Barriers to Adoption: Evidence from Bt Corn*

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Abstract

How well suited are advanced-country technologies to developing countries? This question is central to understanding differences in technology adoption across the development spectrum, but has been challenging for the literature to address empirically. We make progress on this question by exploiting unique characteristics of one of the most important agricultural innovations in recent history, Bt corn. These characteristics allow us to construct a novel dataset matching Bt crops to the insects they kill. Leveraging recent advances in large language models, we then use the scientific literature to assess the importance of each insect across countries. Our approach allows us to directly construct counterfactual yield gains under adoption across the global income distribution. Our analysis yields two surprising results. First, the gradient of potential yield gains with respect to development is flat. Second, potential yield gains are substantial in much of the developing world, particularly in Sub-Saharan Africa, where our baseline estimates average 49%.

JEL Codes: O13, O33, O47, O55, Q16

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1 Introduction

Why do the technologies employed differ across levels of development, and what are the consequences of these differences? One view attributes cross-country differences in technology usage to barriers to adoption, whereby incumbent actors oppose the adoption of new technologies (Parente and Prescott, 1994). Non-adoption, in this view, is a story about cost. Another view attributes differences in technology usage to "inappropriateness," whereby the effectiveness of a technology varies across the development spectrum due to differences in relative factor endowments (Atkinson and Stiglitz, 1969; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006). In other words, the benefits of adoption are low in some settings. These competing explanations have important implications for innovation policy in developing countries. The extent to which non-adoption is driven by inappropriateness of technology, rather than barriers, determines whether countries should optimally choose to innovate, developing their own more appropriate technologies, or imitate, copying or licensing technologies developed in rich nations.

Distinguishing between these two explanations is difficult. Non-adoption can always be rationalized by either sufficiently high fixed costs or sufficiently small productivity benefits, rendering revealed preference arguments based on observed adoption patterns uninformative. Hence, we require information either on the costs of adoption or on the productivity gains that would arise in settings where technologies have not yet been adopted. We make progress on the latter in the setting of agriculture, constructing new estimates of how developed-country technologies would perform in developing countries where they have not yet been adopted.

Agriculture provides a particularly useful setting to study the inappropriateness hypothesis, as cross-country differences in technology usage are especially pronounced. We exploit the unique characteristics of one of the most important agricultural innovations of the past 30 years: Bt corn. These crops have been genetically modified to kill agricultural pests as they feed on the plant, reducing the damage to the plant and thereby increasing yields.[1] The original Bt varieties were developed in the United States to combat the European corn borer (*Ostrinia nubilalis*). Bt corn now accounts for 86% of total corn acreage in the United States (USDA ERS, 2025), and has been approved for cultivation in 45 countries.

In Sub-Saharan Africa, however, adoption has lagged. Genetically modified organism (GMO) varieties of corn remain rare in the region, despite the importance of corn to the

[1] More specifically, these plants have been genetically modified to express δ-endotoxins, commonly known as "cry proteins," which were originally extracted from the bacterium *Bacillus thuringiensis*. This bacterium gives rise to the "Bt" in Bt corn.

local diet. Is slow adoption in Sub-Saharan Africa driven by lower productivity gains from a quintessential developed world technology or by barriers to adoption? This question is of crucial importance, as corn accounts for 30% of caloric intake in Sub-Saharan Africa (Ekpa et al., 2019), and corn yields have stagnated in Sub-Saharan Africa over the past decade (Gressel et al., 2024). Even modest improvements in yield could mean the difference between starvation and satiation for some of the world's poorest people.

To answer this question, we construct a novel dataset that allows us to estimate potential yield gains from the adoption of extant Bt corn technologies. Our dataset is constructed using regulatory data that identifies the genetic modifications embodied in GMO corn varieties and the proteins they express. We then draw on the entomology literature to identify which insect pests each protein protects against. Next, we utilize recent advances in large language models (LLMs) to systematically extract estimates of crop damage caused by these pests, along with the geographic locations of those damages. Combining these estimates with information on the geographic distribution and climatic suitability of each pest, we estimate the yield losses that each GMO variety could prevent in each country, which we convert into counterfactual yield gains from adoption. These counterfactual yield gains provide a direct measure of technological appropriateness, even in countries where the technologies have not been adopted.[2] The relationship between these gains and development then provides a natural empirical test of the inappropriateness hypothesis.

We show two results, both of which challenge the inappropriateness hypothesis. First, despite limited adoption, the potential productivity gains from existing Bt corn technologies are substantial in much of the developing world. In our 2023 counterfactual, the average improvement in yield from adoption would be roughly 49% in Sub-Saharan Africa. These gains were already substantial in our 2000 counterfactual, averaging 11% in Sub-Saharan Africa, and increased further by 2023 following the arrival of fall armyworm in the region. Second, we find no positive correlation between estimated yield gains and development.

If these technologies do not appear to be systematically inappropriate, what then drives the lack of adoption that we see in the data? By weakening the case for technological inappropriateness, our findings point instead to barriers to adoption as the alternative explanation. Although formally identifying the effects of these barriers is beyond the scope of this paper, we provide strong narrative evidence that regulatory barriers in particular explain much of the variation in observed adoption, especially in Sub-Saharan Africa.

Our paper contributes to the literature seeking to understand the enormous disparities in agricultural productivity across countries. Lagakos and Waugh (2013) emphasize the role of

[2]Here, with a slight abuse of terminology, we use yield losses and gains interchangeably. In *Section 3*, we define precisely what is meant by yield losses and gains.

subsistence requirements and selection in explaining cross-country differences in agricultural productivity, while Boppart et al. (2023) emphasize differences in input shares. We contribute to this literature by providing the most granular estimates of the potential productivity gains from adopting developed-country agricultural technologies. Our findings show how the lack of adoption of these technologies contributes to cross-country gaps in agricultural yields.

The closest paper to ours is Moscona and Sastry (2025), which also studies the productivity benefits of adopting advanced-country crop varieties in developing countries. We differ in methodology and, consequently, in our conclusions. Moscona and Sastry (2025) measure the focus of global agricultural research using patent references to specific agricultural pests. Our data, in contrast, allow us to distinguish the direction of innovation, as captured by patents, from its consequences for yields. We match each GMO crop to the insects it kills, then use LLMs to parse scientific articles at scale and measure the geographic importance of those insects.[3] This biological approach allows us to construct a new measure of appropriateness, namely counterfactual yield gains that reflect both the characteristics of each technology and the geographic importance of the pests it targets.

The remainder of the paper is organized as follows. *Section 2* provides an overview of the institutional features of our environment and the dataset we construct. *Section 3* reports our main results and estimates of the yield benefits of adoption. In *Section 4*, we discuss our results relative to the prior literature. Finally, *Section 5* concludes with a discussion of narrative evidence on the barriers to adoption in Sub-Saharan Africa.

2 Institutional Background and Data

The central contribution of our paper is measurement. Before describing how we implement this measurement, it is helpful to outline our general approach. Let V denote the set of available Bt events.[4] Let $Damage_{vj}$ denote the yield losses that are preventable by a variety containing event v in country j. Let I_v denote the set of insects that are affected by event v, and let $Damages_{ij}$ denote damages due to insect i in country j. Mathematically, we can write this as:

$$Damage_{vj} = \sum_{i \in I_v} Damages_{ij} \tag{1}$$

[3]This is crucial because in many countries pest damage is concentrated among relatively few pests. In South Africa, for instance, the major pests of corn are three stem borers: *Busseola fusca*, *Chilo partellus*, and *Sesamia calamistis* (see, e.g., Acuña et al., 2023, Overholt, 2008). All three are controlled by frontier Bt corn varieties.

[4]An event is the classifier used to denote a specific addition of foreign genetic material into a genome. These genetic modifications can then be used to create plant varieties, but the event itself is distinct from a variety, and one event may be used in many varieties.

Accordingly, our measurement exercise consists of recovering three objects: the pool of available events, V; the set of insects that each event protects against, I_v; and the damage that each insect i causes in a given country j, $Damages_{ij}$.[5] We now describe the institutional environment that allows us to measure these three objects.

2.1 Genetically Modified Organisms

The Cartagena Protocol on Biosafety defines a living modified organism as "any living organism that possesses a novel combination of genetic material obtained through the use of modern biotechnology."[6] We refer to these as genetically modified organisms (GMOs). They are classified according to the specific foreign genes that are inserted into the plant genome. The addition of such foreign genetic material is referred to as a transformation event or, more simply, an event (Hain and Lee, 2025). Each event is characterized by the specific site of insertion and the material inserted. The inserted genetic material can serve a variety of functions. Our data, for instance, include genes inserted to enhance yields, increase drought resistance, add resistance to herbicides, and provide resistance to various agricultural pests. Commercially, the most important of these traits are those that provide resistance to herbicides (for instance, "Roundup-Ready" variants) and those that provide resistance to insect pests (for instance, "YieldGard" and "SmartStax" corn varieties).[7] These traits are commercially valuable. In the United States, varieties of GMO corn account for more than 90% of corn planted in a given year. In South Africa, GMO corn accounted for more than 85% of corn planted in the 2022–2023 production season. Of that GMO corn, 70% was Bt.[8]

In part because of the controversial of genetic modifications, the regulatory environment around GMOs is quite stringent. Events must go through several stages of regulatory approval before varieties containing them can be released to the public. The particulars of the regulatory process vary country-by-country but typically entail separate approvals for "food," "feed," and "cultivation," which correspond, respectively, to use for human consumption, use for animal consumption, and the production of varieties containing the event. Regulatory decisions are typically disseminated publicly prior to environmental release, and local laws often require public comment periods. Following regulatory decisions, most countries relay their decisions to the Biosafety Clearing-House (BCH), a mechanism established under the Cartagena Protocol to facilitate information exchange.

[5] For now, we ignore two (closely related) potential complications: competing risks and the possibility that damage from other pests increases in response to Bt control. These will be discussed in *Section 3.3*.

[6] See https://bch.cbd.int/protocol/text/article.shtml?a=cpb-03.

[7] Note the distinction between an event, defined as the addition of foreign genetic material into the genome of a plant, and a variety, defined as a specific genetic line of a plant that has been bred.

[8] See here.

To measure the potential benefits of these technologies, we must also identify the pests they control. This depends on the proteins encoded by the inserted genes, which exhibit insect-specific activity. Cry1Ab, for example, was developed in the mid-1990s and formed the first generation of "YieldGard" varieties. It offers protection against the European corn borer (*Ostrinia nubilalis*) and a collection of other moths, but offers little protection against the western corn rootworm, *Diabrotica virgifera virgifera*.

2.2 Data Construction

Our primary source of regulatory information is the GM Approval Database (GMAD). The GMAD collates regulatory information directly from individual countries and the BCH, including information on the genes inserted into each plant and the proteins those genes encode. We use the event-level records to identify the set of available events and their genetic content, as well as the countries and years in which each event was approved for cultivation.[9]

To identify the set of insects that would be affected by each Cry protein, we turn to the entomology literature, which often tests either existing plant varieties expressing the protein or the specific protein itself against various insects.[10] We use this literature to construct a crosswalk matching each protein to the insect species against which it is effective. For each protein-insect pair, we record the scientific article supporting the match. This allows us to determine the set of pests controlled by each event based on its genetic content, rather than the pests explicitly mentioned in its patents.

Armed with the set of insects that the existing portfolio of GMO varieties protects against, we must then quantify the importance of each of those pests to yield loss. The importance of each of these pests will vary across crops and countries: Acuña et al. (2023), for example, specifically reference four major stalk borers (*Busseola fusca*, *Chilo partellus*, *Eldana saccharina*, and *Sesamia calamistis*) when discussing major pests of corn in Sub-Saharan Africa, all of which are well controlled by frontier GMO varieties.[11]

To generate these damage estimates systematically, we turn to the scientific literature. We download all articles on *Scopus* mentioning any insect identified in the previous step. We split each article into text chunks and use Qwen3-14B to extract the pest, crop, location,

[9] *Appendix A* describes the collection of event-level records and treatment of approvals for stacked events.

[10] *Appendix A.2* provides details about the general approach and specific examples. The entirety of the crosswalk, which includes links to all sources referenced for the evaluation used in each step, is available upon request.

[11] See *Figure A.3* for a measure of the insect damage distribution for corn constructed by experts from land-grant universities.

yield loss, and reporting sentence.[12] We use the model without fine-tuning or task-specific training, with fixed inference settings and no random sampling. Our main findings are robust to alternative prompts and model sizes. Using the reported sentences, we retain quantitative estimates of yield loss and discard measures of pest prevalence or infestation. This yields 1,298 country-level yield-loss observations, which we aggregate into 159 insect-country damage estimates for corn, covering 27 insect species and 58 countries.[13]

Country-level damage data are sparse. To address this, we use damage estimates from other countries in the same region when a pest is present but no direct estimate is available. This requires an independent measure of the geographic distribution of pests. Following Moscona and Sastry (2025), we obtain these distributions from CAB International (CABI). We use country-level damage estimates wherever available. For missing insect-country-crop combinations in countries where CABI records the pest as present, we assign the mean damage estimate for the same insect and crop across countries in the same United Nations Statistics Division region, as detailed in *Appendix A*. The resulting dataset contains 956 insect-country damage estimates, covering 28 insect species across 157 countries. In *Section 3*, we combine these estimates with spatial measures of pest suitability and the distribution of corn production to construct counterfactual yield gains from adoption.

Our analysis focuses on three benchmark years. We use the portfolio of Bt events available in 2000 for our baseline cross-country results, the portfolio available in 2005 for a robustness exercise, and the portfolio available in 2023 to estimate more recent potential yield gains, particularly in Sub-Saharan Africa. We also examine MON89034, first approved in 2008, as an illustrative case study. Importantly, these years refer to our counterfactual exercises rather than a common observation year for the underlying data. Our insect-damage estimates are drawn from scientific studies conducted over different periods.

3 Yield Gains

3.1 Measuring Potential Yield Gains

Our dataset matches Bt corn events to their genetic content, genetic content to insects, and insects to damages. The last step in our measurement process is to aggregate across insects.

We now distinguish between yield losses and yield gains. Yield losses refer to the fraction

[12] *Appendix A.5* reports the model settings and full prompt.

[13] Articles reporting multiple estimates, for example across seasons, sites, or treatments, receive more weight. Averaging within articles before aggregating yields estimates correlated 0.98 with our baseline, raises the average maximum yield gain in Sub-Saharan Africa under the 2023 portfolio from 49.4% to 53.3%, and still produces no statistically significant positive income gradient.

of potential yield lost to insect pests, while preventable yield losses are those attributable to insects controlled by a given Bt event. Yield gains instead measure the proportional increase in yields from adopting that event, relative to yields without adoption. If the preventable yield loss is a fraction L of potential yield, eliminating it generates a proportional yield gain of $G = 1/(1-L) - 1$. We use losses when describing pest damages and gains when reporting the potential productivity benefits of adoption.

Many of the observations in our dataset measure damage to individual farms rather than aggregate country-level damage. This requires a modification of equation (1):

$$\text{Damages}_{vj} = \sum_{i \in I_v} \mathbb{E}[\text{Damage}_{ij} | i \text{ on farm in } j] \mathbb{P}[\text{Insect } i \text{ on farm in } j] \tag{2}$$

As equation (2) suggests, we must also estimate the probability that the insect is present at a random farm in j. Our first approach to doing this relies on information from publicly available biotic risk models provided by the University of Minnesota Genetics, Environment, Management, and Socioeconomics Informatics group (UMN GEMS).[14] These biotic risk models provide spatial representations of climatic suitability for a selection of biotic threats (pests, pathogens, and weeds) that GEMS considers to be of particular importance, at a spatial resolution of 10 arcminutes (roughly 18.5 kilometers at the equator). Six of these pests are present in our dataset: the maize stalk borer (*Busseola fusca*), the spotted stalk borer (*Chilo partellus*), the western corn rootworm (*Diabrotica virgifera virgifera*), the European corn borer (*Ostrinia nubilalis*), the beet armyworm (*Spodoptera exigua*), and the fall armyworm (*Spodoptera frugiperda*).[15]

The biotic risk measures range from 0 to 100, with 0 indicating extremely poor suitability and 100 indicating a high degree of climatic suitability. To convert these spatial data into country-level proxies for the probability of infestation, we first merge them with spatial data on actual corn production in 2000 from the UNFAO GAEZ V4 project. To generate aggregate measures of the probability of infestation, we take a weighted mean of biotic risk across cells within a country, where the weights are actual corn production in the GAEZ data. This measure is designed to be conservative in two related respects. First, in countries that do not use Bt corn, areas with greater pest exposure may have lower yields precisely because of pest damage. Weighting by actual corn production therefore places less weight

[14] See here.

[15] Although the GEMS data cover only six pests, these are the most economically important sources of pest-related yield losses in corn worldwide. The western corn rootworm is among the most important maize pests in North America (Bažok et al., 2021), the two stalk borers are major pests in the East African corn belt, and the fall armyworm is a leading pest in South America and, since its arrival in the mid-2010s, Sub-Saharan Africa (Fatoretto et al., 2017; Day et al., 2017).

on these areas, potentially understating overall pest exposure.[16] Second, it ignores the fact that the geographic distribution of pests can affect where corn is planted. Both effects will tend to underestimate the effective prevalence of these insects.[17]

Our counterfactuals combine information on the timing of regulatory approvals with pest-damage estimates recovered from scientific studies. The year associated with a counterfactual determines two inputs: the portfolio of Bt events approved for cultivation in at least one country by that year, and the set of pests treated as present in each country, which excludes pests first reported in that country by CABI after that year.[18] The damage estimates, the GEMS climatic suitability surfaces, and the 2000 GAEZ production weights are held fixed across counterfactual years, so the year of a counterfactual does not indicate the year in which the underlying damages or climatic suitability were observed.

3.2 Potential Yield Gains Across Countries

We first consider the technology portfolio available in 2000, defined as the set of Bt events approved for cultivation in at least one country by that year. We combine this portfolio with our estimates of pest damages and climatic suitability to construct counterfactual yield gains across countries. Pest presence is evaluated as of 2000, so pests first reported in a country after 2000, (such as fall armyworm), are excluded. We then aggregate across the portfolio of available technologies in two ways. The first is designed to indicate what would happen if farmers had access to the best technology. In that case, the resulting gain would simply correspond to the technology that reduced yield loss the most. The second is a measure of the yield gain that would be realized if a farmer were given a technology at random from the pool of existing GMO events. *Figure 1* plots estimated yield gains against GDP per capita.

Figure 1 suggests a surprising finding: there is virtually no correlation between development and the yield gains associated with the adoption of Bt corn, even when we restrict attention to the pests found in the GEMS biotic risk maps. That is, we do not find evidence in favor of the inappropriateness hypothesis.[19]

Corn accounts for a substantial portion of caloric intake in Sub-Saharan Africa, yet our

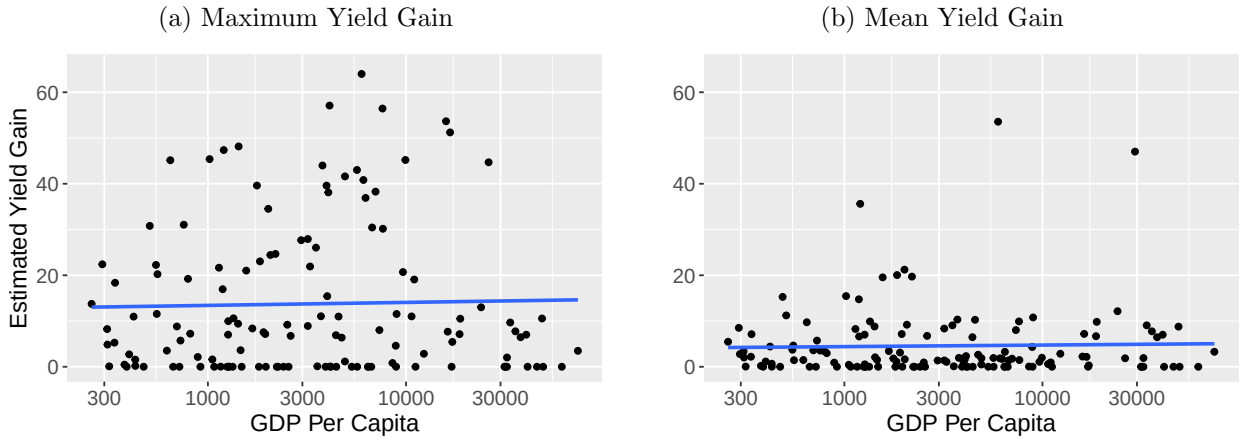
[16] Weighting corn-growing cells equally, or by GAEZ potential corn production, raises the average maximum yield gain in Sub-Saharan Africa under the 2023 portfolio only slightly, to 49.5% and 50.7%, respectively, from 49.4% in our baseline. Neither specification produces a statistically significant positive income gradient.

[17] *Appendix B.1* provides these maps restricted to the geographic ranges of the pests recorded in the CABI.

[18] Pests for which CABI records no first-report date are treated as present in every year.

[19] Regressions of potential yield gains on log GDP per capita confirm this pattern. No specification yields a statistically significant positive gradient, whether we use the 2000, 2005, or 2023 portfolio, control for log GAEZ potential corn yield, or weight countries by corn production. Because concerns about inappropriateness are most relevant for poorer countries, we also restrict the sample to low- and middle-income countries and to developing countries that had not approved Bt corn by the portfolio year or by 2024. The slopes in these samples are imprecisely estimated, and none is positive and statistically significant.

Figure 1: Potential Yield Gains and GDP Per Capita, 2000



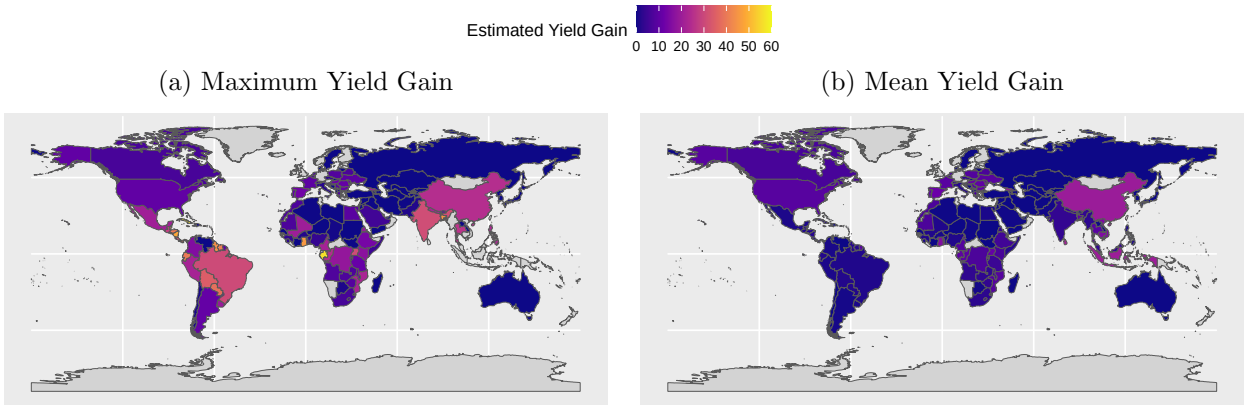
Notes: Estimated yield gains plotted against GDP per capita. The portfolio includes all Bt events approved for cultivation in at least one country by 2000. Panel (a) uses the available event with the highest gain in each country; panel (b) is based on the mean preventable yield loss across available events. Pest presence is evaluated as of 2000; climatic suitability is static. Each dot represents a country.

data indicate that the only country in the region that had adopted a Bt variety in 2000 was South Africa. Was this because the potential gains were low, or because the cost of adoption was high? To get at this question, *Figure 2* plots the spatial distribution of gains implied by our biotic-risk-weighted measure.

Under the 2000 technology portfolio, if Sub-Saharan Africa adopted the optimal variety, yield gains would average 11%, with larger gains in the East African corn belt from eastern South Africa to southern Ethiopia. For reference, the estimated gains in the United States under the same portfolio are 10.6%. This suggests that adoption costs, rather than productivity benefits, are driving differences in technology adoption.

Benchmarking these estimates in Sub-Saharan Africa against observed adoption is difficult, given that most countries in our sample had not adopted as of 2024. However, two pieces of evidence suggest that our estimates of potential yield gains in Sub-Saharan Africa are reasonable. First in South Africa Brookes (2022) reports an average yield gain of 11.0% over the period 1997–2020. Our predictions for South Africa at the midpoint of that period, 2009, before fall armyworm was first reported there in 2017, are 6.4% with the best available event and 3.4% based on the mean preventable yield loss. Second, in January 2024, the Nigerian government approved four varieties of TELA corn for commercial use. These varieties combine two genetic events, MON87460 and MON89034, which confer drought tolerance and insect resistance, respectively. The African Agricultural Technology Foundation

Figure 2: Spatial Distribution of Potential Yield Gains, 2000



Notes: Spatial distribution of gains implied by our measure of biotic risk under the 2000 technology portfolio, Bt events approved for cultivation in at least one country by 2000. Panel (a) uses the event that generates the highest gain in each country. Panel (b) is the mean preventable yield loss across all events.

reports yield improvements of 50% relative to non-GMO hybrids.[20] Our projected yield gains in Nigeria under the 2023 technology portfolio are 29%. We likely understate the true gains because this measure does not include damage caused by *Sesamia calamistis*, which is particularly important in West Africa, and *Chilo partellus* is not present (Ong'amo et al., 2016).[21]

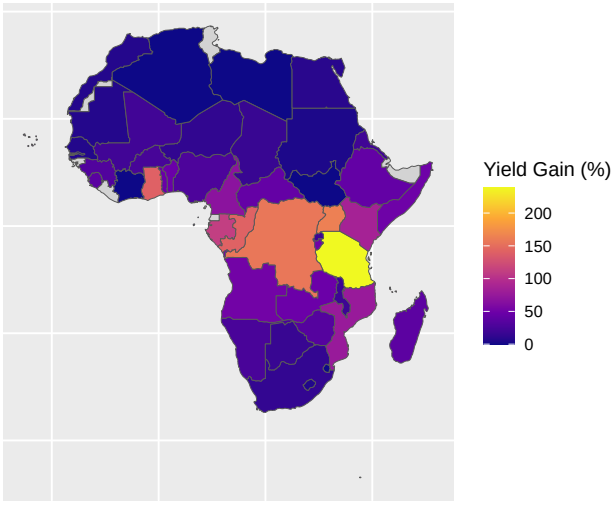
Figure 3 plots the spatial distribution of projected gains in Africa in 2023 under the adoption of the optimal variety. The gains in Sub-Saharan Africa average 49% in 2023, up substantially from our estimates for 2000. This large increase reflects the arrival of fall armyworm, first reported by CABI across much of Sub-Saharan Africa in 2016–2017, together with the region's high climatic suitability for the pest.[22] This is qualitatively consistent with the damage estimates in Day et al. (2017). This also emphasizes a subtle point about

[20] This was relayed to us in an interview and is consistent with evidence on the TELA project webpage here: https://www.aatf-africa.org/tela-corn-project/.

[21] *Table C.1* compares predicted and observed yield gains across a broader sample of countries that adopted Bt corn, including advanced economies and countries outside Sub-Saharan Africa. There, predictions are based on the mean preventable yield loss across available events at the midpoint of each country's adoption period, and they are on average 2.3 percentage points below the observed gains.

[22] Country-level climatic suitability measures for the fall armyworm can be seen in *Figure B.5*. Because the 2023 counterfactual also uses a newer technology portfolio, we recompute the average maximum yield gain for a fixed set of 43 Sub-Saharan African countries under each combination of the 2000 and 2023 portfolios and pest presence, and decompose the increase by pest. On this sample, the average rises from 10.3% to 49.4%. Fall armyworm accounts for 32.6 percentage points of this 39.1-point increase (83%), and the stem borers *Busseola fusca* and *Chilo partellus* account for the remainder (*Figure C.1*). Technology and pest presence interact, so the split between them depends on the order in which they are updated: the newer events raise the average gain by 19.7 percentage points under 2023 pest presence, but by only 3.4 points under 2000 pest presence.

Figure 3: Projected Yield Gains in Africa, 2023



Notes: Distribution of projected yield gains in Africa under optimal 2023 event choice. The 2023 portfolio includes all Bt events approved for cultivation in at least one country by 2023, and pest presence is evaluated as of 2023. Damage estimates, climatic suitability, and production weights are same as 2000 counterfactual.

inappropriateness in this context: it is not a static concept. As new pests arrive and old pests decline because of factors such as climate change, the potential yield gains associated with each technology will change.

3.3 Robustness

Our two findings are that existing Bt corn technologies could generate substantial yield gains, particularly in Sub-Saharan Africa, and that these gains do not systematically increase with income. We now examine the sensitivity of these conclusions to additional assumptions and robustness checks not already discussed above.

One concern is that damages caused by different pests may overlap. Since multiple insects cannot each destroy the same crop, summing their damages could overstate potential yield gains.[23] To address overlapping damages, we alternatively combine pest losses multiplicatively, treating them as independent risks, or retain only the largest single-pest loss. These alternatives reduce the average maximum yield gain in Sub-Saharan Africa under the 2023 portfolio from 49.4% to 40.8% and 29.5%, respectively. Neither generates a statistically

[23] A separate concern is that pests not controlled by a given Bt variety might expand as susceptible pests decline, reducing realized yield gains. Although we cannot quantify this response, observed yield improvements in South Africa and Nigerian field trials, together with the broad activity of Cry proteins (which collectively control 18 of the 22 major pests listed in *Appendix B.2*), provide some reassurance.

significant positive income gradient.[24]

A second concern is that our baseline assumes Bt corn eliminates all losses caused by targeted pests.[25] Reducing assumed efficacy to 75% or 50% mechanically lowers average maximum potential gains in Sub-Saharan Africa to 29.8% and 16.9%, respectively. Although the magnitude of the gains falls, they remain substantial even under considerably lower efficacy, and neither specification generates a statistically significant positive income gradient.

Finally, our procedure for imputing missing insect-country damages could obscure an underlying income gradient. To assess this concern, we estimate regressions using the 2005 technology portfolio, comparing our biotic-risk-adjusted measure with alternative measures based on the sum or maximum of pest damages. We also control for GAEZ potential corn yield and compare results using regionally imputed damages with those based only on directly reported observations. *Tables B.2* and *B.3* report the results for the optimal event and the mean across events, respectively. None of these specifications generates a statistically significant positive income gradient.

4 Reconciling Differences

In the previous section, we estimated substantial productivity gains that are flat across the development spectrum. Prior literature, most notably Moscona and Sastry (2025), finds that technological inappropriateness explains a large share of cross-country differences in agricultural productivity. To understand the source of this discrepancy, we begin by examining a specific genetic event, MON89034.

Figure C.3 presents the geographic distribution of the potential yield losses preventable by MON89034, an event first approved for cultivation in the United States in 2008. Pest presence in the figure is evaluated as of 2008.[26] The key takeaway from this figure is that there are large gains to Sub-Saharan Africa from adopting a technology developed in the United

[24]Because the conversion from preventable losses to yield gains is convex, extreme damage estimates could disproportionately influence average gains. Using median rather than mean damage estimates, winsorizing, or excluding extreme observations yields average maximum gains in Sub-Saharan Africa between 43.7% and 49.4%, while median gains across Sub-Saharan African countries remain between 29% and 34%. None of these specifications generates a statistically significant positive income gradient.

[25]Resistance to Bt proteins may further reduce their efficacy over time. Documented practical resistance events are concentrated in countries with widespread Bt crop adoption, particularly the United States, Brazil, and Argentina (Tabashnik et al., 2023; *Figure C.2*). In South Africa, resistance to the first-generation Cry1Ab protein among *Busseola fusca* was mitigated by the introduction of MON89034 (Kotey et al., 2017). Evidence of susceptibility to Bt corn among *Spodoptera frugiperda* in Sub-Saharan Africa provides some reassurance regarding pre-existing resistance (Chingombe, 2020), although it does not rule out the development of resistance following adoption.

[26]This is a second-generation event that expresses two Cry proteins, Cry1A.105 and Cry2Ab2, and is typically included in the "YieldGard VT Pro" product line.

States. This event also illustrates how relying on patent data can dramatically overstate the mismatch between a technology and local agricultural conditions. The central patent for MON89034 is US8062840B2. The section referencing insect pests reads,

> "The corn plant event MON89034 is particularly resistant to insects in the *Lepidoptera* family such as Fall armyworm (*Spodoptera frugiperda*), European corn borer (*Ostrinia nubilalis*), corn earworm (*Helicoverpa zea*), southwestern corn borer (*Diatraea grandiosella*), and black cutworm (*Agrotis ipsilon*) and the like, all of which are agronomically important insect pests."

Of these pests, only *Agrotis ipsilon* (the black cutworm) was present in South Africa at the time of its approval for cultivation there in 2010. The patent makes no mention of the major pests of concern in South Africa at the time, namely the aforementioned stem borer complex, which could give the misleading impression that MON89034 was poorly suited to the needs of South African corn farmers. Four pieces of evidence suggest that this is incorrect.

First, the scientific literature has documented that MON89034 is highly effective against the four major stem borers: *Busseola fusca* (Strydom et al., 2019), *Chilo partellus* (Jalali et al., 2015), *Sesamia calamistis*, and *Eldana saccharina* (Venter, 2015). Second, consistent with the scientific literature, marketing materials from Bayer Crop Science explicitly mention "excellent control against *Busseola fusca* ... and *Chilo partellus*."[27]

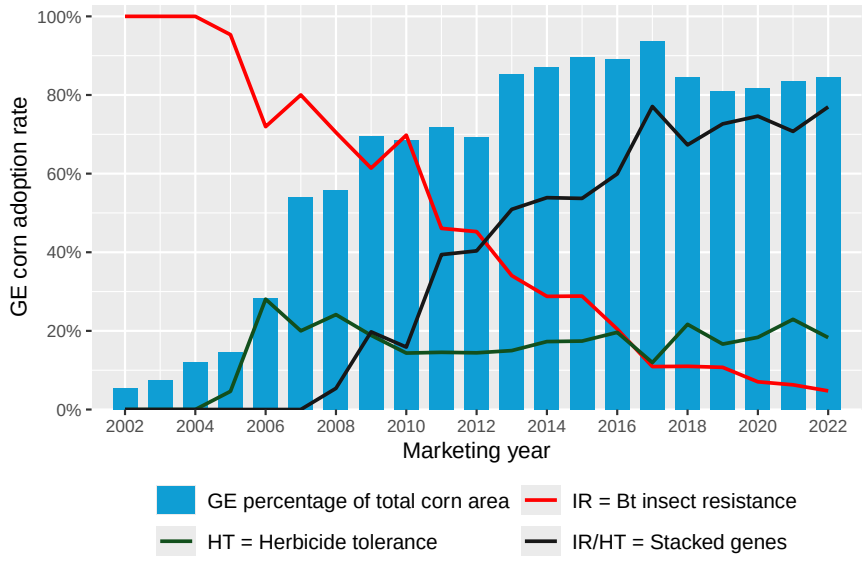
Third, further evidence for the ubiquity of Bt corn, albeit not directly for the ubiquity of MON89034, comes from the United States Department of Agriculture's Foreign Agricultural Service (USDA FAS).[28] *Figure 4* reproduces the GMO corn adoption series, covering the 2002/03 to 2022/23 marketing years, from the 2024 USDA FAS Agricultural Biotechnology Annual for South Africa. Two facts are immediately salient. First, GMO penetration into the South African corn market is substantial, with GMO varieties accounting for more than 80% of corn plantings. Second, among GMO corn varieties, the overwhelming majority of plantings express insect-resistant traits.[29] Both facts are prima facie inconsistent with the notion that there is a substantial mismatch between foreign GMO technology and South African agricultural conditions. Given the substantial overlap in major agricultural pests across the region, this conclusion also extends to much of Sub-Saharan Africa and suggests

[27] Bayer acquired Monsanto, the originator of MON89034, in a transaction that completed in 2018. See https://www.cropscience.bayer.co.za/en/discover/articles/seed-technology/maize-technology/yieldgard-maize-2 for the marketing materials in South Africa.

[28] USDA FAS attachés are based in U.S. embassies worldwide and are charged with providing information about local agricultural conditions and the environment for U.S. agricultural exports. One of these reports is the "Agricultural Biotechnology Annual," which documents both the local regulatory environment surrounding agricultural biotechnology and market information for GMO varieties. The reports for South Africa also included historical measures of GMO penetration in domestic plantings by trait type.

[29] The percentage of GMO corn expressing insect-resistant traits is the sum of the black and red lines.

Figure 4: GMO Penetration by Trait Type in South Africa



Notes: GMO penetration by trait type. Years on the horizontal axis are the first year of each marketing year (2002 is 2002/03). Bars show the GE share of total corn area; lines show the shares of GE corn plantings with insect resistance only (IR), herbicide tolerance only (HT), and both traits stacked (IR/HT). *Source*: USDA FAS GAIN Agricultural Biotechnology Annual for South Africa, 2024, Figure 1 (FAS/Pretoria, using data from the Bureau for Food and Agricultural Policy).

that the mismatch between developed-country technologies and local agricultural conditions would similarly be overstated.

Fourth, this discrepancy between patent descriptions and actual protection is not unique to MON89034. The first generation of Bt corn consisted of a collection of events expressing Cry1Ab—MON810 (Monsanto's "YieldGard"), BT11 (Syngenta's "Agrisure CB/LL"), and BT176 (Syngenta's "NaturGard Knockout"). The patent for BT11 mentions *Ostrinia nubilalis*, *Diatraea grandiosella*, *Helicoverpa zea*, and *Spodoptera frugiperda*. The patent for BT176 mentions *Ostrinia nubilalis*, *Diatraea saccharalis*, the lesser cornstalk borer (*Elasmopalpus lignosellus*), the southwestern corn borer (*Diatraea grandiosella*), and the fall and beet armyworms. The patent for MON810 does not mention any specific insect, referring only to "*Lepidopteran* insect[s]."[30] All of these events are effective against the full complex of stem borers that are important in Sub-Saharan Africa.

Our point here is not that there is no information in patent data. Rather, that while patent data permit us to measure the extent to which innovation in GMO crops is directed at rich countries, they cannot speak to the productivity consequences of that mismatch. Answering this question requires the biological characteristics of the technologies themselves.

[30]Patent numbers US6329575B1, EP0618976B1, and US6713259B2, respectively.

Finally, these productivity consequences cannot be inferred from observed adoption patterns either. Non-adoption may reflect either low productivity gains or high adoption costs, particularly for GMO technologies (Paarlberg, 2008). MON89034 illustrates this distinction: despite substantial estimated potential gains in many countries, it has been approved for cultivation in relatively few. Our approach therefore measures the productivity benefits of adoption independently of observed adoption patterns.

5 Conclusion

In this paper, we have shown that Bt corn, a quintessential developed-country agricultural technology, has the potential to generate enormous productivity gains in developing countries, particularly in Sub-Saharan Africa. We estimate that adoption of existing Bt corn technologies could increase yields by an average of 49% in Sub-Saharan Africa. These potential gains have been substantial since the initial introduction of Bt corn in the mid-1990s, and we find no systematic relationship between potential yield gains and development. Our findings challenge the view that technologies developed in rich countries are poorly suited to the agricultural conditions of developing countries.

If technological inappropriateness does not explain the lack of adoption, what does? Our findings weaken one of the two leading explanations for cross-country differences in technology usage, shifting attention toward barriers to adoption. While identifying the specific barriers that prevent adoption is beyond the scope of this paper, we conclude by discussing suggestive evidence on which barriers may be most important.

One possible explanation is the weakness of intellectual property protections in developing countries. However, this explanation does not appear sufficient in our setting. Bayer Crop Science has provided royalty-free licenses (with the right to sublicense), corn varieties, and scientific assistance for the TELA Corn Project throughout Sub-Saharan Africa (AATF, 2021). Despite these efforts to facilitate adoption, the technology remains largely absent from the region.

The experience of a different GMO project, Banana21, points instead toward the importance of regulatory barriers. Lee (2022) reports that 32.6% of children aged 6–59 months in Uganda suffer from vitamin A deficiency. Banana21 was launched in 2005 to genetically modify the East African Highland Banana, a staple of the Ugandan diet, to contain higher levels of vitamin A. The first Ugandan field trials were completed in 2011 (Banana21, 2021). Yet, as of 2025, Banana21 had still not received regulatory approval (Buah et al., 2025).

Why has Banana21 stalled? The primary obstacle is the continuing lack of local legislation outlining a framework for the adoption and regulation of GMO crops. A biosafety law

was first passed by the Ugandan legislature in 2017. The President of Uganda, Yoweri Museveni, refused to sign it, sending it back to legislators for modifications. Those modifications were made, but he again refused to sign it (Bendana, 2020). As of 2020, the bill remained in legislative limbo, preventing Ugandan farmers from adopting GMO crops, including those developed domestically.

Kenya provides another example of barriers to the adoption of GMO crops. The first application to introduce Bt cotton in Kenya was submitted in 2001. Bt cotton was not approved for commercial cultivation in Kenya until 2020 (ISAAA, 2020a). What drove the long wait? The initial delay was due to the lack of a national biosafety law, which was not passed until 2009 and did not come into force until 2011. In November 2012, the Kenyan Ministry of Public Health enacted a ban on the importation of GMO products and removed them from the market (Snipes, 2012). This ban persisted for the next decade, with an exception for Bt cotton in 2020. The ban on the importation of GMO products was lifted in 2022, but was then subject to a series of legal challenges. In March 2025, the Court of Appeal issued an injunction preventing further steps to lifting of the ban (Kamau, 2025).

Our findings have two immediate implications. First, barriers to technology adoption may substantially depress agricultural productivity in some of the world's poorest countries. Second, removing these barriers generate enormous welfare gains by unlocking the benefits of technologies that already exist. More broadly, technologies developed in rich countries have the potential to dramatically improve the lives of millions of people in developing countries, if only they are adopted.

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Online Appendix

Appendix A Description of Dataset Construction

This appendix describes the construction of our datasets. Answering our question requires four different pieces of information, which are discussed throughout the remainder of this appendix.

1. Information on the universe of genetic modifications to GMO crops and their regulatory approvals.
2. Information matching those genetic modifications to specific pests.
3. Information matching those pests to damages on a country-by-country basis.
4. Information about the geographic extent of those pests.

A.1 Event Data

We extract information about GMOs from the GM Approval Database of the *International Service for the Acquisition of Agri-biotech Applications*. This is a website that collates information about regulatory approvals worldwide from a variety of sources.[31] Specifically, we scrape the *Event* pages. Each event page includes a header with information on the Event Name, the Event Code[32], the Trade Name, the Crop, the Developer, the method of trait introduction, and the GM traits. In addition to the information in the header, each event page also includes two tables. The first table is titled "Basic Genetic Modification" and includes information about the gene that is introduced, the source of that gene, the product of that gene (e.g., the protein produced by the introduced gene), and the function of the introduced gene. The second table is titled "Regulatory Approvals: Country, Year, and Type of Approval" and includes information on each of the three major ISAAA categories of approvals—"Food," "Feed," and "Cultivation."

One subtlety of the data concerns the heterogeneous treatment of stacked approvals across countries. As mentioned in the text, the United States does not in general have separate approval processes for stacked events, while many other countries, including the EU, do (ISAAA, 2020b). This means that when calculating the set of approved products in the

[31] The database was repeatedly mentioned in discussions with industry participants, giving us confidence in its reliability.

[32] This typically corresponds to the OECD code of the GMO variety.

United States, we are forced to make assumptions as to when the stacked events would have become available. We do this by assuming that a stacked event becomes available at the earlier of five years after the approval of the last constituent event in the stack and the date of the first approval for cultivation by another entity.

A.2 Proteins to Pests

Having extracted information about the proteins encoded by the genes inserted into each crop variety in the prior step, we now describe the process used to construct the dataset that matches individual proteins to pests. In contrast to prior literature, we do not rely on patent information for this step, instead relying on scientific articles. This is a crucial distinction—these products are overwhelmingly developed by a small set of agrochemical companies that focus their research efforts on large markets (e.g., the Brazilian soybean market or the U.S. corn market). As a consequence, their patent references will skew towards pests that are present in those countries merely because they are not testing for efficacy in secondary markets. This induces a drastic overstatement of the mismatch between these varieties and the developing world. Most of the information about the efficacy of Bt varieties in local conditions comes from local researchers.

Our solution is to manually search Google Scholar for information that evaluates individual proteins for their efficacy against specific pests. The end result of this exercise is a dataset that includes the following information: the protein, the pest against which it protects, and a link to the scientific article that we relied on to make that determination. As discussed in the text, our explicit claims about the efficacy against stem borers in Sub-Saharan Africa are also supported by Bayer marketing materials in South Africa, which explicitly claim efficacy against stem borers.[33]

As an example of the text that we use to make this determination, consider the following passage, taken from Venter (2015),

> "Studies were conducted on three stem borers *C. partellus, Eldana saccharina* and *Sesamia calamistis* and three nontarget lepidopteran pest species *Agrotis segetum*, *Helicoverpa armigera* and *Spodoptera exempta*. Results showed that MON810 maize was not effective against *A. segetum* larvae feeding on maize seedlings. Differential levels of survival were observed between two *A. segetum* populations on MON89034 with a population from Polokwane showing survival on the stacked maize event. No *S. exempta* 1st instar larvae survived on MON810 and MON89034 but 3rd instar larvae survived on MON810 maize. *Helicoverpa*

[33] See here.

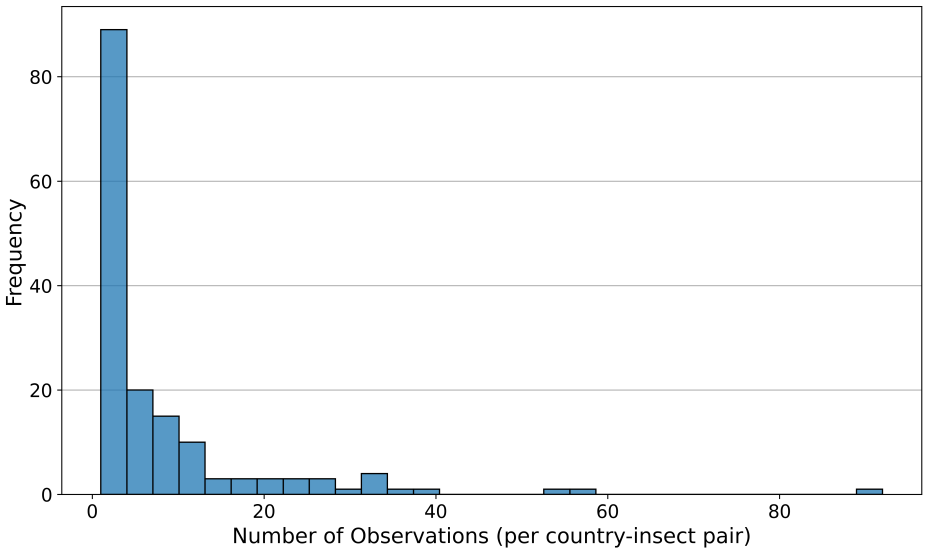
armigera larvae survived on ears of MON810 maize plants but not on events MON89034 or Bt 11. Results further indicated that *C. partellus* larvae were highly susceptible to these three Bt maize events. Larval survival of *S. calamistis* was recorded for larvae feeding on MON810 and Bt11 maize ears but not on MON89034 maize ears. Bt maize during the vegetative growth stages therefore effectively controlled *C. partellus*, *S. calamistis* and *E. saccharina* but the latter two species was not effectively controlled when feeding on ear tissue."

A.3 Pests to Damages

Having constructed a crosswalk matching varieties to pests via their genetic information, we now turn to quantifying the damage caused by each pest on a country-by-country basis. This is the most involved step of our measurement exercise. We download all articles indexed in *Scopus* that mention the scientific name of any insect in our set. Because of license restrictions, we are limited to articles that the University of Minnesota has access to, and we download them with Elsevier's *Scopus Document Download Manager*. The result is a collection of 95,680 PDF files, organized by insect, of which 73,214 are distinct, readable articles. We convert each PDF to text, split the text into chunks, and pass each chunk to Qwen3-14B, an open-weights LLM that we run on a university computing cluster. We ask the model for the pest, the affected crop, the location, the yield loss, and the sentence that reports it. *Appendix A.5* describes the model, its settings, and the prompts.

To construct our damage estimates from the model's output, we use the reported sentence on each extracted row. The prompt instructs the model to leave the damage field blank unless the figure is a loss of crop, so infestation rates and shares of plants damaged should not enter it. We then keep rows on corn with no empty field whose sentence reports a percentage and contains a yield-loss term (*yield loss*, *yield reduction*, *decreased yield*, *harvest loss*, *grain loss*, or *damage*), and we drop figures repeated within an article. In this way, we retain quantitative estimates of yield loss and discard measures of pest prevalence or infestation. Infestation rates mostly appear to measure the share of plants infested on a farm where the pest is present, rather than the probability that a farm is infested, which is the measure used in the main text. We also drop rows that report ear, cob, or foliar damage, name a pest that is not an insect, or give only a global location, as well as 14 rows from two articles whose sentences report leaf or field damage rather than yield loss. Keeping these 14 rows raises the average maximum yield gain in Sub-Saharan Africa under the 2023 portfolio from 49.4% to 58.9%. We map pest names and locations to the insects and countries in our data with lookup tables and treat damage values above 100% as missing. This process yields

Figure A.1: Distribution of Country-Insect Corn Damage Estimates



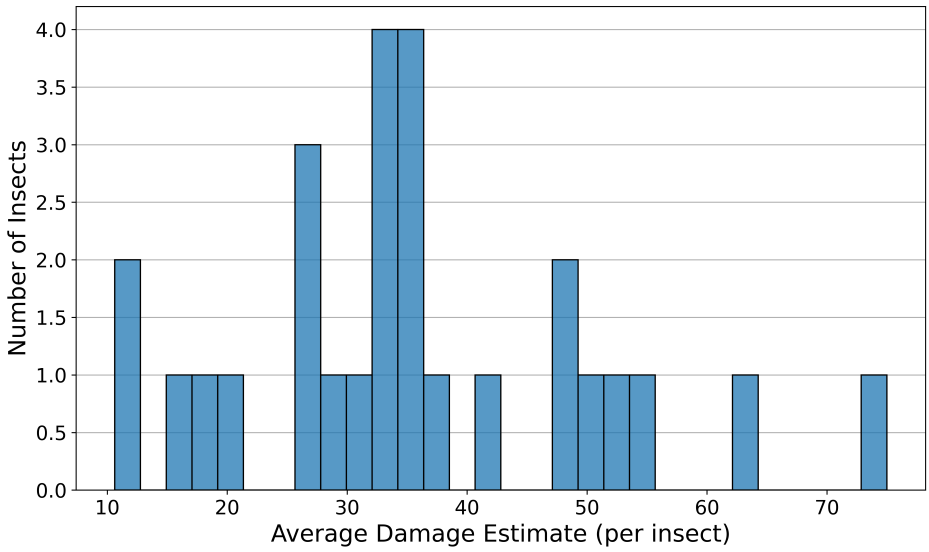
Notes: Distribution of Country-Insect Level Corn Damage Estimates

1,298 country-level estimates of yield loss. *Figure A.1* shows a histogram of the number of damage estimates per insect-country combination. We then average these estimates within each insect-country pair, which yields 159 yield-loss estimates for corn, spanning 27 insect species across 58 countries. *Figure A.2* shows the resulting distribution of yield-loss estimates at the insect-country level. These estimates come from studies conducted in different years, so they do not form an annual panel of observed pest damages.

To impute values for insect-country pairs lacking direct estimates, we match each country to its subregion and region in the United Nations Statistics Division (UNSD) Standard Country or Area Codes for Statistical Use. For each insect-country pair without a direct estimate, we assign the average of the estimates for that insect in the same UNSD subregion or, if there are none, in the same UNSD region. These averages also include estimates whose location is reported only at the subregion or region level (for example, West Africa). After this imputation step, the final dataset includes 956 damage estimates spanning 28 insects across 157 countries.

Recovering damage estimates in this context is important because we are able to directly measure differences in the importance of controlling individual insects. *Figure A.3* plots the observed damage distribution in the United States. Note that, given the near ubiquity of Bt corn in American cornfields, this damage distribution is skewed toward pests against which Bt corn is less effective. Tabashnik et al. (2023) document that *D. virgifera* has developed practical resistance to four of the major Bt proteins. The data are available here.

Figure A.2: Average Country-Level Corn Damages by Insect



Notes: Distribution of Average Country-Level Corn Damages by Insect

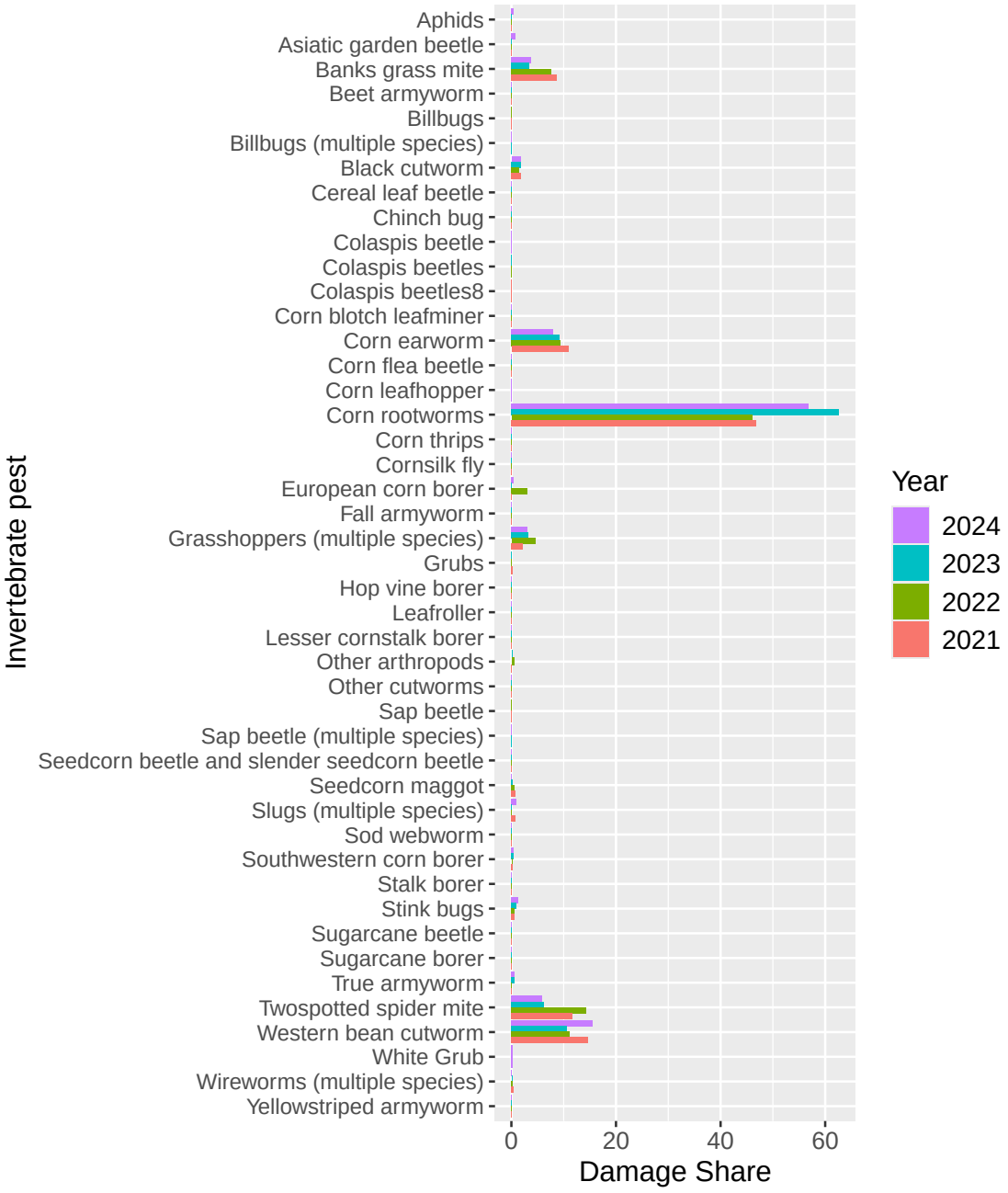
A.4 Pest Geography

The last piece of information required to measure the counterfactual productivity gains from adoption is the geographic extent of the pests that we have documented. In particular, our counterfactual productivity gains only incorporate the yield benefits associated with pests that are actually present in a given country. This information is extracted from the geographic distribution tables on the CABI website.

A.5 Details of Large Language Model

We run our text analysis with Qwen3-14B, an open-weights model, on the cluster of the Minnesota Supercomputing Institute (MSI) at the University of Minnesota. We run the model in 16-bit (bfloat16) precision, served with vLLM 0.31.0, with two NVIDIA A100 GPUs per job. Decoding is greedy (temperature 0), so there is no random sampling, and the model's thinking mode is off. We convert each PDF to text with PyPDF2. We cannot read 1,307 of the 95,680 PDFs, and 110 are scans with no text layer. Among the remaining 94,263, PDFs with identical text are processed once, which leaves 73,214 distinct articles. We split each text into chunks of at most 4,000 characters, with 200 characters of overlap, using LangChain's recursive character splitter. One call on the first chunk asks for the article's title, with answers limited to 150 new tokens. One call per chunk then asks for a table with one row per finding and the columns pest, crop, locality, damage, and statement, with

Figure A.3: Damages from Invertebrate Pests in the United States



Notes: Distribution of damages from invertebrate pests in the United States. Data are taken from loss estimates from the Crop Protection Network, a product of land-grant universities, for 2021–2024.

answers limited to 1,600 new tokens. We keep table rows with exactly five cells and blank any damage cell that contains no digit. Because GPU arithmetic is not exactly reproducible, a rerun can differ slightly. Each extraction call sends the system prompt and user prompt below. The system prompt reads,

> "You are a helpful assistant that extracts and structures information from text. Your job is to identify pests, the crops they affect, the location mentioned, and the damage inflicted. Include a row even if some fields are missing - but do not guess. Output a row per finding with the columns: pest, crop, locality, damage, statement.
>
> ONE ROW PER COMBINATION. When more than one pest, crop, or locality applies to a finding, split it into a separate row for each - do not pick one and discard the rest, and do not put two values in one cell. The damage and the statement are repeated on each row. This applies whether the multiple values sit in the SAME sentence as the number, or are carried in from elsewhere in the chunk: if the sentence carrying the number names no pest and the chunk names two pest species, emit a row for EACH species - do not just take the first one you saw. A finding with 2 candidate pests and 2 localities becomes 4 rows.
>
> EXTRACT EVERY FINDING IN THE CHUNK - but only PEST-RELATED findings (see WHEN TO OUTPUT A ROW AT ALL below). A chunk usually contains several separate findings, often in different paragraphs. Work through the whole chunk to the end and output a row for every one - do not stop after the first, and do not report only the most prominent - a finding late in the chunk counts as much as one in the first sentence. A chunk about unrelated subject matter with no pest content gets ONE empty row, not many.
>
> THE CHUNK IS THE UNIT, NOT THE SENTENCE. A finding's pest, crop, or locality is often named in a nearby sentence rather than in the sentence carrying the number. You may carry those values onto the row. Use anything stated anywhere in this chunk; never invent a value that appears nowhere in it (the single exception is geography: see LOCALITY below). If a value is genuinely absent from the whole chunk, leave that field blank - but still output the row.
>
> EXCEPTION - GEOGRAPHY. Locality is the ONE field where you may use your own knowledge rather than the chunk's words. If the chunk names a place, you may say where it is: e.g. the chunk says 'Chokwe' and you know it is in Mozambique, write 'Mozambique'. Give the geography at whatever level you are MOST CONFIDENT about:

- the COUNTRY, if you are sure of it (preferred);

- otherwise a broader region you ARE sure of ('West Africa', 'Sub-Saharan Africa', 'Africa');

- otherwise the town, district, or province exactly as written;

- and if you cannot place it even at the broadest level, leave locality BLANK. Never make up a place. Work down the ladder above until you reach a level you are actually confident about, and stop there - a blank locality is far better than a wrong country. Do not state a country you are unsure of; step out to a region instead. This exception is for GEOGRAPHY ONLY. Never infer a pest, a crop, or a damage number that is not stated in the chunk.

THE DAMAGE FIELD - apply this test to every number you are tempted to put there: Does this number answer the question: 'How much YIELD, CROP HARVEST, or CROP PRODUCTION was LOST because of a pest?' If YES -> it is damage. If it answers any other question -> leave the damage field BLANK.

It must be a LOSS of yield or crop, not a gain. And the number must quantify that loss as a quantity of crop (tonnage, weight, area, or a percentage of the harvest) - not a count of pests, not a rate of infection or of plants damaged, not money, not grain quality. For example, a 10% yield loss, a loss of 2.5 t/ha, 10% of the national crop lost, and 30% of the crop destroyed all pass the test. When a number does not pass, leave damage blank; the number is still preserved in the statement field.

If damage is described only in words with no number ('severe damage', 'a serious threat'), leave the damage field blank. The sentence still goes in the statement field.

WHEN TO OUTPUT A ROW AT ALL. A row requires a PEST - either a named pest, or a sentence reporting damage/loss clearly caused by a pest even if unnamed. A place or crop mentioned with no pest and no damage is not a finding. Some chunks are not about pest damage at all - for those, output ONE empty row and stop.

ALWAYS OUTPUT THE ROW (once you HAVE a real pest-related finding, per the rule above). Don't discard a finding just because damage, crop, or locality ends up blank on it - output the row with whatever fields you have and the verbatim statement. Never drop a row just because the damage field failed the test.

DAMAGE FORMATTING (separate from the above): once a number passes the

test, write ONLY the bare figure and its unit - '12%', not '12% yield loss'; '2.5 t/ha', not 'yield loss of 2.5 t/ha'. The descriptive words are already preserved verbatim in the statement field.

LOCALITY (see EXCEPTION - GEOGRAPHY above): must be a real geographic place. NOT a crop growth stage (V6, R1), NOT an altitude band ('low altitude', '<1000 m'), NOT a date, NOT an experimental setting ('on-station', 'on-farm', 'farmers' fields'), NOT an experimental treatment. If no real place is named or implied, leave it blank.

STATEMENT: the verbatim sentence from the chunk containing the finding. Do not paraphrase."

The user prompt reads,

"Text chunk (do not use any information outside of this):

{chunk_text}

Extract *verbatim*:

1. Pest name (e.g., 'B. fusca'). Prefer the specific species over a generic group name ("stemborers", "borers", "the pest"): if the chunk names the species, use them - one row each - not the group name. Use a generic name only when no species is named anywhere in the chunk. Likewise, when two or more pests apply to a finding, include a separate row for each pest, repeating the crop, locality, damage, and statement across those rows. This holds whether they are named in the same sentence as the number (e.g. "the stemborers Busseola fusca and Chilo partellus") OR the number's sentence names no pest and the two species are named elsewhere in the chunk - in that case emit a row for each species, not just the first one you saw.

2. The crop(s) that pest affects. If a single finding names more than one crop, include a separate row for each crop.

3. The geography. You MAY use your own knowledge here (this is the only field where you may). Give it at whatever level you are MOST CONFIDENT about:

- the COUNTRY, if you are sure of it (preferred) - including working it out from a town or district named in the chunk, e.g. "Chokwe" -> "Mozambique";

- otherwise a broader region you ARE sure of - "West Africa", "Sub-Saharan

Africa", "Africa";

- otherwise the town, district, or province exactly as written;

- and if you cannot place it even at the broadest level, leave locality BLANK.

Never make up a place. Work down that ladder until you reach a level you are actually confident about, and stop there - a blank locality is far better than a wrong country. Do not state a country you are unsure of; step out to a region instead. This applies to geography only: never infer a pest, a crop, or a damage number that is not stated in the chunk. If two different countries apply to a finding, include a row for each. The geography must be a REAL place - NOT a crop growth stage (V6, V7, VT, R1, R2), NOT an altitude band ('low altitude', '<1000 m'), NOT a date, NOT an experimental setting ('on-station', 'on-farm', "farmers' fields"), NOT an experimental treatment. If the only location-like token is one of these, leave the locality blank.

4. The damage inflicted, as ONLY the bare number and its unit - no describing words (e.g. '10%' not '10% yield loss'; '2.5 t/ha' not 'yield loss of 2.5 t/ha'; '39-100%' not '39-100% loss'; '3-fold' not '3-fold reduction'). Before writing any number here, apply the test:

"Does this number answer: HOW MUCH YIELD, CROP HARVEST, OR CROP PRODUCTION WAS LOST because of a pest?"

YES -> it is damage.

Anything else -> leave the damage field BLANK.

It must be a LOSS of yield or crop, not a gain, and the number must quantify that loss as a quantity of crop - not a count of pests, a rate of infection or of plants damaged, money, or grain quality. If the damage is described only qualitatively with no number (e.g. 'severe damage', 'a serious threat'), leave the damage field blank.

5. The full statement (exact complete line or sentence from the chunk referencing damage inflicted).

- Do not paraphrase.
- Do not invent data. If a pest, crop, or locality is not stated ANYWHERE in this chunk, leave that field blank. But if it IS stated somewhere in the chunk (e.g. the pest is named in the sentence before the one carrying the number), use it. The chunk is the unit, not the sentence.

Output results as a markdown table following the structure below, and nothing else:

[*markdown table row(s) removed for clarity*]

=== The rows below are FORMAT ILLUSTRATIONS ONLY. They are not data. They deliberately use a
=== different crop and pest from anything you will meet in the text. Never copy a pest, crop,
=== locality, number, or statement from them into your output. Every row you output must come
=== from the text chunk above. If the chunk has no findings, output one empty row.

Example 1 - passes the test (a quantity of crop, lost):
Text: "In Ecuador, the banana caterpillar caused 12% yield loss in bananas."
[*markdown table row(s) removed for clarity*]

Example 2 - one sentence, two regions, two numbers -> two rows:
Text: "Bunch yield losses of 30% and 18% were recorded in Ecuador and Costa Rica, respectively, for the banana caterpillar on bananas."
[*markdown table row(s) removed for clarity*]

Example 3 - one sentence, TWO PESTS sharing one damage figure -> two rows. Do not pick one
pest and discard the other; repeat the damage and statement on both rows:
Text: "The banana caterpillar and the banana weevil together caused 22% bunch yield loss in Ecuador."
[*markdown table row(s) removed for clarity*]

Example 4 - FAILS the test, but the row is still output. The number is real and the pest is
named, but it answers "how much MORE crop was produced," not how much was lost. Damage stays
blank; the sentence is still captured:
Text: "Breeding for resistance to the banana caterpillar increased bunch yield by 24% per cycle."
[*markdown table row(s) removed for clarity*]

=== End of illustrations. Extract only from the text chunk."

Appendix B Additional Results

B.1 Biotic Risk Maps

These maps show static GEMS climatic suitability, aggregated to the country level using 2000 GAEZ corn production weights and restricted to countries where CABI records the pest as present. They do not vary across counterfactual years.

Figure B.1: Country-Level Biotic Risk Map: Maize Stalk Borer (*Busseola fusca*)

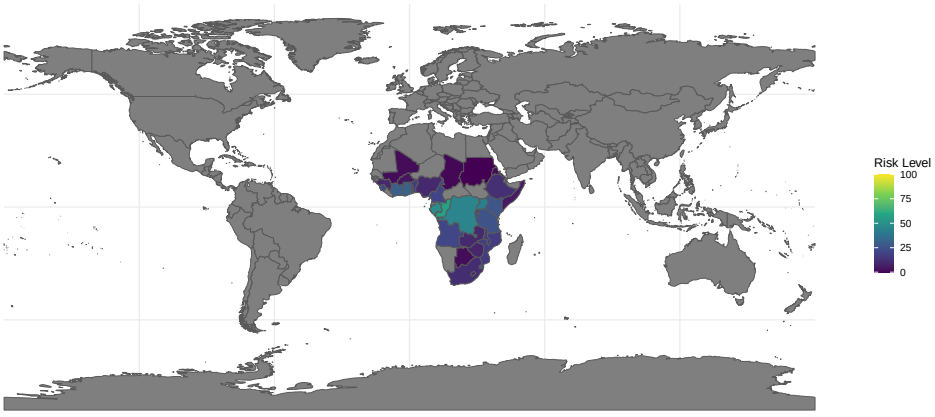


Figure B.2: Country-Level Biotic Risk Map: Spotted Stemborer (*Chilo partellus*)

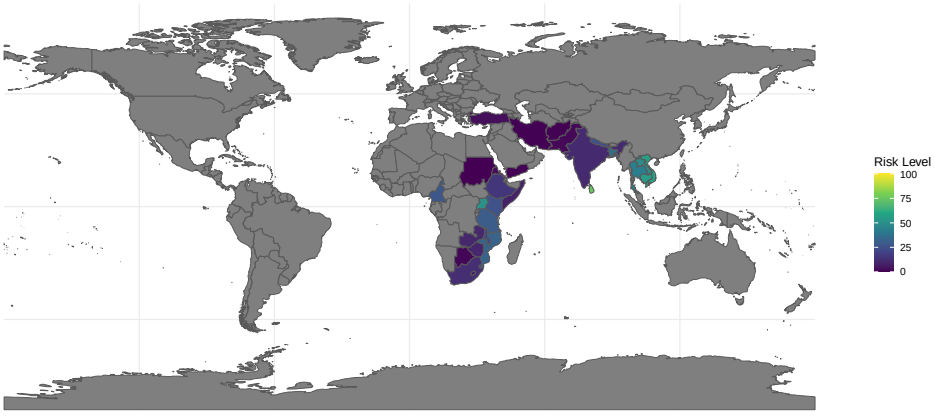


Figure B.3: Country-Level Biotic Risk Map: Maize Leafhopper (*Cicadulina mbila*)

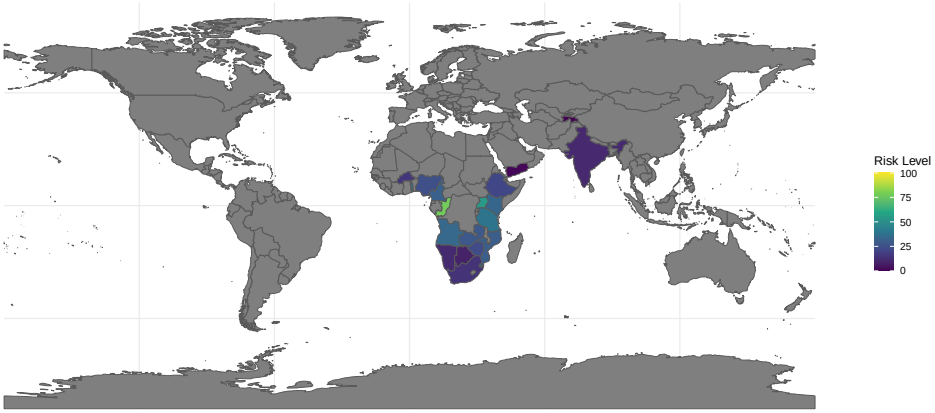


Figure B.4: Country-Level Biotic Risk Map: Beet Armyworm (*Spodoptera exigua*)

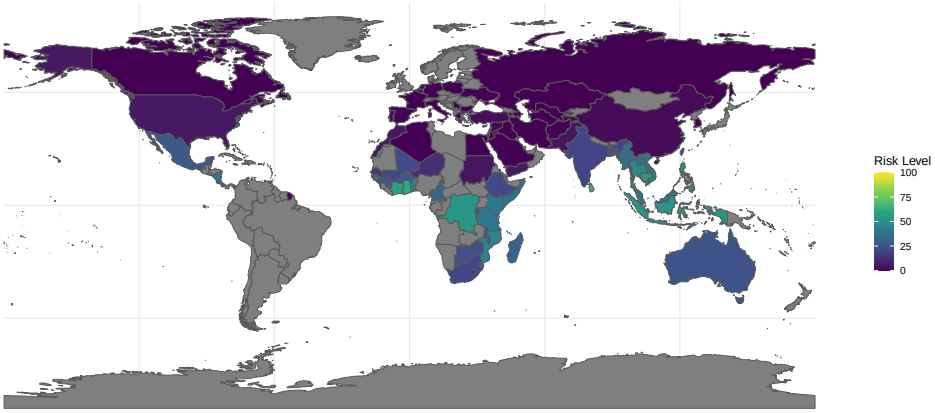
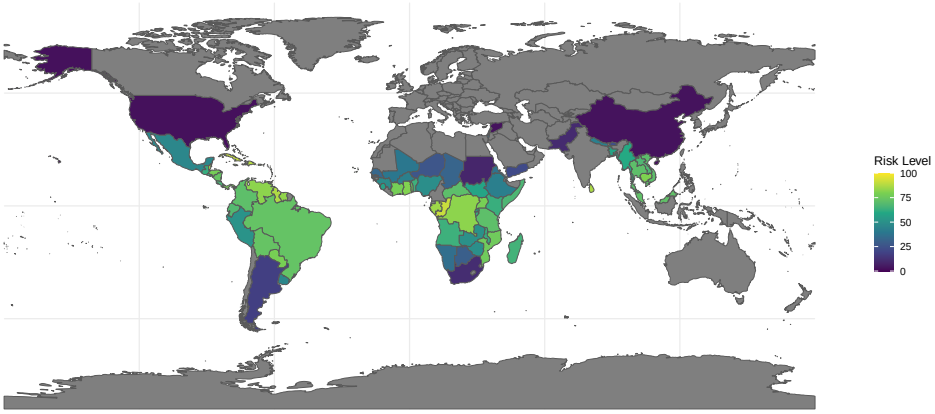


Figure B.5: Country-Level Biotic Risk Map: Fall Armyworm (*Spodoptera frugiperda*)



Notes: Country-Level Biotic Risk Map: Fall Armyworm

Figure B.6: Country-Level Biotic Risk Map: European Corn Borer (*Ostrinia nubilalis*)

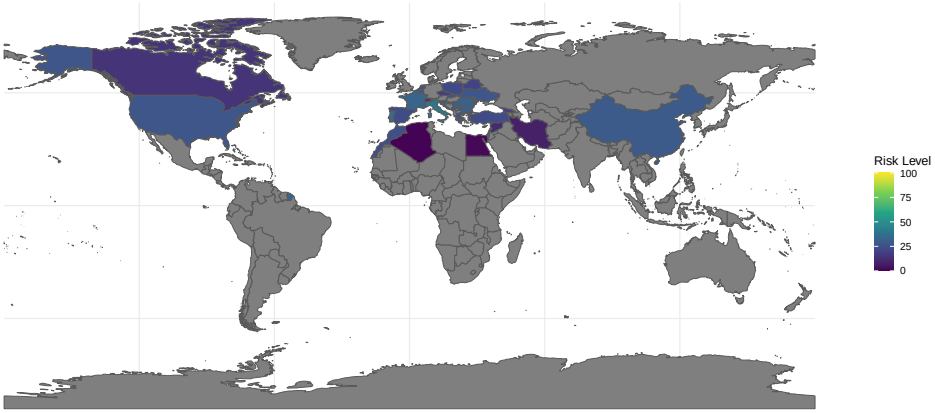
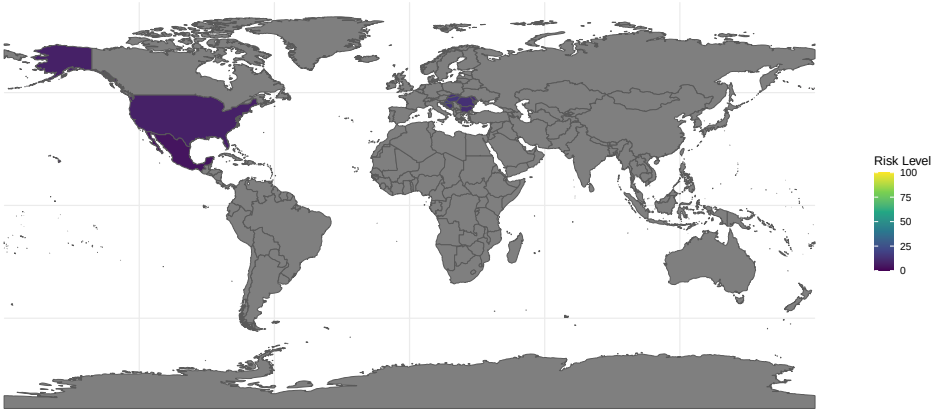


Figure B.7: Country-Level Biotic Risk Map: Western Corn Rootworm (*Diabrotica virgifera virgifera*)



B.2 Major Pests

Table B.1: Major Corn Pests in Arora (2017)

Order	Pest	Controlled by Cry?
Lepidoptera	Ostrinia nubilalis	Yes
Lepidoptera	Ostrinia furnacalis	Yes
Lepidoptera	Chilo partellus	Yes
Lepidoptera	Sesamia nonagrioides	Yes
Lepidoptera	Sesamia cretica	Yes
Lepidoptera	Sesamia calamistis	Yes
Lepidoptera	Sesamia inferens	Yes
Lepidoptera	Busseola fusca	Yes
Lepidoptera	Eldana saccharina	Yes
Coleoptera	Diabrotica virgifera virgifera	Yes
Coleoptera	Diabrotica virgifera zeae	Yes
Coleoptera	Diabrotica undecimpunctata	Yes
Coleoptera	Diabrotica barberi	Yes
Lepidoptera	Diatraea grandiosella	Yes
Lepidoptera	Diatraea saccharalis	Yes
Lepidoptera	Diatraea lineolata	Yes
Lepidoptera	Helicoverpa zea	Yes
Lepidoptera	Spodoptera frugiperda	Yes
Hemiptera	Cicadulina mbila	No
Hemiptera	Rhopalosiphum maidis	No
Coleoptera	Sitophilus zeamais	No
Lepidoptera	Sitotroga cerealella	No

B.3 Income Gradient Regressions with the 2005 Portfolio

A positive income gradient could be obscured by our particular measure of preventable damages or by our procedure for imputing missing insect-country damages, which assigns regional mean damages to countries without direct estimates. To evaluate the sensitivity of our results to these concerns, we construct two additional event-level damage measures that proxy for preventable yield losses. The first measure sums the full extent of damages across insects on a per-variety basis. This measure contains information about the income gradient of preventable yield losses, but not their level. Our second measure, designed to evaluate concerns about pest co-occurrence, takes the maximum of the insect-level damages reported among the insects that a variety protects against. We estimate the gradient for each of these measures and for our baseline biotic-risk-adjusted measure, using both imputed damages and only directly reported damages. To evaluate the inappropriateness gradient, one would also like to control for the production of corn. Unfortunately, actual corn production is affected by the very insects we study, which themselves reduce yields. We address this by instead using measures of potential corn production from the UNFAO GAEZ project, aggregated to the country level.[34]

For these regressions, we estimate $Damage_{j,2005} = \beta_0 + \beta_1 \ln(GDPPC_j) + \beta_2 \ln(CornPotential_j) + \epsilon_j$, separately for the optimal event and the mean across events, and using alternative measures of preventable pest damages. We use the 2005 technology portfolio rather than the 2000 portfolio because MON88017, approved for cultivation in the United States in 2005, introduced protection against the corn rootworm complex, an important source of corn damage in the United States.[35] The 2005 subscript refers to the technology portfolio rather than the dates of the underlying damage studies.

[34]Specifically, we use measures of agro-climatic potential yield based on historical climate data from 1981–2010, which incorporate information on agro-climatic conditions, soil characteristics, and local terrain, along with assumptions about management, such as the availability of fertilizer and irrigation.

[35]The corn rootworm complex includes *Diabrotica virgifera*, *Diabrotica undecimpunctata*, and *Diabrotica barberi*. See the USDA-APHIS approval document at https://www.aphis.usda.gov/sites/default/files/04_12501p_com.pdf.

Table B.2: Cross-Country Preventable Damages in 2005: Optimal

	Imputed Damages			Reported Damages		
Dependent Variables:	Biotic Damages	Sum of Damages	Max of Damages	Biotic Damages	Sum of Damages	Max of Damages
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	9.858	0.5715	32.56	-4.129	-288.4***	-51.75
	(16.74)	(68.79)	(20.07)	(20.87)	(91.94)	(38.01)
lnGDPPC	-0.5387	-5.826	-0.1515	-1.556	-2.503	2.193
	(1.179)	(4.847)	(1.414)	(1.208)	(5.323)	(2.200)
logPotential	0.5971	11.03***	1.259	1.717	22.85***	4.650**
	(0.7548)	(3.102)	(0.9051)	(1.054)	(4.645)	(1.920)
Fit statistics						
Observations	139	139	139	49	49	49
R^2	0.00736	0.10714	0.01506	0.09008	0.34989	0.12574

Notes: IID standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Imputed damages include higher level damage reports attributed to individual countries using pest geography data from CABI in cases where country level information is missing. 2005 refers to the technology portfolio used to construct the dependent variable, not the dates of the underlying damage studies. logPotential is GAEZ agro-climatic potential yield under 1981-2010 climate.

Table B.3: Cross-Country Preventable Damages in 2005: Mean

	Imputed Damages			Reported Damages		
Dependent Variables:	Biotic Damages	Sum of Damages	Max of Damages	Biotic Damages	Sum of Damages	Max of Damages
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	4.044	24.91	38.30*	-3.805	-99.98*	-8.652
	(6.480)	(45.78)	(20.41)	(7.000)	(58.43)	(38.08)
lnGDPPC	-0.0207	-6.051*	-1.602	-0.4642	-4.423	-0.5056
	(0.4566)	(3.226)	(1.438)	(0.4052)	(3.382)	(2.205)
logPotential	0.1392	6.499***	1.175	0.7281**	11.27***	3.081
	(0.2922)	(2.065)	(0.9204)	(0.3536)	(2.951)	(1.924)
Fit statistics						
Observations	139	139	139	49	49	49
R^2	0.00180	0.10684	0.02538	0.11241	0.26862	0.05478

Notes: IID standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Imputed damages include higher level damage reports attributed to individual countries using pest geography data from CABI in cases where country level information is missing. 2005 refers to the technology portfolio used to construct the dependent variable, not the dates of the underlying damage studies. logPotential is GAEZ agro-climatic potential yield under 1981-2010 climate.

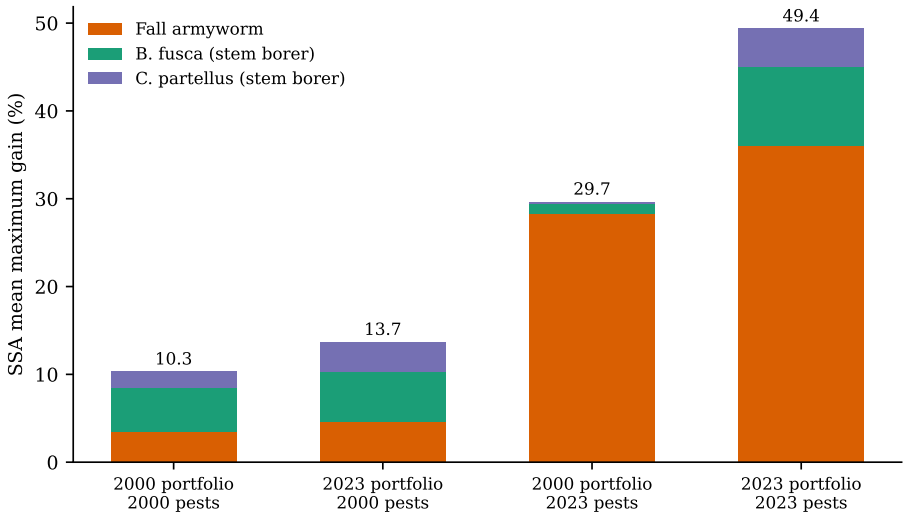
Appendix C Additional Tables and Figures

Table C.1: Predicted and Observed Yield Gains

Country	Observed period	Observed gain (%)	Prediction year	Predicted gain (%)	Predicted minus observed
Honduras	2001–2020	23.9	2011	14.7	−9.2
Colombia	2007–2020	17.1	2014	8.2	−8.9
Portugal	1998–2018	12.5	2008	9.8	−2.7
Spain	1998–2020	11.6	2009	12.0	+0.4
Brazil	2007–2020	11.5	2014	15.0	+3.5
South Africa	1997–2020	11.0	2009	3.4	−7.6
United States	1996–2020	7.0	2008	9.1	+2.1
Canada	1996–2020	7.0	2008	6.3	−0.7
Argentina	1998–2020	5.8	2009	4.1	−1.7
Uruguay	2003–2020	5.6	2012	7.6	+2.0
Mean, 10 countries					−2.3
Nigeria, TELA field trial	2020–2021	19.0	2020	17.6	−1.4

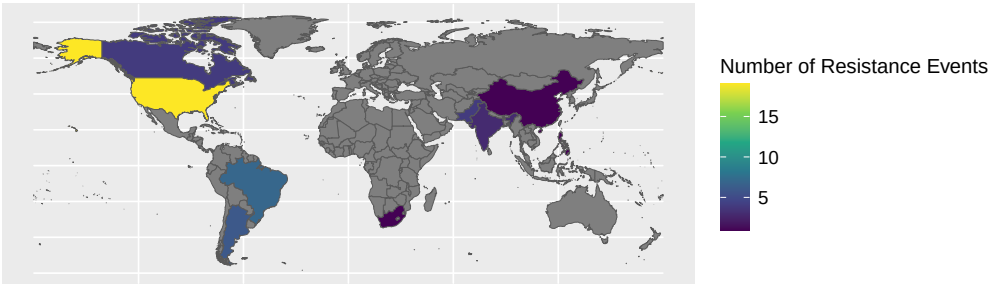
Notes: Observed gains are average yield gains from insect-resistant Bt corn over each country's years of adoption, from Brookes (2022) and, for Portugal, Brookes (2019). Predicted gains are based on the mean preventable yield loss across available events, from all controlled pests except the corn rootworms, using the technology portfolio and pest presence of the prediction year, the midpoint of the observed period. Brookes (2022) sets Canada's gain equal to that of the United States and Uruguay's equal to Argentina's, so these are not independent estimates. TELA hybrids carrying MON89034 against their non-Bt versions under stem borer and fall armyworm infestation, in confined field trials at Zaria in 2020 and 2021 (Oyekunle et al., 2023); not included in the means.

Figure C.1: Mean Maximum Yield Gain in SSA by Pest, Portfolio, and Year



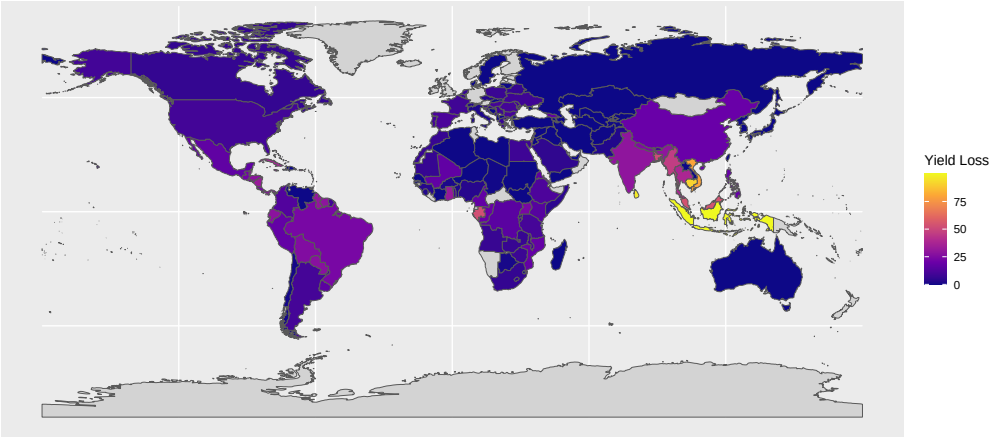
Notes: Mean across 43 Sub-Saharan African (SSA) countries of the maximum yield gain, from the available event with the highest gain in each country. The 2000 and 2023 portfolios include all Bt events approved for cultivation in at least one country by that year. Pest presence excludes pests first reported in a country by CABI after the pest-presence year. Each bar allocates the mean gain to pests in proportion to their shares of each country's preventable yield loss. Fall armyworm's contribution under 2000 pest presence comes from countries for which CABI records no first-report date, and are treated as present in every year.

Figure C.2: Practical Resistance Events by Country



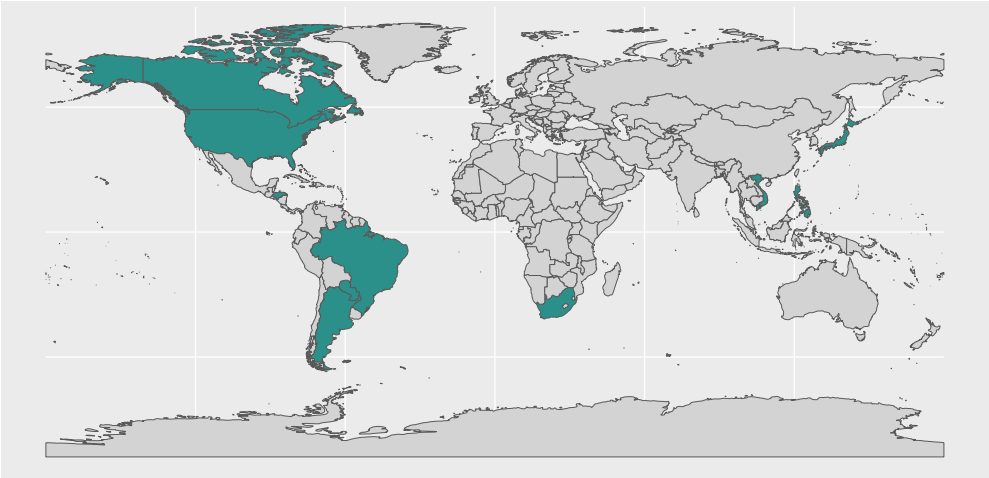
Notes: Distribution of Practical Resistance Events reported in Tabashnik et al. (2023), a review of the first 25 years of Bt crop cultivation.

Figure C.3: Yield Losses from Pests Targeted by MON89034



Notes: Yield losses associated with insects controlled by MON89034. MON89034 was first approved for cultivation in 2008 in the United States, Canada, and Japan. Pest presence is evaluated as of 2008; damage estimates and climatic suitability are not specific to 2008.

Figure C.4: Countries Approving MON89034 for Cultivation



Notes: Countries that ever approve MON89034 for cultivation in our ISAAA GM Approval Database records, which include approvals through 2024.