Biotech Crops, Input Use and Landslides: The case of Genetically Modified Corn in the Philippine Highlands

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Abstract

Improved seeds varieties have led to an increase in agricultural production as well as to a change in agricultural practices and input use. A side effect of these changes that has received little attention to date is the impact of those new technologies on environmental degradation. Using an original survey method of farming households on the Philippine island of Mindanao covering the past ten years, this paper finds a positive correlation between GM corn cultivation and landslide occurrence, which is robust to the inclusion of household fixed effects as well as to the use of matching and survival models. An endogenous allocation of crops on plots can be ruled out as a mechanism. Instead, more aggressive weed control via broad-spectrum herbicide appears to explain the results. Looking at the distribution of landslides as a function of wealth, landslides are found to increase socio-economic inequality as poorer farmers lose on average a significantly larger portion of their plots to landslides while for the top tail of the landholding distribution is less affected.

***JEL* Classification: O13, Q12, Q15, Q54, Q56**
Keywords: Agriculture, Environmental degradation, Landslides, Biotechnology

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> *"Land degradation represents, like climate change, one of the biggest and most urgent challenges for humanity."* (IPCC, 2019)

1 Introduction

Over the past decades, soil erosion has become a major concern for policy makers. In the Report on the Status of the World's Soil Resources, the FAO states that the majority of the world's soil are in "fair, poor or very poor condition". In the Philippines, 10 million ha of land, corresponding to 38% of the total country area, are moderately to extremely affected by water erosion, which is seen as a major threat to food security (FAO, 2015). Agricultural activity is one of the key drivers of soil erosion and the cultivation of row crops, such as corn, is notable for inducing erosion (Pimentel, 2006). Moreover, tropical climate, associated with heavy rains and frequent violent storms, as well as a high population density, induce a strong pressure on the country's agricultural lands.

Corn is the second most common crop in the Philippines after rice, accounting for 18.9% of the total agricultural area in 2017. Since 2003, genetically modified (GM) corn seeds are commercialized and the majority of corn now cultivated exhibits stacked traits of pest and herbicide tolerance (*Bt/Ht*).[1] This new technology induced to a change in the inputs used by farmers, away from pesticide and towards herbicide. Some NGOs have complained that this lead to an increase in soil degradation and landslides occurrence (Masipag, 2013). However, this has only been documented by anecdotal evidence with little regard to causality, mechanisms or overall profitability of the technology. This paper therefore seeks to rigorously examine the relationship between agricultural practices and landslides in a mountainous corn-growing region of the Philippines.

Using recall data covering the past ten years, collected among 444 farming households on the island of Mindanao, I am able to reconstruct the recent history of the farms, including information on crops cultivated, land use and landslide occurrence. Landslides are very common in the region, with 47 percent of the surveyed households experiencing at least one over the past ten years. Controlling for village-year and household fixed effects, results show that landslides are more frequent on farms cultivating biotech corn, compared to alternative corn varieties. The expected income loss associated with this increased risk is almost equal to the average gain in profitability from GM corn cultivation. Regarding the mechanism, the differential impact of GM corn cultivation does not appear to be driven by an endogenous allocation of crops on plots as the results are robust to the inclusion of plot fixed effects and plot-specific time trends. Instead, I find suggestive evidence that a more intensive use of herbicide on biotech corn increases land vulnerability to landslides, through its reduction of plant cover.

Moreover, looking at the distribution of landslide exposure as a function of household wealth, results show that households in the top tail of the landholding distribution are relatively less affected than the rest. The poorer households are therefore relatively more exposed to this environmental hazard, but the poorest of the poor do not suffer more than the median individual.

Several papers have already investigated the link between agricultural productivity and land degradation in

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[1] Bt corn seeds were first commercialized in 2003 while Ht corn seeds were only introduced later in 2006, with stacked traits taking over the whole GM corn seeds market (Aldemita et al., 2014). By 2014, 62% of the hectarage devoted to corn was planted with GM seeds. Since then, the adoption rate has declined by almost 20 percentage points due to the spread of counterfeit seeds locally known as *ukay-ukay* and *sige-sige* (ISAAA, 2017). This sharp decrease and prompted a call for stronger regulation from one of the largest biotech companies of the country (Aguiba, 2018). To date, however, the government of the Philippines does not appear to have taken any significant measure to address this issue.

developing countries (Pender et al., 2004; Raut et al., 2010). Most recent papers, however, look at the adoption of sustainable agricultural practices, such as conservation agriculture, and their impacts on farmers' welfare (Abdulai and Huffman, 2014; Abdulai, 2016; Manda et al., 2016; Michler et al., 2019; Wossen et al., 2015). The present work, on the other hand, investigates the drivers of environmental degradation and is therefore more closely related to a somewhat older literature on the determinants of soil erosion (Ananda and Herath, 2003; Boserup, 1981; Gebremedhin and Swinton, 2003). To the best of my knowledge, this is the first paper in the economics literature focusing specifically on landslides.

Second, this work is related to the large literature in agricultural economics, studying the profitability of GM crops, which has emereged over the past 25 years. Available meta-analyses show that this technology has positive impact on yield and farm profits, especially in developing countries (Carpenter, 2010; Finger et al., 2011; Klümper and Qaim, 2014; Qaim, 2016). In the Philippine, Yorobe and Smale (2012) use an instrumental variable strategy to account for adoption and find that GM corn cultivation increases net farm income by USD 105 per hectare and monthly off-farm income by USD 49 by reducing labor requirements. Moreover, Mutuc et al. (2013) estimate heterogeneous effects with propensity score matching and show that the farmers benefiting the most are smaller, poorer and less likely to adopt biotech seeds.

The most commonly-studied environmental impact of GM crops is the reduction in pesticide use following the adoption of the technology (Qaim, 2016). While a decreased use of pesticide on pest-tolerant crops is intuitive, the impact of herbicide-tolerance on herbicide use is more controversial (Bonny, 2016). On the one hand, the enormous increase in glyphosate based herbicide use over the past 20 years can partly be attributed to the tolerance traits added to specific crops (Benbrook, 2016). On the other hand, this strong increase was accompanied by a substitution away from other types of - more toxic - herbicides, leading to a decrease in herbicide expenditure and, potentially, in herbicide-related environmental impact (Qaim and Traxler, 2005). The global effect of GM crops on herbicide use remains however difficult to estimate due to the scarcity of farm-level data (Brookes and Barfoot, 2017).[2] This is especially true for developing countries where herbicide use has dramatically increased over the past decades and where constructing a reliable counterfactual is therefore especially challenging (Haggblade et al., 2017; Huang et al., 2017). In any case, the actual environmental impact of such change in input use has, so far, remained beyond the scope of the economic literature.[3] The present paper therefore aims at filling this gap.

Lastly, it is also related to the nascent literature investigating the distributional impact of natural disasters, which has so far produced ambiguous results. On the one hand, some papers find an increase in inequality following a natural disaster (Bui et al. (2014) in Vietnam and Sakai et al. (2017) in the Philippines and Yamamura (2015) in a cross-country panel approach) while other research find a decrease in inequality (Feng et al. (2016) in China, Abdullah et al. (2016) in Bangladesh and Keerthiratne and Tol (2018) in Sri Lanka). This paper however departs from the aforementioned research by looking at a more disaggregated measure of exposure to natural disasters, as landslides typically affect a single plot of land, and therefore a single farmer.[4]

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[2] Brookes and Barfoot (2017) actually attempt to estimate this impact for the US using historical data as well as opinion from extension and industry advisers.

[3] There are two papers investigating the effect of agricultural practice change on health: Brainerd and Menon (2014) exploit the timing of crop planting in different regions of India and show that children exposed to a higher concentration of agrichemicals during their first month experience worse health outcomes. Maertens (2016) uses the introduction of the Renewable Fuel Standard in the US to show that a more intensive use of pesticide sharply increases the probability of perinatal death.

[4] Note however that most landslides recorded in the dataset happened during the typhoon years of 2011 and 2012. They can therefore be considered as an additional damage resulting from the natural disaster, which only hits specific farmers

2 Background information

This paper is based on data collected on the island of Mindanao, Philippines, a region locally known as the Upper Pulangi Valley. The main economic activity in this rural area is corn farming, with 50% of the land devoted to this crop according to the 2012 Census of Agriculture and Fisheries (CAF). The production is rainfed, entirely manual and without tillage. Corn growing season lasts four months and there are two production seasons per year: a wet season between April and September and a (relatively) dry one between October and April. Most farmers therefore grow corn twice a year, with little rotation between crops.[5] This lack of rotation is compensated by the application of inorganic fertilizer. Some farmers occasionally try to have a third cropping in a year but this remains an exception.

The Upper Pulangi region is characterized by a weak presence of the state, a poverty rate substantially higher than the national average (79% compared to 22.5%) and very poor infrastructure. As a result, few farmers have direct access to markets, agricultural supplies stores and banking facilities and rely on informal traders and money lenders.

For these reasons, the penetration of GM corn seeds is much lower than in the rest of the country. Illegal GM corn seeds are widespread in the region and are cultivated by a large majority of smallholder farmers. These seeds are sold through an underground market and exchanged between relatives, friends and neighbors. Contrary to reports in the media presenting these seeds as a recent phenomenon (Arcalas, 2018), some farmers in the Upper Pulangi claim to have started cultivating them as early as 2005. According to qualitative interviews conducted by the author, those seeds were allegedly created by a former employee of a biotech company who supposedly stole mother seeds and crossed them with a local white corn variety. It still presents some resistance to glyphosate herbicide, allowing the farmers to spray herbicide on their crop, albeit with a small crop loss (around 5 to 10%). Moreover, as this resistance appears to be stable across generation, farmers usually save some of their seeds and replant them in the following season (hence the local name of the variety: "*sige-sige*", meaning "follow-follow"). On the other hand, this variety does not exhibit the Bt trait and is therefore exposed to corn borer infestation, the most common pest in the Philippines.[6]

Apart from corn, rice is the second main crop grown in the region, accounting to 20% of cultivated area according to the Census of Agriculture and Fisheries (CAF) 2012. It is cultivated on the flat lands in the valley as it needs a substantial amount of water to grow and there is no terracing system in the area. Corn, on the other hand, is sensitive to excess water and is best grown on sloped land from which water can run off. Crop selection is therefore mainly driven by the physical characteristics of the plots.[7] On the contrary, the different varieties of corn (GM and *sige-sige*) are all suited for the same terrains. Qualitative interviews with farmers, extension agents, financiers and input retailers have underscored the important role of financial constraints and risk management in the agricultural decision process. Indeed, biotech seeds are much more expensive than their illegal counterparts and exhibit higher return on fertilizer, which are therefore used more intensively on GM plots. This implies a large upfront cost, and a potentially important loss in case of bad harvest. Biotech seeds

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[5] Apart from corn, the common crops in the area include rice, rubber, ginger, hemp and vegetables

[6] As in many other developing countries, these counterfeit seeds are less productive than proper biotech seeds. However, farmers are very well aware of this productivity gap and asymmetric information does not seem to be an issue. Indeed,*sige-sige* seeds are never fraudulently sold as branded seeds, as documented in other parts of the world (Ashour et al., 2016; Bold et al., 2017). Buying this variety is therefore a deliberate decision of the farmers and seems to be influenced by financial constraints as many declare that they would prefer to plant proper biotech seeds but cannot afford them.

[7] In our data, only two plots have had both corn and rice over the past ten years.

are therefore planted by wealthier households, with more productive land. In the analysis that follows, corn varieties are divided in two main categories: GM corn, which refers to branded Bt/Ht corn seeds[8], and the other corn varieties which group the illegal *sige-sige* and the open-pollinated corn varieties. This grouping is motivated by the fact that open-pollinated varieties had almost disappeared by the time the data was collected.

3 Data and Descriptive Statistics

The data was collected between April and August 2018 in 14 villages (*barangays*) from the municipalities of Malaybalay and Cabanglasan in the province of Bukidnon. In total, 444 households were surveyed using the following selection procedure: the day before the team arrived, an enumerator went around the village informing the farmers of our arrival and inviting them to meet at a specific location the next day. The main purpose of this meeting was to conduct a lab-in-the-field experiment with couples, as part of another research project. Half of the households interviewed for this paper consists of the participants to this experiment. The other half was selected using a random walk technique among the remaining villagers.

In order to be interviewed, farmers needed to meet two criteria : (i) having cultivated corn at some point over the past ten years and (ii) cultivating less than ten hectares of land. The first condition was imposed because we wanted to study the interplay between corn cultivation methods and the incidence of landslides. We included farmers who did not grow corn anymore but who had in the recent past in order to alleviate the survivor bias.

A significant part of the data consists of recall data regarding the past 10-year history of the farm: land owned and cultivated, crops grown, financing as well as major agricultural shocks such as landslides and crop losses. In a pilot survey, we realized that obtaining reliable recall data was going to be a serious issue, especially over a 10-year span and given the low level of respondents' education. To address this issue, the enumerators started every interview by drawing a time-line of the farm with the help of the respondent. This way, they were able to ensure the internal consistency of answers and mitigate issues related to recall bias.[9] Important events (typhoons) were reported on the time-lines to give farmers time marks and improve the accuracy of their answers. Examples of such time-lines can be found in Appendix A. This problem also motivated the decision to exclude large farmers, who control a high number of plots and would not have been able to recall all the information for every one of them. However, large farms are scarce in the area given that the region was recently deforested and is therefore not characterized by large estates dating back to the Spanish era as in other parts of the country.

With the collected information, an unbalanced panel dataset of 631 plots was constructed, covering the 2008-2017 period and totaling 4,684 plot-year observations. The panel is unbalanced because information was only asked for the years during which the farmer was effectively in charge of the agricultural decisions on the plots. For example, if a farmer started using a new plot in 2012, then we only have information after that date, even if the land was already cultivated by someone else beforehand. Likewise, the questionnaire was focused on the plots that were effectively under the control of the farmer and agricultural information was not collected for the plots rented out or pawned to other households. Additional questions were asked regarding the household's agricultural activity for the twelve preceding months[10]. For corn and rice, the two major cash crops, we collected detailed information regarding input use, costs, harvest, price etc following standard LSMS survey instruments.

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[8] All the biotech corn cultivated in the region has stacked traits Bt/Ht.

[9] While the empirical analysis of this paper uses the full 10-year data, robustness checks are run excluding the earliest years.

[10] A few additional questions were asked regarding the 24 preceding months as well.

Appendix B discusses the representativeness of our sample by comparing it to the National Household Targeting System Data (NHTS), a census conducted in the same villages in order to identify households eligible to the national conditional cash transfer program (4Ps). Interviewed households appear to be representative of the area in terms of size, education and ownership of large assets (fridge, washing machine, electrification).

Table 1: Summary statistics

VARIABLES	N	Mean	Std Dev
PANEL A: Cross-section summary statistics			
Slope (percent)	442	0.474	0.284
Ever corn	440	0.986	0.116
Ever GM corn	440	0.375	0.485
Ever landslide	440	0.466	0.499
Stopped GM corn	169	0.503	0.501
PANEL B: Panel summary statistics			
Corn	3,482	0.865	0.342
GM corn	3,482	0.224	0.417
Other crop	3,482	0.146	0.353
Plot fallow	3,482	0.109	0.312
Cultivated area (ha)	3,582	1.877	2.653
Farm size (ha)	3,582	2.321	2.470
Nb of plots owned	3,582	1.012	0.677
Nb of plots used	3,582	1.231	0.544
Landslide	3,482	0.072	0.259
Landslide area (ha)	249	0.455	0.546
Unusable time after landslide	254	1.038	2.095

Panel A presents summary statistics using one observation per household. Slope is the mean slope of the farm over the past ten years. Ever corn, Ever GM corn and Ever landslide are dummy variables equal to one if, over the past ten years, the household has grown corn, GM corn or has been affected by a landslide, respectively. Stopped GM corn is a dummy equal to one if the household has stopped growing GM corn.

Panel B uses all household-year observations. Corn, GM corn, Other crop and Fallow are all dummy variables. Landslide area and unusable time were reported by the farmer for each landslide.

Table 1 presents the descriptive statistics for the cross-sectional and panel household data. As expected from the sampling procedure, almost all households have cultivated corn over the past 10 years and 37.5% of them have planted GM seeds. Landslides are very common, with 46.6% of households hit at some point over the past 10 years. This high number can partially be explained by the steepness of cultivated plots, as the mean slope is 47%, corresponding to a 25-degree angle.[11]

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[11] Note that the slope information was not collected on the field or through satellite imagery but asked directly to farmers, who were shown a series of pictures representing various angles, between 10% and 100% (respectively 5.7 and 45 degrees). Respondents were not shown the gradient or angles corresponding to the pictures, which can be found in Appendix C. While the actual gradient of the slope is certainly prone to measurement error and should be used with caution, there is no reason why this measure should

In the panel data, households planted corn 86.5% of the time, with biotech corn accounting for 22.4%. Other crops were cultivated 14.6% of the time while plots were left fallow 10.9% of the time. The average farm size is 2.3 ha but only 1.9 ha are effectively cultivated. The average number of plots cultivated per household is 1.2, with 78% of the respondents cultivating only one plot. The probability that a household experienced a landslide during any single year over the past 10 year was 7.2%. Following a landslide, farmers wait on average one year before replanting on the affected area. In 72% of the time, they do not wait and replant the following season. The majority of the landslides are small, with a mean area of 0.45 ha (median = 0.25 ha), as reported by the farmers.[12]

The evolution of the relative share of land occupied by GM corn, *sige-sige* corn, non-GM (open-pollinated and hybrid) corn and other crops is presented in Figure 1. In 2008, the cultivated area was almost equally divided between each category. Over time, the share of biotech corn and other crops remained relatively stable while that of *sige-sige* corn increased at the expense of the non-GM varieties, which had almost disappeared from the fields by the time the data was collected. For the rest of the analysis, these two types of corn will be grouped together and compared to the GM variety.[13]

Although the share of land devoted to GM corn appears relatively stable over time, there is substantial movement within the group of farmers cultivating biotech seeds. As reported in the first panel of Table 1, 50% of the farmers who grow GM corn at some point later revert to another crop (*sige-sige* corn in 60% of the cases). Moreover, 15% of those who stop do it twice over the 10-year period. In qualitative interviews, farmers reported bad harvests and expensive inputs as the main reasons for moving away from biotech seeds. Incidentally, the two years with the highest number of disadoptions are 2013 and 2016, which respectively follow Typhoon Pablo and the driest year of the period.

Figure 2 presents the probability that a plot is hit by a landslide for different crops and land uses. The vast majority of landslides occur on plots planted in corn, which is in line with the agronomy literature showing that row crops induce erosion. More surprisingly, plots planted in GM corn are 3.7 percentage points more likely to be hit by a landslide than those planted in other corn varieties. This difference is statistically significant and corresponds to a 55% increase in the probability of experiencing a landslide. Obviously, such a difference can be explained by time variations in weather and in crop cultivation or by differences in location, farm and farmer characteristics. In the rest of the paper, I show that this gap between GM corn and other corn varieties is robust to controlling for both observable and unobservable characteristics as well as to various model specifications. I then explore two mechanisms: (i) a change in land use and an endogenous allocation of crops on plots and (ii) a shift in agricultural practices inducing an increased use of herbicide.

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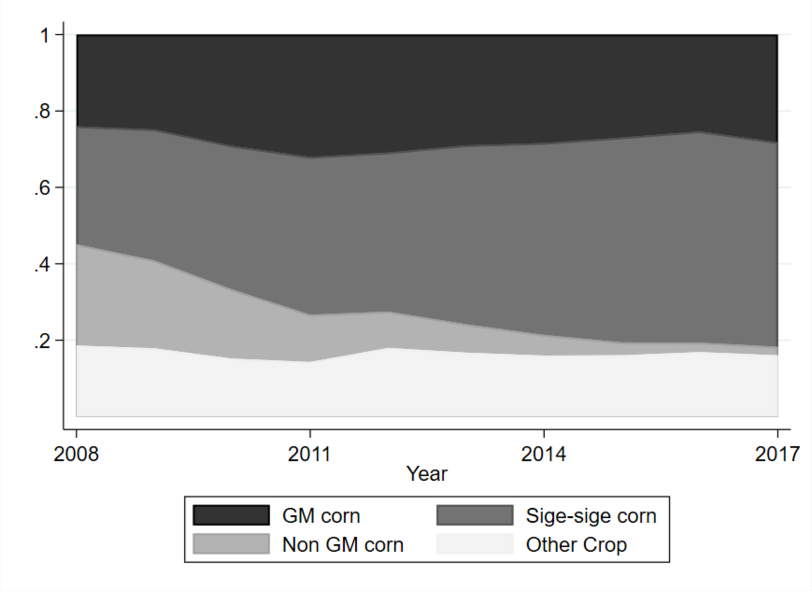
be biased in either direction or that the measurement error should be correlated with any variable of interest. No indication was given to the farmers as to whether they should state the slope of the steepest part of the plot, or the average slope. However, given that most plots are relatively small, with a median surface of 1 ha, there is little intra-plot slope variability.

[12] The term landslides covers a set of complex and diverse phenomena that involve the "*movement of a mass or rock, debris or earth down a slope*" (Cruden and Varnes, 1996). According to this classification by Varnes (1978), revised by Cruden and Varnes (1996) and Hungr et al. (2014), the type of landslides relevant for this study are called earth slumps and are characterized by a rotational sliding of earth (see Appendix D for photographic examples). They are associated with slopes ranging between 20 and 40 degrees (between 36% and 83%) and are triggered by intense and/or sustained rainfall leading to the saturation of the soil. See Highland and Bobrowsky (2008) for more details.

[13] It is interesting to note that, in our research area, the spread of *sige-sige* corn did not lead to the disadoption of biotech corn but, instead, drove out the more traditional varieties. This sharply contrasts with the recent spread of illegal seeds documented at the national level as well as with accounts of GM crops driving out traditional varieties.

Figure 1: Temporal variation of crop repartition



The figure shows the share of cultivated land allocated to specific crop categories. GM corn represents all biotech corn seeds; *sige-sige* corn, the illegal GM corn seeds, with some herbicide resistance and Non GM corn, all other open-pollinated corn varieties.

4 Results

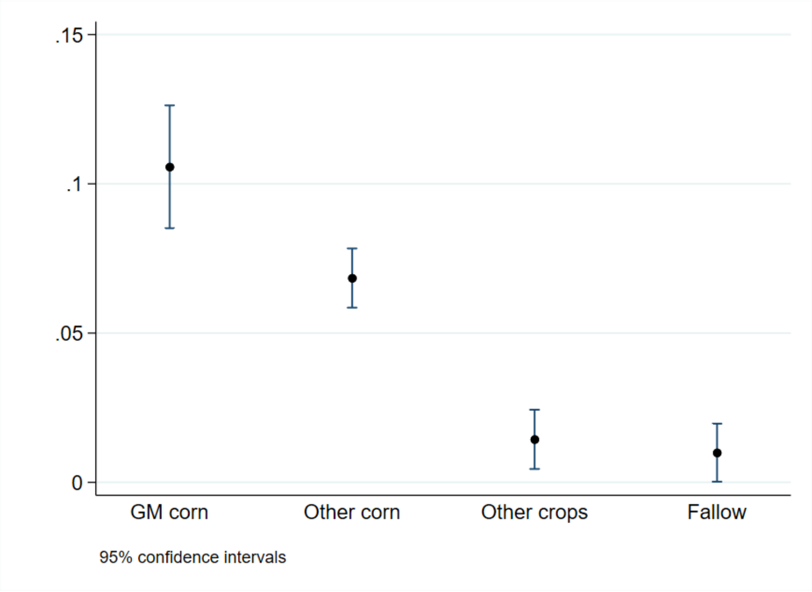
The empirical strategy used to address this question is a fixed effects linear probability model. More specifically the equation estimated is:

$$landslide_{ijt} = \beta_1 crop_{ijt} + \gamma_{jt} + \theta_i + \epsilon_{ijt} \tag{1}$$

Where $landslide_{ijt}$ is a dummy variable equal to one if the household i from village j experienced a landslide during year t. $crop_{ijt}$ is a vector of dummy variables, each representing a category of crops and equal to one if the crop was cultivated by household i at time t. γ_{jt} and θ_i respectively represent village-year and household fixed effects.

The main issue with this model is that there are no clear treatment and control groups, with GM corn being randomly allocated to the earlier. The inclusion of village-year fixed effects controls for aggregate and village-level time-varying shocks, such as rainfall, extreme weather events, general perception of the GM technology, price of agricultural goods and access to public services and infrastructure. Household fixed effects account for all time-invariant observable and unobservable differences between households, such as location and farmer's education. For households who do not change their landholdings over the period, it also controls for the physical characteristics of the farm (area, soil quality, ruggedness, etc.). Some specifications include household-specific time-trends in Equation 1, in order to control linearly for changes in household characteristics. Households are therefore assumed to have different baseline probabilities of being hit by a landslide and the evolution of this baseline probability is allowed to vary between households over time. Finally, ϵ_{ijt} is clustered at the village-year level to take into account correlation between observations.

Figure 2: Crop-specific landslide incidence



The figure shows the unconditional mean of landslide incidence per crop category.

4.1 Landslides and GM Corn

The results of the estimation of Equation 1 are presented in Table 2. The *crop* vector is composed of dummy variables for corn and GM corn cultivation as well as fallow land, the omitted category being a combination of all the other crops cultivated in the area. A household growing GM corn will have a value of 1 for the variable Corn as well as for GM corn. The GM corn coefficient is therefore to be interpreted as the additional effect of cultivating biotech corn compared to other corn varieties. Without household fixed effect (column 1), the probability of being hit by a landslide is 6.2 percentage points higher when corn is cultivated. Going from non-GM to GM corn further increases this probability by 3.3 percentage points. When adding household fixed effects (column 2), both point estimates increase, especially GM corn which almost doubles. Controlling for all time-invariant farm characteristics, the probability of being hit by a landslide increases by 6.1 percentage points in years in which GM corn is cultivated compared to years with other corn varieties. The difference in the point estimates of GM corn between columns 1 and 2 is however not statistically significant. In column 3, the sample is restricted to the balanced panel of households for whom we have information over the whole 10-year period and who did not change the area cultivated over that period. This allows to control for the physical characteristics of the farm and the coefficient of GM corn remains positive and strongly significant. Adding household specific time trends in column 4 increases even more the point estimate (though it is not different from the coefficient in column 2).

The main identification assumption is that there is no time-varying variable correlated with GM corn cultivation and with the error term. This would be the case, if farmers took specific measures that affect the probability of landslide – such as investing in erosion-control techniques – when changing the type of crop they grow. However, such investments are more likely to happen when switching to GM corn as the returns are higher when the crop is more productive. This should therefore bias our results downwards and we would estimate a lower bound effect.

All these results use data from the entire ten-year recall period. It is however likely that the quality of the answers will decrease with the distance to the time of enumeration. If this recall bias is uniformly distributed among respondents, then it should be absorbed by the year fixed effects and would only add noise to the data. However, if some farmers are more likely to remember accurately than others and this bias is correlated to the crop they were farming at the time, this might bias our estimates. To address this issue, Column 5 shows that the result still holds when restricting the sample to the years 2012-2017, therefore excluding the first four years.[14] Alternatively, column 6 uses the same specification as column 2 but weighs observations linearly as a function of time, giving a higher weight to recent years (1 for 2017) and decreasing with the recall period (0.1 for 2008). The point estimate slightly decreases to 5.3 percentage points but remains statistically significant.

Table 2: Landslide occurrence and crop planted

VARIABLES	(1) Village-Year FE	(2) HH FE	(3) Constant land	(4) HH Time Trend	(5) 2012 - 2017	(6) Weighted by year
Corn	0.062***	0.069***	0.030	0.082***	0.052*	0.063***
	(0.015)	(0.020)	(0.025)	(0.029)	(0.027)	(0.021)
GM corn	0.033**	0.061***	0.100***	0.093**	0.064**	0.053**
	(0.015)	(0.022)	(0.034)	(0.038)	(0.031)	(0.022)
Fallow	0.022*	0.069***	0.024	0.061*	0.051	0.065**
	(0.013)	(0.022)	(0.032)	(0.032)	(0.031)	(0.025)
Observations	3,482	3,466	2,057	3,466	2,284	3,466
R-squared	0.220	0.320	0.347	0.457	0.373	0.315
Village-Year FE	YES	YES	YES	YES	YES	YES
HH FE	NO	YES	YES	YES	YES	YES
HH Time Trend	NO	NO	NO	YES	NO	NO

Robust standard errors clustered at the village-year level in parentheses.

Linear probability model with dependent variable = 1 if the plot was hit by a landslide in year t. All explanatory variables are dummy variables and the omitted category is any crop except corn.

Column 3 restricts the sample to household with constant landholding over the period. Column 5 only uses observations between 2012 and 2017. Column 6 gives increasing weight according to the year.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2 Profitability of Biotech Corn

The previous results establish a strong link between biotech corn cultivation and the probability of landslides, which inevitably lead to crop loss and potentially to a decrease in soil productivity. However, it is clearly established in the literature that biotech crops are more productive and more profitable than other varieties. If this difference in profitability is large enough, it may be completely rational for farmers to plant GM corn even though this increases the risk of landslides. To address this issue, I use the information on recent agricultural activity, including harvest, income and costs for each crop variety over the past growing season. Table 3 compares the profitability of biotech and *sige-sige* corn in 2017 and shows that the expected income loss due to landslide is almost equal to the average difference in profit.[15]

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[14] The choice of the interval is motivated by the fact that many landslides were reported in 2011 and 2012 and very few in the subsequent two years. Because of the use of fixed effects, we need farmers who have switched to/from GM corn during the period and who have also been hit by a landslide in order to estimate the coefficients. Excluding the year 2012 leads to a sharp reduction in the number of farmers meeting both criteria and estimates the coefficient of GM corn based only on 13 observations.

[15] The comparison is between GM and *sige-sige* corn because, at the time of the survey, theses were the only two varieties still cultivated in the area.

As expected, GM corn is much more productive and its gross income per hectare is twice as large as that of *sige-sige* (PHP 30,000 roughly corresponds to EUR 500). For every landslide in the data, the measure of direct income loss is computed by multiplying this variety-specific mean income by the size of the area affected. To take into account the losses resulting from the impossibility to farm the land for several seasons following a landslide, I add to this direct income loss the average variety-specific profit per hectare multiplied by the area of the landslide and the number of seasons that the land was unusable. Compared to the mean quasi-profit (i.e. income minus expenditures excluding labor and imputed land prices), the damage caused by landslides can be significant. Indeed, the direct income loss is higher than the average profit for GM corn and represents more than 60% of profit for *sige-sige* whereas the cumulative income loss is higher than the average profit for both varieties.

The probabilities of landslide are taken from the second column of Table 2. Because traditional corn had almost disappeared from the survey area in 2018, the coefficient of corn is imputed to *sige-sige*. The probability of landslides for GM corn is the sum of both corn and GM corn coefficients. These probabilities are multiplied by the direct and cumulative income losses to get a measure of expected losses due to landslides. The expected cumulative losses represent 19% and 8% of quasi-profit for GM corn and *sige-sige* respectively. The difference between the expected losses is almost equal, in magnitude, to the difference in quasi-profit between both varieties. This implies that the increased risk of GM corn almost completely cancels the profitability advantage of this variety.[16]

Table 3: Expected loss of income due to landslides

Mean(PHP)	(1) **GM Corn**	(2) **Sige-sige corn**	(1) - (2)
Income per ha	30,532	14,965	15,567
Direct income loss	13,070	5,927	7,143
Cumulative income loss	15,902	10,958	4,944
Quasi-profit per ha	10,992	9,505	1,487
Probability of landslides	13%	6.9%	6.1%
Expected direct income loss	1,699	409	1,290
Expected cumulative income loss	2,067	756	1,311

All monetary measures are computed using the municipality-specific median price of corn during the harvest preceding the survey. Income per ha is computed by taking the mean of the quantity harvested over the two years preceding the survey multiplied by the price. Direct income loss is the product of the area damaged by the landslide by the mean income per hectare. The cumulative income loss adds to the direct income loss the product of the area damaged in subsequent years by the time it is damaged and the mean quasi-profit per hectare in 2017. Quasi-profit is the farm profit excluding labor expenditures and imputed land prices.

Probability of landslide are taken from the second column of Table 2.

This analysis should however be subject to caution for different reasons. First, the average income and profitability was only computed for the twelve months prior to the survey. Despite the fact that this year was not reported as being particularly good or bad, it may not be representative. Second, the measurement of the landslide-affected area is not perfect, as the question was asked directly to the farmer and the enumerators did not visit the plots themselves. Even though there is no reason to believe that measurement error differs between

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[16] The small difference in quasi-profit between both varieties is surprising and is at odds with the agricultural economics literature on GM crops (Qaim, 2016). While we do find a large difference in yield between GM corn and *sige-sige*, it is mostly offset by more expensive seeds and a more intensive use of chemical fertilizer. Indeed, fertilizer use per hectare of *sige-sige* farmers is on average 50% lower than that of GM corn farmers.

GM and non-GM corn, it is possible that the farmers systematically over-reported the affected area. In this case, the computed and expected income losses would be inflated and the actual difference between GM and *sige-sige* would be smaller. On the other hand, the computation of income losses only take into account the time during which the plot was not cultivated by the farmer and not the loss in soil fertility following the landslide. It is indeed very likely that the affected area becomes less productive as some of the top soil was washed away, which is not included in our analysis.

4.3 Robustness analysis

This section present three robustness tests confirming the results of Table 2. First, I re-estimate Equation 1 and interact the crop vector with a dummy equal to one if the farmer cultivates GM corn at some point over the past ten years. If the results presented in Table 2 are driven by differential trends between adopters and non-adopters that have not been properly controlled for, we should expect that adopters have a higher probability of landslide even when they are not cultivating biotech seeds. The first column of Table 4 shows that this is not the case as both interaction coefficients are insignificant (the interaction between adopters and GM corn cannot be estimated and is therefore not reported).

The other columns show the result of placebo tests using lags or leads of the cultivated crop vector: Column 2 uses the crop cultivated in t-2; column 3 using that of t-1, column 4 of t+1 and column 5 of t+2. In all those regressions, the coefficients of corn and GM corn are close to zero and insignificant. This shows that landslide occurrence is correlated with the contemporaneous agricultural practices.

Table 4: Placebo tests

VARIABLES	(1) GM adoption	(2) 2nd lag	(3) 1st lag	(4) 1st lead	(5) 2nd lead
Corn	0.061**	0.011	0.024	0.031	0.020
	(0.026)	(0.031)	(0.021)	(0.022)	(0.028)
GM corn	0.060**	-0.019	-0.003	-0.002	-0.014
	(0.024)	(0.026)	(0.022)	(0.019)	(0.019)
Fallow	0.055*	0.057*	0.019	0.023	0.044
	(0.031)	(0.031)	(0.026)	(0.025)	(0.035)
GM adopter * Corn	0.014				
	(0.040)				
GM adopter * Fallow	0.024				
	(0.058)				
Observations	3,466	2,583	3,010	3,010	2,583
R-squared	0.320	0.337	0.327	0.344	0.375
Village-Year FE	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES

Robust standard errors clustered at the village-year level in parentheses.
Linear probability model with dependent variable = 1 if the plot was hit by a landslide in year t. All explanatory variables are dummy variables and the omitted category is any crop except corn.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Lagged values of cultivated crops can also be used to investigate whether landslide probability increases with every additional year of GM cultivation or whether the shift is a discrete one, with no cumulative effect. To address this issue, I re-estimate column 3 of Table 4, including the non-lagged variables, and present the results in Appendix E. In column 1 of Table E.1 the lagged variables have a negative and non-significant coefficient. To get a better understanding of the transition to and from biotech cultivation, we can add an interaction between present and past varieties (column 2). A significant coefficient of GM corn, coupled with a non significant coefficient for the interaction term implies that there are no cumulative effects. Furthermore, the non-significance of the lagged GM coefficient shows that the impact of biotech corn is not persistent in time as landslide probabilities come back to their original level when GM corn cultivation is stopped.

To further assess the robustness of the results, Tables F.1 and F.2 of Appendix F use propensity score matching and survival models respectively to estimate the impact of GM corn cultivation on landslide occurrence. In Table F.1, the probability of cultivating biotech corn is estimated and households are then matched based on their propensity score. To control for aggregate time shocks, exact matching is used along the time dimension. Because we want to assess the robustness of the difference between GM corn and other corn varieties, all the reported regressions exclude years in which households did not cultivate corn, and the coefficients reported can therefore be interpreted in the same way as the GM corn coefficient of Table 2. The positive effect of biotech corn on the probability of landslide is slightly smaller but otherwise similar to that obtained in Table 2 and is very robust to using various matching algorithms and different parameter values.

Columns 1 and 2 of Table F.2 show the hazard rates obtained from using Cox proportional-hazard model and Weibull survival model, both allowing for shared frailty at the household level. Because crop planted can change from year to year, the data is set up such that every observation ends either with a landslide (failure) or with a crop change (censoring). For this reason, the number of observation is higher than the number of households. A hazard ratio higher than one indicates an increase in failure probability, which is the case for GM corn in both specifications. The last two columns present the incidence-rate ratios of Poisson regressions with and without conditional household fixed effects. The dependent variable is the number of landslides over the period and the explanatory variables count the number of years a specific crop was cultivated. As previously, each observation relates to the period in time during which the same crop (or crop mix) was planted, but in this model, a landslide event does not end the observation. Once again, GM crop cultivation is associated with an increase in landslide occurrence, which is even bigger when time-invariant household characteristics are controlled for.

5 Mechanisms

In order to derive policy recommendations, it is important to identify the mechanisms that could explain the positive correlation between GM corn cultivation and landslide occurrence documented so far. This section will discuss three potential mechanisms: (i) a difference in root structure between GM corn and other corn varieties, (ii) an endogenous allocation of crops on plots and (iii) the role of soil-cover loss due to a more intensive use of herbicide. This last explanation appears as the most likely candidate to explain our results, even though more agronomic research is needed to firmly confirm it.

5.1 Difference in root structure

The first potential mechanism is that there are physical differences in the root structure of different corn varieties, thus making GM corn intrinsically more prone to landslide. This would be the case if *sige-sige* and traditional varieties have deeper roots than biotech corn. Unfortunately, it is not possible to formally dismiss this hypothesis given that *sige-sige* corn remains completely unstudied. However, given that corn is already notorious for inducing erosion, it seems highly unlikely that altering a few genes to get pest and herbicide tolerance traits would induce changes in its root structure leading to the large increase in landslide probability documented in Table 2. Moreover, such a difference is completely absent from the literature on GM crops and was never reported by farmers during the qualitative interviews conducted by the author.

5.2 Endogenous allocation of crops on plots

Farmers do not decide randomly what crop to plant on their plot, and take into account the physical characteristics of their land when making their decision. So far, the regressions included household fixed effects or time trends which controlled for many confounding factors but did not rule out a possible reallocation of crops within a given farm. It is therefore possible that our results are driven by the fact that biotech corn is planted on plots that are intrinsically more prone to landslides. First, GM corn might be planted on larger plots than other corn varieties. In that case the landslide probability would mechanically increase with no direct connection to the crop itself. Second, given that biotech corn is more profitable, it may be cultivated on more marginal land than other varieties. However, GM corn is also much more costly to cultivate, as these seeds are more expensive and require more fertilizer than other varieties. Rational farmers would therefore prefer to grow it on good land in order to maximize the return on investment (as well as minimize the risk of negative return).

To address this issue, I re-estimate Equation 1, this time adding plot fixed effects instead of household fixed effects and thereby controlling for all time-invariant physical characteristics of the plot, even within a given household. Results are presented in Table 5 and are very similar to those reported in Table 2 the coefficient of GM corn only changes by 0.3 percentage point between the household and the plot fixed effect models.

Table 5: Plot fixed effect regressions

VARIABLES	(1) HH FE	(2) Plot FE	(3) Plot Time Trends	(4) Single plots	(5) Ever GM	(6) 2012 - 2017	(7) Weighted by year
Corn	0.067***	0.059**	0.074**	0.063*	0.064*	0.062	0.068**
	(0.020)	(0.025)	(0.035)	(0.034)	(0.038)	(0.038)	(0.029)
GM corn	0.061***	0.064***	0.097**	0.090***	0.064**	0.068**	0.056***
	(0.022)	(0.022)	(0.038)	(0.027)	(0.025)	(0.029)	(0.021)
Fallow	0.067***	0.035	0.028	0.067	0.059	0.030	0.039
	(0.022)	(0.028)	(0.040)	(0.046)	(0.047)	(0.041)	(0.033)
Observations	3,466	4,274	4,274	2,356	1,516	2,798	4,274
R-squared	0.320	0.316	0.462	0.328	0.379	0.385	0.326
Village-Year FE	YES	YES	YES	YES	YES	YES	YES
Plot FE	NO	YES	YES	YES	YES	YES	YES
Plot Time Trends	NO	NO	YES	NO	NO	NO	NO

Robust standard errors clustered at the village-year level in parentheses.
Linear probability model with dependent variable = 1 if the plot was hit by a landslide in year t. All explanatory variables are dummy variables and the omitted category is any crop except corn.
Column 4 restricts the sample to households cultivating at most one plot over the period. Column 5 to plots that have been planted in GM corn at some point over the period. Column 6 only uses observations between 2012 and 2017. Column 7 gives increasing weight according to the year (2008 = 0.1, 2017 = 1).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Columns 4 and 5 present the additional results for restricted sample analyses, which all confirm the previous findings. First, the sample is restricted to households who farm, at most, one plot over the period and who, therefore do not make a joint crop-plot decision (column 4). Second, our results might be driven by a selection of plots for GM corn that is not appropriately controlled for by the fixed effects. To address this issue, column

5 only keeps plots that have been planted in biotech corn at some point over the past ten years, i.e. those that have been selected into GM corn. The last two columns check for recall bias by restricting the sample to recent years (column 6) and by using year-specific observation weighting (column 7). For all specifications, the effect of GM corn cultivation on landslide incidence is positive and strongly significant. We can therefore reject the hypothesis that the correlation observed in Figure 2 is due to an endogenous allocation of crops on plots.

5.3 Agricultural practices and herbicide use

Plant-cover is a well-established technique to control erosion in the agronomic literature (Durán Zuazo and Rodríguez Pleguezuelo, 2008). Indeed, plants slow the runoff and infiltration of rain water, therefore limiting the risk of runoff erosion and of water saturation, leading to landslides. Moreover, root systems fix the top layer of the soil, further reducing the risk of erosion. Systematic and frequent application of herbicide, however, decreases plant cover and therefore leads to erosion. Multiple studies therefore recommend only partial weeding when cultivating on slopes, as a way to strike a balance between the benefits of weeding - less competition for the crops - and its costs - increased erosion (Lenka et al., 2017; Liu et al., 2019; Utomo and Senge, 2002). These papers, however, only look at runoff erosion and, to the best of my knowledge, no study has examined the impact of weed management on landslide occurrence.

The farm-level recall data collected for this paper does not contain information on herbicide use during the past ten years as it is highly unlikely that farmers would have been able to give a reliable answer to this question. However, input information - including herbicide use - were collected for each crop over the two preceding years (i.e. four growing seasons). The most common type of herbicide is glyphosate and it is mostly applied on corn and rice fields, either during land preparation or during the growing cycle if the crop exhibits herbicide tolerance. Both GM and *sige-sige* corn have this trait but the resistance is more reliable with the former. Moreover, farmers planting these seeds are richer and therefore more likely to use inputs more intensively.

Table 6: Herbicide use per hectare in 2016-2017

VARIABLES	(1)	(2)
Corn	2.543***	1.719*
	(0.606)	(1.025)
GM Corn	1.903***	1.061*
	(0.468)	(0.551)
Observations	826	715
R-squared	0.043	0.938
Growing season FE	YES	YES
Household FE	NO	YES

Robust standard errors clustered at the household level in parentheses.
Farm-level measure of herbicide use per hectare over the 24 months preceding the survey. Genetically Modified corn is the omitted category.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This is confirmed by Table 6, in which the quantity of herbicide used per hectare is regressed on crop dummies for corn and GM corn. Given that this information was only asked for corn and rice, the omitted category is rice. As expected, farmers use more herbicide when cultivating GM corn. When household fixed effects are included, in column 2, the difference decreases and loses some significance but remains significant at the 10% level. Households cultivating both GM and non-GM corn use on average one liter more of glyphosate herbicide per hectare on their GM corn compared to other corn varieties (for an average use of 4.3 liters). This difference in herbicide use is therefore not entirely explained by differences in financial constraints between farmers but may be due to a difference in herbicide tolerance between varieties and/or marginal returns of input use.

While data limitation does not allow to estimate directly the correlation between herbicide use and landslide occurrence in any given year, we can look at whether households who use more herbicide in 2016-2017 have been more affected by landslides in the past. This assumes that input use exhibits some serial correlation and that current use of glyphosate is indicative of past use. Furthermore, to interpret the results as the impact of herbicide on landslide occurrence, we need to assume that past landslide experience does not determine current herbicide use. This reverse causality should, however, play against us as landslides are more likely to decrease herbicide use either because farmers notice the connection between the two or because of an increase in financial constraints following a loss of harvest. Moreover, during all the qualitative interviews conducted in preparation for the survey, no farmer ever stated that herbicide use could lead to landslides and it is therefore unlikely that they would take this risk into account when making agricultural input decisions.

Table 7: Herbicide use in 2016-2017 and landslide occurrence

VARIABLES	(1)	(2)	(3)	(4)
Corn	0.063***	0.083***	0.079***	0.095***
	(0.017)	(0.027)	(0.021)	(0.024)
GM corn	0.040**	0.054**	-0.015	-0.007
	(0.016)	(0.021)	(0.018)	(0.029)
Fallow	0.029*	0.084***	0.022*	0.067***
	(0.016)	(0.028)	(0.013)	(0.022)
Std quant. of herbicide (2018)	0.004			
	(0.009)			
Corn * std. herbicide	-0.010	-0.021		
	(0.012)	(0.016)		
GM corn * std. herbicide	0.028**	0.033*		
	(0.013)	(0.019)		
Percentile in the herbicide use distribution			0.022	
			(0.020)	
Corn * herbicide (CDF)			-0.043	-0.054
			(0.029)	(0.041)
GM corn * herbicide (CDF)			0.118***	0.139**
			(0.041)	(0.058)
Observations	3,036	3,024	3,450	3,434
R-squared	0.224	0.320	0.224	0.322
Village-Year FE	YES	YES	YES	YES
HH FE	NO	YES	NO	YES

Robust standard errors clustered at the village-year level in parentheses.
Linear probability model with dependent variable = 1 if the plot was hit by a landslide in year t. Std herbicide is a household-level crop-specific measure of herbicide use in 2016-2017, standardized by its crop-specific mean and standard deviation. Herbicide (CDF) is the percentile of the household in the crop-specific distribution of herbicide use in 2017.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 presents the results of regressing the probability that a farmer experiences a landslide on the crops he cultivates, interacted with current herbicide use. Because farmers do not necessarily plant the same crop as they did in the past and different crops lead to a different intensity in herbicide use, herbicide measure is standardized using variety-specific mean and standard deviation. The resulting measure is then averaged at the household level for farmers cultivating different crops over the two-year period. This transformation is motivated by the fact that we want to distinguish which farmers are heavy herbicide users in 2016-2017, while taking into account differences in herbicide use between crops. Results show that a one standard deviation increase in herbicide use in 2016-2017 is associated with a 2.8 percentage point increase in landslide probability, only during years when GM corn was cultivated. Controlling for household fixed effects, the point estimate increases slightly to 3.3 pp but loses some significance. This effect of herbicide use is confirmed using an alternative measure of intensity. Columns 3 and 4 use the percentile of the household in the crop-specific standardized herbicide distribution and show that every decile in the distribution is associated with an average increased probability of landslide by 1.4 percentage point, when controlling for household fixed effects.

6 Discussion

This section further discusses the main results of the paper. First, it addresses the potential causal link between herbicide tolerance and herbicide use in the context of the Philippines. Then, it questions the rationality behind the choice of farmers to adopt unsustainable agricultural practices. The last two subsection focus more on landslides themselves, by looking at (i) their distribution along the landholding distribution and (ii) the moderating effect of extreme weather and slope in their occurrence.

6.1 Herbicide tolerance and herbicide use

Heavy herbicide users in 2016-2017 appear to have experienced higher landslide occurrence during the years in which they were cultivating GM corn. While this does not prove a causal link between herbicide use and landslides, it is consistent with the idea that biotech corn has led to a more intensive use of herbicide, which have had adverse effects in terms of environmental degradation.

However, the link between biotech crop cultivation and herbicide use is not straightforward. As discussed earlier, the scientific literature finds that herbicide tolerant seeds lead to a substitution from more toxic herbicides to broad-spectrum glyphosate, at least in developed countries. In our survey area, however, herbicide penetration was relatively low in the years preceding the introduction of Ht corn seeds. According to the 1991 Census of Agriculture and Fisheries, only 46.16% of farmers in the Philippines used herbicide in 1991.[17] This proportion decreases to 26% when focusing on the villages in the Upper Pulangi region. Nowadays, only 7% of the respondents in our survey declared not using any herbicide during the preceding season. It therefore appears that herbicide use increased at the same time than GM seeds were being adopted by farmers. We can thus reject the hypothesis that glyphosate herbicide simply replaced other narrower chemicals.

Moreover, herbicide is generally sprayed three times during the growing cycle, once before planting and twice during the growth period. With non-Ht seeds, such an intensive use would simply be impossible. While we do not have a proper counterfactual to properly address this question, it seems very plausible that herbicide use would be lower in the absence of GM seeds.

In developed countries, the use of broad-spectrum herbicide reduces the need of tillage, thereby avoiding land disturbance and potentially reducing landslide risk. However, corn agriculture in the area is still entirely manual

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[17] 1991 is the only recent wave of the CAF asking about herbicide use. It is therefore impossible to get a measure closer to the introduction of GM seeds.

and tillage is almost nonexistent. Herbicide use is therefore unlikely to reduce soil erosion through this channel.

6.2 Farmers' choice

If a more intensive use of herbicide on plots planted with GM seeds lead to a higher probability of landslide, thereby canceling the gains in productivity, why do farmers keep on adopting this unsustainable practice? Indeed, we would expect rational farmers to take into account the additional risk resulting from the more aggressive weed-control technology and either decrease the use of herbicide or switch to another variety exhibiting lower marginal returns on inputs, such as *sige-sige* corn.

A potential explanation is that learning is slow and complex because crop decisions are only made twice a year and that the probability of landslide is relatively small. Moreover, most of the reported landslides occurred during the typhoon years of 2011 and 2012, making it difficult for farmers to disentangle both effects. Also, while it is costless to observe the occurrence of landslides on neighboring plots, the cultivated variety and the amount of inputs used may be harder to observe.For these reasons, it is possible that farmers have simply not had the time to notice this correlation, given that GM corn was introduced 15 years before the survey. In qualitative interviews, none of the respondents cited herbicide use or corn variety as a factor inducing a landslide.

6.3 Distribution of landslide damage

Given the high poverty rate in the area, how landslides affects different categories of farmers is an important and relevant policy question. I therefore estimate the following equation:

$$landslide_{ijt} = \beta_1 wealth_{ij} + \beta_2 \mathbf{X}_{ijt} + \gamma_{jt} + \epsilon_{ijt} \tag{2}$$

Where $landslide_{ijt}$ is one of three possible measures of landslide exposition: landslide incidence per hectare, share of land affected by landslides and share of land unusable because of landslides. The difference between the last two measures is that the former is only positive when a landslide hits, while the latter remains positive if the farmer decides not to cultivate that land in the years following the landslide, due to important soil loss. Because larger farms are mechanically more likely to be hit by a landslide, those measures are divided by total land area. The main variable of interest is $wealth_{ij}$, which represents household wealth. Unfortunately, wealth measures were only collected in 2018 and are potentially endogenous to both biotech corn cultivation and landslide occurrence. I therefore use the area of inherited land as a proxy since it is strongly correlated to the amount of land owned by the household and is pre-determined. Because inherited land is a household-specific time-invariant measure, it is not possible to include household fixed effects. Instead, all regressions control for village-year fixed effects γ_{jt} as well as a series of household control variables $\mathbf{X}_{ijt}$.[18]

Inherited land is negatively associated with all three measures of landslide exposure, as reported in Table 8. On average, wealthier households suffer significantly less from landslides than poorer households. In terms of magnitude, an increase in land inherited by one standard deviation decreases the probability of landslide per hectare by 1 percentage points, the share of area damaged by 0.3 pp and the share of farm area unusable by 0.45 pp.

To refine these results and explore potential non-linearities, I re-estimate Equation 2 using categorical variables

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[18] These control variables include remoteness, total farm area, ethnicity, household head's age and education.

Table 8: Distribution of landslides by wealth

VARIABLES	(1) Occurrence	(2) Damage	(3) Unusable land
Inherited area	-0.006***	-0.002***	-0.003***
	(0.002)	(0.001)	(0.001)
Observations	3,405	3,441	3,441
R-squared	0.160	0.124	0.111
Village-Year FE	YES	YES	YES
HH Controls	YES	YES	YES

Robust standard errors clustered at the village-year level in parentheses.

OLS estimation. Occurrence is a variable = 1 if the household experienced a landslide in year t, Damage is the area damaged by the landslide and Unusable is the area that is left unused by the farmer following a landslide (including the year it happened). All three dependent variables are divided by the farm size.

Inherited area is the amount of land cultivated by the household that was received by either spouse from their parents.

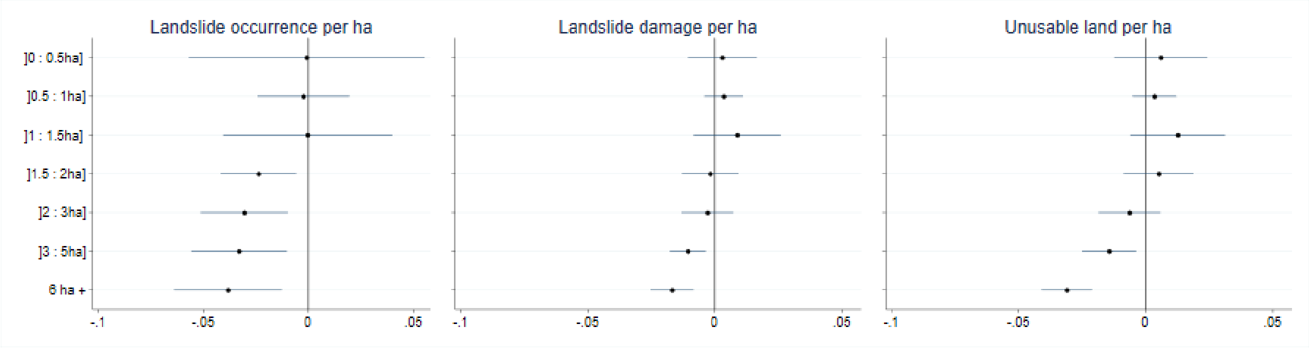
Household controls include remoteness, total farm area, ethnicity, household head's age and education.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of land inheritance instead of a continuous variable, with the omitted category equal zero, i.e. to households who did not inherit any land. The results are plotted in Figure 3, which shows that the bottom of the wealth distribution is equally affected by landslides. The probability of being hit by a landslide decreases monotonically beyond 1.5 ha. For the measure of damage, this threshold is higher, at 3 ha. With respect to the distribution of land inheritance, these values respectively correspond to the top quartile and top decile.

For the last category, the coefficient is very similar to the mean of the dependent variable. Indeed, households who inherited 6 hectares or more have a probability of landslide per hectare 4 percentage points lower than for those who did not inherit anything. This effect is close to the mean landslide probability per hectare (4.8%). Wealthier households are therefore much less exposed to landslides than the rest of the sample. This effect is also found using alternative measures of wealth in Appendix G.[19]

Figure 3: Landslide occurrence per hectare along the wealth distribution



Graphs report the point-estimate and 95% confidence interval of wealth proxy categories. The omitted category is variable = 0. All regressions include village-year fixed effects and household controls.

Standard errors are clustered at the village-year level.

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[19] The measures used in Appendix G are time-varying measures of cultivated and owned land as well as the number of owned plots.

Landslides are therefore unevenly distributed among farmers, with the top of the wealth distribution experiencing relatively less damage.[20] This means that the people most exposed to this risk are those that are relatively the worst hit when a landslide happens. Several policy measures have already been put in place, such as free crop insurance and farmer's compensation during climatic disasters through a "calamity fund" but they remain unknown to most farmers. Despite free provision by the local government, only 10% of our sample were covered by a crop insurance in 2018. Improving this coverage could have a tremendous impact on the affected households but would require better information provision as well as a simplification in the application process.

6.4 Moderating effects of slope and weather

Rainfall and slope gradients are both obvious factors influencing the probability of landslides. So far, they have been controlled for by village-year and plot fixed effects. However, it might be interesting to investigate how these determinants interplay with the type of crop cultivated and the probability of landslide.

Froude and Petley (2018) report that 42% of rainfall-triggered landslides in the Philippines are caused by typhoons. Such extreme weather events are frequent in the country, which have been described as the "most storm-exposed country on Earth" (Brown, 2013). Indeed, an average of twenty tropical cyclones enter its Area of Responsibility every year, nine of which actually cross the country (Cinco et al., 2016). Most of these storms affect the northern island of Luzon while the island of Mindanao, situated off the typhoon path, is usually spared. Over the past ten years, only two major storms have hit our study area: Washi in 2011 and Bopha in 2012, locally known as Sendong and Pablo, respectively.

In Appendix H, the passage of Washi and Bopha is clearly marked, with the number of landslide-affected households almost ten times higher during the years 2011 and 2012 (24.5% compared to 2.8% on average during non-typhoon years). The dotted line represents the share of days with rainfall above the normalized rainfall Intensity-Duration threshold computed by Guzzetti et al. (2008).[21] 2011 and 2012 are among the years with the highest share but the relationship between this measure and typhoon occurrence is weak.

To examine the differential impact of GM corn on landslide in case of extreme weather, I estimate Equation 1 and interact the crop dummies with two rainfall measures: (i) a dummy variable equal to one for the typhoon years, 2011 and 2012, and (ii) the share of days above the normalized ID threshold. The results of these regressions are presented in columns 1 and 2 of Table 9. The probability of landslide increases significantly during typhoon years for plots planted in corn, but there is no significant additional effect of GM corn. Notice that the difference between GM corn and other corn varieties remains significant during the years without typhoon, even though their magnitude decreases slightly. Using the continuous variable for extreme weather yields a slightly different picture as the interaction of biotech corn becomes statistically significant. The differential impact of GM corn is therefore present when considering more common episodes of wet weather but disappears in case of extreme events. The point estimates imply that every day spent above the threshold increases, by 0.1 percentage point, the probability that the household is hit by a landslide over the year if he is cultivating corn, and by an

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[20] Note that our survey did not cover the very top of the distribution as we excluded households cultivating over 10 hectares of land. However, qualitative evidence suggests that the few people controlling more than 10 hectares usually do not own them but use them as part of a *prenda* agreement. According to several informants in the region – including some of those big farmers themselves –, they only take *prenda* on valuable and productive land. As a result, they tend to control the best lands, i.e. those that are less prone to be hit by a landslide. It is therefore likely that landslides affect even less the top of the land distribution than what is documented here. Omitting the large farmers from our analysis therefore does not change our results regarding the distribution of affected farmers.

[21] See Appendix H for details on this ID threshold.

additional 0.12 percentage point if it is GM corn. In this specification, the estimates of Corn and GM corn become insignificant, which clearly shows that wet weather is driving landslides.

Table 9: Moderating effects of weather and slope

VARIABLES	(1)	(2)	(3)
Corn	0.038**	-0.092	0.038
	(0.018)	(0.061)	(0.025)
GM corn	0.045**	-0.134	-0.035
	(0.019)	(0.091)	(0.038)
Fallow	0.069***	0.059***	
	(0.022)	(0.021)	
Corn*Typhoon	0.187***		
	(0.046)		
GM Corn*Typhoon	0.060		
	(0.044)		
Corn*Days over threshold		0.356**	
		(0.141)	
GM Corn*Days over threshold		0.432**	
		(0.212)	
Corn*Slope			-0.015
			(0.057)
GM Corn*Slope			0.221**
			(0.085)
Observations	3,466	3,466	3,380
R-squared	0.331	0.323	0.327
Village-Year FE	YES	YES	YES
HH FE	YES	YES	YES

Robust standard errors clustered at the village-year level in parentheses.
Linear probability model with dependent variable = 1 if the plot was hit by a landslide in year t.
Typhoon is a dummy variable = 1 for years 2011 and 2012. Days over threshold is the share of days above the NID threshold from Guzzetti et al. (2008). Slope is the slope of the plot reported by the respondent.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In the last column of Table 9, the slope of the plot is interacted with cultivated crops. The only statistically significant differential effect is that of GM corn. Comparing two plots, which differ by 10 percentage points in slopes, the probability of landslide on the steeper one is 2.2 percentage point higher when both are planted in GM corn compared to when they are planted in another corn variety.

7 Conclusion

The introduction of biotech corn has doubtlessly improved the livelihoods of many farmers in the Philippines. However, the change in agricultural practices induced by those new varieties appears to have increased the occurrence of landslides, an environmental cost that has received very little attention in the literature. In a context in which extreme weather events are likely to become more frequent as the global climate changes (Knutson et al., 2015), it is important to better understand the drivers of landslides in order to decrease their damage.

Promotion of sustainable land management techniques by agricultural extension officers appears as an important measure. However, if these techniques have a detrimental impact on the yield, they will be difficult to implement for poor farmers already struggling in the everyday life. Developing poverty alleviating projects and investing in infrastructure therefore appear as important steps toward environmental sustainability. Increasing employment opportunities outside of the agricultural sector could also decrease pressure on the land, and limit the need to cultivate steep marginal lands in mountainous areas.

Moreover, when assessing new agricultural varieties, regulatory authorities should also take into account their potential impacts on farming practices. When farmers change the type of seeds they plant, they are likely to change the type and mix of inputs they use and this whole system should be studied, rather than just the seeds themselves. At the very least, agricultural extension offices should take a closer look at the environmental impact of new farming practices and promote alternatives that are both environmentally and economically sustainable. Taking into account how such a system impacts different agro-ecological zones and taking appropriate conservation measures is necessary to preserve agricultural productivity and food security in the most marginalized regions of the developing world.

The policy recommendation of this paper is therefore to pay attention to the way new agricultural technologies can transform agricultural practices and to the environmental impact of these new practices. Frequent and systematic use of herbicide may not be the optimal technique on steep plots due to the increased risk of landslide and it may be more sustainable to cultivate something else than corn on some of them. Defining the optimal crop choice or the optimal amount of herbicide as a function of the plot characteristics is however beyond the scope of this paper and should be addressed by agronomists, who are better equipped to answer such questions.

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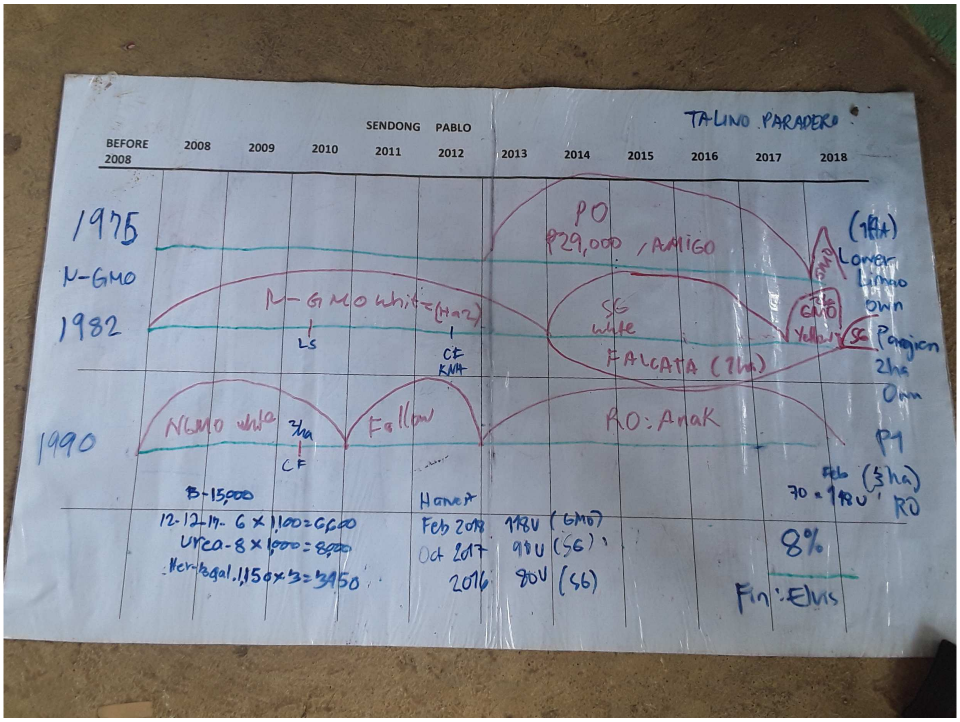
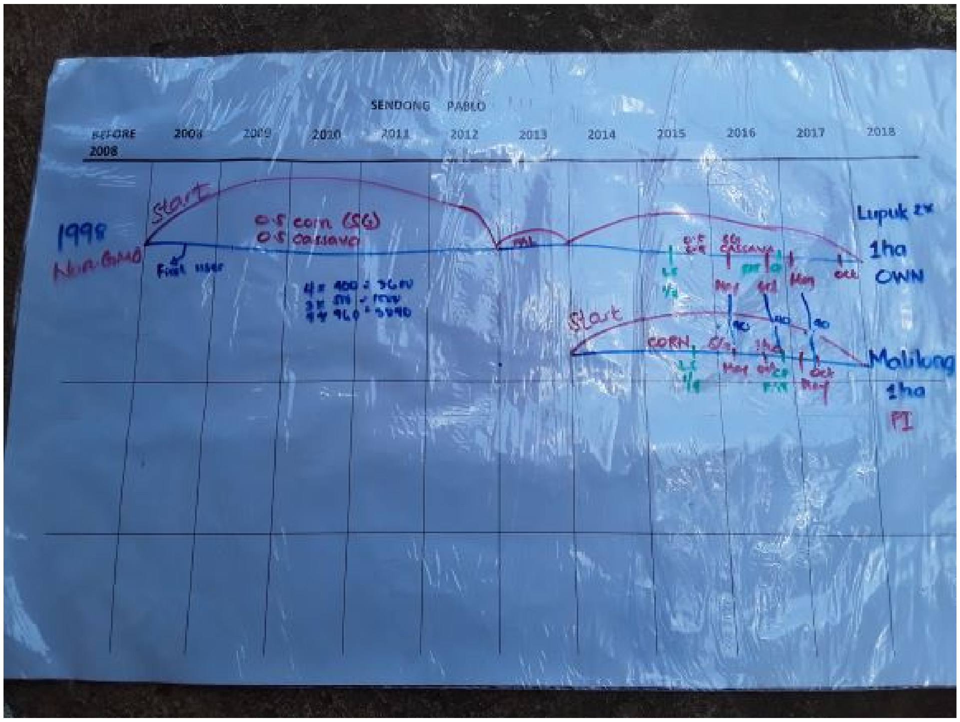
Appendix

A Timeline photographs





B Representativeness of the sample

The following table shows the comparison between our sample and the households identified as farmers in the NHTS-PR. Due to data limitation, it is unfortunately not possible to determine whether the landholding or the agricultural practices differ between the two samples. For the rest, households are similar in terms of size, education, access to electricity and ownership of large assets (fridge, washing machine). For most other assets, our sample appears wealthier. Restricting the NHTS-PR data to corn farmers yields the same results. However, since the purpose of NHTS-PR data was to identify poor households, it is likely that respondents under-reported ownership of small assets such as phones, radio or television which are easy to hide. Our interviewed households therefore appear to be relatively representative of the survey area.

Representativeness of the surveyed households

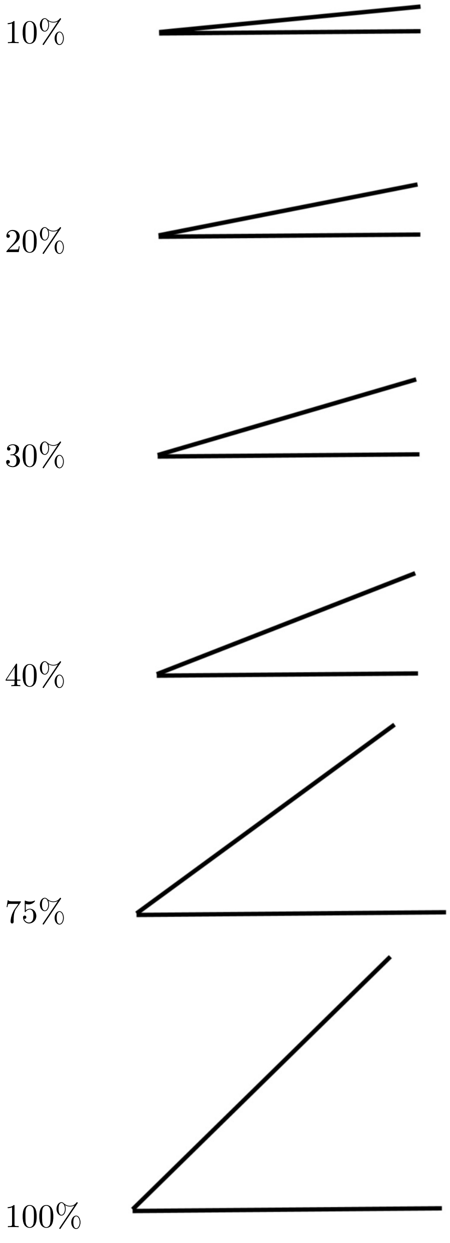
	(1) Survey data		(2) NHTS farmers		T-test P-value
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
Indigenous	454	0.425 (0.023)	3295	0.509 (0.009)	0.001***
Household size	454	5.216 (0.095)	3295	5.008 (0.043)	0.083*
Head's education	454	5.229 (0.145)	3295	5.302 (0.063)	0.683
Electricity	453	0.567 (0.023)	3295	0.545 (0.009)	0.372
Radio	454	0.416 (0.023)	3295	0.329 (0.008)	0.000***
Television	454	0.416 (0.023)	3295	0.343 (0.008)	0.002***
Stereo	454	0.110 (0.015)	3295	0.076 (0.005)	0.013**
Cell phone	454	0.656 (0.022)	3295	0.354 (0.008)	0.000***
Computer	454	0.015 (0.006)	3295	0.016 (0.002)	0.916
Fridge	454	0.104 (0.014)	3295	0.098 (0.005)	0.728
Washing machine	454	0.079 (0.013)	3295	0.059 (0.004)	0.089*
Car	454	0.007 (0.004)	3295	0.020 (0.002)	0.046**
Motorcycle	454	0.317 (0.022)	3295	0.171 (0.007)	0.000***

Survey data is the sample of households interviewed for this research. NHTS farmers is the subset of NHTS census data who reported agriculture as the principal activity of the household head.
Indigenous is a dummy variable equal to one if the household head is Lumad. Head's education is the household head's number of years of education. All other variables are dummy variables = 1 if the household owns the asset.

P-values for two-sided t-tests. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C Pictures Used for Slope Measurement

Question: "In general, what is the slope of your plot?"



Note: Gradients not shown to respondents

D Landslide photographs

E Cumulative and lagged effects

Table E.1: Lagged effects of GM corn on landslides

VARIABLES	(1)	(2)
Corn	0.081***	0.098***
	(0.023)	(0.032)
GM corn	0.074***	0.092***
	(0.027)	(0.032)
Fallow	0.069***	0.065**
	(0.025)	(0.025)
Lag Corn	-0.004	0.013
	(0.015)	(0.027)
Lag GM	-0.035	-0.017
	(0.025)	(0.029)
Corn * Lag Corn		-0.033
		(0.038)
GM * Lag GM		-0.038
		(0.038)
Observations	3,010	3,010
R-squared	0.334	0.334
Village-Year FE	YES	YES
HH FE	YES	YES

Robust standard errors clustered at the village-year level in parentheses.

Linear probability model with dependent variable = 1 if the plot was hit by a landslide in year t. All explanatory variables are dummy variables and the omitted category is any crop except corn.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

F Alternative specifications of Table 2

Table F.1: Propensity score matching - Landslide occurrence and GM corn cultivation

MODEL	PARAMETER	ATT
Nearest-neighbor		0.059 *** (0.018)
	Trim = 5%	0.063 *** (0.019)
	Trim = 10%	0.067 *** (0.02)
	Trim = 20%	0.072 *** (0.023)
Radius	Caliper = 0.001	0.028 (0.017)
	Caliper = 0.005	0.032 *** (0.015)
	Caliper = 0.01	0.037 *** (0.014)
	Caliper = 0.05	0.039 *** (0.014)
Kernel	Bandwidth = 0.01	0.04 *** (0.014)
	Bandwidth = 0.02	0.042 *** (0.014)
	Bandwidth = 0.05	0.039 *** (0.014)
	Bandwidth = 0.1	0.041 *** (0.013)
Rosenbaum Bounds	Γ	1.85

ATT coefficients of GM corn cultivation using matching models and excluding non-corn plots.

Matching using exact matching on year and PSM on municipality, remoteness, farm size, number of plots, inherited land area, average slope, household head's education, age and ethnicity.

Γ is log odds of differential assignment to treatment due to unobservables. Value reported is *Gamma* at which the critical p-value for the estimate implies the effect is insignificantly different from zero at p = 0.10.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table F.2: Survival analysis - Landslide occurrence and GM corn cultivation

VARIABLES	(1) Cox	(2) Weibull	(3) Weibull	(4) Poisson	(5) Poisson
Corn	6.791***	6.923***		9.737***	7.547***
	(2.976)	(3.045)		(4.270)	(4.035)
GM corn	1.561***	1.768***		1.356**	2.275***
	(0.206)	(0.233)		(0.179)	(0.619)
Fallow	1.485	1.675**		1.220	1.982
	(0.365)	(0.414)		(0.300)	(1.072)
Constant		0.003***		0.042***	
		(0.001)		(0.018)	
Observations	957	957	957	670	185
Number of groups	437	437	437		
HH RE	YES	YES	YES		
HH FE				NO	YES
Number of hhid					83

Hazard ratios reported for Cox and Weibull models. Incidence-rate ratios reported for Poisson regressions.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

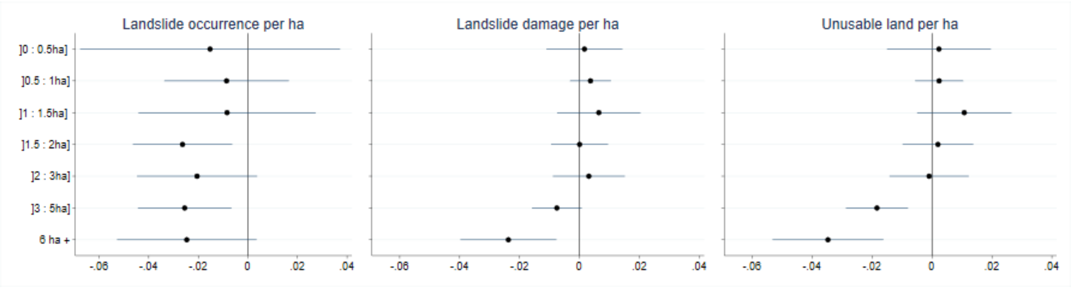
G Additional wealth measures for distributional analysis

Distribution of landslides by wealth

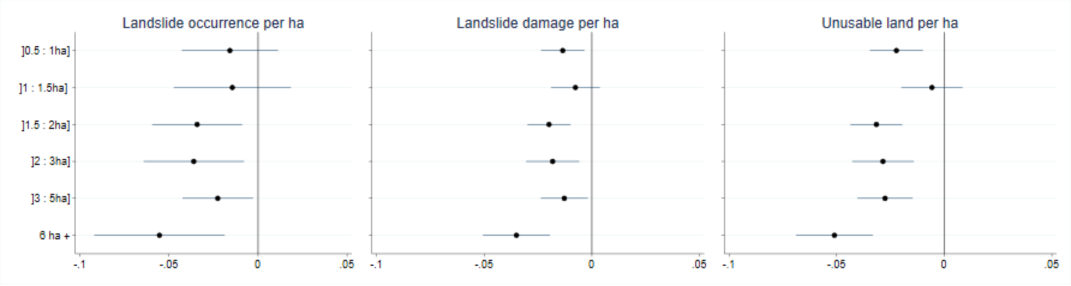
VARIABLES	(1) Occurrence	(2) Occurrence	(3) Occurrence	(4) Damage	(5) Damage	(6) Damage	(7) Damage	(8) Unusable	(9) Unusable
Owned area	-0.002			-0.002			-0.003**		
	(0.002)			(0.001)			(0.001)		
Cultivated area		-0.012***			-0.007***			-0.011***	
		(0.002)			(0.002)			(0.002)	
Nb of plots owned			-0.011**			-0.003**			-0.003*
			(0.005)			(0.001)			(0.002)
Observations	3,414	3,414	3,414	3,450	3,450	3,450	3,450	3,450	3,450
R-squared	0.158	0.161	0.159	0.124	0.130	0.124	0.110	0.120	0.109
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Village FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
HH Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at the village-year level in parentheses.
OLS estimation. Occurrence is a variable = 1 if the household experienced a landslide in year t, Damage is the area damaged by the landslide and Unusable is the area that is left unused by the farmer following a landslide (including the year it happened). All three dependent variables are divided by the farm size.
Owned area is the amount of land owned by the household in year t. Cultivated area is the area of land effectively under cultivation. Number of plots owned is the number of different plots of land owned by the household.
Household controls include remoteness, total farm area, ethnicity, household head's age and education. Village-year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

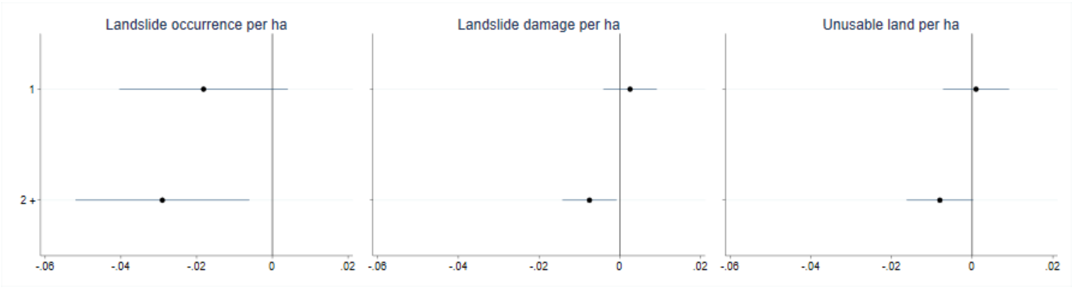
Land owned by the household



Land cultivated by the household



Number of plots owned by the household

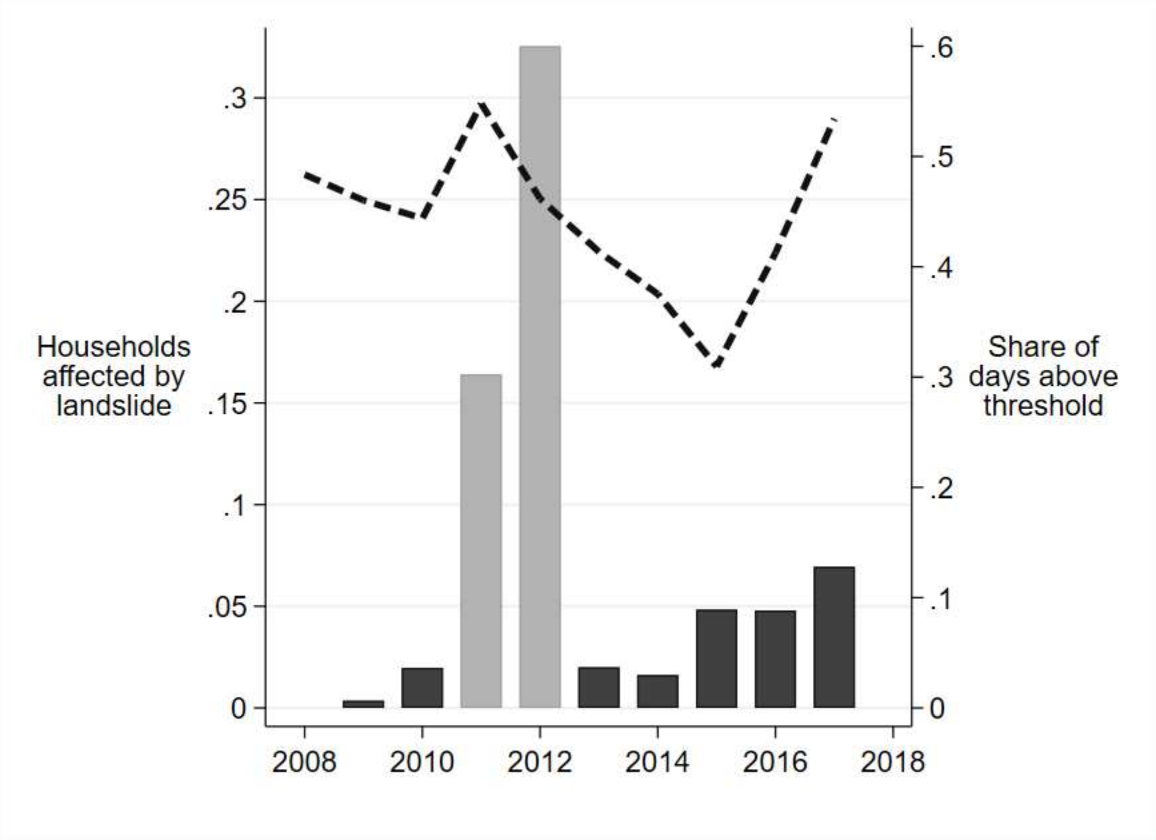


Graphs report the point-estimate and 95% confidence interval of wealth proxy categories. The omitted category is variable = 0, except for the cultivated land for which the omitted category is variable <= 0.5ha. All regressions include village-year fixed effects and household controls.

Standard errors are clustered at the village-year level.

H Share of households affected by landslides and extreme weather

The dotted line represents the share of days with rainfall above the normalized rainfall Intensity-Duration threshold computed by Guzzetti et al. (2008). Following the pioneering work of Caine (1980), an important literature has developed on rainfall thresholds for landslides (the recent literature is reviewed by Segoni et al. (2018)). The most commonly used threshold take into account the fact that landslides can be induced by intense as well as sustained rainfall. Most papers therefore compile slope failure events, cross them with meteorological data and empirically estimate a relationship between rainfall Intensity and Duration above which landslides are likely to occur, known as ID thresholds. In the Philippines, this exercise was carried out by Nolasco-Javier and Kumar (2018) using data from the Baguio district in the north of the country. Unfortunately, it is not possible to apply their threshold to weather data from Mindanao as extremely few days are reported as being landslide-prone. Over the past ten years, this threshold is only surpassed in 2011 and 2014, whereas landslides have been reported every year. This might be due to the fact that Baguio is one of the wettest places of the country. As second-best measure, I use the global threshold computed by Guzzetti et al. (2008) using data from countries all around the world.



Source: Own data and Tropical Rainfall Measuring Mission (TRMM) from Huffman et al. (2012)
Histogram presents the share of plots affected by landslide for every year of the period (Left axis). Dotted line shows the share of days above the NID rainfall threshold from Guzzetti et al. (2008) (Right axis)