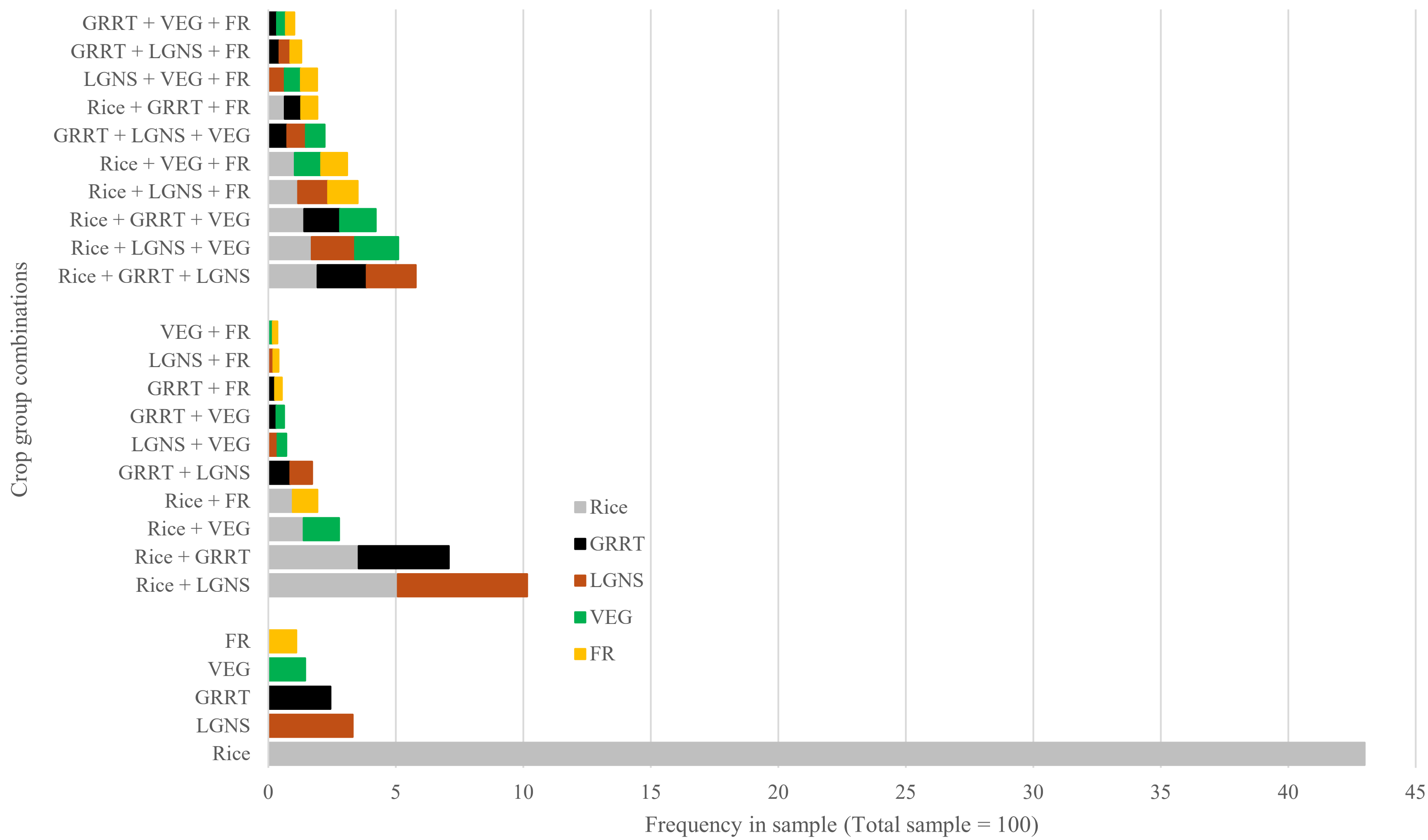

Figure 3. Relative frequency of crop-groups grown under different levels of crop diversification
Source: Authors' computation from MAPS data.
Note: [a]GRRT = Grain excluding rice + Root crop; LGNS = Legumes (Pulses/Peas)/Nuts/Seeds; VEG = Vegetables/Leaves; FR = Fruits

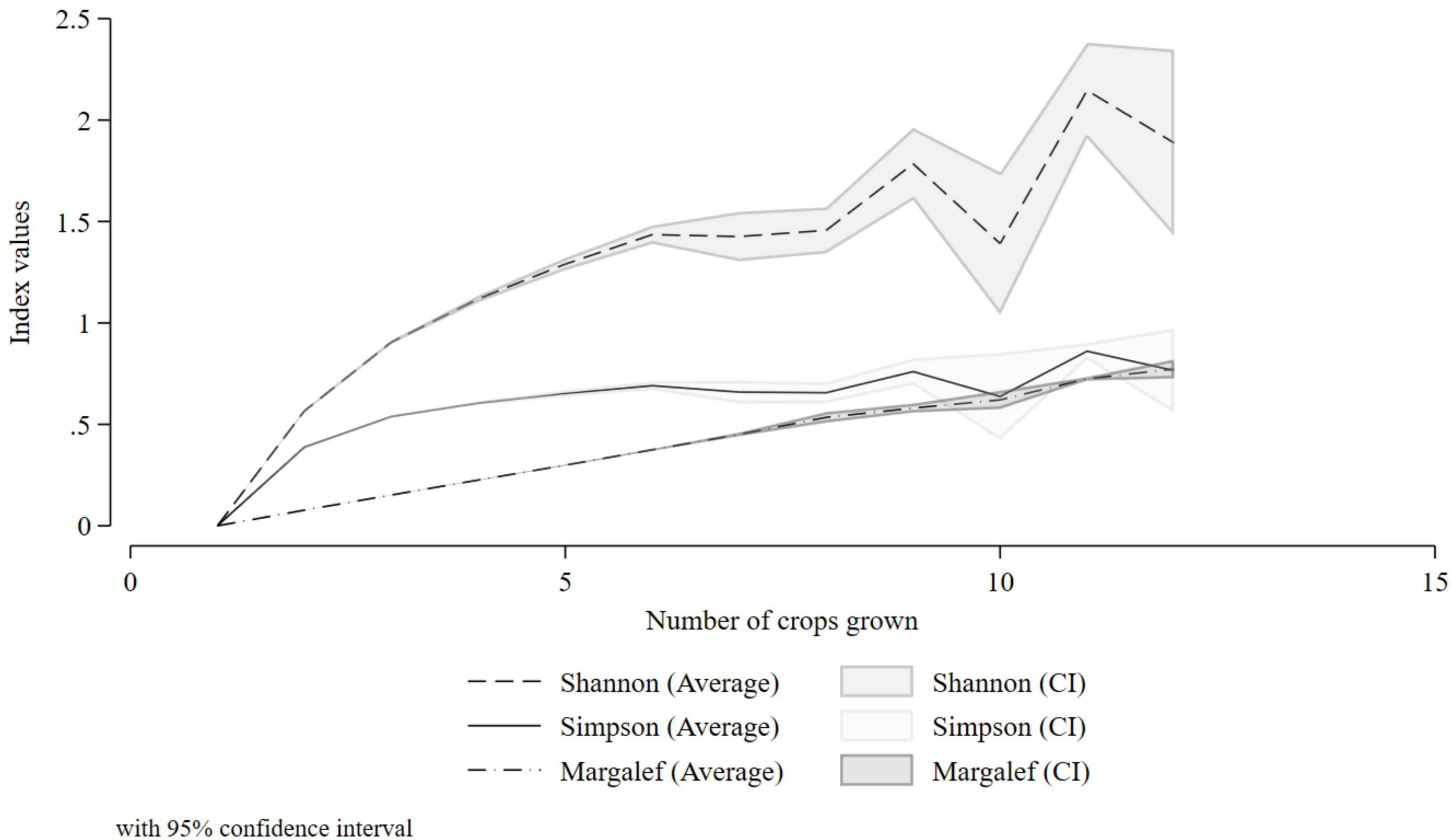

Figure 4. Relations between the number (count) of crops grown and other crop diversification indices in the monsoon season
Source: Authors' computation from MAPS data.

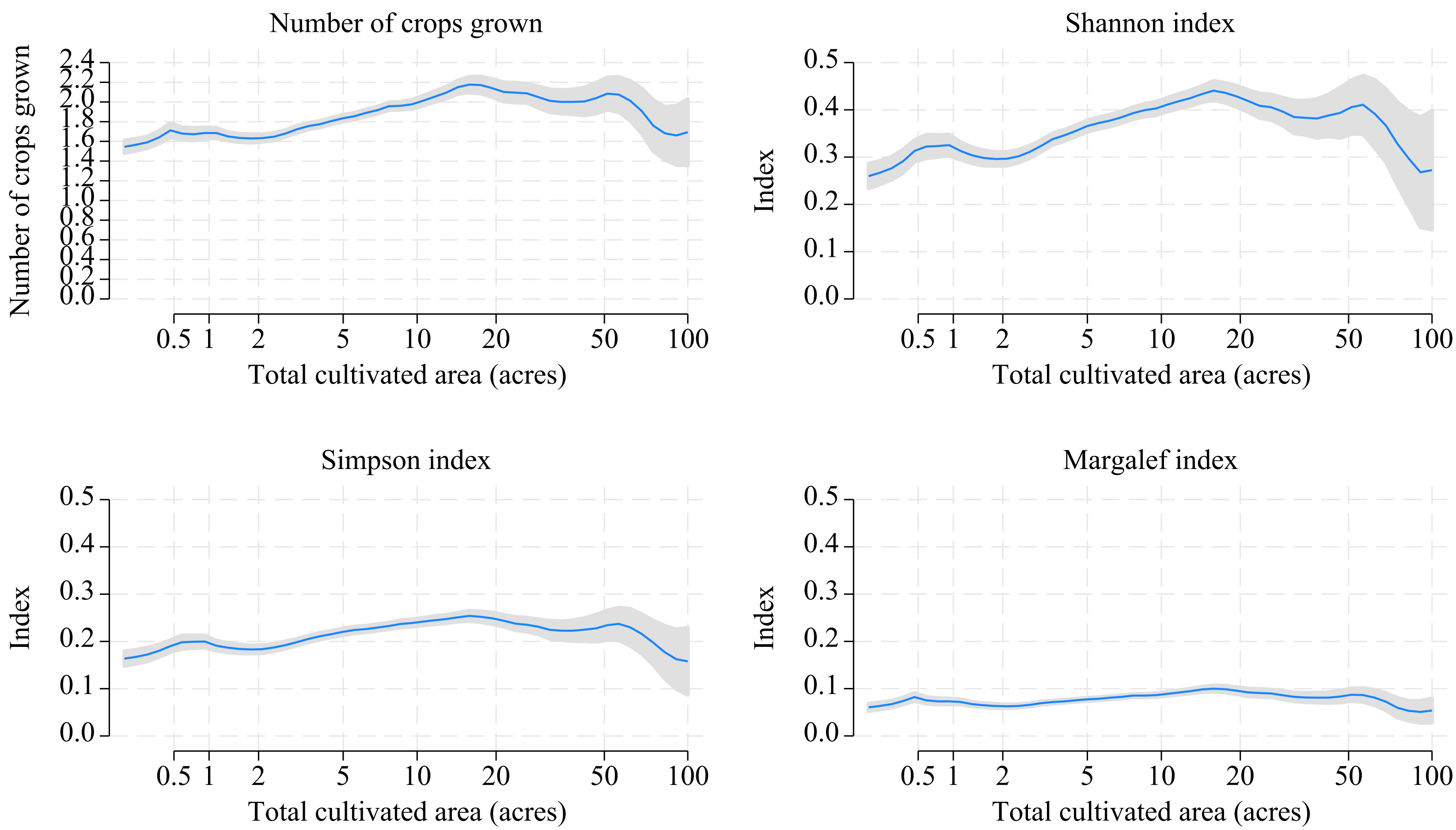

Figure 5. Relatively stable crop diversification indices across farm size (monsoon season)[a]

Source: Authors' computation from MAPS data.

Note: [a]Solid lines and gray areas indicate the point estimates and 95 percent confidence intervals based on the local polynomial regressions.

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