Agricultural Productivity and Biodiversity Effects: Theory and Evidence

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Abstract

Agricultural specialization maximizes land use efficiency but it also amplifies pest pressure, thereby requiring heavy pesticide use. This paper evaluates the economic benefits of reducing specialization to leverage natural pest control. We develop a model in which the resilience of a farmer's field is endogenous to the crop and pesticide choices of neighboring farmers. We account for both within-crop and between-crop cross-field externalities. Using global data on 40 crops and 41,820 counties, we estimate the impact of these externalities on crop productivity with novel instrumental variables. Our results show that maintaining a high diversity of crop species at the county level significantly increases yields of major crops like maize, rice, and wheat.

Keywords: crop yield, biodiversity, crop diversity, pest control, ecosystem services
JEL codes: Q15, Q51, Q57

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1 Introduction

This paper evaluates the economic benefits of reducing agricultural specialization to leverage natural pest control. Farmers face a complex dilemma, pondering two factors critical to crop survival: abiotic factors, related to weather and soil conditions, and biotic factors, related to the proliferation of pests. On one hand, specializing in the most suitable crop enables to exploit the abiotic characteristics of the land, increasing yield returns. On the other, specialization provides an ideal environment for pests to spread, decreasing yield returns. The result is a dilemma between maximizing individual yields through monoculture and minimizing the risk of pest damages (Weitzman, 2000). Uncontrolled, pest damage can be severe: yield losses for staple crops like maize, rice, and wheat could range between 50% and 70% (Oerke, 2006).

The standard response to pest threats is the use of pesticides, which comes at a high ecological cost (Tilman, 1999). Pesticides contaminate groundwater, degrade soils, and drive biodiversity loss.[1] Pesticide use also imposes a social cost as biodiversity loss undermines key ecosystem services like pollination and natural pest control.[2] Additional costs arise from the negative effects of degraded ecosystem services on human health (Frank, 2024; Frank and Sudarshan, 2024).

To limit the detrimental effects of pesticides, several countries have banned the most dangerous substances and intend to limit the use of remaining chemicals through successive regulations. However, such restrictions may reduce yields, while global food demand is projected to rise by 46% over the next three decades (Gouel and Guimbard, 2017). In this context, reducing specialization and increasing crop diversity emerges as a promising solution to balance the need for both environmental sustainability and high productivity. Experimental studies have demonstrated that diverse ecosystems are generally more productive (Tilman, Polasky, and Lehman, 2005). Regarding agriculture, increasing crop diversity has the potential to naturally reduce pest pressure. The presence of multiple crops dilutes the availability of a pest's preferred food source, making it harder for the pest to proliferate (Pianka, 2011). In addition, crop diversity fosters a more complex ecosystem by attracting pollinators and natural pest predators (Bianchi, Booij, and Tscharntke, 2006;

[1]Insecticides are identified as a major factor in the global 1% annual decline of insect populations (Van Klink et al., 2020), with losses reaching 76% near agricultural zones. In France, farmland bird populations fell by 25% between 1989 and 2009, the largest drop across habitats (Jiguet et al., 2012).

[2]In the US, the insect-mediated services are valued at $57 billion annually (Losey, 2009).

Redlich, Martin, and Steffan-Dewenter, 2018; Noack et al., 2022; Strobl, 2022). However, evidence on the economic viability of increasing crop diversity remains limited.

In this paper, we quantify global productivity gains from diversification. We combine a probabilistic model for crop production with geo-spatial data on land use, using a novel identification strategy. Our analysis thus contributes to the literature in two main ways. The first contribution is to propose a new model of crop production with endogenous biotic risk, stemming from pests. Building on the ecological approach of Weitzman (2000), Brock and Xepapadeas (2003), and Bellora and Bourgeon (2019), we assume that crop production is stochastic due to abiotic and biotic factors. Farmers choose which crop to grow and how much pesticide to use to maximize expected profits. Crucially, biotic risk depends not only on a farmer's own decisions but also on the crop and pesticide choices of neighboring farmers, generating *cross-field* biotic externalities. Accordingly, we distinguish two theoretical mechanisms: specialization effects, characterized as within-crop externalities following a change in a crop's land share, and diversification or biodiversity effects characterized as between-crop externalities following a change in the mix of other crops. Specifically, a field's survival probability decreases with the number of neighboring fields growing the same crop (specialization) and increases with the diversity of other crops species grown on neighboring fields (biodiversity) and pesticide use. Using this model, we derive the equilibrium land distribution among crops based on individual farmers' decisions and a testable equation for crop productivity.

Our second contribution is to empirically estimate the specialization and biodiversity effects on productivity. We operationalize these mechanisms at the county level: crop-specific farmland shares capture specialization effects, while an index of crop diversity, the Shannon index, which accounts for both crop richness and relative abundance, captures biodiversity effects. We then address endogeneity, e.g., current productivity responding to prior crop diversity, by implementing an identification strategy designed to recover causal effects. Using this strategy, which we discuss below, we find that both specialization and biodiversity effects significantly impact productivity. Moreover, analyzing 40 crops, we find heterogeneity across major monoculture crops. A 1% increase in crop diversity increases maize, rice, and wheat yields by 6%, 3.8% and 1.7% respectively. Finally, we demonstrate the potential gains of diversification on production and revenue using simulations. First, we investigate the effects of reducing specialization in each county. We redistribute 1% of the dominant crop's area equally to all other cultivated crops and show that the production of the dominant crop *increases* by 8% on average. In other words, the reduction in production due to the decrease in cultivated area is more than offset by the increase in productivity. Second, we simulate the rent-maximizing allocation of farmland, demonstrating that revenue maximization is achieved by increasing crop diversity by an average of 33% across counties.

Prior studies on the productivity-biodiversity relationship in agriculture focused on wheat *genetic* diversity: planting fewer wheat varieties lowers yields in Canada (Carew, Smith, and Grant, 2009), and a 1% increase in genetic diversity raised mean wheat yields by 0.11% in southern Italy (Di Falco and Chavas, 2006). Smale et al. (1998) find more nuanced results: greater wheat genetic diversity increases yields in Pakistan's rainfed areas but has a small negative effect in irrigated regions. Expanding the scope, Bellora et al. (2018) use satellite data from South Africa to show that higher crop diversity enhances resilience and productivity across various crops. Focusing on northwestern France, Bareille and Dupraz (2020) show that wheat and milk yields increase with farm-level crop diversity. Our paper also complements empirical studies on the benefits of crop diversity on alternative agricultural outcomes than crop yields, e.g. Di Falco and Chavas (2009) and Groom and Pereira Fontes (2021) on cereal *production* in Ethiopia, Auffhammer and Carleton (2018) on *revenue* resilience to droughts in India, and Renard and Tilman (2019) on the stability of national *harvests* across 91 countries. Overall, the literature indicates a positive and significant productive value of crop diversity, as demonstrated in the recent meta-analysis of Bareille and Largier (2025). Spanning 52 studies, they find that a 1% increase in crop biodiversity increases economic outcomes (including, but not limited to, crop yields) by 0.75% on average.

Our work distinguishes itself in several ways. First, we move beyond localized perspectives by assembling a global dataset covering over 40,000 counties. To do so, we combine geospatial data from FAO-GAEZ, on the potential suitability and productivity of land, and Earthstat, on actual yields and harvested areas. Second, our analysis spans a larger crop coverage that allows measuring *between-crop* diversity more consistently. Third, we estimate crop-specific productivity gains, which allows to explore heterogeneity. Eventually, we propose a new identification strategy that leverages exogenous variations in cropland patterns driven by local climate and soil conditions. Specifically, we use FAO-GAEZ suitability scores to construct *potential* counterparts to actual farmland shares and crop diversity, which serve as instrumental variables (IV). These exogenous measures minimize concerns about endogeneity since FAO-GAEZ scores derive from agronomic models rather than statistical relationships.

The paper proceeds as follows. Section 2 presents the probabilistic model. Section 3.1 describes the data, while Section 3.2 outlines the empirical and identification strategy. Section 4 presents the estimated parameters, which are also used to conduct simulation exercises. Eventually, Section 5 concludes.

2 Theoretical Framework

2.1 General Setup

We consider a world of N countries, where each country n is divided into J_n spatial units. For convenience, these units are referred as counties, though the model can be applied at other scales. Each county $j \in \{1, \dots, J_n\}$ is subdivided into fields of equal size. Each field, or unit of land, is cultivated by a farmer who grows a single crop using one unit of labor and pesticides. Each crop $k = \{1, \dots, K\}$ is treated as a homogeneous good.

2.1.1 Productivity

Productivity varies across crops and locations. The *actual* output of crop k per unit of land and labor in area j will always be lower than or equal to its *potential* output. Factors reducing production fall into two categories: abiotic (weather and soil conditions such as temperature, light and precipitation) and biotic (pests and interactions among plants, insects, and bacteria).

Farmers use pesticides to mitigate production losses due to biotic factors, but at a cost to human health and the environment. Governments limit this externality by taxing pesticide use with the environmental tax τ_j.[3] To maintain neutrality in government budget and farmers' income, we suppose that the tax policy is offset by a subsidy T_j^k, equal to the average tax payment in county j for crop k. Farmers choose pesticide intensity ρ to maximize profits:

$$\pi_j^k \equiv \max_{\rho} \mathbb{E}[\tilde{y}_j^k] p_j^k - \tau_j \rho + T_j^k - c_j \tag{1}$$

[3]For simplicity, we abstract away from the production and market dynamics of agrochemicals. Implicitly, we assume that farmers are endowed with a large stock of agrochemicals that is not depleted by farming activities, resulting in a zero market price.

with $\tilde{y}_j^k$ the farmer's stochastic production level, p_j^k the price of crop k, and c_j the cost of labor and land in county j.

2.1.2 Crop Resilience

Adverse abiotic and biotic shocks occur independently across fields. However, biotic risks depend not only on a farmer's own decisions but also on the crop and pesticide choices of neighboring farmers due to *cross-field* biotic externalities. The resilience of a field growing crop k in county j is thus a function of the farmer's pesticide intensity, ρ, as well as the cross-field biotic effects within the county. Let $\psi_j^k(\rho; \boldsymbol{S_j}, \boldsymbol{\rho_j})$ denote the resilience function, with $\boldsymbol{S_j} \equiv \{S_j^k : k = 1, \ldots, K\}$ the distribution of fields between crops, and $\boldsymbol{\rho_j} \equiv \{\bar{\rho}_j^k : k = 1, \ldots, K\}$ the vector of average pesticide use. S_j^k is the share of fields dedicated to crop k in county j, with $S_j^k \geq 0$ and $\sum_k S_j^k = 1$, while $\bar{\rho}_j^k$ denotes the average treatment applied to all fields growing crop k in j. Using this notation, (1) becomes

$$\pi_j^k = \max_{\rho} \bar{a}_j^k \psi_j^k(\rho; \boldsymbol{S_j}, \boldsymbol{\rho_j}) p_j^k - \tau_j \rho + T_j^k - c_j, \tag{2}$$

where $\bar{a}_j^k$ is the potential productivity of crop k in county j. Hence, the expected productivity z is given by

$$z_j^k = \psi_j^k(\rho_j^{k\star}; \boldsymbol{S_j^\star}, \boldsymbol{\rho_j^\star}) \bar{a}_j^k. \tag{3}$$

Assuming that adverse weather shocks and pest attacks occur independently, the resilience function is the product of three stochastic components, i.e.[4]

$$\psi_j^k(\rho; \boldsymbol{S_j}, \boldsymbol{\rho_j}) \equiv A_j^k \mu_j^k(\rho) B_j^k(\boldsymbol{S_j}, \boldsymbol{\rho_j}), \tag{4}$$

where $A_j^k < 1$ is the probability that a field survives abiotic shocks, $\mu_j^k(\rho)$ is the within-field biotic probability, and $B_j^k(\boldsymbol{S_j}, \boldsymbol{\rho_j})$ captures cross-field biotic effects. We specify the within-field biotic probability as

$$\mu_j^k(\rho) \equiv \exp\left[-(\hat{\rho}_j^k - \rho)^2 / 2\lambda_j^k\right], \tag{5}$$

with $\hat{\rho}_j^k$ the unrestricted treatment level of pesticides and $\lambda_j^k > 0$ a measure of pests

[4] Allowing for dependence between weather shocks and pest attacks would complicate the model without changing our decomposition. We keep independence for tractability and control for potential dependence empirically.

resistance, such that the larger λ_j^k the more effective the pesticides. By choosing pesticide intensity $\rho = \hat{\rho}_j^k$, the farmer ensures that this probability equals one. However, this is not the farmer's optimal strategy when $\tau_j > 0$.

The cross-field biotic effects are defined as:

$$B_j^k(\boldsymbol{S_j}, \boldsymbol{\rho_j}) \equiv \prod_{\ell=1}^{K} \mu_j^\ell(\bar{\rho}_j^\ell) \exp\left[-\hat{\kappa}_k(S_j^\ell)\right]. \tag{6}$$

The first term, $\mu_j^\ell(\bar{\rho}_j^\ell)$, measures the fraction of fields sown with crop ℓ that survive direct biotic factors. The second term, $\exp\left[-\hat{\kappa}_k(S_j^\ell)\right]$, captures the biotic externalities from crop ℓ to crop k, conditional on crop ℓ surviving. The sign and magnitude of these externalities depend on ℓ and on its share in county j through function $\hat{\kappa}_k(\cdot)$, specified below.

2.2 Market Equilibrium

We assume perfect competition, with farmers atomistic in county j. In Appendix A, we show that the equilibrium pesticide use for crop k is a dominant strategy, $\rho_j^{k\star} = \hat{\rho}_j^k - \lambda_j^k \tau_j / c_j$, regardless of $\boldsymbol{S}_j^\star$ and $\boldsymbol{\rho}_j^\star$. Moreover, since at the land and labor market equilibrium farmers' expected profit is zero for any crop choice, expected gross revenue of land is equalized across crops: $p_j^k z_j^k = c_j$ for all k. As a result, farmers play mixed strategies over crop choices, yielding the equilibrium land allocation $\boldsymbol{S}_j^\star$.[5] We also obtain the following result:

Proposition 1. *In equilibrium, actual productivity for crop k in area j is given by*

$$z_j^{k\star} = \frac{a_j^k \exp\left[-\sum_\ell \hat{\kappa}_k(S_j^{l\star})\right]}{t_j^k \prod_\ell t_j^\ell}, \tag{7}$$

with $a_j^k = \bar{a}_j^k A_j^k$ and $t_j^k \equiv \exp\left[\lambda_j^k (\tau_j/c_j)^2/2\right]$.

Proof. See Appendix A.1.

Actual productivity, as defined in (7), depends on the potential productivity, accounting for abiotic risk, a_j^k, cross-field effects, $\exp\left[-\sum_\ell \hat{\kappa}_k(S_j^{\ell\star})\right]$, and pest policy effects t_j^k and $\prod_\ell t_j^\ell$. The first pest policy effect, $t_j^k = 1/\mu_j^k(\bar{\rho}_j^{k\star})$, corresponds to the inverse of the survival

[5] $S_j^{k\star}$ refers both to the probability that a farmer in j chooses crop k and to the equilibrium share of that crop in j.

probability of crops to direct biotic factors, while the second policy effect arises from cross-field externalities. Thus, an increase in the environmental tax τ_j reduces pesticide use in *all* fields, thereby diminishing the positive cross-field externalities of pesticides on k's survival. This is reflected by an increase in t_j^k and all t_j^ℓ in the denominator of (7).

2.3 Cross-Field Biotic Effects

To further investigate the model's predictions, we assume a functional form that decomposes the cross-field biotic term in Eq. 6, $\hat{\kappa}(\cdot)$, into within- and between-crop effects:

Assumption 1 (Decomposition of cross-field biotic externalities). *For crop k,*

$$\hat{\kappa}_k(S_j^k) = \kappa_{0k} S_j^k \quad \textit{(within-crop effects),}$$

and, for all $\ell \neq k$

$$\hat{\kappa}_k(S_j^\ell) = -\kappa_k \left[\frac{1}{K-1} \ln\left(\frac{1}{K-1}\right) - \frac{S_j^\ell}{1-S_j^k} \ln\left(\frac{S_j^\ell}{1-S_j^k}\right)\right] \quad \textit{(between-crop effects).}$$

Under this assumption, we have

$$B_j^k(\boldsymbol{S_j}, \boldsymbol{\rho_j}) = \prod_{\ell=1}^{K} \mu_j^\ell(\bar{\rho}_j^\ell) \exp\left[-\kappa_{0k} S_j^k - \kappa_k \left(\bar{H} - H_j^k\right)\right],$$

with

$$H_j^k \equiv -\sum_{\ell \neq k} \frac{S_j^\ell}{1-S_j^k} \ln \frac{S_j^\ell}{1-S_j^k} \tag{8}$$

the *leave-one-out* Shannon index, which measures the diversity of crops $\ell \neq k$, and $\bar{H} \equiv \ln(K-1)$ its maximum. The difference $\bar{H} - H_j^k$ measures the gap between *maximum* diversity—when all other existing crops are equally represented—and *actual* diversity. This specification aligns with standard ecological diversity measures and ensures that $B_j^k(\boldsymbol{S_j}, \boldsymbol{\rho_j}) \leq 1$. Replacing, (7) becomes

$$z_j^{k\star} = \frac{a_j^k \exp\left[-\kappa_{0k} S_j^{k\star} - \kappa_k(\bar{H} - H_j^{k\star})\right]}{t_j^k \prod_\ell t_j^\ell} \tag{9}$$

This specification allows us to distinguish two biotic externalities affecting crop k's productivity. The first externality is a *specialization* effect, captured by the within-crop coefficient κ_{0k}, which is linked to an increase in the crop's land share. The second externality is a *biodiversity* effect, captured by the between-crop coefficient κ_k, which is linked to a decrease in the diversity of non-k crops relative to the maximum level. Both effects are expected to reduce productivity: higher specialization increases pest pressure, while lower diversity weakens area j's ecosystem, reducing natural pest control.[6]

2.4 Rent-Maximizing Equilibrium

So far, we analyzed allocation choices made by atomistic farmers who do not coordinate. We now consider a benevolent social planner who aims to determine the land allocation $\boldsymbol{S_j} \equiv \{S_j^k\}_{k=1}^K$ that maximizes total agricultural revenues in county j, taking into account cross-field externalities. The planner solves

$$\max_{\boldsymbol{S_j}} \left\{ \sum_k p_j^k z_j^k S_j^k : \sum_k S_j^k = 1 \right\}.$$

Our second proposition follows from this maximization problem:

Proposition 2. *To maximize total agricultural revenues, the share of crop k in area j must satisfy*

$$S_j^k = \frac{1}{\sum_{\ell\in\mathcal{K}} \frac{\kappa_{0k}}{\kappa_{0\ell}} \frac{p_j^k z_j^k}{p_j^\ell z_j^\ell}} \left[1 + \sum_{\ell\in\mathcal{K}} \frac{1}{\kappa_{0\ell}} \left(\frac{p_j^k z_j^k}{p_j^\ell z_j^\ell} - 1 \right) \right. \\ \left. + \sum_{\ell\in\mathcal{K}} \sum_{m\in\mathcal{K}} \frac{p_j^\ell z_j^\ell}{p_j^m z_j^m} \frac{\kappa_\ell S_j^\ell}{\kappa_{0m}} \left(\frac{\partial H_j^\ell}{\partial S_j^k} - \frac{\partial H_j^\ell}{\partial S_j^m} \right) \right]. \tag{10}$$

Proof. See Appendix A.3.

3 From Model to Data: Empirical Implementation

This section outlines our empirical strategy for estimating the model predictions regarding specialization and biodiversity effects. We first describe the data sources and variable

[6] The corresponding equilibrium farmland shares are derived in Appendix A.2.

construction, including measures of actual and potential productivity. We then link the model theoretical predictions to the data and discuss the identification strategy.

3.1 Data

We use two types of data: (i) *potential* measures of land suitability and productivity, and (ii) *actual* measures of yields and harvested areas. All measures are crop-specific and at a 5-arc-minute resolution (grid cells equivalent to 10km$\times$10km at the equator). We map cells to countries using the Global Administrative Areas Database (GDAM v4.0), and then aggregate cell measures at the *county* level j, defined as the country's second-level administrative unit. This aggregation trades off two considerations: minimizing measurement error, because cell-level measures are sometimes downscaled estimates of larger administrative units and can be noisy, and analyzing at a scale relevant for pest spread, which argues against overly large areas. Overall, our sample covers 41,820 counties, 148 countries and 40 crops. Appendix Tables B1 and B2 list the crops and countries.

3.1.1 Potential Measures

We source *potential* measures from version 4.0 of the Global Agro-Ecological Zoning (GAEZ) project (Fischer et al., 2021). GAEZ has the advantage of estimating yields from an agronomic model, which assesses the suitability of each cell for each crop based on edaphic and climatic resources, matched to crop-specific requirements. As a result, we obtain *exogenous* productivity measures for each cell and crop, independent of the actual land use (e.g., the cell being cultivated with another crop).

Suitability. Cells are assigned to a suitability class based on land quality: *very suitable*, *suitable*, *moderately suitable*, *marginally suitable*, *very marginally suitable* and *not suitable*. A normalized suitability index ranging from 0 to 10,000 is then computed for each cell, indicating the proportion of maximum yields that can be achieved. Cells corresponding to urban areas, protected areas and areas of high biodiversity are identified and assigned a suitability index of 0 for all crops.

Productivity. Based on the suitability predictions, potential productivity (t/ha) is assessed for various combinations of input levels (*high* or *low*)[7] and sources of water supply (*rainfed* or *irrigated*). Among the available combinations, we select the potential production density variable for a high level of inputs[8] and rainfed water source.[9] This measure averages potential production across the entire cell, regardless of the actual percentage of cultivated area. Following Costinot, Donaldson, and Smith (2016), when FAO-GAEZ distinguishes between species (e.g., *dryland rice* vs. *wetland rice*), but only aggregate information is available in the actual measures (e.g., *rice*), we use the maximum value between the two species.

3.1.2 Actual Measures

We use year-2000 measures of *actual* production (metric tons, t), harvested area (hectares, ha), and yields (t/ha) from the EarthStat database (Monfreda, Ramankutty, and Foley, 2008). These variables are observed or estimated by combining high-resolution data on cultivated areas with averages of agricultural census and survey statistics carried out between 1997 and 2003. To match weight units between *actual* and *potential* measures, we apply crop-specific wet-to-dry conversion factors provided by FAO-GAEZ.

The agricultural sector shows a high degree of specialization (see Appendix Tables B1 and B2). Ten crops account for nearly 79% of the global harvested area, and 50 countries represent over 87% of total crop production. In some cases, actual yields exceed potential yields (see Appendix Figure C1). This discrepancy may arise from reporting errors in EarthStat or inaccuracies in FAO-GAEZ's agronomic predictions.[10] We address these issues in the estimation below.

3.2 Estimation and Identification Strategy

3.2.1 Estimating Equation

Building on the model, we estimate the log form of (9):

[7] A high level represents advanced land management and market-oriented agriculture, and a low level represents traditional land management and subsistence agriculture.

[8] As potential yields are by definition greater than or equal to actual yields in our model, we prefer to select the highest values available for potential yields.

[9] Data for irrigated potential yields is limited, excluding major crops like rice and maize.

[10] One limitation of the potential productivity measure is that it does not account for genetically modified organisms and irrigation.

$$\ln z_j^k = \ln a_j^k - \kappa_{0k} S_j^k - \kappa_k(\bar{H} - H_j^k) - \ln t_j^k - \sum_{\ell} \ln t_j^{\ell},$$

where county j is the spatial unit of observation. Because information on pesticide regulations and pest resistance is imperfect, we proxy t_j^k with country×crop fixed effects, which absorb country–crop determinants of pesticide use. This rich set of fixed effects captures factors such as nationally set pesticide taxes, crop-specific pest resistance, and any country–crop co-movement between climate and pest pressure. Eventually, we estimate the following equation:

$$\ln z_j^k = \alpha_k \ln a_j^k + \beta_{0k} S_j^k + \beta_k H_j^k + \gamma_i^k + \epsilon_j^k. \tag{11}$$

For each crop k, we regress log actual productivity, $\ln z_j^k$, on: (i) log potential productivity, $\ln a_j^k$ (abiotic factors), (ii) the crop k's *farmland share*, S_j^k, which represents the share of county j's cultivated area devoted to crop k (*specialization effects*), (iii) the county crop diversity index, H_j^k (*biodiversity effects*)[11], and (iv) country i fixed effects, γ_i^k. ϵ is the usual error term. As potential yields a_j^k are estimated by GAEZ under the assumption of advanced land management everywhere, we expect $\alpha_k < 1$. Consistent with the model, we also expect $\beta_{0k} < 0$ and $\beta_k > 0$ for all k, reflecting negative specialization effects and positive biodiversity effects. Finally, because counties differ in size, we augment specification (11) with total agricultural area, L_j, ensuring that the estimated effect of farmland shares S_j^k is comparable across counties.

3.2.2 Measuring Crop Diversity

Mean Proportional Abundance. As defined in the theoretical section, we measure crop diversity by using the (leave-one-out) Shannon index H_j^k (see Eq. 8). The standard index is widely used in the ecological literature as a measure of the mean proportional abundance of crops in in a location.[12] It captures both crop richness and relative abundance (Shannon, 1948). Higher values indicate greater farmland heterogeneity, with a maximum value equals to $\ln K$ when all crops are grown in equal proportions.

[11] As $\bar{H}$ is constant across all observations, we omit it from the regression.

[12] The standard index is defined as $-\sum_{\ell=1}^{K} S_j^{\ell} \ln(S_j^{\ell})$.

Effective Diversity. To provide a more intuitive measure of biodiversity than the mean proportional abundance, we use Hill's numbers, known as the effective number of crops:

$$D_j^q \equiv \left[\sum_{\ell=1}^{K}(S_j^\ell)^q\right]^{1/(1-q)} \tag{12}$$

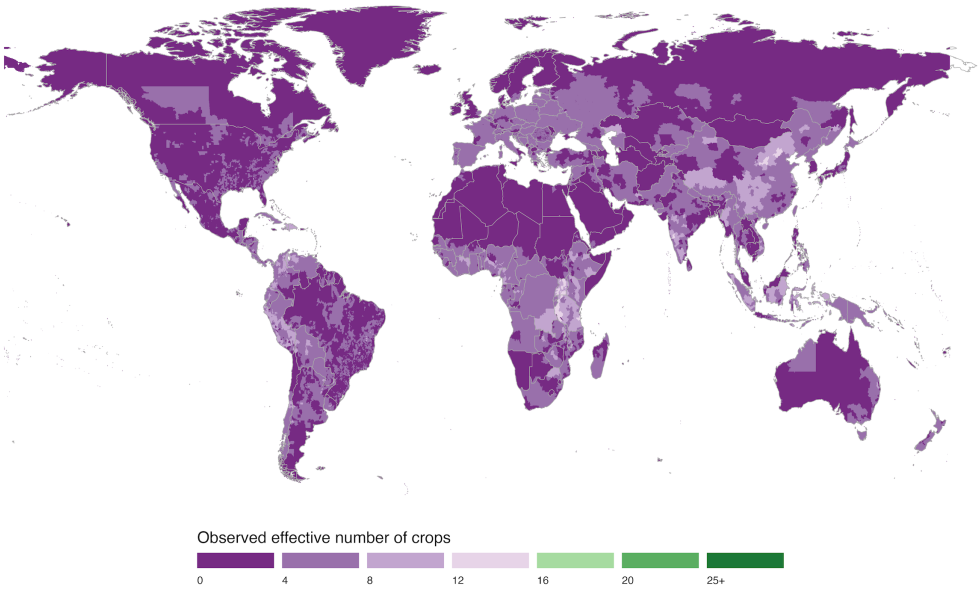
where $q \geq 0$ determines the sensitivity of the biodiversity measure to the relative abundance of crops. The index D_j^q represents biodiversity by considering both the total number of crops and their relative abundance. In other words, D_j^q represents the number of equally abundant crops needed to match the observed mean proportional abundance in country j, where crops may not be equally distributed. As $q \to 1$, Hill's numbers corresponds to the exponential of the Shannon index. Consequently, β_k in our estimated equation (11) can be interpreted as the elasticity of the actual yield of crop k with respect to effective diversity in the other crops, derived from the leave-one-out Shannon index H_j^k.

We compute the effective number of crops (12) for all counties in our sample. Figure 1 shows that counties around the world are highly specialized. On average, the potential effective number of crops is 4.5 (Panel A), while the observed number of crops grown is 17.2 (Panel B), reflecting the dominance of a few crops.

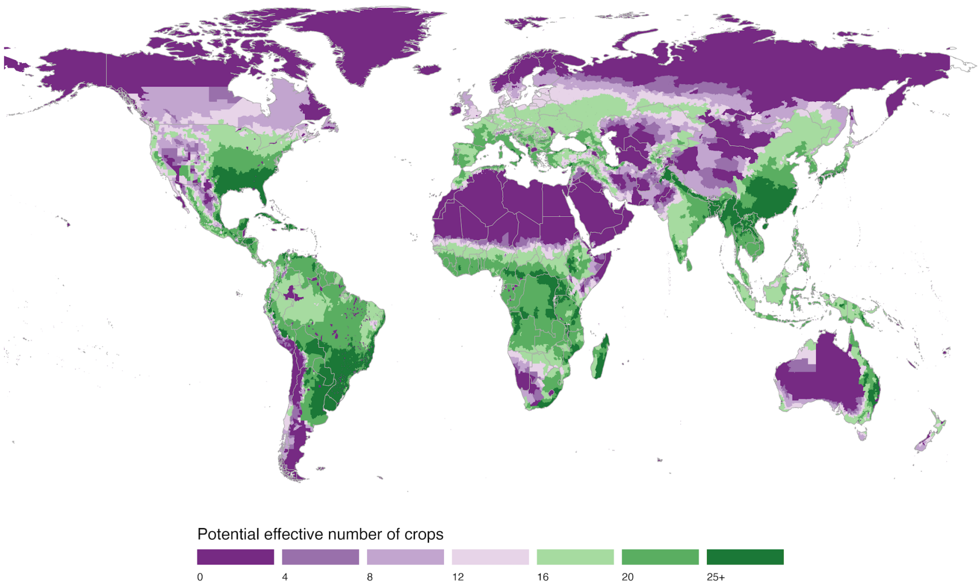
3.2.3 Accounting for Endogeneity

In practice, crop diversity and farmland shares may be endogenous to actual yields. First, since actual yields in our data are averaged over a six-year period, productivity in a given year may influence crop diversity in subsequent years. For example, improved wheat yields could encourage specialization in wheat, increasing its farmland share and reducing overall diversity. In this case, OLS estimates are likely downward-biased in absolute terms, for both specialization and biodiversity effects. Second, omitted factors unrelated to soil and climate conditions may influence both agricultural productivity and diversity. For instance, counties with better access to pesticide markets might exhibit higher yields and greater specialization, leading to upward-biased OLS estimates.

Our identification strategy leverages FAO-GAEZ suitability data to construct novel instrumental variables for farmland shares and crop diversity. Because suitability is derived from agronomic models and lab experiments rather than observed crop patterns, these instruments are likely to satisfy the exclusion restriction.



(a) Actual



(b) Potential

Figure 1: Effective crop diversity (Hill's numbers)

Notes: Actual effective number of crops (1a) and potential effective number of crops (1b) at the county level. Computed based on FAO-GAEZ, Earthstat.

Instruments for Farmland Shares. We consider two instruments for S_j^k, the share of county j's cultivated area devoted to crop k. The first instrument is the average share of land assessed by FAO-GAEZ as very suitable (when farmers can reach 80 to 100% of the maximum attainable yield for crop k) or suitable (60 to 80%). This variable is provided by FAO-GAEZ. The second instrument is built from our estimation of *potential* farmland share. In each county j, we compute the potential farmland share of crop k, $\tilde{S}_j^k$, as the ratio of the suitability of crop k, SI_j^k to the sum of the suitability of all crops:[13]

$$\tilde{S}_j^k = \frac{\mathrm{SI}_j^k}{\sum_{\ell=1}^K \mathrm{SI}_j^\ell}.$$

If land allocation prioritizes crops whose growth requirements align most effectively with local climate and soil characteristics, the two instruments should satisfy the relevance condition. Reassuringly, regressing actual shares on potential shares across all crops and counties reveals a positive and significant coefficient of value 0.770. We also plot our measure of potential against actual farmland shares for six major crops in Appendix Figure C2 and observe positive correlations.

Instrument for Crop Diversity. We construct an index of potential crop diversity using our estimated potential shares $\tilde{S}_j^k$:

$$\tilde{H}_j = -\sum_{\ell=1}^{K} \tilde{S}_j^\ell \ln(\tilde{S}_j^\ell).$$

Exponentiating gives the corresponding potential Hill's numbers ($\tilde{D}_j^1$), displayed in Figure 1b. We also compute the leave-out-one version of the potential Shannon index for each crop k, which serves as an instrument for its actual counterpart:

$$\tilde{H}_j^k = -\sum_{\ell \neq k} \frac{\tilde{S}_j^\ell}{1-\tilde{S}_j^k} \ln\left(\frac{\tilde{S}_j^\ell}{1-\tilde{S}_j^k}\right).$$

The relevance of the instrument is straightforward: counties whose natural conditions are suitable to a very limited number of crops are more likely to specialize in these crops, resulting in lower diversity indices. This pattern matches our data, where actual and potential diversity measures are positively and significantly correlated.[14]

[13]Such index of relative suitability is also used in Berman et al. (2023) to construct price indexes.
[14]As shown in Appendix Figure C3, this result holds for all but one continent, South America, where

Table 1: Parameters estimates

Dependent variable:	ln (Actual Yields)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln (Potential Yields)	0.098***	0.004***	0.007***	0.113***	0.049***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Farmland Shares	0.372***	0.874***	0.811***	-10.254***	-5.241***	-4.628***
	(0.01)	(0.01)	(0.81)	(0.56)	(1.14)	(0.81)
Crop Diversity	0.105***	-0.501***	-0.526***	1.397***	5.272***	4.272***
	(0.01)	(0.01)	(1.28)	(0.10)	(1.57)	(1.28)
Method	OLS	OLS	OLS	IV	IV	IV
Country×Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes
Pasture incl.	No	No	Yes	No	No	Yes
K.-P. F-stat[a]	–	–	–	233.3	10.7	27.8
Observations	589,958	589,958	589,958	589,958	589,958	589,958

Notes: Standard errors, robust to heteroskedasticity and clustering at the county level, are in parentheses with *, **, and *** denoting significance at the 1, 5, and 10% levels. Crop diversity is measured using the leave-one-out Shannon index, and specialization with farmland shares. Both instruments for farmland shares are used in IV regressions. In all columns but (1) and (4), we add county fixed effects. In the third and sixth columns, pasture area is included when farmland shares and leave-one-out Shannon indexes are computed based on FAO-GAEZ, Earthstat. [a]K.-P. F-stat denotes Kleibergen-Paap F-stat.

Identifying Assumptions. We require three assumptions to identify specialization and biodiversity effects. Conditional on potential yields and country fixed effects: (1) there must be sufficient within-country variation in farmland shares and diversity; (2) natural conditions must explain variations in farmland shares and diversity (relevance assumption); and (3) potential farmland shares and diversity must not have a direct effect on yields (exclusion restriction).

4 Empirical Results

4.1 Aggregate Estimates

We first estimate Eq. 11 assuming that cross-field biotic externalities are the same for all crops, that is $\beta_{0k} = \beta_0$ and $\beta_k = \beta$ for all k. Results are reported in Table 1. Columns

the correlation is statistically significant but surprisingly negative.

(1)-(3) display ordinary least squares (OLS) estimates on potential yields (α), farmland shares (β_0), and crop diversity (leave-one-out Shannon index) (β). Columns (4)-(6) report the instrumental variable (IV) estimates. All specifications include country×crop fixed effects (FE) and cluster standard errors are the county level. Columns (2), (3), (5), and (6) add county fixed effects. Finally, columns (3) and (6) include pasture area in the computation of farmland shares and leave-one-out Shannon indexes. Instrument strength is not a concern as the Kleibergen-Paap Wald F-statistics vary between 10.7 and 233.3.

As expected, actual yields are quite inelastic to potential yields, with an elasticity below 0.2 across all columns.[15] This reflects the fact that many farmers do not use the advanced technologies assumed by FAO-GAEZ when predicting potential yields. However, the coefficient always remains positive and statistically significant, indicating that agronomic potential retains predictive power for realized yields despite management constraints.

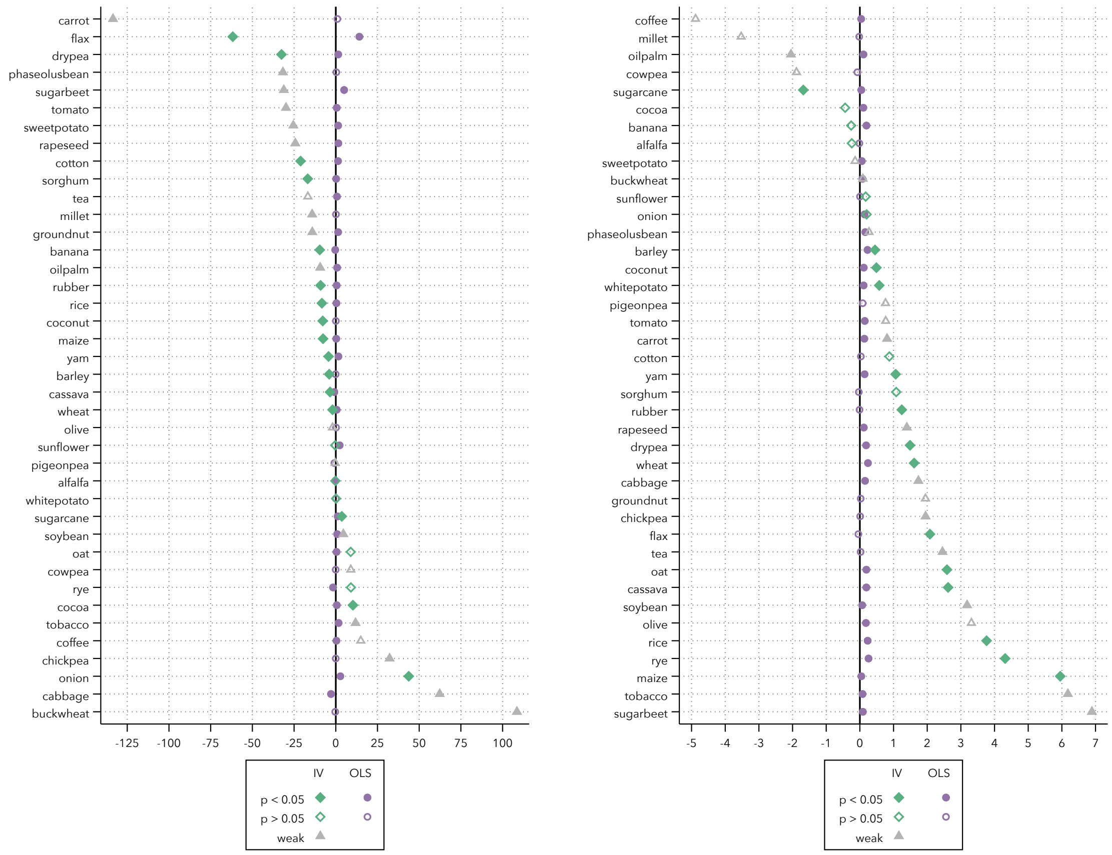
OLS coefficients on farmland shares and Shannon index (except in column 1) have the opposite of the expected sign. By contrast, the IV estimates have the expected sign, confirming that OLS estimates are downward biased even with county fixed effects. Shannon indexes capture biodiversity or *between*-crop effects. A 1% increase in effective diversity is associated with a 1.4-5.3% increase in actual yields (columns 4-6), consistent with Auffhammer and Carleton (2018).[16] Farmland shares capture specialization or *within*-crop externalities. A 1 standard deviation increase (≈ 0.14 in our sample) reduces actual yields by 47.7 to 76.7%, comparable in magnitude to global potential pest losses in Oerke (2006). Finally, including pasture slightly attenuates the magnitude of farmland shares and Shannon index estimates, likely because pasture constitutes a large share of agricultural land in many counties.

4.2 Crop-specific Estimates

We next compute crop-specific estimates to look at the heterogeneity of cross-field externalities. Crops face different potential pest pressures (Oerke, 2006), and may therefore respond heterogeneously to changes in crop patterns. We estimate Eq. (11) for each of the 40 crops in our sample, using both OLS and IV. As we have more than one instru-

[15] Costinot and Donaldson (2012) found a coefficient of 0.2 in a simple regression of the log of actual output on the log of predicted output, which they computed based on FAO-GAEZ data.

[16] By comparison, the OLS elasticity (without county fixed effects) is 0.1, closer to Di Falco and Chavas (2006) on wheat genetic diversity: a 1% increase in genetic diversity raised mean wheat yields by 0.11% in southern Italy.



(a) Specialization effects (β_{0k}) **(b)** Biodiversity effects (β_k)

Figure 2: Estimates of crop-specific biotic externalities

Notes: The figures display estimates from OLS and IV regressions of Eq. (11), controlling for total harvested area in the county. Instruments used are described in Subsection 3.2.3. Standards errors are clustered at the country level and robust to heteroskedasticity. The notation "weak" refers to weak instrumentation, i.e., when the Kleibergen-Papp rank Wald F-statistic is below 10. Computed based on FAO-GAEZ, Earthstat.

ment for farmland shares, we allow for flexibility and select, for each crop, the instrument or combination of instruments that yields the highest Kleibergen-Paap Wald F-statistics. These statistics are reported in Appendix C4. Overall, 21 crops out of 40 exceed the usual rule-of-thumb of 10. Estimates for within-crop (β_{0k}) and between-crop (β) effects are displayed in Fig. 2a and 2b.

As for aggregate results, OLS estimates of specialization effects (within-crop, β_{0k}) appear upward biased in most cases. For 24 of the 40 crops, the estimates even contradict our theoretical prediction that a higher share of farmland should reduce yields due to greater pest pressure ($\beta_{0k} < 0$). With IV, only 3 crops contradict this prediction. More importantly, IV estimates are significantly negative for 13 (accounting only for strong instruments) to 22 crops. Notably, major crops such as wheat, maize, rice and cotton exhibit non-negligible specialization externalities, despite being predominantly grown in monocultures. We also find substantial heterogeneity across crops: a 1 standard deviation (s.d.) increase in farmland share s associated with productivity declines exceeding 80% for maize (s.d. of 0.24) and rice (s.d. of 0.23), and about 33% for wheat (s.d. of 0.21). The smallest negative effect is for yam (7.81%, s.d. of 0.02), consistent with lower pest pressure for an underground crop.[17]

Most estimates of biodiversity effects (β_k), whether by OLS or IV, are in line with our predictions. The only statistically significant exceptions are IV coefficients for oil palm (weak IV) and sugarcane. When instrumenting, crop diversity has a significant, positive and strong effect on the yields of 13 crops (22 when including weak IV). The elasticities of yields with respect to effective diversity (Hill's numbers) are higher than OLS estimates and vary between 0.45 (barley) and 6.89 (sugar beet, but weak IV). These results indicate heterogeneity in the way crops benefit from the richness and relative abundance of other species within a county. We find that major crops are particularly sensitive to *between*-crop externalities: a 1% increase in effective diversity results in a productivity increase of 5.95% for maize, 3.76% for rice and 1.61% for wheat.

4.3 Simulations

Provided with the estimated cross-field parameters, we simulate different land allocations. First, we investigate the effects of marginally reducing dominance in each county. More precisely, we simulate a 1% decrease in the dominant crop's area that we redistribute equally to all other crops already grown. This counterfactual scenario assesses the effect of diversification on production. Second, we solve numerically for Eq. (10) to obtain the rent-maximizing farmland distribution.

[17] Our model does not account for differences in land quality within counties. Note, however, that negative estimates may also partly reflect the fact that expanding a crop's cultivated area can involve bringing less productive land into use.

Table 2: Mean effects of redistributing 1% of the dominant crop's area

Crop	Counties where crop dominates				All counties			
	$\hat{P}$	$\hat{S}$	$\hat{z}_S$	$\hat{z}_H$	$\hat{P}$	$\hat{S}$	$\hat{z}_S$	$\hat{z}_H$
Alfalfa	0.99	0.99	1.00	1.00	3.19	3.19	1.00	1.00
Banana	1.04	0.99	1.05	1.00	8.05	8.07	1.00	1.00
Barley	1.02	0.99	1.02	1.01	4.30	4.24	1.00	1.01
Buckwheat	0.75	0.99	0.76	1.00	3.20	3.09	1.04	1.00
Cabbage	0.78	0.99	0.78	1.01	5.31	4.88	1.02	1.04
Carrot	1.66	0.99	1.66	1.02	90.86	93.93	0.96	1.02
Cassava	1.09	0.99	1.02	1.09	23.47	22.04	1.00	1.07
Chickpea	0.90	0.99	0.88	1.03	174.71	165.37	1.01	1.05
Cocoa	0.95	0.99	0.95	1.00	5.52	5.51	1.00	1.00
Coconut	1.04	0.99	1.04	1.01	5.10	5.02	1.00	1.01
Coffee	0.99	0.99	1.00	1.00	5.34	5.34	1.00	1.00
Cotton	1.09	0.99	1.11	1.00	31.31	31.53	1.00	1.00
Cow pea	0.99	0.99	1.00	1.00	3.81	3.81	1.00	1.00
Dry pea	1.07	0.99	1.07	1.01	6.14	5.92	0.99	1.03
Flax	.	.	.	.	47.94	46.51	0.99	1.03
Groundnut	1.06	0.99	1.07	1.00	46.19	46.44	1.00	1.00
Maize	2.25	0.99	1.04	2.15	2.64	1.94	1.01	1.46
Millet	1.06	0.99	1.07	1.00	9.58	9.62	1.00	1.00
Oat	1.27	0.99	1.00	1.28	2.41	2.27	1.00	1.06
Oil palm	0.98	0.99	1.04	0.95	6.90	7.30	1.00	0.96
Olive	0.99	0.99	1.00	1.00	1226.92	1226.92	1.00	1.00
Onion	0.84	0.99	0.84	1.00	37.85	37.17	1.01	1.00
Phaseolus bean	1.15	0.99	1.16	1.00	378.71	381.62	0.99	1.00
Pigeon pea	.	.	.	.	3.73	3.73	1.00	1.00
Rapeseed	1.12	0.99	1.09	1.03	8.29	8.02	0.99	1.04
Rice	1.28	0.99	1.05	1.23	189.31	172.59	1.01	1.13
Rubber	1.05	0.99	1.04	1.02	8.96	8.77	1.00	1.04
Rye	1.10	0.99	1.00	1.11	11.31	9.86	1.00	1.09
Sorghum	1.07	0.99	1.08	1.00	4.09	4.11	1.00	1.00
Soybean	1.13	0.99	0.98	1.17	12.65	11.21	1.00	1.08
Sugar beet	1.15	0.99	1.10	1.05	43.95	38.25	0.99	1.15
Sugarcane	0.89	0.99	0.98	0.92	683.81	707.39	1.00	0.95
Sunflower	0.99	0.99	1.00	1.00	16.47	16.47	1.00	1.00
Sweet potato	1.06	0.99	1.07	1.00	160.28	161.51	0.99	1.00
Tea	1.05	0.99	1.00	1.06	21.88	20.44	1.00	1.06
Tobacco	1.13	0.99	0.95	1.21	104.93	90.62	1.00	1.15
Tomato	1.15	0.99	1.16	1.00	45.34	45.99	0.99	1.00
Wheat	1.06	0.99	1.01	1.06	2.17	2.05	1.00	1.05
White potato	1.00	0.99	1.00	1.01	25.11	24.89	1.00	1.01
Yam	1.01	0.99	1.01	1.01	2.33	2.27	1.00	1.03
Total	1.08	0.99	1.03	1.06	86.85	86.25	1.00	1.04

Notes: Simulation results are not available for flax and phaseolus bean in the first three columns as there exist no county in which these crops dominate. Computed based on FAO-GAEZ, Earthstat.

4.3.1 Marginal Farmland Redistribution

Decomposition of the Production Effect. For each crop k, let S^k_{new} denote the new farmland share and H^k_{new} the new leave-one-out Shannon index after redistribution.[18] Keeping input prices and pests resistance constant, our model predicts that new expected yields z^k_{new} is given by

$$z^k_{new} = z^k \exp\left[\kappa_{0k}(S^k_{new} - S^k) + \kappa_k(H^k_{new} - H^k)\right],$$

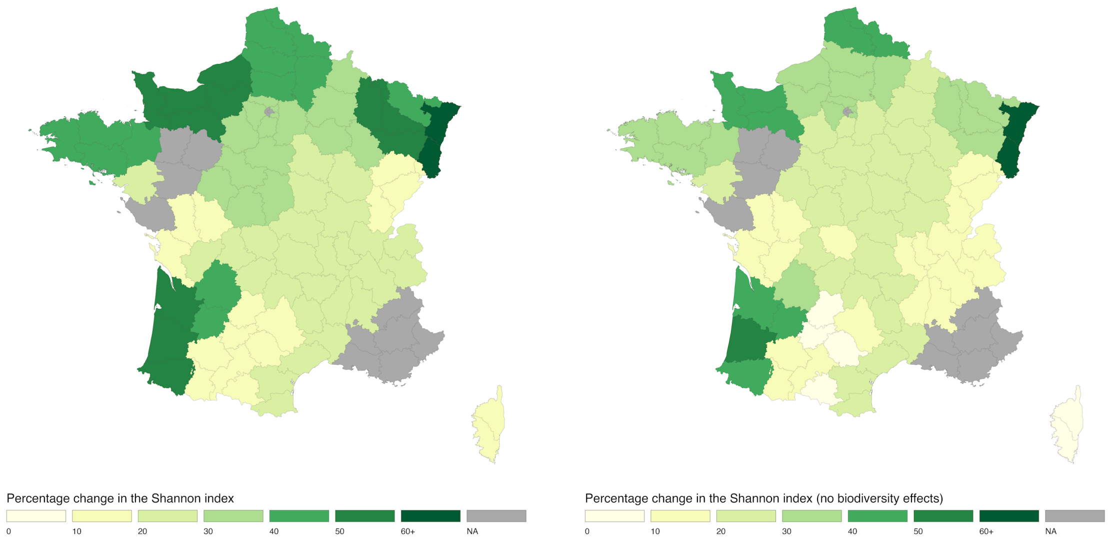
for all $k \in \mathcal{K}$, where $\mathcal{K}$ is the set of crops with strictly positive production under market equilibrium. We thus only allow for changes at the intensive margin. The total variation in expected productivity can therefore be broken down into the product of variations due to changes in farmland share, $\hat{z}^k_S = \exp\left[\kappa_{0k}(S^k_{new} - S^k)\right]$, and changes in crop diversity, $\hat{z}^k_H = \exp\left[\kappa_k(H^k_{new} - H^k)\right]$. Similarly, the variation in production breaks down as

$$\hat{P}^k = \hat{z}^k_S \times \hat{z}^k_H \times \hat{S}^k$$

with $\hat{x}^k = x^k_{new}/x^k$ denotes the variation in variable x. Theoretically, the effect of redistribution on $\hat{P}^k$ is ambiguous and depends on the parameters κ_{0k} and κ_k. We calibrate these using our estimates from Fig. 2. By construction, $\beta_k = -\kappa_k$ and $\beta_{0k} = -\kappa_{0k}$. When an estimate is not statistically significant, we set the corresponding parameter to zero.

Predictions. Table 2 reports mean production changes and their decomposition. Restricting to counties where the crop dominates, i.e. where it has a larger farmland share than all other crops, average production increases by 8% after redistribution. This implies that the drop in production associated with the reduction in harvested area (-1%) is more than offset by an increase in productivity (+9%). The decomposition indicates that most of the increase stems from the diversity component (+6%), with additional gains from reduced specialization (+3%). Maize seems to benefit particularly from the redistribution: a 1% reduction in its harvested area translates on average into a doubling of its yields. Looking at average variations across all counties, production is expected to increase by a factor of 86.85, of which 99.5% is explained by variations in harvested area. The average is therefore driven up by crops that previously accounted for only a small

[18] For clarity, county subscripts are omitted; the unit of observation is unchanged.



(a) Considering all cross-field externalities **(b)** Considering within-crop externalities only

Figure 3: Simulated change in the Shannon index after the rent-maximizing farmland distribution is implemented

Notes: The figures display the simulated percentage change in the Shannon index after the rent-maximizing distribution is implemented for a subsample of 84 French counties. We reallocate farmland within a group of eight cereal and oil crops (barley, maize, oat, rapeseed, sorghum, soybean, sunflower and wheat), keeping other crops' area constant. "NA" values are attributed to counties where at least one of the eight crops considered was not grown initially. In Fig. 3b, we solve for rent-maximizing shares considering that $\kappa_k = 0$ for all crops k, i.e., there are no between-crop externalities. Computed based on FAO-GAEZ, Earthstat.

proportion of the agricultural area. The remainder of the effect reflects productivity gains due to greater diversity. Overall, simulations highlight the large potential for reallocating farmland towards more diversified patterns, especially for dominant crops.

4.3.2 Rent-Maximizing Farmland Allocation

As a second simulation exercise, we consider a benevolent social planner who maximizes agricultural revenue, as described in Subsection 2.4. For each county and crop, we solve numerically for the rent-maximizing farmland sharesfrom Eq. (10), parameterized with our estimates from Fig. 2. As an illustration, we focus on a subsample of 84 French counties and eight crops commonly grown in monocultures: barley, maize, oat, rapeseed, sorghum, soybean, sunflower and wheat. We only allow for reallocation of land area between these crops and keep other crops' area constant. After solving for the eight rent-maximizing farmland shares in each county, we calculate the resulting Shannon index. This allows us to study how the social planner's allocation compares to the allocation when biotic externalities are not internalized.

Figure 3a maps the simulated percentage change in the Shannon index at the county level. On average, crop diversity increases by 33%, indicating that the social planner selects more diversified allocations than non-cooperating farmers do in the data. We also observe significant spatial heterogeneity, with a minimum increase of 10% and a maximum at 81%. However, this heterogeneity mostly reflects initial differences in diversity.

To assess the role of between-crop externalities in the planner's allocation, we set $\kappa_k = 0$ for all crops in the subsample and solve for the rent-maximizing shares. Results appear in Figure 3b. The Shannon index is, on average, 26% higher than in the data, indicating that most of the gap between the rent-maximizing and initial allocations in Figure 3a stems from the internalization of within-crop externalities, which should therefore be considered first-order.

5 Conclusion

Absent any external control, conventional ecological wisdom holds that more specialized fields are subject to a higher risk of crop failure. Concentrating production in the most suitable crops, whether at the farm level to maximize returns or globally to exploit abiotic comparative advantage, should reduce agricultural productivity. Yet, the economic literature provides limited insight into the underlying mechanisms.

In this paper, we develop a probabilistic model of agricultural production that captures two cross-field biotic externalities: specialization (within-crop effects, associated with changes in a crop's land share) and biodiversity (between-crop effects, associated with changes in the mix of other crops). We derive farmers' equilibrium choices of crop and pesticide intensity and obtain a testable equation for crop productivity that we take to the data. We assemble a large county-level dataset combining potential and actual land use. We also propose a new instrumental-variables strategy that exploits variation in land suitability for particular crops and for supporting greater crop diversity. We find that both *within*- and *between*-crop externalities significantly affect productivity. We also find heterogeneity across the 40 crops in our sample. A key finding is that major crops, such as maize, rice, and wheat, would benefit globally from a reduction in their farmland share and from county-level increases in other crop species richness and relative abundance. We illustrate these benefits with two simulation exercises.

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Appendix

This appendix provides proofs of the theoretical predictions (section A) and presents additional empirical results as tables (Section B) and figures (Section C).

A Proofs and Farmland Shares in Equilibrium

A.1 Proof of Proposition 1

Differentiating profits (2) with respect to ρ, and conditional on crop choice k, the symmetric Nash equilibrium between farmers is such that

$$\psi_j^{k\prime}(\rho_j^{k\star}; \boldsymbol{S_j^\star}, \boldsymbol{\rho_j^\star}) = \tau_j/(\bar{a}_j^k p_j^k). \tag{13}$$

The average tax payment for crop k in area j is then $\tau_j \rho_j^{k\star} = T_j^k$. Competition for farmland implying $r_j^k = 0$, it follows that at equilibrium in area j

$$p_j^k \psi_j^k(\rho_j^{k\star}; \boldsymbol{S_j^\star}, \boldsymbol{\rho_j^\star})\bar{a}_j^k = c_j. \tag{14}$$

Thus, crop revenues should be equalized. Since a negative externality on production may result from excessive use of chemicals, the optimum of the farmer's program is such that $\rho_j^k \leq \hat{\rho}_j^k$. Then, combining (4), (13) and (14), the equilibrium—dominant—strategy of a farmer growing k in area j is

$$\rho_j^{k\star} = \hat{\rho}_j^k - \lambda_j^k \tau_j / c_j.$$

The field resilience to direct biotic factors becomes $\mu_j^k(\rho_j^{k\star}) = 1/t_j^k$, with

$$t_j^k \equiv \exp\left[\lambda_j^k (\tau_j/c_j)^2/2\right]$$

an index measuring the extent to which pesticides regulation and pest resistance in area j reduce resilience. *Cross-plot* biotic factors being separable between crops, we also have:

$$B_j^k(\boldsymbol{S_j}, \boldsymbol{\rho_j}) = \frac{\exp\left[-\sum_\ell \hat{\kappa}_k(S_j^\ell)\right]}{\prod_l t_j^\ell}$$

Eventually, using the developed expressions for all factors, the equilibrium resilience function satisfies

$$\psi_j^k(\rho_j^{k\star}; \boldsymbol{S_j^\star}, \boldsymbol{\rho_j^\star}) = \frac{A_j^k \exp\left[-\sum_\ell \hat{\kappa}_k(S_j^{\ell\star})\right]}{t_j^k \prod_\ell t_j^\ell}.$$

Writing $a_j^k = \bar{a}_j^k A_j^k$ the *potential* yield absent biotic factors, the *actual* productivity for a given crop k in country j becomes

$$z_j^{k\star} = \frac{a_j^k \exp\left[-\sum_\ell \hat{\kappa}_k(S_j^{l\star})\right]}{t_j^k \prod_\ell t_j^\ell},$$

which accounts for the direct (t_j^k) and indirect ($\prod_\ell t_j^\ell$) effects of a reduction in pesticides use. Using $p_j^k z_j^k = c_j$ for all $k \in \mathbb{K}$, we also have

$$\frac{p_j^k a_j^k}{p_j^{k'} a_j^{k'}} = \frac{t_j^{k'}}{t_j^k} \exp\left[-\sum_\ell \hat{\kappa}_k(S_j^{\ell\star}) - \hat{\kappa}_{k'}(S_j^{\ell\star})\right]$$

for any pair of crops $(k, k') \in \mathbb{K}^2$.

A.2 Farmland Shares in Equilibrium

Given functional forms in Assumption 1, we have

$$\frac{p_j^\ell a_j^\ell}{p_j^k a_j^k} = \frac{t_j^\ell}{t_j^k} \exp\left[\kappa_{0\ell} S_j^{\ell\star} - \kappa_{0k} S_j^{k\star} + (\kappa_k - \kappa_\ell)\bar{H} + \kappa_{k'} H_j^{k'\star} - \kappa_k H_j^{k\star}\right].$$

Taking logs, dividing by κ_{0l}, summing over all ℓ and using $\sum_{l=1}^K S_j^\ell = 1$, it comes

$$\begin{aligned} S_j^{k\star} = \frac{1}{\kappa_{0k}} \Bigg[\frac{\bar{\kappa}_0}{K} &+ \left(\ln\left[p_j^\ell a_j^\ell\right] - \frac{1}{K}\sum_{\ell=1}^K \ln\left[(p_j^\ell a_j^\ell)^{\bar{\kappa_0}/\kappa_{0\ell}}\right] \right) \\ &- \left(\ln t_j^k - \frac{1}{K}\sum_{\ell=1}^K \ln\left[(t_j^\ell)^{\bar{\kappa_0}/\kappa_{0\ell}}\right] \right) \\ &+ \left(\kappa_k \left(\bar{H} - H_j^{k\star}\right) - \sum_\ell \kappa_\ell \frac{\bar{\kappa}_0}{\kappa_{0\ell}} \left(\bar{H} - H_j^{\ell\star}\right) \right) \Bigg] \end{aligned} \tag{15}$$

with $\bar{\kappa}_0 \equiv K / \sum_{\ell=1}^K (1/\kappa_{0\ell})$ is the harmonic mean of the within-crop parameters.

To illustrate the mechanisms at play, consider the special case where specialization effects are the same for all crops, i.e., $\kappa_{0\ell} = \kappa_0$, and biodiversity effects are absent, i.e., $\kappa_\ell = 0$ for all ℓ. As $\bar{\kappa_0} = \kappa_0$, (15) simplifies to

$$S_j^{k\star} = \frac{1}{K} + \frac{1}{\kappa_0}\left[\left(\ln(p_j^k a_j^k) - \frac{1}{K}\sum_{\ell=1}^K \ln(p_j^\ell a_j^\ell)\right) - \left(\ln t_j^k - \frac{1}{K}\sum_{\ell=1}^K \ln t_j^\ell\right)\right].$$

In this case, the difference between crop acreages is only due to their differences in potential revenue $p_j^k a_j^k$ and the impact of the environmental tax. The first bracketed term $\ln(p_j^k a_j^k) - 1/K \sum_{\ell=1}^K \ln(p_j^\ell a_j^\ell)$ corresponds to the difference between the potential revenue of crop k and the average revenue (in the geometric mean sense). Similarly, the second bracketed term measures the relative impact of the pesticides tax on crop k compared to the other crops. The largest areas are then devoted to crops whose difference between relative potential revenue and relative tax impact is the largest. If crop k suffers for higher direct specialization effects than the others, i.e. $\kappa_{0k} > \kappa_{0k'} = \kappa_0$ for $k' \neq k$, then

$$S_j^{k\star} < \frac{1}{K} + \frac{1}{\kappa_0}\left(\ln(p_j^k a_j^k / t_j^k) - \frac{1}{K}\sum_{\ell=1}^{K} \ln(p_j^\ell a_j^\ell / t_j^\ell)^{\bar{\kappa_0}/\kappa_{0\ell}}\right)$$

and

$$S_j^{k'\star} > \frac{1}{K} + \frac{1}{\kappa_0}\left(\ln(p_j^{k'} a_j^{k'} / t_j^{k'}) - \frac{1}{K}\sum_{\ell=1}^{K} \ln(p_j^\ell a_j^\ell / t_j^\ell)^{\bar{\kappa_0}/\kappa_{0\ell}}\right).$$

Hence, a reallocation of crops occurs with a relative decrease in the acreage of crop k and a relative increase in the acreage of the other crops.

A.3 Proof of Proposition 2

We want to solve

$$\max_{\boldsymbol{S}} \left\{ \sum_k p_k z_k S_k : \sum_k S_k = 1 \right\}$$

where

$$z_k \equiv \frac{a_k e^{-\kappa_{0k} S_k - \kappa_k (\bar{H} - H_k(\boldsymbol{S}))}}{t_k \prod_\ell t_\ell}.$$

The Lagrangian of this program is

$$\mathcal{L} = \sum_k (p_k z_k - \theta) S_k$$

where θ denotes the multiplier associated to the surface constraint. The first order condition with respect to S_k gives

$$p_k z_k \left(1 - \kappa_{0k} S_k\right) + \sum_{\ell \in \mathcal{K}} p_\ell z_\ell \kappa_\ell S_\ell \frac{\partial H_\ell}{\partial S_k} = \theta$$

for all $k \in \mathcal{K} \equiv \{k = 1, \ldots, K | S_k > 0\}$, the subset of crops actually grown at the optimum. Using

$$S_k = \frac{1}{\kappa_{0k}} + \sum_{\ell \in \mathcal{K}} \frac{p_\ell z_\ell \kappa_\ell S_\ell}{p_k z_k \kappa_{0k}} \frac{\partial H_\ell}{\partial S_k} - \frac{\theta}{p_k z_k \kappa_{0k}}$$

and summing over k gives

$$1 = \sum_{\ell \in \mathcal{K}} \frac{1}{\kappa_{0\ell}} + \sum_{\ell \in \mathcal{K}} \sum_{m \in \mathcal{K}} \frac{p_\ell z_\ell \kappa_\ell S_\ell}{p_m z_m \kappa_{0m}} \frac{\partial H_\ell}{\partial S_m} - \theta \sum_{\ell \in \mathcal{K}} \frac{1}{p_\ell z_\ell \kappa_{0\ell}},$$

hence

$$\theta = \frac{\sum_{\ell \in \mathcal{K}} 1/\kappa_{0\ell} - 1 + \sum_{\ell \in \mathcal{K}} \sum_{m \in \mathcal{K}} \frac{p_\ell z_\ell \kappa_\ell S_\ell}{p_m z_m \kappa_{0m}} \frac{\partial H_\ell}{\partial S_m}}{\sum_{\ell \in \mathcal{K}} 1/(\kappa_{0\ell} p_\ell z_\ell)}.$$

Replacing, it comes

$$S_k = \frac{1}{\kappa_{0k}} + \sum_{\ell\in\mathcal{K}} \frac{p_\ell z_\ell \kappa_\ell S_\ell}{p_k z_k \kappa_{0k}} \frac{\partial H_\ell}{\partial S_k} - \frac{\sum_{\ell\in\mathcal{K}} 1/\kappa_{0\ell} - 1 + \sum_{\ell\in\mathcal{K}} \sum_{m\in\mathcal{K}} \frac{p_\ell z_\ell \kappa_\ell S_\ell}{p_m z_m \kappa_{0m}} \frac{\partial H_\ell}{\partial S_m}}{\sum_{\ell\in\mathcal{K}} p_k z_k \kappa_{0k}/(p_\ell z_\ell \kappa_{0\ell})},$$

which simplifies to

$$S_k = \frac{1}{\sum_{\ell\in\mathcal{K}} \frac{p_k z_k}{p_\ell z_\ell} \frac{\kappa_{0k}}{\kappa_{0\ell}}} \left(1 + \sum_{\ell\in\mathcal{K}} \frac{1}{\kappa_{0\ell}} \left(\frac{p_k z_k}{p_\ell z_\ell} - 1 \right) + \sum_{\ell\in\mathcal{K}} \sum_{m\in\mathcal{K}} \frac{p_\ell z_\ell}{p_m z_m} \frac{\kappa_\ell S_\ell}{\kappa_{0m}} \left(\frac{\partial H_\ell}{\partial S_k} - \frac{\partial H_\ell}{\partial S_m} \right) \right)$$

where

$$\frac{p_k z_k}{p_\ell z_\ell} = \frac{p_k a_k t_\ell}{p_\ell a_\ell t_k} e^{-(\kappa_{0k} S_k - \kappa_{0\ell} S_\ell) + \kappa_k H_k(\boldsymbol{S}) - \kappa_\ell H_\ell(\boldsymbol{S})}.$$

B Additional Tables

Table B1: Crop sample description

Crop	Mean yield (t/ha)		Share in harvested area (%)		Share of counties where crop dominates (%)
	Actual	Potential	Actual	Potential	
Alfalfa	6.41	8.03	2.01	3.10	2.31
Banana	1.81	1.17	0.39	0.90	0.60
Barley	1.06	2.10	5.35	2.93	4.35
Buckwheat	0.31	0.50	0.26	2.52	0.01
Cabbage	2.89	1.79	0.27	2.85	0.03
Carrot	2.65	3.31	0.09	3.88	0.00
Cassava	1.51	2.21	1.52	2.03	2.68
Chickpea	0.04	0.64	1.02	1.88	0.02
Cocoa	0.10	0.28	0.66	0.81	0.87
Coconut	1.88	0.50	1.03	0.73	1.60
Coffee	0.27	0.36	1.00	0.95	2.85
Cotton	0.16	0.22	2.90	3.33	1.28
Cow pea	0.10	0.61	0.88	2.59	0.34
Dry pea	0.72	0.78	0.61	2.46	0.01
Flax	0.10	0.33	0.05	2.64	0.00
Groundnut	0.40	0.76	2.20	2.82	0.42
Maize	2.13	3.35	13.38	3.78	25.74
Millet	0.32	1.21	3.33	3.41	0.80
Oat	0.77	1.14	1.31	2.83	0.32
Oil palm	0.67	0.41	0.95	0.42	0.76
Olive	0.08	0.08	0.67	0.55	1.03
Onion	12.93	3.30	0.26	3.51	0.01
Phaseolus bean	1.19	1.59	0.02	4.37	0.02
Pigeon pea	0.01	0.75	0.42	2.34	0.00
Rapeseed	0.66	1.13	2.42	2.93	0.05
Rice	1.44	1.69	14.79	2.22	15.02
Rubber	0.26	0.17	0.76	0.59	0.32
Rye	0.57	1.33	0.94	2.91	0.47
Sorghum	0.87	2.34	3.84	5.71	1.97
Soybean	0.77	1.75	7.45	3.71	4.20
Sugar beet	1.16	1.61	0.60	1.71	0.05
Sugarcane	2.31	1.87	1.92	1.15	3.42
Sunflower	0.56	1.72	2.02	3.91	0.22
Sweet potato	1.12	2.39	0.89	2.52	0.16
Tea	0.09	0.12	0.24	0.83	0.07
Tobacco	0.64	0.40	0.41	2.78	0.22
Tomato	6.82	2.33	0.34	3.24	0.08
Wheat	1.31	2.46	20.55	3.56	18.19
White potato	2.20	3.44	1.90	2.73	1.82
Yam	0.98	1.83	0.36	1.87	0.07

Notes: The statistics for each of the 40 crops are computed for the sample of 41,820 counties considered in this paper. The second and third columns indicate the average yield of each crop as estimated by FAO-GAEZ (potential) Earthstat (actual), respectively; the fourth and fifth columns indicate average, weighted by county-level total harvested area, and maximum share of each crop in harvested area, respectively ; the sixth column indicates the percentage of counties in which the crop has the largest share in harvested area. Computed based on FAO-GAEZ, Earthstat.

Table B2: Country sample description

Country	Harvested area		Effective diversity	
	Total (Mha)	Share (%)	Actual	Potential
Afghanistan	2.62	0.27	2.55	12.79
Albania	0.32	0.03	5.16	26.20
Algeria	2.31	0.23	3.25	21.45
Angola	1.85	0.19	5.06	24.51
Argentina	24.84	2.52	4.78	25.48
Australia	20.05	2.04	4.08	19.28
Austria	0.98	0.10	6.55	20.00
Azerbaijan	0.89	0.09	3.96	23.77
Bangladesh	12.19	1.24	2.11	28.26
Belarus	3.14	0.32	7.18	19.88
Belgium	0.27	0.03	4.71	20.02
Benin	1.38	0.14	5.37	22.16
Bhutan	0.09	0.01	4.30	15.17
Bolivia	1.90	0.19	6.33	16.79
Bosnia and Herzegovina	0.45	0.05	5.68	23.16
Botswana	0.11	0.01	2.69	15.43
Brazil	41.97	4.26	3.52	25.32
Brunei	0.00	0.00	2.50	17.30
Bulgaria	2.68	0.27	5.63	23.12
Burkina Faso	3.36	0.34	4.48	17.27
Burundi	0.79	0.08	7.75	24.11
Cambodia	2.20	0.22	1.88	24.66
Cameroon	2.21	0.22	7.63	23.30
Canada	28.99	2.94	4.06	17.55
Central African Republic	0.59	0.06	6.43	24.68
Chad	1.67	0.17	3.98	15.24
Chile	0.72	0.07	6.95	14.85
China	128.30	13.02	6.73	25.21
Colombia	2.92	0.30	7.32	18.02
Costa Rica	0.32	0.03	6.58	19.88
Croatia	0.98	0.10	6.81	23.76
Cuba	1.72	0.17	5.03	26.50
Czechia	1.84	0.19	6.09	19.81
Côte d'Ivoire	5.26	0.53	7.05	24.47
Dem. Rep. of the Congo	5.23	0.53	5.77	24.89
Denmark	1.70	0.17	4.27	16.47
Dominican Republic	0.74	0.07	9.04	26.26
Ecuador	2.05	0.21	6.84	19.33
Egypt	0.42	0.04	6.77	2.05
El Salvador	0.60	0.06	4.39	23.55
Equatorial Guinea	0.10	0.01	4.41	20.89
Eritrea	0.30	0.03	3.83	13.09
Estonia	0.34	0.03	5.12	15.65
Ethiopia	4.46	0.45	6.56	22.01
Finland	1.25	0.13	4.23	11.70
France	11.78	1.20	5.92	23.13
French Guiana	0.01	0.00	2.52	19.98
Gabon	0.13	0.01	7.26	23.11
Gambia	0.20	0.02	3.86	17.20
Georgia	0.49	0.05	5.99	24.26
Germany	7.45	0.76	5.51	19.80

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Table B2 – *Continued from previous page*

Country	Harvested area		Mean effective diversity	
	Total (Mha)	Share (%)	Actual	Potential
Ghana	3.97	0.40	5.84	23.78
Greece	2.38	0.24	4.40	25.06
Guatemala	1.27	0.13	4.79	21.56
Guinea	1.35	0.14	5.57	22.98
Guinea-Bissau	0.13	0.01	5.14	19.17
Guyana	0.20	0.02	3.41	21.75
Haiti	0.83	0.08	9.28	26.52
Honduras	0.79	0.08	4.73	25.67
Hungary	3.46	0.35	6.23	22.76
India	145.19	14.74	4.85	21.96
Indonesia	27.03	2.74	6.29	21.21
Iran	9.86	1.00	4.48	16.73
Iraq	0.32	0.03	4.48	14.80
Ireland	0.34	0.03	3.63	13.96
Italy	5.82	0.59	5.83	26.11
Japan	2.43	0.25	3.99	25.87
Jordan	0.07	0.01	4.59	14.35
Kazakhstan	12.18	1.24	3.96	14.96
Kenya	3.02	0.31	7.17	21.10
Kosovo	0.31	0.03	6.11	22.33
Kyrgyzstan	0.82	0.08	4.72	19.00
Laos	0.83	0.08	2.28	26.10
Latvia	0.50	0.05	6.02	16.49
Lebanon	0.16	0.02	5.98	23.18
Liberia	0.33	0.03	5.71	22.98
Lithuania	1.17	0.12	5.86	17.33
Luxembourg	0.02	0.00	4.57	19.88
Madagascar	1.93	0.20	4.42	26.06
Malawi	1.32	0.13	6.42	23.01
Malaysia	5.36	0.54	3.42	19.53
Mali	2.43	0.25	3.80	14.19
Mauritania	0.24	0.02	3.61	3.27
Mongolia	0.24	0.02	1.41	11.17
Morocco	5.67	0.58	3.66	21.36
Mozambique	2.47	0.25	4.63	22.69
Myanmar	8.87	0.90	5.93	25.85
México	12.61	1.28	2.59	19.87
Namibia	0.15	0.01	1.99	14.55
Nepal	3.42	0.35	4.61	27.93
Netherlands	0.46	0.05	6.68	18.41
New Zealand	0.21	0.02	6.37	18.93
Nicaragua	0.64	0.06	4.89	24.15
Niger	10.18	1.03	2.91	8.92
Nigeria	32.57	3.31	5.86	20.37
North Korea	1.92	0.19	6.96	23.05
Norway	0.20	0.02	3.67	13.72
Oman	0.00	0.00	2.66	1.60
Pakistan	16.95	1.72	5.82	17.57
Palestine	0.07	0.01	6.84	22.07
Panama	0.25	0.03	5.85	22.95
Papua New Guinea	0.68	0.07	7.08	20.51
Paraguay	2.33	0.24	4.99	29.34

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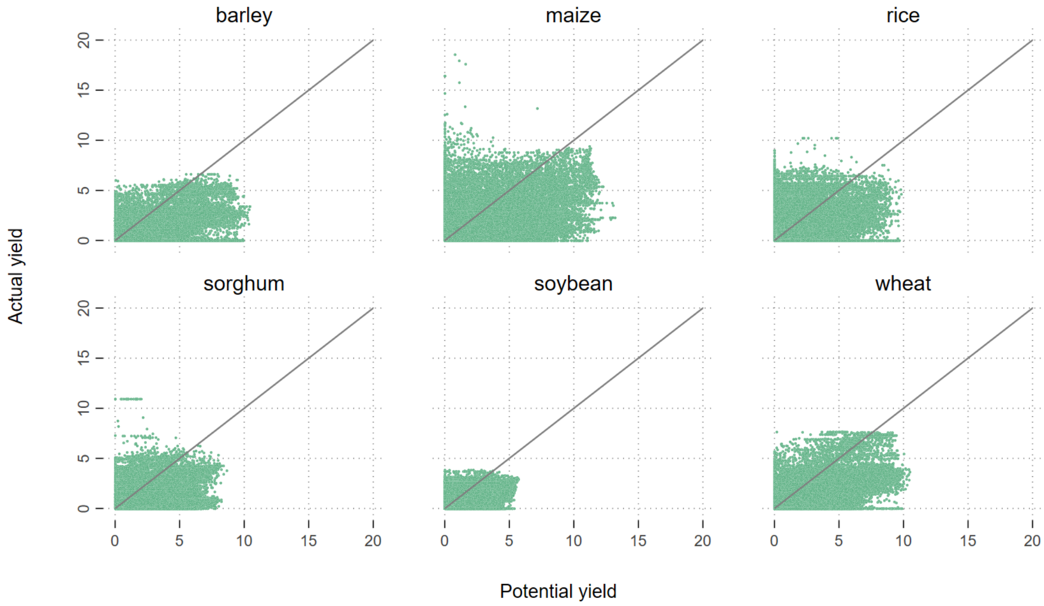
Table B2 – *Continued from previous page*

Country	Harvested area		Mean effective diversity	
	Total (Mha)	Share (%)	Actual	Potential
Peru	1.89	0.19	8.30	13.77
Philippines	10.78	1.09	3.97	21.22
Poland	8.39	0.85	6.25	19.65
Portugal	1.02	0.10	6.18	24.42
Republic of the Congo	0.16	0.02	6.06	24.54
Romania	7.58	0.77	5.15	21.86
Russia	47.84	4.86	5.56	18.93
Rwanda	0.65	0.07	7.25	22.02
Senegal	1.70	0.17	4.09	14.86
Serbia	2.30	0.23	6.09	23.58
Sierra Leone	0.36	0.04	4.63	24.12
Slovakia	1.13	0.12	7.32	20.07
Slovenia	0.11	0.01	5.29	21.86
Somalia	0.41	0.04	2.84	10.62
South Africa	5.64	0.57	4.50	22.62
South Korea	1.33	0.14	2.91	25.73
South Sudan	1.03	0.10	3.33	20.09
Spain	10.72	1.09	5.66	23.23
Sri Lanka	1.73	0.18	3.75	23.44
Sudan	8.07	0.82	2.67	11.62
Suriname	0.05	0.01	3.19	22.47
Swaziland	0.15	0.02	3.68	23.35
Sweden	1.09	0.11	3.61	14.72
Switzerland	0.22	0.02	6.28	18.66
Syria	3.70	0.38	4.33	18.78
Taiwan	0.49	0.05	4.34	28.39
Tajikistan	0.70	0.07	3.96	20.60
Tanzania	4.54	0.46	9.83	24.49
Thailand	15.87	1.61	4.18	24.40
Timor-Leste	0.15	0.02	4.33	24.67
Togo	1.16	0.12	4.88	23.14
Tunisia	1.47	0.15	3.71	23.14
Turkey	16.96	1.72	4.55	21.97
Turkmenistan	1.19	0.12	3.39	10.33
Uganda	3.52	0.36	10.97	25.80
Ukraine	18.53	1.88	6.57	22.09
United Kingdom	3.95	0.40	4.01	14.89
United States	107.56	10.92	3.40	24.79
Uruguay	0.68	0.07	5.06	31.72
Uzbekistan	2.63	0.27	3.63	18.23
Venezuela	1.45	0.15	7.32	23.57
Vietnam	9.54	0.97	4.56	25.28
Yemen	0.31	0.03	7.05	11.01
Zambia	1.03	0.10	4.43	22.50
Zimbabwe	2.12	0.21	5.42	21.21

Notes: The statistics for each of the 148 crops are computed for the sample of 40 crops considered in this paper. The second and third columns indicate the total harvested area in the county and the share of each country in global harvested area; the fourth and fifth columns indicate average actual and potential effective crop diversity (Hill's numbers), with the Shannon index used as the underlying measure of mean proportional abundance. For instance, a number of 4 indicates that, on average, the country is as diversified as if it was growing 4 crops in equal proportions. Details on the computation of these indexes are available in Subsections 3.2.2 and 3.2.3. Computed based on FAO-GAEZ, Earthstat.

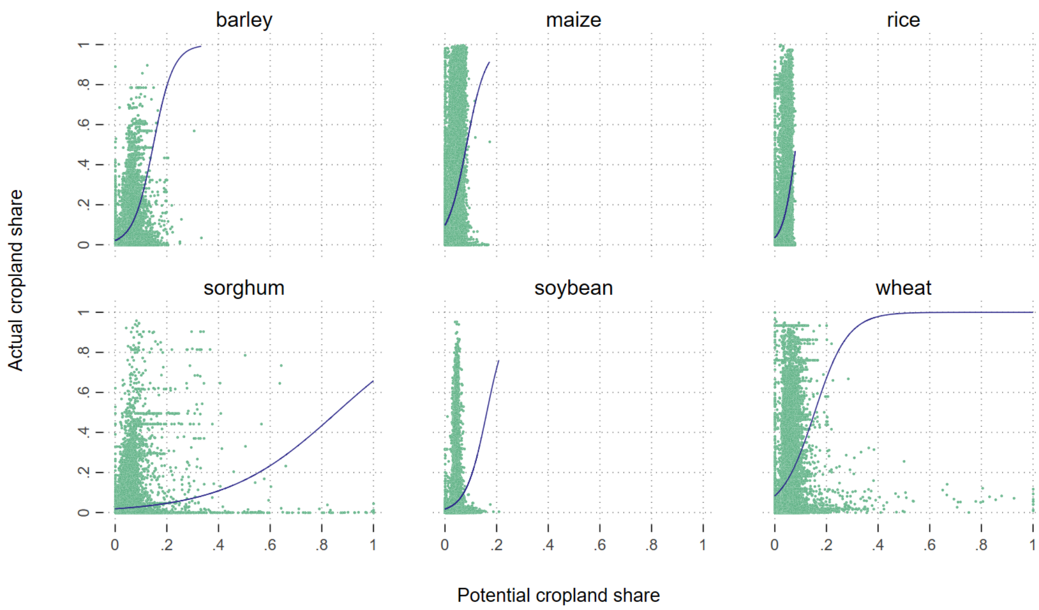
C Additional Figures

Figure C1: Actual vs. potential yields



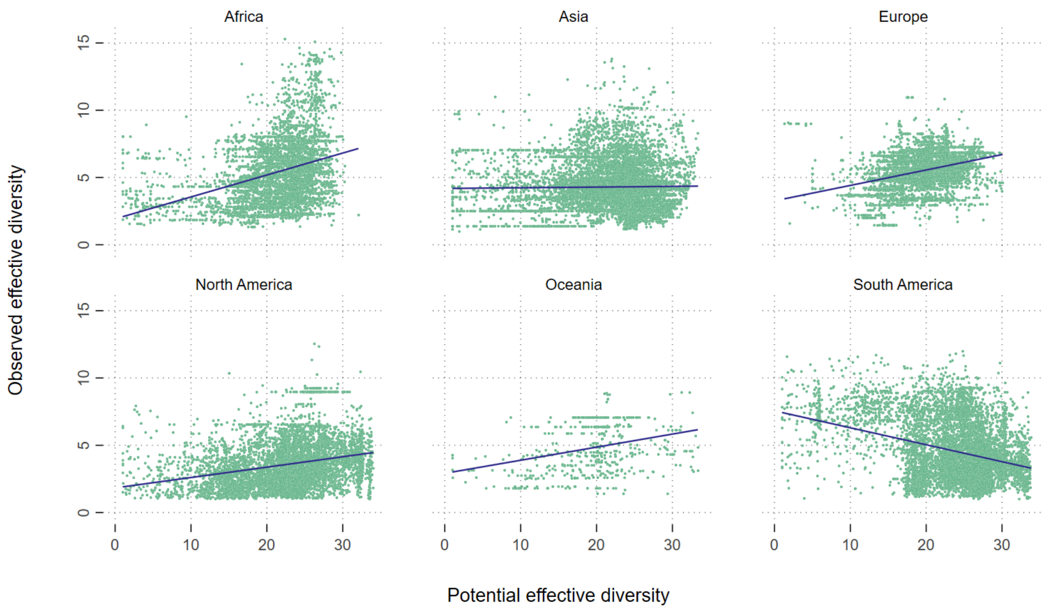
Notes: The figure displays scatterplots of actual (vertical axis) and potential (horizontal axis) yields for the six major crops in terms of average actual shares in harvested area. The 45-degree line is also shown. Computed based on FAO-GAEZ, Earthstat.

Figure C2: Actual vs. potential farmland shares



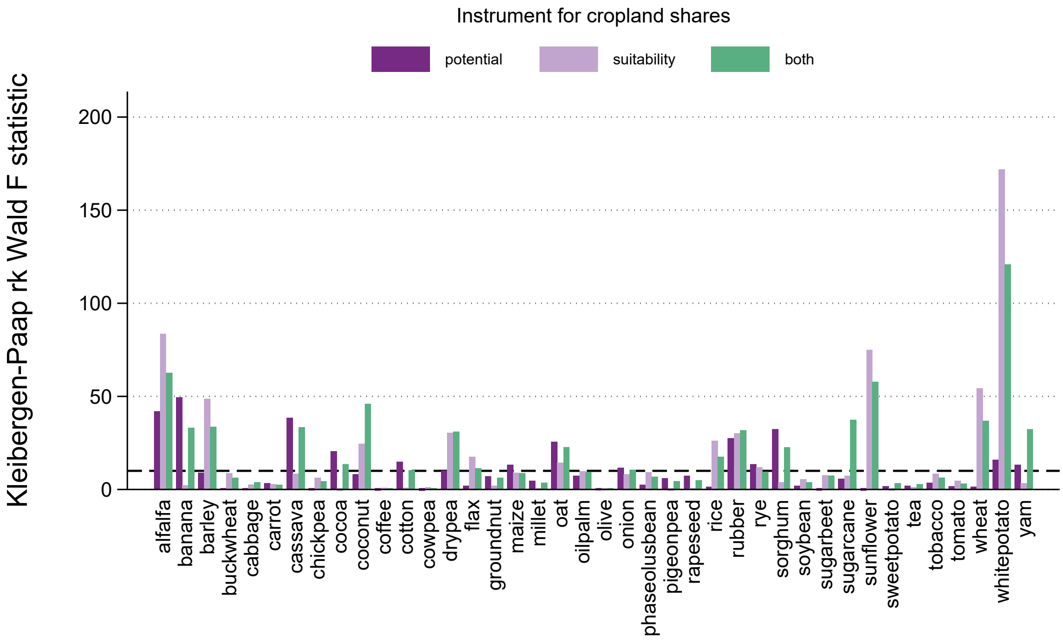
Notes: The figure displays scatterplots of actual (vertical axis) and potential (horizontal axis) farmland share along with generalized linear fits (purple curve) for the six major crops in terms of average actual shares in harvested area. The fits are obtained from generalized linear regressions specifying a binomial distribution and the logit link. Details on the computation of potential shares are available in Subsection 3.2.3. Computed based on FAO-GAEZ, Earthstat.

Figure C3: Actual vs. potential effective diversity



Notes: The figure displays scatterplots of actual (vertical axis) and potential (horizontal axis) effective crop diversity along with linear fits (purple line) for Africa, Asia, Europe, North America, Oceania and South America. Effective crop diversity corresponds to Hill's numbers with the Shannon index used as the underlying measure of mean proportional abundance. Details on the computation of these indexes are available in Subsections 3.2.2 and 3.2.3. Computed based on FAO-GAEZ, Earthstat.

Figure C4: Instrument choice for farmland shares



Notes: The figure displays Kleibergen-Papp rank Wald F-statistics for each crop and three different instrumental variables strategies. Farmland shares are either instrumented by: (1) their potential counterpart, computed as the ratio of the crop's suitability index over the county-level sum of a suitability indexes ("potential"); (2) the share of the county's area assessed as suitable or very suitable for the crop's cultivation as provided by FAO-GAEZ ("suitability"); (3) both. In all cases, the leave-one-out Shannon index is instrumented by its potential counterpart. The selected instrument for the estimation is the one which yields the highest F-statistic. The dashed line indicates the level below which it is generally considered that the instrumentation is weak, i.e. $F = 10$. Computed based on FAO-GAEZ, Earthstat.