Agriculture, Trade and Biodiversity*

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Abstract

Does agricultural trade liberalization erode biodiversity, or can it help preserve it? I build and estimate a new multicountry general-equilibrium model with explicit extensive and intensive margins of land use, in which biodiversity is both an endogenous outcome and a determinant of production. For birds, a standard indicator of ecosystem health, model counterfactuals show that trade preserves global biodiversity. It delivers land sparing at the scale of the trading system: on net, the habitat released saves more species than intensification costs. The liberalization of 1980 to 2017 spared about 26 bird species from eventual global extinction and averted some 2,200 local extinctions, in both cases about a tenth of what agriculture has committed. Undoing it would also cost farmers about $5.5 billion a year in farm revenue, through the ecosystem services birds provide. The gain is unevenly shared: biodiversity falls in a fifth of ecoregions. Restricting trade as a whole, however, would harm biodiversity overall. Mapping how extinctions respond to trade costs link by link shows, to first order, that a schedule protecting more biodiversity than current trade costs keeps most trade open, including every flow from rich temperate regions into the tropics, and concentrates restrictions on trade in animal products.

Keywords: biodiversity, land use, land sparing, ecosystem services, trade policy
JEL Codes: F13, F18, Q15, Q17, Q24, Q57

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1 Introduction

Biodiversity is being run down: over the past century, vertebrate species have gone extinct at up to 100 times the background rate (Ceballos et al., 2015), and around one million species are now threatened with extinction (IPBES, 2019). Those species provide services that human activity depends on, from pest control to clean water, and most of these services rise with diversity (Moffett et al., 2026). Single episodes of species collapse have raised human mortality, by more than 4% in India after its vultures collapsed and by 8% among infants in U.S. counties that lost their bats, because substitutes were lacking or themselves harmful (Frank and Sudarshan, 2024; Frank, 2024). Farming in particular depends on these services as inputs: between $235 and $577 billion of annual global crop output depends on animal pollination (Potts et al., 2016), and bird declines are estimated to cost billions of dollars a year in national farm revenue (Noack, Engist, and Larsen, 2025). Yet agriculture itself is the leading cause of biodiversity loss on land (IPBES, 2019). It raises output on two margins, each at the expense of wild species: clearing new land removes habitat, and intensifying existing farmland erodes the wildlife that remains (Li, Miao, and Khanna, 2020).

Habitat is not always cleared where food is eaten: land cannot be moved, but its services travel embodied in crops and livestock. The location and intensity of production are therefore determined in part by demand elsewhere. In the case of deforestation, roughly a quarter of that driven by agriculture in the tropics has been traced to goods consumed abroad (Pendrill et al., 2019). Accordingly, agricultural trade is widely seen as a major driver of habitat loss, and governments have begun to respond through trade policy. The European Union's Deforestation Regulation will bar imports tied to forest loss from December 2026,[1] while comparable measures are pending in the United Kingdom and have been proposed in the United States. But does freer trade erode biodiversity, or can it help preserve it? Answering this question is crucial to the design of future trade policies that weigh what a restriction costs against the biodiversity it protects.

This paper examines how agricultural trade shapes where and how intensively land is farmed, and what the historical fall in trade costs did to the species that land supports. Two challenges have kept this question open. The first is that *the effect of trade on the amount of farmland is theoretically ambiguous.* Trade raises yields, by making inputs cheaper and by shifting production toward regions with a comparative advantage, so that a given quantity of food can be grown on less land. The same forces, however, raise farmland rents, and higher rents draw new land into

[1] Regulation (EU) 2023/1115 covers cattle, cocoa, coffee, oil palm, rubber, soya and wood, and applies from 30 December 2026 to large and medium operators under Regulation (EU) 2025/2650. It targets the conversion of forest as FAO defines it, land of more than half a hectare with more than 10% canopy cover of trees taller than 5 meters: open savanna and natural grassland are outside its scope.

cultivation. Which force dominates is a quantitative question, and the answer can differ across countries. The second challenge is that *farmland area is a poor proxy for biodiversity loss*, for two reasons. The first is intensity: a hectare farmed with more inputs supports less wildlife (Rigal et al., 2023), so a smaller but more intensively farmed area can cost more species. The second is location. Measures such as forest area count every hectare alike, but the biodiversity cost of clearing a hectare varies widely across the world. Where species are numerous, clearing it displaces more of them. Where they are endemic, living nowhere else, a local loss is a global extinction. Where farming is concentrated, the ecosystem services that species provide to nearby farms, such as pest control, are worth the most. A hectare spared in one country therefore need not offset a hectare cleared in another: whether trade spares species depends on where, across the whole world, it clears land and where it spares it.

I address both challenges with a general-equilibrium trade model that predicts how biodiversity responds when trade costs change, and with the global dataset needed to calibrate it. My first contribution is to count the biodiversity cost of both margins of land use: the extensive margin, how many hectares are farmed, and the intensive margin, how intensively they are farmed with fertilizer, pesticides and machinery. For each ecoregion, the model computes how many species it will eventually lose under the resulting land use, so that a hectare costs more in species-rich ecoregions. It then converts these regional losses into global extinctions by weighting each ecoregion by the vulnerability of its species, so that a hectare also costs more where species are endemic. My second contribution is to close the feedback loop between farming and biodiversity. Biodiversity is an input to farming as well as an outcome of it: when farming displaces species, the ecosystem services they provide to nearby farms decline, productivity falls, and land use adjusts again. The feedback therefore lets me measure what farmers lose in revenue when a change in trade costs erodes the ecosystem services they depend on. I apply this framework to birds, first because their effect on farm revenue has been estimated causally (Noack, Engist, and Larsen, 2025), which the feedback requires. Birds are also a standard indicator of ecosystem health.[2] The framework itself, however, extends to other taxa.

Section 2 documents five facts. First, extinction risk rose in 83% of countries over the past two decades. Second, output grows on an extensive and an intensive margin whose rates are uncorrelated across countries, so the model lets output grow on either. Third, the ecoregions whose birds are most vulnerable are not those with the most species: the two rankings share one ecoregion among their 25 highest (rank correlation 0.16), so the model weights losses by vulnerability. Fourth,

[2]They occur in nearly every terrestrial habitat, are sensitive to environmental change, and their trends often track those of other taxa (Furness and Greenwood, 1993; Padoa-Schioppa et al., 2006; Gregory and van Strien, 2010).

the cross-country correlation between agricultural trade and biodiversity is indistinguishable from zero. Fifth, higher world crop prices convert natural land, and the conversion they cause commits species to extinction. Counting that conversion in species, I find that the rise in crop prices since 2001 accounts for 39% of the tree cover lost in tropical places between 2001 and 2018, a loss that commits 14 bird species to global extinction. The design extends that of Berman et al. (2023), comparing tropical places in the same country and year that world prices reach with different force because they suit different crops. Prices also drive the loss of wooded savanna, so in the model conversion responds to prices on all natural land, not forest alone. The last two facts also explain why the model is one of general equilibrium. The correlation mixes the effects of trade with everything else that moves extinction risk, and the price design compares places only within a country and year, so it cannot say how much land a world price change converts in total, or whether land cleared in one country is offset by land spared in another. The model I develop determines prices, and with them land use, jointly across countries, and can therefore answer both.

Section 3 develops the model. It builds on Farrokhi and Pellegrina (2023), in which landowners choose whether to farm each plot, which crop to grow and whether to use a low-input or a high-input technology, and outputs and inputs are traded subject to bilateral trade costs. It departs from that model in four ways, each motivated by how agriculture affects biodiversity. First, livestock farming affects 29% of threatened bird species, so livestock holds land directly and competes with crops field by field. As with crops, producers choose between an extensive technology, which grazes, and an intensive one, which also buys a mix of feed crops, aggregated as in Gouel and Laborde (2021). Second, conversion at the frontier has its own elasticity, because the data reject tying it to crop choice: the odds of converting land respond three times as strongly to the return from farming as the odds of choosing one crop over another (Section 4). Third, households buy food rather than farm goods, so farm-gate demand responds to farm prices only in proportion to the farm share of the food dollar; inelastic farm-gate demand is one of the conditions under which cheaper inputs spare land. Fourth, biodiversity is endogenous and feeds back into productivity. Because no landowner pays for the species lost, or for the services other farms lose with them, trade operates in a second-best environment (Lipsey and Lancaster, 1956; Chichilnisky, 1994).

Section 4 estimates the model on 66 countries, including a rest-of-world aggregate, 35 agricultural outputs, three inputs and 822,053 5-arcminute fields. To calibrate it, I harmonize agro-climatic potential yields, satellite land cover, protected-area boundaries, bilateral trade flows, production accounts, species pools and vulnerability scores. Together they measure what each field could produce, how much of it is farmed or could still be converted, and which species its ecoregion holds. The feedback elasticity is taken from Noack, Engist, and Larsen (2025). The one

new parameter, the conversion elasticity, is estimated by indirect inference: the model reproduces how much agricultural land expands with population, a coefficient I estimate following Farrokhi et al. (2025), instrumenting population change with initial age structure. Expansion is capped at a convertible ceiling built from agro-climatic suitability, natural vegetation and protected areas. I then confront the model with moments it was not asked to match. Its committed bird losses rank ecoregions in line with the birds the IUCN Red List records as threatened by agriculture (rank correlation 0.35), and not with those threatened only by other causes (-0.12).

Section 5 runs six counterfactuals, all with the biodiversity feedback. Three reset trade costs to their 1980 levels, for inputs and outputs together and then separately. A fourth shuts down agricultural trade altogether. The last two shut down trade in feed and in meat and dairy, which relocate cropland and pasture respectively.

The counterfactuals deliver three findings. The first is that *liberalization spared species on net*. Under the observed 2017 regime, agriculture has committed about 240 bird species to global extinction: the number that current land use will eventually lose, not the number already lost.[3] Resetting trade costs to their 1980 levels raises that count by about 26, or 11%. The model of Farrokhi and Pellegrina (2023), which has no pasture, gives a third as many when scored the same way (Appendix I). The mechanism is land sparing at the scale of the trading system. Habitat is unpriced, but it is cleared to obtain land, which is priced, and liberalization lowers the demand for land: world agricultural area ends about 7% smaller than it would have been. Inputs and outputs contribute about equally, by different routes. Cheaper fertilizer and machinery substitute for land, raising the high-input share of cropland; on its own, input liberalization spares 12.9 species. Cheaper outputs barely change technique but let countries import livestock and feed, so pasture contracts even as cropland moves to where it grows best; on its own, output liberalization spares 14.5, and reversing it costs more world real income.

The second finding is that *the gain is unevenly shared*. About a fifth of ecoregions lost species, mostly in Australia and New Zealand, the former Soviet Union and Brazil, while nearly every ecoregion of tropical Asia and sub-Saharan Africa gained. The global count weights these losses by vulnerability, and the gains elsewhere outweigh them. The same unevenness appears in farm revenue: through the biodiversity feedback, undoing liberalization would cost farmers in 48 of the 66 countries about $6.0 billion a year, China the most. These figures value the services of birds alone.

[3] Committed extinctions are an extinction debt: the species–area relationship gives the number of species a landscape can support once it has adjusted to its land use, a process that can take decades. Regional losses are converted into global extinctions with the vulnerability scores of Chaudhary and Brooks (2018), which reflect how much of each species' range lies in the ecoregion and how threatened the species is.

The third finding is that *the effect of a restriction depends on which goods it covers.* Autarky bounds the exercise: it commits 118 further species and costs 14.2% of world real income, as a closed world clears habitat to grow at home what it imported. Shutting down trade in feed alone commits 33 further species: without imported feed, livestock reverts to grazing, and pasture expands onto species-rich land even as cropland contracts. Shutting down trade in meat and dairy is close to neutral, committing 4 species. Importers that raise intensive herds of their own, as in East Asia and Europe, spare pasture abroad, while those whose herds graze, as in the rest of the world, clear more, and the two nearly offset.

Section 6 asks whether a different configuration of trade costs could spare more species. I raise the cost of trade in one block at a time, one pair of regions in one class of goods, and record how committed extinctions respond, for the 122 blocks that carry a material share of world agricultural trade. Restricting flows from rich temperate regions into tropical regions costs species in every such block. Restricting flows in the other direction saves species in only half of them, livestock accounting for most of the species saved, and the largest savings come from restricting livestock shipped into the intensive producers of East Asia and Europe from outside those regions. Among tropical exports to Europe, only South American livestock would save species if made costlier, while raising the cost of tropical crop exports would cost species. To first order, a schedule of trade costs set block by block would spare about twice as many species as uniform liberalization while keeping three-quarters of its gain in world real income.

In sum, my results contradict the premise that trade harms biodiversity as such: it spares land at the scale of the trading system, even though liberalization cost species in a fifth of ecoregions. Lowering trade costs as a whole spares species, but not every flow does. Sparing more species therefore calls neither for uniform liberalization nor for uniform restriction, but for an asymmetric schedule: open for flows from rich temperate regions into the tropics, costlier for livestock shipped into East Asia and Europe from outside them. Trade policy can serve biodiversity, provided it targets flows by direction and by good rather than restricting trade as a whole.

Contribution to the literature. This paper contributes to four literatures.

First, footprint studies attribute the species loss embodied in agricultural production to the countries that consume it, using physical trade matrices (Chaudhary and Kastner, 2016) or multiregional input-output tables (Lenzen et al., 2012; Cabernard, Pfister, and Hellweg, 2024). Weighting deforestation by species vulnerability, Lauro et al. (2026) show that hectares cleared and biodiversity at risk do not coincide: Indonesia bears the largest share of global risk despite a far smaller footprint than Brazil. This accounting takes trade flows as given. I ask instead how biodiversity

responds when trade costs change. The closest antecedent is Polasky, Costello, and McAusland (2004), who derive conditions under which trade raises or lowers biodiversity in a two-country, two-good model with a species–area relationship. I bring the question to data in a many-country model with an intensive margin and a feedback from biodiversity to productivity, and find that liberalization spared species on net.

Second, quasi-experimental studies estimate the effect of trade on forests. Regional trade agreements raise deforestation over the following three years, mostly in tropical developing countries (Abman and Lundberg, 2020), and extreme heat on the agricultural frontier leads farmers to clear forest rather than cede production elsewhere (Hsiao et al., 2026). I extend the price design of Berman et al. (2023) beyond dense forest, to wooded savanna and cropland expansion, and translate its estimates into committed extinctions. I am not aware of earlier work that does so; the closest link from prices to birds traces how expected commodity prices move cropland in the US Midwest, and with it the abundance of 22 grassland bird species (Evans and Potts, 2015). Such designs identify where trade adds pressure on habitat, but not what it does to biodiversity worldwide, which requires netting habitat cleared in one country against habitat spared in another. That is what the model does.

Third, I contribute to quantitative models of trade and the environment. In environmental science, ten Brink et al. (2006) link a computable general-equilibrium trade model to land-use and biodiversity models (van Meijl et al., 2006; Eickhout et al., 2007; Alkemade et al., 2009) and reach the opposite conclusion to mine: full liberalization of agricultural trade lowers mean species abundance by a further 1.3 percentage points by 2050, as world agricultural area rises by 6.5%, concentrated in Latin America and Southern Africa. Here, liberalizing output trade alone spares species, mostly because pasture contracts as countries import livestock and feed. In economics, quantitative trade models have studied climate change (Costinot, Donaldson, and Smith, 2016; Gouel and Laborde, 2021), deforestation (Dominguez-Iino, 2025; Farrokhi et al., 2025; Gollin and Wolfersberger, 2025) and water (Carleton, Crews, and Nath, 2025). The model keeps the crop and technology choice of Farrokhi and Pellegrina (2023), adds livestock that holds land and substitutes feed for it, with the feed mix of Gouel and Laborde (2021), and governs conversion separately from crop choice. Closest in subject, Farrokhi et al. (2025) study how agricultural trade shapes deforestation. Biodiversity, though as tightly tied to agricultural land use as forest cover, has not yet been taken up in this literature, and it differs from forest area in two ways that matter for trade. First, its cost is heterogeneous: what a hectare costs in species depends on where it lies and on how intensively it is farmed, whereas forest area counts every hectare alike. Second, it feeds back into production: the species that farming displaces provide ecosystem services to nearby

farms, so their loss lowers productivity and moves land use and trade again. Adding it, I find that the habitat liberalization releases saves more species than the intensification it induces costs.

Finally, an emerging literature measures what biodiversity loss costs. The collapse of India's vultures raised human mortality by more than 4%, at a social cost of roughly $70 billion a year (Frank and Sudarshan, 2024), and the 30% decline in North American bird abundance has cut U.S. farm revenue by about 4% (Noack, Engist, and Larsen, 2025). This paper studies one driver of that loss, trade policy, and finds that, through the services of birds alone, undoing liberalization would cost farmers about $5.5 billion a year. It also lets that cost feed back into land use and trade flows. In doing so it closes a feedback loop that captures how changes in biodiversity *shape* and *are shaped* by economic outcomes.

2 Motivating facts

This section documents five facts about biodiversity, agricultural land use, and trade that guide the model developed in Section 3. Data sources and supporting results are collected in Appendix A.

Fact 1: Extinction risk is rising almost everywhere

The starting point is the phenomenon itself. I measure it with the Red List Index, an index of aggregate extinction risk that rises as species become less threatened, scored for each country by the Environmental Performance Index (EPI); the average country score fell steadily from about 61 to 53 on the EPI's 0 to 100 scale between 2000 and 2023. The decline is widespread: extinction risk rose in 83% of countries, and the steepest declines are in South, Southeast and East Asia, in island states from Palau to the Comoros, and in France (Appendix Figure A.1). For birds, agriculture is the leading threat. In the species-level assessments underlying the IUCN Red List, agriculture threatens 72% of the 1,256 globally threatened bird species, ahead of logging (49%) and invasive species (44%), and roughly twice the share affected by climate change (35%; Appendix Figure A.2) (IUCN, 2025; BirdLife International, 2025). Within agriculture, crop farming affects 65% of threatened species and livestock farming 29%; together, the two agricultural land uses at the heart of the model affect 70%, and wood plantations and aquaculture, which the IUCN also classes as agriculture, account for the rest. Extinction risk is thus rising broadly, and agriculture is the leading threat to birds.

Fact 2: Output grows on two uncorrelated margins

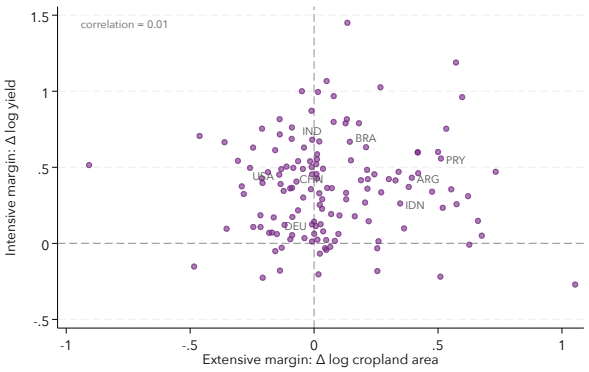
Agriculture raises output in two ways: by bringing new land into cultivation (the extensive margin) and by producing more on land already farmed (the intensive margin), the latter achieved primarily through greater use of purchased inputs. Panel (a) of Figure 1 decomposes the growth of real crop output between the 1993 to 1997 and the 2016 to 2020 averages, for 139 countries, into these two components: the change in log cropland area (horizontal axis) and the change in log yield, that is output per hectare (vertical axis), whose sum is the change in log output. Two patterns stand out. First, yields rose in 124 of the 139 countries, so the intensive margin is nearly universal. Second, large cropland expansion is confined to a subset: 31 countries expanded cropland by more than 0.25 log points, while 59 held it flat or reduced it. Large producers, including the United States, China, India, and Western Europe, expanded output almost entirely through yields, with cropland flat or declining (by 0.13 to 0.18 log points in Spain, the United States and Italy). Land-abundant developing economies, including Brazil, Argentina, Indonesia, Malaysia, and Paraguay, combined intensification with substantial cropland expansion. The two margins are uncorrelated across countries (correlation 0.01, with a bootstrap 95% interval from -0.17 to 0.19), so one margin does not predict the other. The intensive margin operates through greater input use: panel (b) shows that world fertilizer application per hectare has risen more than fivefold since 1961 and pesticide use per hectare has nearly doubled since 1990, consistent with the model's treatment of intensification as the adoption of input-using technologies, and with the cross-country evidence of Farrokhi and Pellegrina (2023) that input cost shares rise systematically with agricultural productivity. This heterogeneity motivates a model in which both margins are present and their relative use is determined endogenously, because the two carry different biodiversity consequences.

Fact 3: Where birds are most numerous is not where their loss counts most

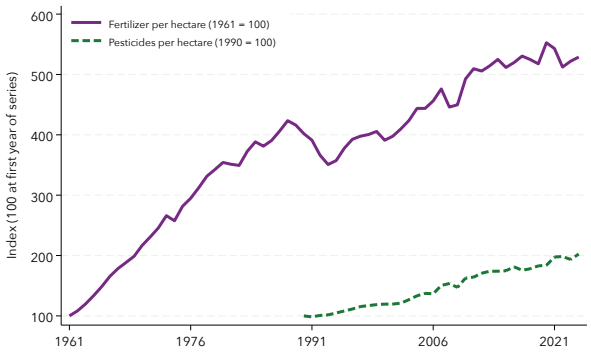
Whether that conversion threatens biodiversity depends on where it occurs. The stakes are unevenly distributed to begin with, and not in proportion to species counts. Figure 2 maps both. Where the stakes are highest is not where species are most numerous, and the two panels do not coincide: the Amazon and Congo basins hold many wide-ranging birds, while the Andes, Madagascar and the island archipelagos hold fewer species with far narrower ranges. Appendix Figure A.3 overlays, across ecoregions, recent cropland expansion (from the GLAD land-use-change product) with the vulnerability of resident bird communities (Chaudhary and Brooks, 2018). The two overlap only in part. A third of the expansion lies in ecoregions of below-median vulnerability, mostly temperate, in Europe, northern China and the Canadian prairies, where the species cost

Figure 1: The two margins of agricultural output growth

(a) Sources of output growth across countries



(b) Global input use over time



Notes: Panel (a): each point is a country; the horizontal axis is the change in log cropland area and the vertical axis the change in log real crop yield, between the 1993 to 1997 and 2016 to 2020 averages, whose sum is the change in log real crop output. The sample is the 139 countries above the 25th percentile of initial output with data for both margins. Panel (b): world fertilizer use per hectare of cropland (nitrogen, phosphate and potash nutrients, = 100 in 1961) and pesticide use per hectare (= 100 in 1990). All series are from FAOSTAT.

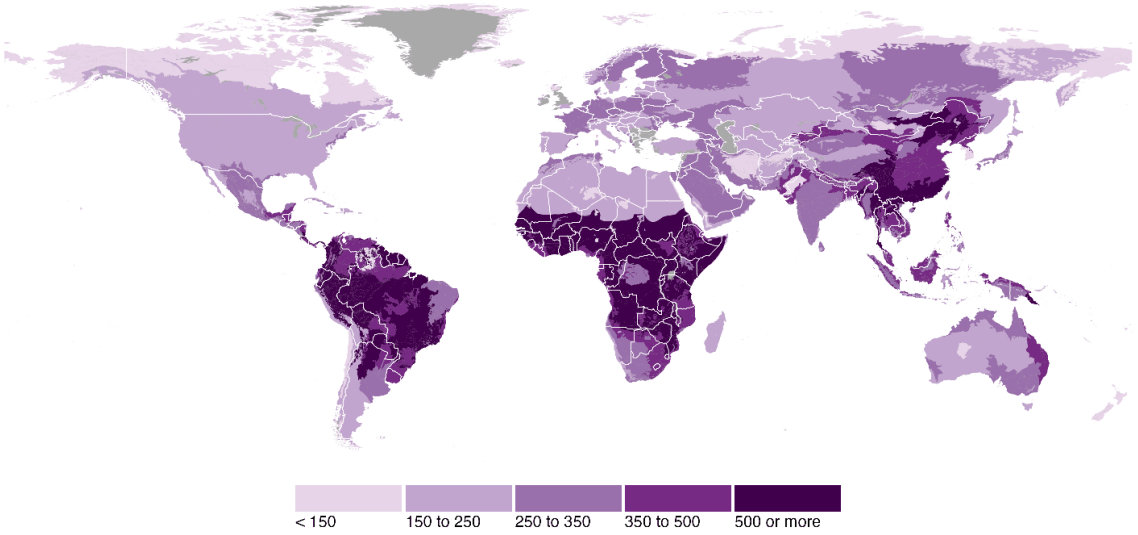
of conversion is small. The other two-thirds lies on more vulnerable land, chiefly the tropical and subtropical savannas and dry forests of West and southern Africa, the Brazilian Cerrado, the Pampas and the Chaco, India and mainland Southeast Asia. The biodiversity cost of a given quantity of land conversion is therefore highly heterogeneous across space; footprint accounting reaches the same conclusion from observed deforestation, with hectares cleared and biodiversity risk failing to coincide spatially (Lauro et al., 2026). The location of loss matters for two distinct reasons. First, endemism: species in tropical hotspots have small ranges, so a regional loss there is far more likely to be a global, irreversible extinction than the same loss in a temperate ecoregion (Chaudhary and Brooks, 2018). Second, ecosystem services: birds supply pest control to the farms around them, so losses concentrated in regions where agriculture is economically central destroy productive inputs, not only conservation value (Noack, Engist, and Larsen, 2025). This dual heterogeneity motivates measuring biodiversity loss by weighting land-use change by ecoregion-level vulnerability, as the ecological module developed below does, rather than by counting converted area, and it is why the model lets biodiversity feed back into agricultural productivity.

Fact 4: Trade and biodiversity are uncorrelated across countries

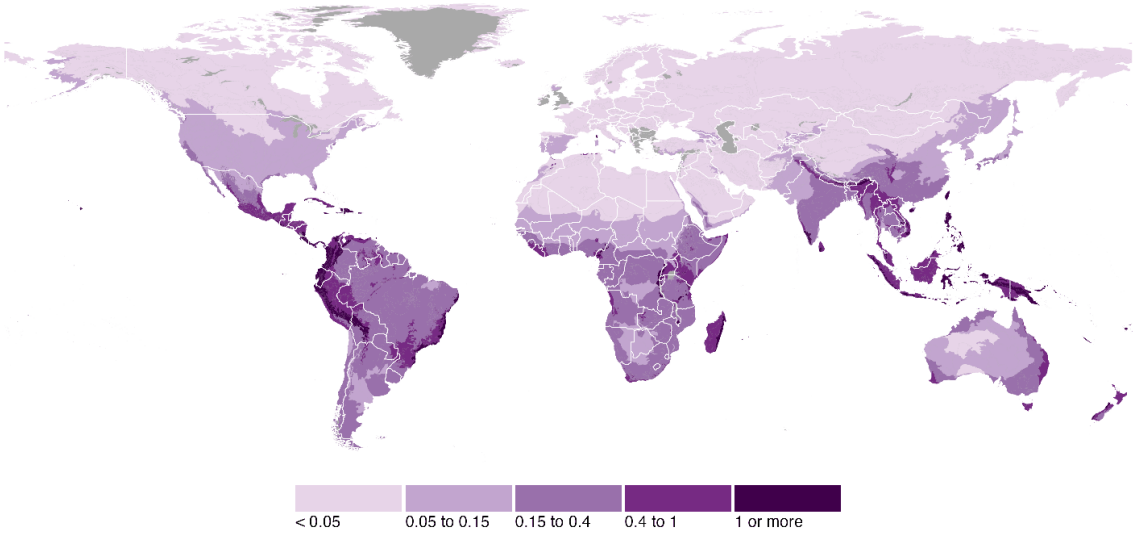
Yet agricultural trade bears no systematic relationship to biodiversity across countries. Figure 3 plots the Red List Index of Fact 1 against two measures of agricultural trade exposure: aggregate trade openness (panel a) and net-exporter status (panel b), for the same 147 countries. Neither measure shows an association: the bivariate correlations are 0.05 and 0.04, and both fitted slopes

Figure 2: Where birds are, and where their loss counts

(a) Bird species richness, by ecoregion



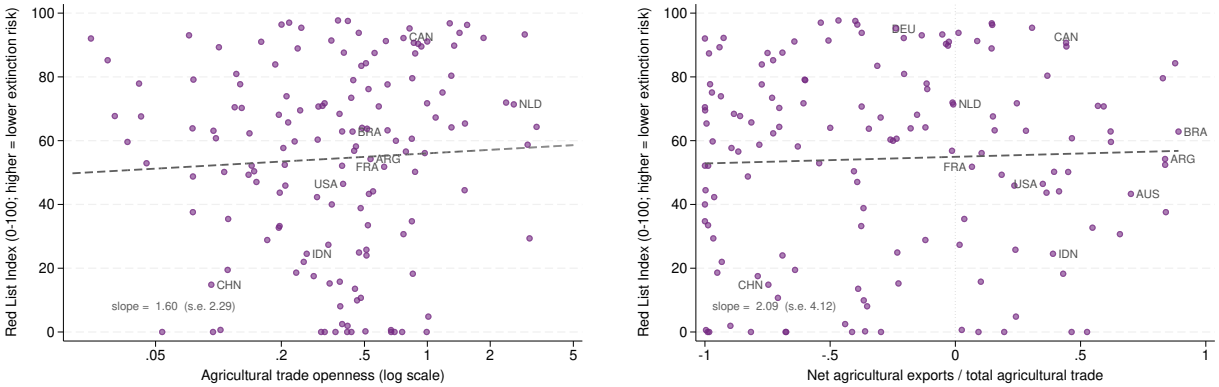
(b) Vulnerability-weighted species at stake, per 10,000 km^2



Notes: Panel (a) plots the baseline bird species pool of each ecoregion. Panel (b) plots that pool weighted by the Chaudhary and Brooks (2018) vulnerability score and divided by ecoregion area, so it measures the globally irreplaceable bird diversity riding on a unit of land, which is what conversion there destroys. Darker is higher in both panels; grey marks ecoregions outside the sample. The rank correlation between the two is 0.23, and they share no ecoregion among their 25 highest, partly because panel (b) is per unit area, which favors small ecoregions such as islands.

Figure 3: Agricultural trade and biodiversity across countries

(a) Trade openness **(b)** Net exporter status



Notes: Each point is a country; the Red List Index (EPI/IUCN indicator, 0 to 100) is higher where aggregate extinction risk is lower. Panel (a) measures trade exposure by log agricultural trade openness, exports plus imports over production; panel (b) by net agricultural exports as a share of total agricultural trade. All variables are country averages over 2018 to 2022, and dashed lines are bivariate OLS fits. Both panels use the same countries: entrepôts and countries with negligible agricultural trade (openness outside [0.02, 7.4], 7 of 154 countries) are excluded for legibility; including them leaves the near-zero association unchanged.

are smaller than their standard errors.

The informative feature of the figure is the vertical spread rather than the slope. At every level of trade exposure the index runs across almost its full range, so most of what separates countries on extinction risk in this sample is something other than trade exposure, and nothing is held fixed here. The nulls are therefore imprecise rather than tight, and several readings survive the figure equally well: trade exposure may matter little for national extinction risk, it may raise conversion in some countries and spare it in others so that the two offset, or a real effect may be hidden by the differences in income, area and endemism that also move the index. What the figure establishes is not which of these holds but that the sign of the effect cannot be read off a cross-country correlation, which is the reason for the general-equilibrium framework developed in Section 3.

Fact 5: World crop prices drive land conversion

Fact 4 leaves open whether trade moves land at all. If it does, it works through prices: trade changes the prices farmers receive for their crops, and with them the return to clearing land. Berman et al. (2023) estimate this response in the tropics. They follow 12,295 cells of half a degree, about 55 km across, from 2001 to 2018, and give each cell a price index that weights the world price of each crop by the cell's suitability for it, from the Global Agro-Ecological Zoning project (GAEZ). When the world price of one crop rises, the index rises most in the cells best

Table 1: Crop prices and land conversion in the tropics

	(1) Forest loss (canopy ≥25%)	(2) Wooded-savanna loss (canopy 10–25%)	(3) Cropland gain (ESA-CCI)
Log crop price (suitability-weighted)	1.267***	0.908***	1.284***
	(0.088)	(0.092)	(0.196)
	[0.380]	[0.383]	[0.581]
Share of cell-years with any change	0.97	0.82	0.27
Cell fixed effects	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes
Observations	221,184	221,130	159,744
Years	2001–2018	2001–2018	2001–2014, excl. 2004

Notes: Half-degree cell × year panel for the tropics (93 countries), from the replication data of Berman et al. (2023): estimates of Eq. (1), with standard errors clustered by cell in parentheses and by country in brackets; stars refer to the cell-clustered errors. Columns 1 and 2 count the 30 m pixels (Hansen et al., 2013) lost in year t among those with canopy cover in 2000 of at least 25% (column 1, the published baseline of Berman et al. (2023)) or between 10% and 25% (column 2, cells with some cover in that band). Column 3 uses ESA-CCI 300 m annual land cover (cropland = classes 10 to 30), whose conservative change detection attenuates it toward zero; its window drops 2015, which is truncated, and 2004, which carries an Americas-only reclassification (Appendix Table A.3). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

suited to it. For cell c in country i and year t, they estimate

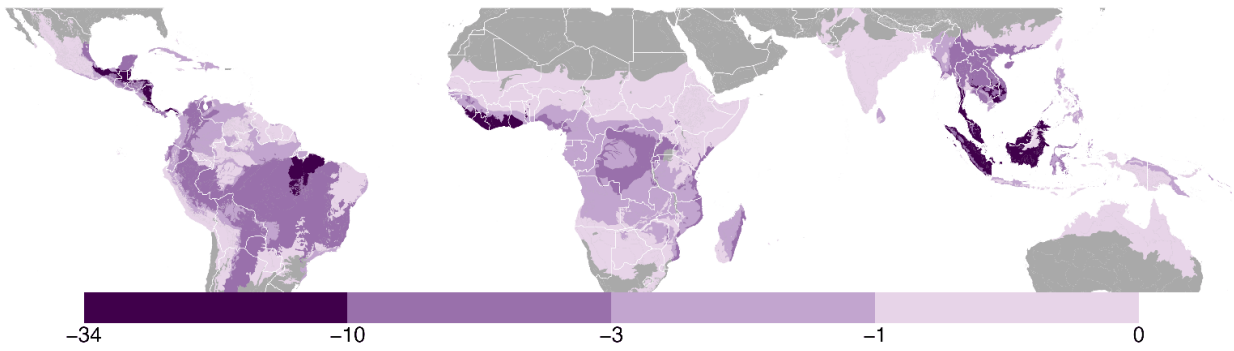
$$\operatorname{asinh}(Y_{ct}) = \beta \ln P_{ct} + \gamma_c + \delta_{it} + \varepsilon_{ct}, \tag{1}$$

where Y_{ct} is the tree cover lost in the year (below, also the cropland gained), P_{ct} the price index, asinh the inverse hyperbolic sine, which behaves like a logarithm but is defined at zero, and γ_c and δ_{it} are cell and country × year fixed effects. The country × year effects absorb everything that changes for a whole country in a given year, such as its exchange rate, wages or policy, so the estimate compares cells of the same country that the same world price movements reach with different force, because they suit different crops. I reproduce their estimate exactly: $\beta = 1.27$, with a standard error of 0.38 clustered by country and 0.09 clustered by cell (Table 1, column 1). A 10% rise in the world prices of the crops a cell is suited to raises its forest loss that year by about 13%.[4]

I extend this evidence in three directions: to land that is not forest, to land put under crops, and to the bird species this conversion costs. First, I measure tree loss where canopy cover in

[4]Tree loss also responds to the next year's price, more strongly than to the current one, and, with standard errors clustered by country, significantly to neither the previous year's price nor the price two years ahead; the response to the next year's price survives cell-specific trends (Appendix A). Cropland gain responds only to the current price. This timing may explain why Hsiao et al. (2026) find little effect on deforestation of world price movements caused by heat shocks abroad: those movements are short-lived, whereas clearing land is an investment that responds to the prices farmers expect.

Figure 4: Change in the number of bird species per ecoregion from price-driven forest loss, 2001 to 2018



Notes: Change in the number of bird species each ecoregion supports because world crop prices rose above their 2001 level: the ecoregion's species pool times the change in its species-remaining share, with the estimate of Table 1, column 1, applied to each cell of Berman et al. (2023) and cleared land counted as no habitat (Appendix A). As in Figure 5, a species present in several ecoregions is counted in each, and the bins are the same; the total is −936, or 14 species committed to global extinction once weighted by global vulnerability (Appendix Figure A.4). No ecoregion gains species: prices stayed above their 2001 level in 99.8% of cell-years, and the satellite data record tree loss, not regrowth. Grey: ecoregions with no cell in the sample.

2000 was between 10% and 25%, below the 25% threshold of Berman et al. (2023) though above the 10% of the FAO forest definition; three-quarters of such land in the tropics lies in savanna ecoregions, so I refer to it as wooded savanna. Its loss also rises with crop prices, with a coefficient of 0.91 (s.e. 0.38 clustered by country; column 2). The coefficient is smaller than for forest, but less wooded savanna is lost each year: in proportion to its baseline rate of loss, it responds as strongly as forest (Appendix Table A.2).[5] Second, prices put land under crops, not only take it out of forest: replacing forest loss with the cropland gained, measured in the European Space Agency's annual land-cover maps (ESA-CCI), which are built independently of the forest data, gives 1.28 (s.e. 0.58 clustered by country; column 3).[6] This agrees with Miranda, Britz, and Börner (2024), who find with the same maps that the share of land under crops and pasture in tropical regions rises with an index of agricultural commodity prices. Open savanna and grassland have no trees to count, and for them the evidence is inconclusive: in the ESA-CCI maps, the loss of natural land rises with prices when measured as a share of the cell, but not in the form of Eq. (1) (Appendix

[5]The satellite data count trees taller than 5 meters, so this band is wooded savanna and open woodland; open grassland is not measured. In levels (Poisson pseudo-maximum likelihood) the point estimate is similar, 0.92 (s.e. 1.16 clustered by country).

[6]The ESA-CCI column runs from 2001 to 2014 and excludes 2004: the product's final year, 2015, is truncated, and 2004 carries a reclassification confined to the Americas (Appendix Table A.3). Because the outcome has many zeros, the size of the coefficient depends on the unit of measurement (Chen and Roth, 2024), from 0.57 in square kilometers to 1.64 in pixels; in levels it is 0.64 (s.e. 1.35 clustered by country).

Table A.1).

Third, I count the price-driven loss in species. Holding world crop prices at their 2001 level, as Berman et al. (2023) do, the estimate attributes 39% of the tree cover lost in these cells between 2001 and 2018 to the rise in prices: 70 of 177 million hectares, or 19% to 53% across the 95% confidence interval clustered by country. With the species measure of the counterfactuals in Section 5, this loss commits 14 bird species to global extinction (7 to 18), out of 33 committed by all the tree cover lost in these cells. A committed extinction is one that follows once ecosystems have adjusted to the habitat lost, which can take decades. Counted ecoregion by ecoregion, with a species present in several ecoregions counted in each, the same loss lowers the number of bird species the affected ecoregions support by about 940 (Figure 4). Latin America accounts for 40% of the 14 global extinctions, tropical Asia for 34%, Africa for 19% and the islands of eastern Indonesia, New Guinea and the Solomons for 7%; a hectare cleared costs the most species on those islands, and next in tropical Asia. The same loss removed at least 1% of the range of 5,064 bird species, 487 of them threatened (Appendix A).[7]

Three features of the model rest on this fact. First, its extensive margin works through the same channel: the share of a field converted to agriculture rises with the return to farming it (Eq. (12)), which combines the prices farmers receive for each crop with the field's GAEZ yield for that crop, so a change in a crop's price moves the return most where the crop grows best. Second, because the response reaches beyond dense forest, the model applies one land-supply response to all natural land; the evidence above supports this for wooded savanna, and for open grassland it is an assumption. Third, the design identifies how conversion in one cell responds relative to another of the same country, not how much land a price change converts in total. The country $\times$ year effects absorb national responses, such as changes in wages or input costs, and the counterfactual above, like that of Berman et al. (2023), holds them fixed, so it assumes they neither offset nor add to the local response. The design also sees only one side of trade. World crop prices stayed above their 2001 level in almost every cell and year, and the satellite data record clearing, not regrowth, so the design cannot show the land that trade can release where it lowers the prices farmers receive or raises yields through cheaper inputs. Computing both sides, within countries and across trading partners, is what the model adds.

[7]The translation counts tree cover only, so other natural land is left out, while the satellite measure of loss also includes plantation rotation, fire and storms. Counting cleared land as low-intensity pasture rather than as no habitat gives 12 species instead of 14.

3 A model of agricultural trade, land use and biodiversity

In this section, I present the general equilibrium model that links changes in trade costs to changes in bird biodiversity. It builds on the model of Farrokhi and Pellegrina (2023) and departs from it in four ways. First, livestock holds land directly and competes with crops field by field, produced with an extensive technology that grazes and an intensive one that buys a mix of feed crops, aggregated as in Gouel and Laborde (2021). Second, converting natural land has its own elasticity, θ_1: the conversion cost is drawn independently of crop productivities, so land supply is not tied to the dispersion across crops; each field is split into a part where crops can grow and a part that can only be grazed, and in the counterfactuals conversion is capped by the natural land each field can convert. Third, households buy food, a composite of farm goods and marketing services, so farm-gate demand responds to farm prices only in proportion to the farm share of the food dollar. Fourth, it adds a biodiversity component, drawing on Scherer et al. (2023): land use determines bird species richness in each ecoregion and the abundance of insectivorous birds in each field, and the ecosystem services these birds provide feed back on farm productivity (Noack, Engist, and Larsen, 2025). Appendix I compares the two models under the same trade-cost shocks.

3.1 Environment

I consider a world composed of multiple countries, indexed by $i \in \mathcal{I} \equiv \{1, \ldots, I\}$, and multiple ecoregions, indexed by $e \in \mathcal{E} \equiv \{1, \ldots, E\}$, which delimit distinct ecosystems. A country may contain several ecoregions, and an ecoregion may span several countries. Each country i is endowed with a quantity L_i of land, N_i of labor and V_i of raw fertilizer. Land is divided into heterogeneous fields f. Each field lies in one country i, such that $\sum_{f \in \mathcal{F}_i} L_{fi} = L_i$, and may overlap several ecoregions: λ_{fe} denotes the share of field f's area that falls within ecoregion e, and L_e the total area of ecoregion e. All fields correspond to 5-arcminute grid cells and consist of a continuum of heterogeneous plots $\omega \in f$.

Goods are indexed by $g \in \mathcal{G}$ and include: (1) an outside good $g = 0$, (2) agricultural inputs, indexed by $j \in \mathcal{J} \subset \mathcal{G}$, and (3) agricultural outputs, indexed by $k \in \mathcal{K} \subset \mathcal{G}$. Agricultural outputs consist of crops, indexed by $k \in \mathcal{K}^c$, and a livestock product, $k = \ell$, so that $\mathcal{K} = \mathcal{K}^c \cup \{\ell\}$.

3.1.1 Preferences

I assume that consumers' preferences follow a nested structure. In the upper tier, the representative household in field f derives utility from the outside good composite, C^0_{fi}, and food, C^F_{fi}, according

to a CES aggregator:

$$C_{fi} = \left[\left(b_i^0\right)^{1/\eta} \left(C_{fi}^0\right)^{(\eta-1)/\eta} + \left(b_i^F\right)^{1/\eta} \left(C_{fi}^F\right)^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}, \tag{2}$$

where η is the elasticity of substitution and b_i^0 and b_i^F are exogenous demand shifters. Food combines the agricultural consumption bundle C_{fi}^a with non-farm marketing services D_{fi} (processing, wholesale and retail) in fixed proportions:

$$C_{fi}^F = \min \left\{ \frac{\bar{P}_i^a \, C_{fi}^a}{\mu_i}, \; \frac{\bar{P}_i^0 \, D_{fi}}{1-\mu_i} \right\}, \tag{3}$$

where $\bar{P}_i^a$ and $\bar{P}_i^0$ are constants, equal to the price indexes of the agricultural consumption bundle and of the outside good in the baseline equilibrium (both indexes are defined in Eqs. (25) and (26) below and are common to all fields of country i). A unit of food therefore costs one at baseline prices, and $\mu_i \in (0, 1]$ is the farm share of the food dollar. Marketing services are produced with the outside good. Setting $\mu_i = 1$ recovers the agricultural upper tier of Farrokhi and Pellegrina (2023), in which households buy farm goods directly. In the middle tier, the agricultural consumption bundle aggregates the consumption of agricultural outputs $k \in \mathcal{K}$ according to CES preferences with elasticity of substitution κ and exogenous demand shifters b_i^k:

$$C_{fi}^a = \left[\sum_{k \in \mathcal{K}} \left(b_i^k\right)^{1/\kappa} \left(C_{fi}^k\right)^{(\kappa-1)/\kappa} \right]^{\kappa/(\kappa-1)}. \tag{4}$$

Finally, in the lower tier, the representative household purchases varieties of each good g from different origin countries according to a CES function with elasticity of substitution σ_g and exogenous demand shifters b_{ni}^g:

$$C_{fi}^g = \left[\sum_{n \in \mathcal{I}} \left(b_{ni}^g\right)^{1/\sigma_g} \left(C_{nfi}^g\right)^{(\sigma_g-1)/\sigma_g} \right]^{\sigma_g/(\sigma_g-1)}. \tag{5}$$

3.1.2 Technology

Agricultural production. Each plot ω is initially natural habitat, which cannot be farmed until it is converted. I assume that farmers must pay a fixed cost to convert their plot for agricultural use, equal to $a_{fi}^0 \, z_{fi}^0(\omega)$ units of the outside good per hectare, where a_{fi}^0 is a field-specific cost shifter and $z_{fi}^0(\omega)$ a plot-specific draw. They then choose which agricultural product $k \in \mathcal{K}^c \cup \{\ell\}$ to produce and which technology $\tau \in \mathcal{T}$ to use on that plot. By combining land $L_{fi}^{k\tau}(\omega)$, labor

$N_{fi}^{k\tau}(\omega)$ and intermediates $M_{fi}^{k\tau}(\omega)$, the farmer of plot ω can produce:

$$Q_{fi}^{k\tau}(\omega) = \left[\frac{1}{\gamma_L^{k\tau}} z_{fi}^{k\tau}(\omega) L_{fi}^{k\tau}(\omega)\right]^{\gamma_L^{k\tau}} \left[\frac{1}{\gamma_N^{k\tau}} N_{fi}^{k\tau}(\omega)\right]^{\gamma_N^{k\tau}} \left[\frac{1}{\gamma_M^{k\tau}} M_{fi}^{k\tau}(\omega)\right]^{\gamma_M^{k\tau}} \tag{6}$$

where $z_{fi}^{k\tau}(\omega)$ is the productivity of land for the product-technology pair (k, τ) in plot ω. The technology can be either low-input, $\tau = 0$, or high-input, $\tau = 1$, and is characterized by intensity parameters $\gamma_L^{k\tau} \in (0, 1]$, $\gamma_N^{k\tau} \in [0, 1]$ and $\gamma_M^{k\tau} = 1 - \gamma_L^{k\tau} - \gamma_N^{k\tau} \in [0, 1]$. For crops, the low-input technology is traditional ($\gamma_M^{k0} = 0$, land and labor only) and the high-input technology is modern (land, labor and intermediates). For livestock, the low-input technology is extensive ($\gamma_M^{\ell 0} = 0$, land and labor only) and the high-input technology is intensive (land, labor and feed).

The nature of intermediates M differs between crops and livestock. For crops ($k \in \mathcal{K}^c$), $M_{fi}^{k\tau}(\omega)$ is a Cobb-Douglas combination of importable agricultural inputs j:

$$M_{fi}^{k\tau}(\omega) = \prod_{j \in \mathcal{J}} \left(\frac{M_{fi}^{k\tau j}(\omega)}{\gamma_M^{kj}}\right)^{\gamma_M^{kj}}, \tag{7}$$

where $M_{fi}^{k\tau j}(\omega)$ denotes the use of agricultural input j. The intensity parameters $\gamma_M^{kj} \in [0, 1]$ satisfy $\sum_{j \in \mathcal{J}} \gamma_M^{kj} = 1$. Farmers can buy agricultural inputs from different origins according to CES preferences with elasticity of substitution σ_j and exogenous demand shifters b_{ni}^j:

$$M_{fi}^{k\tau j}(\omega) = \left[\sum_{n \in \mathcal{I}} \left(b_{ni}^j\right)^{1/\sigma_j} \left(M_{nfi}^{k\tau j}(\omega)\right)^{(\sigma_j - 1)/\sigma_j}\right]^{\sigma_j/(\sigma_j - 1)}. \tag{8}$$

For livestock ($k = \ell$), intermediates take the form of a feed mix, $M_{fi}^{\ell 1} = F_{fi}$, which is a CES aggregate of importable crops with elasticity of substitution ζ and exogenous demand shifters $b_i^{k,feed}$:

$$F_{fi} = \left[\sum_{k \in \mathcal{K}^c} \left(b_i^{k,feed}\right)^{1/\zeta} \left(F_{fi}^k\right)^{(\zeta - 1)/\zeta}\right]^{\zeta/(\zeta - 1)} \tag{9}$$

where F_{fi}^k is the use of crop k in the feed mix of field f, which in turn aggregates over all varieties of crop k. I assume that the preferences of livestock producers over crop origins are the same as those of the representative household, with the same b_{ni}^k and σ_k:

$$F_{fi}^k = \left[\sum_{n \in \mathcal{I}} \left(b_{ni}^k\right)^{1/\sigma_k} \left(F_{nfi}^k\right)^{(\sigma_k - 1)/\sigma_k}\right]^{\sigma_k/(\sigma_k - 1)} \quad \forall k \in \mathcal{K}^c. \tag{10}$$

In each plot, the land productivities $z_{fi}^{k\tau}(\omega)$ are drawn from a field-specific two-level nested Fréchet distribution:

$$\Pr\left(\mathbf{z}_{fi}(\omega) \leq \mathbf{z}_{fi}\right) = \exp\left\{-\bar{\phi} \sum_{k \in \mathcal{K}^c \cup \{\ell\}} \left[\sum_{\tau \in \mathcal{T}} \left(\frac{z_{fi}^{k\tau}}{a_{fi}^{k\tau}}\right)^{-\theta_3}\right]^{\theta_2/\theta_3}\right\} \tag{11}$$

where $\bar{\phi} \equiv [\Gamma(1 - 1/\theta_2)]^{-\theta_2}$ is a normalizing constant, θ_2 governs substitution between agricultural products and θ_3 between technologies within a given product.

I depart from Farrokhi and Pellegrina (2023) in the treatment of the *extensive* margin. In their model the cost of converting a plot to agriculture is drawn jointly with the crop productivities, so that moving land into or out of agriculture is as elastic as switching between crops. I instead give the conversion margin its own elasticity: the plot-specific conversion draw $z_{fi}^0(\omega)$ is independent of the crop draws and follows a log-logistic distribution with shape θ_1, the distribution of the ratio of two Fréchet draws of common shape, one on the plot's value in agriculture and one in natural use. The odds that a plot of the field is converted to agriculture then respond iso-elastically to the ratio of its expected agricultural return H_{fi}^a (Eq. (33)) to its conversion cost $a_{fi}^0 P_{fi}^0$:

$$\frac{\alpha_{fi}^a}{1 - \alpha_{fi}^a} = \left(\frac{H_{fi}^a}{a_{fi}^0 P_{fi}^0}\right)^{\theta_1}. \tag{12}$$

The parameter θ_1 is the elasticity of these conversion odds, and so governs land supply: the elasticity of the agricultural share itself is $(1 - \alpha_{fi}^a)\,\theta_1$. Unlike in a nested Fréchet structure, θ_1 is not constrained by the across-crop dispersion θ_2. Appendix B.1 derives Eq. (12) and shows why the nested alternative caps it at θ_2.

Non-agricultural production. All other sectors work as in Farrokhi and Pellegrina (2023). Processed fertilizers, denoted $v \in \mathcal{J}$, are produced using the domestic supply of raw fertilizers: $Q_i^v = V_i$. The outside good $g = 0$ and nonfertilizer agricultural inputs $j \in \mathcal{J} \setminus \{v\}$ are produced under constant returns to scale using labor only: $Q_i^g = A_i^g \tilde{N}_i^g$, where $\tilde{N}_i^g$ are the efficiency units employed in g and A_i^g is their productivity.

3.1.3 Labor market

Workers are mobile between sectors but immobile between countries. Each worker φ in country i is endowed with efficiency units $\epsilon_i^s(\varphi)$ for each sector s drawn from Fréchet distribution:

$$\Pr(\epsilon_i^s(\varphi) \leq \epsilon) = \exp\left\{-\left[\Gamma(1-1/\psi)\right]^{-\psi}\left(\frac{\epsilon}{g_i^s}\right)^{-\psi}\right\} \tag{13}$$

where ψ is the between-sector labor supply elasticity, and g_i^s is a scale parameter. Workers can supply their efficiency units either to the non-agricultural sector ($s = 0$) for wage w_i^0 or to the agricultural sector ($s = 1$) for wage w_i^1, according to which yields the highest revenue $w_i^s \epsilon_i^s(\varphi)$.

3.1.4 Trade costs

Goods are traded across fields via a *hub-and-spoke* system, subject to iceberg trade costs: $d_{fif'n}^g \geq 1$ units of g must be shipped from field f in country i to field f' in country n to sell 1 unit. This trade cost can be decomposed as:

$$d_{fif'n}^g = d_{fi}^g \times d_{in}^g \times d_{f'n}^g \tag{14}$$

where d_{fi}^g is the domestic trade cost between field f and its nearest hub in origin country i, d_{in}^g is the hub-to-hub international trade cost, and $d_{f'n}^g$ is the domestic trade cost between field f' and its nearest hub in destination country n. I make three assumptions regarding domestic trade costs. First, the outside good is not subject to any domestic trade costs, i.e. $d_{fif'n}^0 = d_{in}^0$. Second, agricultural inputs are not subject to domestic trade costs in the origin country, i.e. $d_{fif'n}^j = d_{in}^j \times d_{f'n}^j$. Third, agricultural outputs, crops and the livestock product, are not subject to domestic trade costs in the destination country when households buy them, i.e. $d_{fif'n}^k = d_{fi}^k \times d_{in}^k$; crops bought as feed also bear the domestic cost of reaching the livestock producer's field, $d_{f'n}^k$. As such, everything works as if all goods but agricultural outputs were produced in hubs, and all goods but agricultural inputs and feed were consumed in hubs. The domestic trade cost of a field is common to all goods, $d_{fi}^g = d_{fi}$. Similarly, w_i^0 can be interpreted as an *urban* wage and w_i^1 as a *rural* wage.

Goods are not differentiated by fields or hubs. As a result, producer prices including domestic trade costs must be equalized in origin country i, i.e. $p_{fi}^k d_{fi}^k = p_i^k$; producers in more remote fields receive a lower price for agricultural output k. Purchase prices including domestic trade costs must also be equalized in destination country n, i.e. $P_{f'n}^j = d_{f'n}^j P_n^j$; farmers in more remote fields pay a higher price for agricultural input j, and livestock producers for feed.

3.1.5 Biodiversity

Land can be categorized as either natural habitat or agricultural.[8] I then decompose *current* land use in ecoregion e as:

$$L_e = L_e^{nat} + \sum_k \sum_\tau L_e^{k\tau} \tag{15}$$

where $L_e^{k\tau} = \sum_i \sum_{f \in \mathcal{F}_i} \lambda_{fe} \, L_{fi} \, \pi_{fi}^{k\tau}$ is the area dedicated to the product-technology pair (k, τ) in ecoregion e, with $\pi_{fi}^{k\tau}$ the share of field f allocated to (k, τ), derived below, and $L_e^{nat} = L_e - \sum_k \sum_\tau L_e^{k\tau}$ is the remaining natural habitat, including land outside the model's fields.

Species richness. Given this distribution of land, the Countryside Species–Area model (Pereira and Daily, 2006) predicts the number of bird species expected to persist in ecoregion e:

$$B_e^{SAR} = S_e^0 \left(\frac{L_e^{nat} + \sum_k \sum_\tau \chi_e^{k\tau} \times L_e^{k\tau}}{L_e} \right)^{z_e}, \tag{16}$$

where S_e^0 is the number of bird species originally present in ecoregion e prior to any land conversion. The parameters $\chi_e^{k\tau} \in [0, 1]$ capture birds' affinity for land under each product-technology pair (k, τ), which depends on the product only through its land-use type (annual crop, permanent crop or pasture): $\chi_e^{nat} = 1$ (natural habitat can support all bird species), and affinity decreases as land use becomes increasingly hostile for birds. The exponent z_e is the elasticity of species persistence with respect to effective habitat: with a small z_e, few species are lost until little habitat remains; with z_e close to one, species are lost nearly in proportion to habitat. Prior to any alteration in land use, $B_e^{SAR} = S_e^0$. Because each ecoregion harbors a distinct assemblage of endemic species, the index is expressed in levels rather than fractions, so that biodiversity-rich ecoregions receive proportionally greater weight. The index is mapped to fields via a row-normalized area-weighting matrix: $B_{fi}^{SAR} = \sum_e \lambda_{fe} B_e^{SAR}$, with the area shares λ_{fe} defined above.

Abundance. As a complementary biodiversity metric, I measure the relative abundance of insectivorous birds, the guild that delivers pest control, in each field, using an index inspired by the GLOBIO framework (Alkemade et al., 2009). Denoting by α_{fi}^u the share of field f in land use $u \in \{c, m, p\}$ (annual crops, permanent crops and pasture) and by $\alpha_{fi}^{u,high}$ the high-intensity share

[8] I exclude other human-modified land categories, such as urban areas, which are quantitatively negligible relative to agricultural areas.

within each, the index is a habitat-weighted average of relative bird densities:

$$B_{fi}^{abun} = \underbrace{\left(1 - \sum_{u} \alpha_{fi}^{u}\right)}_{\text{natural land}} + \sum_{u \in \{c,m,p\}} \alpha_{fi}^{u} \left[\delta_{u}^{low} \left(1 - \alpha_{fi}^{u,high}\right) + \delta_{u}^{high}\, \alpha_{fi}^{u,high}\right], \tag{17}$$

where $\delta_u^{low}, \delta_u^{high} \in [0,1]$ are the abundances of insectivorous birds in low- and high-intensity use u relative to primary vegetation (Section 4.4). In natural habitat the relative density is one; B_{fi}^{abun} is thus a weighted average of bird densities across natural land, cropland, and pasture. The species-richness index of Eq. (16) treats pasture symmetrically, through the habitat affinity $\chi_e^{\ell\tau}$ of the livestock product.

Biodiversity–productivity feedback. Biodiversity sustains ecosystem services that raise agricultural productivity; the service modeled here is pest control by insectivorous birds. I let the productivity of each product-technology pair (k,τ) in field f, livestock included, be its baseline level scaled by a biological modifier,

$$a_{fi}^{k\tau} = f_{fi}^{bio}\, \tilde{a}_{fi}^{k\tau}, \tag{18}$$

where $\tilde{a}_{fi}^{k\tau}$ is productivity at the baseline equilibrium and f_{fi}^{bio} measures the change in ecosystem services relative to that equilibrium. Because land returns in Eqs. (28) to (33) depend on $a_{fi}^{k\tau}$, the modifier enters every land-use decision.

Ecosystem services are measured as in Noack, Engist, and Larsen (2025): they aggregate the abundances x_s of the bird species present with a CES function, $ES = (\sum_s x_s^{\rho})^{1/\rho}$, where $\sigma_{ES} = 1/(1-\rho)$ is the elasticity of substitution among species. If the S species present in a field share its total abundance A evenly, $ES = A\, S^{1/(\sigma_{ES}-1)}$ (Appendix B.3): services rise with abundance, and with richness at a rate that falls with σ_{ES}. Measuring abundance by the index B_{fi}^{abun} of Eq. (17) and richness by the species–area index B_{fi}^{SAR} of Eq. (16), carried from ecoregions to fields by the area shares λ_{fe}, services relative to the baseline are

$$\frac{ES'_{fi}}{ES_{fi}} = \frac{B'^{abun}_{fi}}{B_{fi}^{abun}} \left(\frac{B'^{SAR}_{fi}}{B_{fi}^{SAR}}\right)^{\frac{1}{\sigma_{ES}-1}}, \tag{19}$$

where primes denote values in a counterfactual equilibrium. The modifier is

$$f_{fi}^{bio} = \left(\frac{ES'_{fi}}{ES_{fi}}\right)^{\beta}, \tag{20}$$

where β is the elasticity of yields with respect to ecosystem services. As $\sigma_{ES} \to \infty$, species are perfect substitutes and only abundance matters; a low σ_{ES} makes the loss of species weigh heavily.[9]

Two properties follow. First, the aggregate effect of the feedback depends on the policy. A policy that relocates agriculture lowers productivity where land expands and raises it where land contracts, so the two partly offset, while a policy that expands agriculture lowers ecosystem services on net; β governs the magnitude of the feedback, not its sign. Second, the feedback is an externality at two scales. The abundance term is local: converting a plot lowers bird abundance, and with it productivity, on every plot of the same field. The richness term is regional: because species persistence is evaluated at the ecoregion level, conversion anywhere in an ecoregion lowers f_{fi}^{bio} on every field in it, although at high σ_{ES} it carries little weight. In both cases the landowner who converts or intensifies does not bear the productivity loss imposed on other plots. Habitat itself has no value to households in the model; the feedback adds one distortion, an unpriced productivity spillover between producers, which a framework without the feedback cannot represent.

3.2 General equilibrium

3.2.1 Demand

Given equations (2), (4), (5) and (14), utility maximization by the representative household in field f requires

$$C_{fi}^F = \left(\frac{P_{fi}^F}{P_{fi}}\right)^{-\eta} b_i^F C_{fi}, \qquad C_{fi}^a = \frac{\mu_i}{\bar{P}_i^a} C_{fi}^F, \qquad D_{fi} = \frac{1-\mu_i}{\bar{P}_i^0} C_{fi}^F, \tag{21}$$

$$C_{fi}^k = \left(\frac{P_{fi}^k}{P_{fi}^a}\right)^{-\kappa} b_i^k C_{fi}^a, \tag{22}$$

and

$$C_{nfi}^g = \left(\frac{p_n^g d_{ni}^g d_{fi}^g}{P_{fi}^g}\right)^{-\sigma_g} b_{ni}^g C_{fi}^g. \tag{23}$$

[9] Writing the feedback in changes, as in exact hat algebra (Dekle, Eaton, and Kortum, 2008), means that baseline productivity never has to be split between agro-climatic and biological sources, a split that is neither identified nor needed: $\tilde{a}_{fi}^{k\tau}$ already embeds whatever biodiversity contributes at the baseline, and f_{fi}^{bio} carries only the deviation from it. The ratio also makes the feedback invariant to the normalization of the biodiversity indices, which matters because β comes from a literature whose index is scaled differently, and it equals one at the baseline, so the baseline equilibrium is reproduced exactly. Because the feedback enters land allocation, it is solved jointly with the general equilibrium: land use determines the biodiversity indices, which update f_{fi}^{bio}, which in turn shifts land use, until convergence (Appendix E.2).

Price indexes that enter the above tiers are:

$$P_{fi} = \left[b_i^0 (P_{fi}^0)^{1-\eta} + b_i^F (P_{fi}^F)^{1-\eta}\right]^{\frac{1}{1-\eta}}, \qquad P_{fi}^F = \mu_i \frac{P_{fi}^a}{\bar{P}_i^a} + (1-\mu_i)\frac{P_{fi}^0}{\bar{P}_i^0}, \tag{24}$$

$$P_{fi}^a = \left[\sum_{k\in\mathcal{K}} b_i^k (P_{fi}^k)^{1-\kappa}\right]^{\frac{1}{1-\kappa}}, \tag{25}$$

and

$$P_{fi}^g = \left[\sum_{n\in\mathcal{I}} b_{ni}^g (p_n^g d_{ni}^g d_{fi}^g)^{1-\sigma_g}\right]^{\frac{1}{1-\sigma_g}}. \tag{26}$$

Given assumptions on domestic trade costs, $P_{fi}^g = P_i^g = \left[\sum_{n\in\mathcal{I}} b_{ni}^g (p_n^g d_{ni}^g)^{1-\sigma_g}\right]^{\frac{1}{1-\sigma_g}}$ for $g = 0$ and $g \in \mathcal{K}$, and for all fields $f \in \mathcal{F}_i$; for agricultural inputs, $P_{fi}^j = d_{fi}^j P_i^j$. Because farm goods are only a share of the cost of food, a change in farm prices moves the food price by only a fraction, μ_{fi}^F, of that change, and demand at the farm gate inherits that fraction. Holding other prices and expenditure fixed,

$$\frac{\partial \ln C_{fi}^a}{\partial \ln P_{fi}^a} = -\mu_{fi}^F \left[\eta\left(1 - s_{fi}^F\right) + s_{fi}^F\right], \tag{27}$$

where s_{fi}^F is the share of food in total spending and μ_{fi}^F the farm share of the food dollar at current prices (μ_i at baseline); Appendix B.2 derives it. Spending on marketing services is spending on the outside good, so it enters non-agricultural labor demand in the labor-market clearing conditions below. Inelastic demand at the farm gate is one of the two conditions under which cheaper inputs spare land rather than clear it (Appendix B.5).

3.2.2 Production

Agricultural production. The marginal cost of product $k \in \mathcal{K}^c \cup \{\ell\}$ using technology τ in plot ω of field f, $c_{fi}^{k\tau}(\omega)$, is

$$c_{fi}^{k\tau}(\omega) = \left(\frac{r_{fi}^{k\tau}(\omega)}{z_{fi}^{k\tau}(\omega)}\right)^{\gamma_L^{k\tau}} \left(w_i^1\right)^{\gamma_N^{k\tau}} \left(m_{fi}^k\right)^{\gamma_M^{k\tau}}$$

where $r_{fi}^{k\tau}(\omega)$ is the gross rental price of plot ω and m_{fi}^k is the price index of intermediates: for crops, $m_{fi}^k \equiv \prod_{j\in\mathcal{J}} \left(P_{fi}^j\right)^{\gamma_M^{kj}}$; for livestock, $m_{fi}^\ell \equiv d_{fi} P_i^{feed}$, the feed price index delivered to the

field. Perfect competition implies $c_{fi}^{k\tau}(\omega) = p_{fi}^{k}$. Thus, as shown in Farrokhi and Pellegrina (2023),

$$r_{fi}^{k\tau}(\omega) = z_{fi}^{k\tau}(\omega) h_{fi}^{k\tau} \tag{28}$$

with

$$h_{fi}^{k\tau} \equiv p_{fi}^{k} \underbrace{\left(\frac{w_i^1}{p_{fi}^k}\right)^{-\gamma_N^{k\tau}/\gamma_L^{k\tau}} \left(\frac{m_{fi}^k}{p_{fi}^k}\right)^{-\gamma_M^{k\tau}/\gamma_L^{k\tau}}}_{\equiv \tilde{h}_{fi}^{k\tau}}$$

summarizing market-price effects. In equilibrium, the land share of the product-technology pair (k, τ) in field f, $\pi_{fi}^{k\tau}$, is

$$\pi_{fi}^{k\tau} = \alpha_{fi}^{a} \times \alpha_{fi}^{k} \times \alpha_{fi}^{k\tau} \tag{29}$$

where

$$\alpha_{fi}^{k\tau} = \frac{\left(a_{fi}^{k\tau} h_{fi}^{k\tau}\right)^{\theta_3}}{\left(H_{fi}^{k}\right)^{\theta_3}} \tag{30}$$

is the share of land within product k allocated to technology τ,

$$\alpha_{fi}^{k} = \frac{\left(H_{fi}^{k}\right)^{\theta_2}}{\left(H_{fi}^{a}\right)^{\theta_2}} \tag{31}$$

is the share of agricultural land allocated to product k, and

$$\alpha_{fi}^{a} = \frac{\left(H_{fi}^{a}\right)^{\theta_1}}{(a_{fi}^{0} P_{fi}^{0})^{\theta_1} + \left(H_{fi}^{a}\right)^{\theta_1}} \tag{32}$$

is the share of land allocated to agriculture. The term H_{fi}^{k} denotes the aggregate return to product k and H_{fi}^{a} the aggregate return to agriculture:

$$H_{fi}^{k} = \left[\sum_{\tau \in \mathcal{T}} \left(a_{fi}^{k\tau} h_{fi}^{k\tau}\right)^{\theta_3}\right]^{1/\theta_3}, \qquad H_{fi}^{a} = \left[\sum_{k \in \mathcal{K}^c \cup \{\ell\}} \left(H_{fi}^{k}\right)^{\theta_2}\right]^{1/\theta_2}. \tag{33}$$

Let $\Omega_{fi}^{k\tau}$ be the set of plots ω in field f to which product-technology (k, τ) is optimally allocated.

Combining Eq. (28)-(33), production of (k,τ) in plot ω is given by

$$Q_{fi}^{k\tau}(\omega) = \begin{cases} \left(\gamma_L^{k\tau}\right)^{-1} \tilde{h}_{fi}^{k\tau} z_{fi}^{k\tau}(\omega), \ \omega \in \Omega_{fi}^{k\tau} \\ 0, \ \omega \notin \Omega_{fi}^{k\tau}, \end{cases} \tag{34}$$

and at the field level by

$$Q_{fi}^{k\tau} = L_{fi} \left(\gamma_L^{k\tau}\right)^{-1} \tilde{h}_{fi}^{k\tau} a_{fi}^{k\tau} \, \alpha_{fi}^{a} \left(\alpha_{fi}^{k}\right)^{(\theta_2-1)/\theta_2} \left(\alpha_{fi}^{k\tau}\right)^{(\theta_3-1)/\theta_3}. \tag{35}$$

Because the conversion cost is drawn independently of crop productivity, the plots converted to agriculture are a representative sample of the field: output is *linear* in the agricultural share α_{fi}^{a}, rather than carrying the selection term $\left(\alpha_{fi}^{a}\right)^{(\theta_1-1)/\theta_1}$ that a nested draw would imply. Equivalently, average yield within a field does not rise as the agricultural frontier contracts. In the quantitative model each field is further split into a part that FAO-GAEZ rates suitable for crops, where all products compete, and a part that can only be grazed, each with its own conversion margin; Appendix B.1 derives field output and describes the split.

Aggregate output of product k, Q_i^k at the location of hubs in country i is

$$Q_i^k = \sum_{\tau \in \mathcal{T}} Q_i^{k\tau} \tag{36}$$

with

$$Q_i^{k\tau} = \sum_{f \in \mathcal{F}_i} \frac{Q_{fi}^{k\tau}}{d_{fi}^{k}}. \tag{37}$$

Lastly, the quantity of outside good required for setting up land in country i, FC_i^0, is the conversion cost summed over the plots that are actually converted. Since a plot is converted when $z_{fi}^0(\omega)$ falls below the threshold in equation (12), this is the *partial* mean of the conversion draw over the plots that convert, not the converted share itself:

$$FC_i^0 = \sum_{f \in \mathcal{F}_i} L_{fi} \, a_{fi}^0 \, \mathbb{E}\left[z_{fi}^0 \, \mathbf{1}\{z_{fi}^0 \le \bar{z}_{fi}\}\right] = \sum_{f \in \mathcal{F}_i} L_{fi} \, a_{fi}^0 \, B\left(\alpha_{fi}^a; \, 1 + \tfrac{1}{\theta_1}, \, 1 - \tfrac{1}{\theta_1}\right), \tag{38}$$

where $\bar{z}_{fi} = H_{fi}^a / (a_{fi}^0 P_{fi}^0)$ and $B(x;\cdot,\cdot)$ is the incomplete Beta function. The log-logistic draw matters here: a Pareto conversion cost of the same shape, scaled to a mean of one, would instead give $1 - (1 - \alpha_{fi}^a)^{(\theta_1-1)/\theta_1}$, which charges a strictly positive cost to the first plot converted and so overstates the bill on fields that are only lightly cultivated (Appendix B.1 derives both bills).

Feed-mix demand. Every field of country i faces the same relative crop prices, so the demand for crop k relative to the feed mix is the same in all of them; at the hubs it is

$$\frac{F_i^k}{F_i} = b_i^{k,feed} \left(\frac{P_i^k}{P_i^{feed}} \right)^{-\zeta}, \tag{39}$$

where $F_i^k \equiv \sum_{f \in \mathcal{F}_i} d_{fi} F_{fi}^k$ and $F_i \equiv \sum_{f \in \mathcal{F}_i} d_{fi} F_{fi}$ count the feed shipped from the hubs, with the feed price index

$$P_i^{feed} = \left[\sum_{k \in \mathcal{K}^c} b_i^{k,feed} (P_i^k)^{1-\zeta} \right]^{\frac{1}{1-\zeta}}. \tag{40}$$

3.2.3 Labor supply

The share of labor supply in sector s, n_i^s, equals

$$n_i^s = \frac{N_i^s}{N_i} = \frac{\left(g_i^s w_i^s\right)^{\psi}}{\sum_{s' \in \{0,1\}} \left(g_i^{s'} w_i^{s'}\right)^{\psi}} \tag{41}$$

and aggregate supply of efficiency units to sector s, $\tilde{N}_i^s$, is

$$\tilde{N}_i^s = g_i^s \left(n_i^s\right)^{(\psi-1)/\psi} N_i. \tag{42}$$

3.2.4 International trade

Total demand for crop $k \in \mathcal{K}^c$ in country i, from all origins including itself, is the sum of household consumption and feed

$$\frac{X_i^k}{P_i^k} = C_i^k + F_i^k \tag{43}$$

where X_i^k is total spending on crop k and $C_i^k \equiv \sum_{f \in \mathcal{F}_i} C_{fi}^k$. The share of origin n in the spending of destination field f on good g is

$$\frac{X_{nfi}^g}{X_{fi}^g} = b_{ni}^g \left(\frac{p_n^g d_{ni}^g d_{fi}^g}{P_{fi}^g} \right)^{1-\sigma_g}. \tag{44}$$

Because the domestic trade cost d_{fi} multiplies every origin alike, $\frac{X_{nfi}^g}{X_{fi}^g} = \frac{X_{ni}^g}{X_i^g}$ for every good and all fields $f \in \mathcal{F}_i$.

3.2.5 Market clearing

The goods market clears for the outside good $g = 0$, agricultural inputs $j \in \mathcal{J}$, and agricultural outputs $k \in \mathcal{K}$ when supply in the origin country n equals world demand:

$$p_n^0 Q_n^0 = \sum_{i \in \mathcal{I}} b_{ni}^0 \left(\frac{p_n^0 d_{ni}^0}{P_i^0} \right)^{1-\sigma_0} \left(1 - \mu_i^F s_i^F\right) E_i + P_n^0 FC_n^0, \tag{45}$$

$$p_n^j Q_n^j = \sum_{i \in \mathcal{I}} b_{ni}^j \left(\frac{p_n^j d_{ni}^j}{P_i^j} \right)^{1-\sigma_j} \sum_{k \in \mathcal{K}^c} \gamma_M^{kj} \gamma_M^{k1} p_i^k Q_i^{k1}, \tag{46}$$

$$p_n^k Q_n^k = \sum_{i \in \mathcal{I}} b_{ni}^k \left(\frac{p_n^k d_{ni}^k}{P_i^k} \right)^{1-\sigma_k} \left[b_i^k \left(\frac{P_i^k}{P_i^a} \right)^{1-\kappa} \mu_i^F s_i^F E_i + b_i^{k,feed} \left(\frac{P_i^k}{P_i^{feed}} \right)^{1-\zeta} \gamma_M^{\ell 1} p_i^\ell Q_i^{\ell 1} \right] \quad \forall k \in \mathcal{K}^c, \tag{47}$$

$$p_n^\ell Q_n^\ell = \sum_{i \in \mathcal{I}} b_{ni}^\ell \left(\frac{p_n^\ell d_{ni}^\ell}{P_i^\ell} \right)^{1-\sigma_\ell} b_i^\ell \left(\frac{P_i^\ell}{P_i^a} \right)^{1-\kappa} \mu_i^F s_i^F E_i, \tag{48}$$

where $Q_i^{k\tau}$ is output at the hubs (Eq. (37)), so that $p_i^k Q_i^{k\tau} = \sum_{f \in \mathcal{F}_i} p_{fi}^k Q_{fi}^{k\tau}$ is the value of output at farm-gate prices, and μ_i^F and s_i^F, the farm share of the food dollar and the food share of spending of Eq. (27), are common to the fields of country i. Spending on the outside good includes marketing services, and the conversion bill FC_n^0 of Eq. (38) is spent on the converting country's own outside good, valued at its price index P_n^0.

Labor market clearing in every country i requires that labor supply in each sector equal labor demand in that sector:

$$w_i^0 \tilde{N}_i^0 = p_i^0 Q_i^0 + \sum_{j \in \mathcal{J} \setminus \{v\}} p_i^j Q_i^j, \tag{49}$$

$$w_i^1 \tilde{N}_i^1 = \sum_{k \in \mathcal{K}^c \cup \{\ell\}} \sum_{\tau \in \mathcal{T}} \gamma_N^{k\tau} p_i^k Q_i^{k\tau}. \tag{50}$$

3.2.6 Expenditures

Total expenditure in country i, E_i, equals the sum of factor rewards

$$E_i = w_i^0 \tilde{N}_i^0 + w_i^1 \tilde{N}_i^1 + R_i + p_i^v V_i. \tag{51}$$

where R_i denotes aggregate net land rents in country i.

3.2.7 Equilibrium

Definition 1. For all countries $i, n \in \mathcal{I}$, ecoregions $e \in \mathcal{E}$, fields $f \in \mathcal{F}_i$, goods $g \in \mathcal{G}$ consisting of an outside good, agricultural inputs $j \in \mathcal{J}$, agricultural outputs $k \in \mathcal{K}$, sectors $s \in \{0, 1\}$, and technologies $\tau \in \mathcal{T}$, a global economy is characterized by endowments $\mathcal{D}$, supply parameters Ω_S, demand and trade parameters Ω_D and ecological parameters Ω_E:

$$\begin{aligned}
\mathcal{D} &\equiv \{L_{fi}, N_i, V_i, L_e\}, \\
\Omega_S &\equiv \{\theta_1, \theta_2, \theta_3, \psi, g_i^s, A_i^g, \gamma_L^{k\tau}, \gamma_M^{k\tau}, \gamma_N^{k\tau}, \gamma_M^{kj}, a_{fi}^0, s_{fi}, q_{fi}, \tilde{a}_{fi}^{k\tau}\}, \\
\Omega_D &\equiv \{\eta, \kappa, \zeta, \sigma_g, b_i^0, b_i^F, \mu_i, \bar{P}_i^a, \bar{P}_i^0, b_i^k, b_i^{k,feed}, b_{ni}^g, d_{ni}^g, d_{fi}\}, \\
\Omega_E &\equiv \{S_e^0, \chi_e^{k\tau}, z_e, \delta_u^{low}, \delta_u^{high}, \lambda_{fe}, \beta, \sigma_{ES}, B_{fi}^{SAR}, B_{fi}^{abun}\},
\end{aligned}$$

where s_{fi} is the crop-usable share of a field and q_{fi} its convertible-land ceiling (Appendix B.1), the conversion cost shifter a_{fi}^0 is set separately for the two parts of a field, and B_{fi}^{SAR} and B_{fi}^{abun} are the baseline values of the biodiversity indices.

Definition 2. Given a global economy characterized by $\{\mathcal{D}, \Omega_S, \Omega_D, \Omega_E\}$, a general equilibrium consists of prices $\{p_i^g\}$ in all countries $i \in \mathcal{I}$ and for all goods $g \in \mathcal{G}$, wages $\{w_i^0, w_i^1\}$ and biological modifiers $\{f_{fi}^{bio}\}$, such that Eqs. (15)–(20) and the demand, production, market-clearing and expenditure conditions of Eqs. (21)–(51) hold (Eq. (27) is a comparative static, not a condition), with the U.S. non-agricultural wage as numeraire and, in counterfactuals, each field's agricultural share capped at q_{fi}. Appendix E.1 describes the algorithm that solves for it.

Because domestic trade costs are fixed, every field of a country faces the same proportional price changes. The species a shock commits therefore depend on it only through 41 prices in each country and, with the feedback, each field's productivity multiplier. Once a shock's effect on those prices is known, from this model or any other, the land allocation and the species count follow from explicit formulas (Proposition B.2).

4 Model estimation

In order to simulate the model described in the previous section, data on endowments, as well as estimates of the demand, supply and ecological parameters, are required. In this section, I present the data used and the methods employed to estimate the parameters missing from the literature. Finally, I evaluate the model's fit. Unless stated otherwise, the data construction and the parameters set outside the model follow Farrokhi and Pellegrina (2023); Tables 2 and 4 give the source of each.

4.1 Data

The model is calibrated at three spatial scales: countries, ecoregions, and individual fields. The dataset includes 66 countries (with one representative for the rest of the world)[10], 760 world ecoregions, and 822,053 fields. It covers 35 agricultural outputs (34 crops and a livestock aggregate) and three agricultural inputs: pesticides, fertilizers, and farm machinery. I choose 2017 as the baseline year. Appendix C lists every source (Tables C.1 and C.2) and reports descriptive statistics at each spatial scale (Table C.3).

Country-level data. For the outside good, agricultural inputs and the agricultural output sector as a whole, I rebuild the bilateral trade flows and gross outputs of Farrokhi and Pellegrina (2023) for 2017, following their construction, from BACI-CEPII, the OECD Inter-Country Input-Output tables, STAN, UNIDO and the World Development Indicators; food expenditure shares are from the 2017 round of the International Comparison Program. I also collect data on bilateral trade flows, production weight, production value, land-use, and producer prices for each agricultural output from FAOSTAT. Data for the livestock good are derived by aggregating data on meat, eggs, milk and dairy products. The demand of a crop for feed is calculated using FAOSTAT Food Balance Sheets. Livestock technology shares, the split between extensive and intensive production, are calibrated using data from FAO-GLEAM v3 (2015). Bilateral agricultural trade is rebuilt from the FAOSTAT detailed trade matrix at farm-gate value, with processed products converted to primary equivalents and routed to their destination; land endowments are FAOSTAT land area, averaged over 2016–2018; fields are assigned to countries with geoBoundaries.

Ecoregion-level data. Global ecoregions are defined by WWF as "a large unit of land or water containing a geographically distinct assemblage of species, natural communities, and environmental

[10]The model has 63 individual countries, two aggregates for the former Soviet Union and the former Yugoslavia, and a rest-of-world aggregate pooling all other countries.

conditions". I recover the boundaries of each ecoregion from Olson et al. (2001) and the original number of bird species, S_e^0, from Chaudhary and Brooks (2018). Fields cover 66% of an ecoregion's area on average, and hold 91% of the world's cropland but 45% of its grazing land (Klein Goldewijk et al., 2025). Field areas are scaled so that each country's land matches FAOSTAT, and the biodiversity module places the farmland that exceeds a field's physical area on the country's cells outside the grid, in proportion to their HYDE cropland or grazing land, so the ecological measures cover each country's farmland, not only the part on the grid (Appendix C). The original number of bird species varies from 20 to 847, highest in the tropics. The habitat affinity parameters $\chi_e^{k\tau}$ and SAR exponents z_e are constructed from the countryside-SAR data repository of Chaudhary and Brooks (2018), the habitat-type exponents of Drakare, Lennon, and Hillebrand (2006), and the PREDICTS meta-analysis of Newbold et al. (2015); the construction is detailed in Section 4.4. I distinguish three land-use *types* (cropland, plantation, and pasture), each at two use intensities. I assume that the 'minimal' intensity corresponds to the low-input technology $\tau = 0$ in my model, and 'intensive' to the high-input technology $\tau = 1$. I assign each crop to a type by its agronomic nature: the 8 perennial crops (banana, citrus, cocoa, coconut, coffee, oil palm, olive, and tea) belong to the 'plantation' (permanent-crops) type, the remaining 26 annual crops to 'cropland', and livestock to 'pasture'.[11]

Field-level data. Potential yields are sourced from the Global Agro-Ecological Zoning (GAEZ) project (Fischer et al., 2021). The GAEZ agronomic model produces field-level yield estimates by evaluating each field's edaphic and climatic attributes, including dominant soil type, altitude, slope, temperature, precipitation, and related variables, against the specific requirements of individual crops; I denote the resulting potential yield of product-technology pair (k, τ) in field f by $y_{fi}^{k\tau}$. In this framework a 'field' corresponds to a 5'×5' grid cell, about 9 km across at the equator. As is common in the literature, I select the estimates for the reference period 1961–1990 under rain-fed conditions. GAEZ also provides yields for different levels of input use. I map these input regimes onto the technology parameter τ in my model: the low-input regime, representing traditional, subsistence-oriented land management, corresponds to $\tau = 0$ (traditional); the high-input regime, reflecting intensive, market-oriented management with fertilizer, chemical pest control and mechanization, corresponds to $\tau = 1$ (modern). To anchor the model in observed land-use patterns, I use the shares of each field under cropland and pasture (HYDE's grazing land) in 2017 from HYDE 3.5 (Klein Goldewijk et al., 2025), which allocates national agricultural statistics to

[11] Sugar crops and tropical roots are borderline (sugarcane is a perennial grass; cassava a perennial harvested young) and are classed as annual cropland by default, matching FAO arable-land accounting.

grid cells using satellite land cover; at the world level they match FAOSTAT cropland and pasture to within 2%. For the convertible-land ceiling imposed in the counterfactuals (Section 5), I additionally use natural-vegetation cover from ESA-CCI land cover (ESA, 2017) and protected-area boundaries from the World Database on Protected Areas (UNEP-WCMC and IUCN, 2011).

4.2 Demand-side parameters

The demand elasticities are taken from the literature, and the demand shifters are recovered from the model's demand equations; Table 2 summarizes them.

Lower-tier demand for agricultural outputs. I set the elasticity of substitution between origins to $\sigma_k = 5.4$ for every product, the estimate of Costinot, Donaldson, and Smith (2016), which Gouel and Laborde (2021) also use; it implies a trade elasticity of $\sigma_k - 1 = 4.4$, within the range of estimates surveyed by Head and Mayer (2014). I do not re-estimate it, or the elasticities of the upper nests below: Gouel and Laborde (2021) show that the sequential estimation of these elasticities in a model of this class is fragile, the across-crop elasticity losing significance once its standard error accounts for the earlier steps. Given σ_k, Eq. (44) implies

$$\log\left(\frac{X_{ni}^k}{X_i^k}\right) - (1-\sigma_k)\log p_n^k = \delta_i^k + \epsilon_{ni}^k$$

where

$$\delta_i^k \equiv -\log\left[\sum_{n\in\mathcal{I}} b_{ni}^k (p_n^k d_{ni}^k)^{1-\sigma_k}\right]$$

is an importer-product fixed effect and $\epsilon_{ni}^k \equiv \log\left[b_{ni}^k \left(d_{ni}^k\right)^{1-\sigma_k}\right]$ is a residual. Setting $\sum_{n\in\mathcal{I}} \epsilon_{ni}^k = 0$, the residuals recover $b_{ni}^k \left(d_{ni}^k\right)^{1-\sigma_k}$.

Lower-tier demand for other goods. I set $\sigma_g = 4$ for the manufacturing good and for agricultural inputs (Simonovska and Waugh, 2014), and use 2017 BACI flows. For each good g among manufacturing, pesticides and machinery, I estimate:

$$\log\left(\frac{X_{ni}^g}{X_i^g}\right) - (1-\sigma_g)\log w_n = \delta_i^g + \delta_n^g + \epsilon_{ni}^g$$

where $\delta_i^g \equiv -(1-\sigma_g)\log P_i^g$ is a destination fixed effect, $\delta_n^g \equiv (\sigma_g - 1)\log A_n^g$ is an origin fixed effect and $\epsilon_{ni}^g \equiv \log\left[b_{ni}^g \left(d_{ni}^g\right)^{1-\sigma_g}\right]$. This recovers $b_{ni}^g \left(d_{ni}^g\right)^{1-\sigma_g}$ and A_n^g. For fertilizers, I estimate:

$$\log\left(\frac{X_{ni}^g}{X_i^g}\right) - (1-\sigma_g)\log p_n^g = \delta_i^g + \epsilon_{ni}^g$$

and recover $b_{ni}^g \left(d_{ni}^g\right)^{1-\sigma_g}$ from residuals.

Middle-tier demand for agricultural outputs. I set the elasticity of substitution between agricultural products to $\kappa = 0.6$, following Gouel and Laborde (2021). The own-price elasticity of demand for a product with a small budget share is close to $-\kappa$, so this value targets the food price elasticities of the demand literature, which lie between about -0.3 and -0.9 in meta-analyses for the United States and China and in cross-country estimates.[12] Given κ, Eq. (22) implies

$$\log\left(\frac{X_i^k}{X_i^1}\right) - (1-\kappa)\log P_i^k = \delta_i + \epsilon_i^k$$

where $\delta_i \equiv -(1-\kappa)\log P_i^a$ is a country fixed effect and $\epsilon_i^k \equiv \log b_i^k$, normalized so that $\sum_{k\in\mathcal{K}} \epsilon_i^k = 0$. P_i^k is constructed from σ_k and the lower-tier shifters following Eq. (26), and the residuals recover b_i^k. The equation is fitted on non-feed use (production less exports plus imports, net of feed, at farm-gate prices), since feed demand is modeled separately below.

Upper-tier demand. I borrow from Comin, Lashkari, and Mestieri (2021) and set the elasticity of substitution between food and other goods to $\eta = 0.5$. Households spend their observed food share of income on food, but only part of that spending reaches farms: a unit of food combines farm goods and non-farm marketing margins in fixed proportions, with a country-specific farm share μ_i. I calibrate μ_i so that each country's farm-gate absorption matches the trade data, which pins aggregate farm spending at its farm-gate level, 4.2% of world value added in 2017, rather than at retail food expenditure, which would overstate farm revenue roughly fivefold. The farm share of the food dollar ranges from 0.10 in Japan and 0.14 in the United States to 0.24 in China and 0.46 in India. In four sub-Saharan African economies (Burkina Faso, Cameroon, Ghana and Mali), observed farm-gate absorption exceeds measured food spending and the share is capped at one. Given these, I recover b_i^0 and b_i^F based on Eq. (21) and Eq. (24).

Middle-tier demand for feed. I set the elasticity of substitution between crops in the feed mix to $\zeta = 0.9$, as in Gouel and Laborde (2021). Based on Eq. (39), I then estimate feed demand

[12] Estimating κ by instrumental variables on these data, following Farrokhi and Pellegrina (2023), gives 3.53 (s.e. 0.59), with a strong first stage but an overidentifying restriction that is rejected (Hansen $p = 0.01$). With small budget shares, that value would imply crop-level demand elasticities near -3.5. Recalibrating the model at $\kappa = 3.53$ leaves the headline almost unchanged, 25.8 species committed under de-liberalization against 26.4 at the benchmark, but moves its division between the two trade-cost channels: inputs account for 17.1 species and outputs for 9.7, against 12.9 and 14.5 at the benchmark, while outputs remain the costlier channel to reverse in welfare terms. The total barely depends on κ; its division does, and I report it at the benchmark, whose implied demand elasticities match the literature's.

Table 2: Demand-side parameters

Parameter	Description	Source	Value
σ_k	Elast. of subst. between origins, ag. products	Costinot, Donaldson, and Smith (2016), as in Gouel and Laborde (2021)	5.4
σ_g, $g = 0$, $g \in \mathcal{J}$	Elast. of subst. between origins, other goods	Simonovska and Waugh (2014), as in Farrokhi and Pellegrina (2023)	4
κ	Elast. of subst. between ag. products	Gouel and Laborde (2021)	0.6
ζ	Elast. of subst. between crops in feed	Gouel and Laborde (2021)	0.9
η	Elast. of subst. between food and other goods	Comin, Lashkari, and Mestieri (2021)	0.5
μ_i	Farm share of food spending	Calibrated: farm-gate absorption	–
b_i^0, b_i^F	Demand shifters, food and other goods	Calibrated: food expenditure shares (ICP 2017)	–
$b_{ni}^k (d_{ni}^k)^{1-\sigma_k}$	Bilateral demand shifters, ag. products	Residuals, gravity eq. (FAOSTAT, 2016–2018 average)	–
b_i^k	Demand shifters across ag. products	Residuals, middle-tier eq.	–
$b_i^{k,feed}$	Demand shifters of crops in feed	Residuals, feed-share eq.	–
$b_{ni}^g (d_{ni}^g)^{1-\sigma_g}$	Bilateral demand shifters, other goods	Residuals, gravity eq. (BACI 2017)	–
d_{fi}^g	Domestic trade costs	Farrokhi and Pellegrina (2023)	–

Notes: Elasticities are taken from the literature; demand shifters are recovered as residuals of the model's demand equations, given those elasticities, on 2017 data (Section 4).

shifters $b_i^{k,feed}$ using:

$$\log F_i^k + \zeta \log P_i^k = \delta_i^{feed} + \epsilon_i^{k,feed}$$

where $\delta_i^{feed} \equiv \log F_i + \zeta \log P_i^{feed}$ is a country fixed effect and $\epsilon_i^{k,feed} \equiv \log b_i^{k,feed}$ is a residual.

4.3 Supply-side parameters

I adopt most of the supply-side parameters from Farrokhi and Pellegrina (2023). For crops, the factor- and input-share values are taken as constant. Accordingly, I set: $\gamma_L^{k1} = 0.206$, $\gamma_N^{k1} = 0.207$, $\gamma_M^{k1} = 0.587$ for the modern technology; $\gamma_L^{k0} = 0.551$, $\gamma_N^{k0} = 0.449$ and $\gamma_M^{k0} = 0$ for the traditional technology; $\gamma_M^{fertilizers} = 0.256$, $\gamma_M^{pesticides} = 0.158$ and $\gamma_M^{machinery} = 0.586$ for agricultural input shares within the modern technology. For livestock, the two technologies are extensive ($\gamma_L^{\ell 0} = 0.60$, $\gamma_N^{\ell 0} = 0.40$) and intensive ($\gamma_L^{\ell 1} = 0.33$, $\gamma_N^{\ell 1} = 0.15$, $\gamma_M^{\ell 1} = 0.52$), and each country's intensive share

of production is calibrated to FAO-GLEAM v3. These land shares are not accounting shares, which put land far lower; I retain them because they reproduce the extent of pasture, which is what the ecological module needs: the model's world grazing area is within 12% of FAOSTAT's (Section 4.6). The across-crop dispersion is set to $\theta_2 = 1.6$, the estimate of Sotelo (2020) from land shares and prices across Peruvian regions, also used by Gollin and Wolfersberger (2025), and the across-technology dispersion to $\theta_3 = 2.29$. I estimate the latter on the moment Farrokhi and Pellegrina (2023) use for it, the slope of the modern-to-traditional land ratio in within-country trade cost across their six micro-data countries, by matching the model's binned counterpart; re-estimating on the recalibrated baseline returns 2.36, close to the value used. Farrokhi and Pellegrina (2023) obtain 4.51 from the same moment by indirect inference. The land-supply elasticity θ_1 is estimated internally, as described below. The source and value (when applicable) of all supply-side parameters is reported in Table 4.

Productivity shifters. Given the demand-side parameters, I recover the product-technology productivity shifters and solve for the equilibrium wages and prices. Each shifter is the GAEZ potential yield scaled by a calibrated productivity level,

$$\tilde{a}_{fi}^{k0} = \delta_{0,i}^{k}\, y_{fi}^{k0}, \qquad \tilde{a}_{fi}^{k1} = \delta_{0,i}^{k}\, \delta_{1}^{k}\, y_{fi}^{k1}, \tag{52}$$

where $y_{fi}^{k\tau}$ is the GAEZ potential yield of (k,τ) in field f, $\delta_{0,i}^{k}$ the product's productivity level in country i and δ_1^k its modern-technology factor. Each crop's modern-technology factor δ_1^k is set to match a modern share of land at an anchor country $a(k)$, $\alpha_{a(k)}^{k1}(\delta_1^k) = \alpha_{a(k)}^{k1,\text{data}}$. For 22 crops the target is the crop's own share in the farm micro data of Farrokhi and Pellegrina (2023), at its largest producer in those data; for nine crops led by the United States, among them maize, wheat and cotton, it is the U.S. benchmark of 95% used by Farrokhi and Pellegrina (2023); and for buckwheat, olives and tea, which the micro data do not cover where they are grown, it is the share of a proxy (oats in Brazil, olives and coffee in Colombia). Targets are capped at 95%. The productivity level is country-specific for every product, $\delta_{0,i}^{k}$, set so that every producer matches its own observed output, $Q_i^k(\delta_{0,i}^k) = Q_i^{k,\text{data}}$: GAEZ potential yields measure agro-climatic suitability, not realized productivity, which also depends on infrastructure, policy and farm organization, so for many crops they place production differently from the data.[13] The productivity shifters, the farm shares μ_i and the general-equilibrium solve are iterated until the targeted moments (output

[13] Without the soybean shifter the model would place 54% of world soybean output in China, against 4% in the data, because China is climatically well-suited to soy yet is in fact its largest net importer.

by producer, modern shares at the anchors, farm-gate absorption by country, and labor-market clearing with balanced trade) are matched. Appendix E.3 describes the algorithm and the accuracy of the match.

Land-supply elasticity. The land-supply elasticity θ_1 governs how the converted share of a field responds to the return to farming it (Eq. (12)). It is the model's one new parameter, and I estimate it inside the model by indirect inference, following Farrokhi et al. (2025). The auxiliary moment is the elasticity of agricultural land to population: as population grows, food demand rises and agriculture expands, at a rate that θ_1 governs. I estimate it across the model's country units c that have a continuous FAOSTAT series (61 of 66; Table 3),

$$\Delta \ln L_c^a = \beta_0 + \beta_1 \Delta \ln \mathrm{Pop}_c + \varepsilon_c, \tag{53}$$

where L_c^a is agricultural land, Pop_c population, and Δ the change between 1990 and 2020. By OLS, a 1% increase in population is associated with a 0.38% expansion of agricultural land, and the analogous regression for forest, on all 186 countries, gives a 0.18% contraction (Table 3).[14] Because population growth may itself respond to agricultural opportunity, I instrument it with the country's initial age structure, the 1990 youth share entered as a cubic: age structure predicts subsequent growth through demographic momentum but is predetermined with respect to later land conversion. The instrument is strong (robust first-stage $F = 120.4$), and the IV estimate of β_1 is 0.45.[15]

I set θ_1 so that the model reproduces the IV estimate of β_1 when Eq. (53) is estimated on model output, on the same country aggregates.[16] The estimate is $\theta_1 = 4.80$, with a ± 1 standard-error

[14] My measure of agricultural land differs from that of Farrokhi et al. (2025). They construct agricultural area as total *harvested* area plus grazing land imputed at 0.75 hectares per head of cattle, and report population–agricultural-land elasticities between 1.04 and 1.21 across specifications. I use FAOSTAT's agricultural land instead (arable land, permanent crops, and permanent meadows and pastures). Rebuilding their measure on my country aggregates over 1961–2020, with the 1961 youth share as instrument, gives 0.93, against 0.48 for my measure on the same window, aggregates and instrument, so the gap is one of measurement, not of sample or specification. Their measure suits their object: harvested area rises with multiple cropping even when no land is converted, and imputed pasture moves with herd size rather than with hectares. Mine suits this one, because the model's land variable is a *physical* area share and the biodiversity module maps hectares of habitat, not cropping intensity, into species loss. Targeting their elasticity here would read intensification as conversion and overstate habitat loss.

[15] A second, unrelated instrument built from the predicted mortality declines of Acemoglu and Johnson (2007) leaves the coefficient unchanged and passes the overidentification test (Hansen J, $p = 0.46$), although on its own it is weak (first-stage $F = 2.9$), so the test has limited power. The IV estimate exceeds OLS (0.38), the opposite of what frontier-pull endogeneity would produce and consistent instead with attenuation in long-difference growth rates; OLS is therefore the conservative target and is reported as robustness.

[16] The model's coefficient is evaluated in its small-shock limit. It is an arc elasticity that declines mechanically with the size of the population shock fed in, whereas its empirical counterpart is stable across estimation windows (between 0.32 and 0.38 across windows from 1961–2020 to 2000–2020; Appendix Table D.1), so the curvature is a property of the model rather than of the data and would otherwise be absorbed into the parameter. Estimation and recalibration are iterated to a joint fixed point; a full iteration moves the estimate by less than a tenth of a standard

band of [3.7, 6.2] obtained by mapping the heteroskedasticity-robust standard error of the target through the estimated binding function; the OLS target gives 3.7, at the lower end of the band. Appendix D details the reduced form, the binding function and the joint fixed point of estimation and calibration, and reads θ_1 as a measure of the dispersion of conversion costs within a field.

Two points help interpret the estimate. First, θ_1 is the elasticity of the conversion *odds* to the return from farming, $d\ln\big(\alpha/(1-\alpha)\big)/d\ln H^a = \theta_1$. The implied elasticity of agricultural area is $(1-\alpha^a_{fi})\,\theta_1$ field by field, about 1.96 on average over agricultural land, and smaller still in general equilibrium; θ_1 is therefore a structural parameter of land supply, which plays the role of the land-clearing technology of Farrokhi et al. (2025), calibrated there to the same population moment, and is not comparable to reduced-form acreage elasticities. The same holds for the price response of Fact 5, which measures the land cleared within a year or two of a price change, whereas θ_1 governs the share of a field in agriculture across equilibria decades apart. Second, θ_1 is three times the across-crop dispersion $\theta_2 = 1.6$, and more than twice it at the lower end of the band: the odds of conversion respond three times as strongly as the odds of choosing one crop over another, and the nested formulation, which requires $\theta_1 \leq \theta_2$, is rejected throughout the band. Appendix Table H.1 recalibrates the model and re-runs the counterfactuals at both ends of the band: the headline scales with θ_1 at between two-fifths and a little over a half of the proportional rate, while the split between the two channels and the welfare cost barely move.

4.4 Ecological parameters

The biodiversity sub-model requires, for each ecoregion e, the original bird richness S^0_e, the species–area exponent z_e, and a habitat affinity $\chi^{k\tau}_e$ for every product-technology pair, together with the relative-abundance parameters δ of the complementary index and the feedback elasticity β. I describe each in turn, distinguishing the calibration of cropland from that of pasture.

Species pools and species–area exponents. The original number of bird species S^0_e is taken from the countryside-SAR data repository of Chaudhary and Brooks (2018), which reports the pre-conversion species pool by ecoregion. The SAR exponent z_e governs the concavity of species accumulation. My baseline specification uses the habitat-type values of Drakare, Lennon, and Hillebrand (2006) (island $z = 0.258$, forest $z = 0.344$, non-forest $z = 0.211$), assigned to ecoregions through the habitat classification in the Chaudhary repository. As a robustness check I also use the continent-specific bird exponents of Storch, Keil, and Jetz (2012) (Eurasia and Africa 0.21, North

error of the target.

Table 3: Population growth and land-use change

	(1)–(2) Δ ln Ag. land OLS	IV	(3) Δ ln Forest OLS	(4) Δ ln Ag. land interacted
Δ ln Population	0.376^{***}	0.446^{***}	-0.185^{***}	0.587^{***}
	(0.065)	(0.071)	(0.054)	(0.083)
Δ ln Pop. × initial ag. share				-0.610^{***}
				(0.162)
Window	1990–2020	1990–2020	1990–2020	1961–2020
Units	61	61	186	61
First-stage F		120.4		
Hansen J p (overid.)		0.46		
R^2	0.25		0.09	0.51

Notes: Long-differenced cross-country regressions of the log change in agricultural land (columns 1, 2, 4) and forest (column 3) on log population growth (FAOSTAT land use and population; specification follows Farrokhi et al. (2025), eq. 1). Columns 1, 2 and 4 are estimated on 61 of the model's 66 country units, the units on which its model counterpart is computed: the former Soviet Union, the former Yugoslavia, Czechia and Ethiopia lack a continuous FAOSTAT series across their border changes of the early 1990s, and China is not in the sample (including it moves the column-2 estimate from 0.446 to 0.447); column 3 uses all countries. Column 2 instruments population growth with the 1990 youth share (population aged 0–14, World Bank), entered as a cubic: initial age structure predicts subsequent growth through demographic momentum but is predetermined. The Hansen J test adds a second instrument built from Acemoglu and Johnson (2007) predicted mortality declines from airborne diseases. Column 4 adds the interaction of population growth with the initial agricultural share of land, on the 1961–2020 window, where the interaction is precisely estimated: countries closer to full conversion expand less (Appendix D). The coefficient is stable across estimation windows (0.32–0.38 over 1961–2020, 1980–2017, 1990–2020, 2000–2020). Heteroskedasticity-robust (HC1) standard errors in parentheses, and the first-stage F is the robust Wald statistic; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The land-supply elasticity θ_1 is set so the model, evaluated in its small-shock limit on the same aggregates, reproduces the column-2 coefficient.

America 0.19, South America 0.17, Australia 0.15). Because the affinities below are themselves constructed with z_e in the exponent, that robustness check recomputes them at the alternative value rather than substituting the exponent alone; Panel A of Appendix Table H.1 reports the counterfactuals under the benchmark, under the exponent substituted on its own, and under the complete alternative, together with a further row that combines the Storch exponents with the flat global cropland ratios of Scherer et al. (2023). The level of committed extinctions moves with the exponent, which sets how fast species are lost as habitat shrinks. The Storch exponents are lower, so a given conversion destroys fewer species and the baseline stock falls by close to 30%. The division between the input and output channels, and the size of the de-liberalization relative to the baseline stock, are not.

Habitat affinities. I follow the two-step construction of Chaudhary and Brooks (2018). First, for each ecoregion e and each of the three land-use *types* T (cropland, plantation, pasture), their data repository provides a bird-specific *broad* habitat affinity, recovered from the local characterization factor as $\chi_{e,T}^{broad} = (1 - \mathrm{CF}_{local})^{1/z_e}$ (their Eq. 3). Second, their Eq. 4 splits this broad

Table 4: Supply-side parameters

Parameter	Description	Source	Value
θ_1	Land-supply elasticity (conversion odds)	Estimated: population–land elasticity, following Farrokhi et al. (2025)	4.80
θ_2	Productivity dispersion between products	Sotelo (2020)	1.6
θ_3	Productivity dispersion between technologies	Estimated: farm micro-data moment of Farrokhi and Pellegrina (2023)	2.29
ψ	Between-sector labor supply elasticity	Farrokhi and Pellegrina (2023)	2
g_i^s	Sectoral labor efficiency scale	Normalized	1
$y_{fi}^{k\tau}$	Potential yields	FAO-GAEZ v4	–
$\delta_{0,i}^k$	Productivity level by producer and product	Calibrated: FAOSTAT output	–
δ_1^k	Modern-technology productivity factor	Calibrated: modern land share at an anchor country, micro data or U.S. benchmark of Farrokhi and Pellegrina (2023)	–
a_{fi}^0	Conversion-cost shifter	Calibrated: field land shares, HYDE 3.5 (2017)	–
A_i^0, A_i^j	Productivity of non-ag. good and inputs	Origin effects, gravity eq. (BACI 2017)	–
$\gamma_L^{k\tau}$, $\gamma_N^{k\tau}$, $\gamma_M^{k\tau}$	Crop factor shares	Farrokhi and Pellegrina (2023)	see text
γ_M^{kj}	Crop input shares	Farrokhi and Pellegrina (2023)	see text
$\gamma_L^{\ell\tau}$, $\gamma_N^{\ell\tau}$, $\gamma_M^{\ell\tau}$	Livestock factor shares	Set to reproduce grazing-land extent	see text

Notes: Calibrated parameters are set so that the model matches the listed targets at the 2017 baseline (Section 4). The intensive share of livestock production is calibrated to FAO-GLEAM v3.

affinity into intensity-specific values by scaling it with the fractional relative richness f_{RR}:

$$\chi_e^{k\tau} = \chi_{e,T(k)}^{broad} \times \left(f_{RR}^{T(k),\tau}\right)^{1/z_e}, \tag{54}$$

where $T(k)$ is the ecological type of product k (annual crops map to cropland, the 8 perennial crops to plantation, livestock to pasture) and $\tau \in \{0, 1\}$ indexes minimal versus intense use. As defined by Chaudhary and Brooks (2018), $f_{RR}^{T,\tau}$ is the local bird richness in intensity class τ of type T *divided by the average richness across the intensities of that broad type.* So defined, f_{RR} is centered on one and carries only the *within-type* intensity gradient, while $\chi_{e,T}^{broad}$ sets the ecoregion-specific level. The broad-class-versus-natural loss is thus encoded once, in χ^{broad}, and is not double-counted. The exponent $1/z_e$ converts the richness ratio into an affinity ratio through the countryside SAR, in which local richness scales as χ^z. I compute f_{RR} from Table S1 of Newbold et al. (2015), taking $\chi_{e,T}^{broad}$ from the matching column of the Chaudhary repository (annual crops,

permanent crops, pasture). For *cropland*, richness 73.1/61.9/63.7 (minimal/light/intense), mean 66.2, gives $f_{RR}^{crop} = 1.10/0.96$; for *plantation* (Newbold's "plantation forest" class), 80.8/73.1/60.6, mean 71.5, gives $f_{RR}^{plant} = 1.13/0.85$; for *pasture*, 78.2/70.6/62.9, mean 70.6, gives $f_{RR}^{past} = 1.11/0.89$. The PREDICTS data thus imply that extensive pasture retains slightly *more* bird richness than minimal-input cropland, while intensive plantations and pastures are comparably hostile.

Abundance weights. The abundance index uses the abundance of insectivorous birds in each managed land use relative to primary vegetation, matching the guild whose services Noack, Engist, and Larsen (2025) value: species with more than a quarter of their diet in invertebrates over the growing season, from the SAviTraits 1.0 database (Murphy et al., 2023), weighted equally. I estimate the weights from the PREDICTS database (Hudson et al., 2017) by Poisson pseudo-maximum likelihood with study fixed effects, so that land uses are compared within studies. Low-input annual cropland has $\delta_c^{low} = 0.90$, permanent crops (plantations) $\delta_m^{low} = 0.83$ and $\delta_m^{high} = 0.61$, and extensive pasture $\delta_p^{low} = 0.81$. Low intensity pools the minimal and light use classes of PREDICTS. The database has too few within-study contrasts between low- and high-intensity annual cropland or pasture to estimate the high-intensity weights (its one direct pasture estimate, 1.17, rests on a thin sample), so I impute both with the within-study plantation ratio, $\delta^{high}/\delta^{low} = 0.74$: $\delta_c^{high} = 0.67$ and $\delta_p^{high} = 0.60$. The cropland weights are close to the all-bird totals of Newbold et al. (2015) (0.89 and 0.69); permanent crops and pasture are lower, because insectivores lose more of their abundance there than birds as a whole.

Feedback elasticity. The biodiversity–productivity feedback of Eq. (18) is calibrated to the causal estimates of Noack, Engist, and Larsen (2025), who instrument bird abundance in U.S. counties with conditions in the South American wintering grounds of migratory species, which drive how many birds return, to recover the elasticity of U.S. agricultural yields with respect to bird-provided ecosystem services. Their estimates depend on the elasticity of substitution among species: where it is low (forests), species richness governs services, and where it is high (agriculture), total abundance does. I use their high-substitutability estimates for agricultural landscapes, $\sigma_{ES} = 10$ and $\beta = 0.15$, in the index of Eq. (19). As robustness, a richness-only feedback with $\beta = 0.08$, their low-substitutability estimate, is reported alongside.

4.5 Other parameters

I consider $d_{fi}^g = d_{fi}$ and take the values of domestic trade costs estimated with the methodology of Allen and Arkolakis (2014) and data on the transportation networks of all countries. I set the labor supply elasticity to 2, i.e. $\psi = 2$, and normalize the shifters of labor supply to 1, i.e. $g_i^1 = g_i^0 = 1$.

Table 5: Model fit: untargeted moments

Moment	Pearson	Spearman	n
Production, employment and land use			
Agricultural employment share	0.80	0.88	66
Crop share of farmland, by country	0.58	0.62	66
Labor per hectare*	0.79	0.77	66
Fertilizer per hectare*	0.65	0.76	66
Fertilizer per worker*	0.72	0.74	66
Purchased-input cost share	0.42	0.52	66
Crop area, by country and crop*	0.80	0.78	1037
Output per hectare, by country and crop*	0.37	0.34	1037
Biodiversity			
Committed extinctions, vs. Chaudhary–Brooks*	0.74	0.82	712
shares of world total, by realm	0.98	0.96	7
vs. IUCN threatened birds, all causes*	0.32	0.38	741
threatened by crops or livestock*	0.24	0.35	712
threatened by other causes only*	−0.11	−0.12	441

Notes: All statistics are computed on the calibrated 2017 baseline at $\theta_1 = 4.80$. "Chaudhary–Brooks" is Chaudhary and Brooks (2018). The moments the calibration *does* target are not reported here: every producer's output of every product, each crop's modern-technology share at its anchor country, each country's farm-gate absorption, and the observed field-level agricultural land shares. They are matched to within 0.11%, except for 40 producer–crop pairs, 0.8% of world crop output by value, that the model does not produce (Appendix E.3). Net agricultural trade is therefore matched by construction and is not a test; crop area and output per hectare are, because the calibration pins output but not the hectares that produce it, although crop area partly inherits the scale of output. Correlations across countries are population-unweighted; Pearson coefficients are computed on logs for the rows marked $*$, whose variables span orders of magnitude. The resolution of each comparison is given by n. The IUCN rows compare the number of species the model commits to local extinction, unweighted, with the threatened birds present in each ecoregion, built from BirdLife range maps with marine species excluded; the vulnerability-weighted measure is used only against the Chaudhary–Brooks benchmark, which shares its weights. See also Appendix Table F.1 and Appendix Figures F.3–F.5.

4.6 Model fit and validation

Table 5 reports the model's fit on untargeted moments; supporting scatter plots and maps are in Appendix F.

Employment and land use. The calibration targets each country's total farmland but not how it divides between crops and pasture, nor the land each crop occupies, nor employment. The crop share of farmland correlates with the data at 0.58 across countries. It is close for the large frontier exporters, 24% in the model against 27% in the data for Brazil, 30% against 36% for Argentina and 10% against 9% for Australia, and furthest off in Egypt, India and land-scarce high-income countries; pasture in total is within 12% of FAOSTAT (Appendix Figure F.1). Crop areas match FAOSTAT harvested area across country–crop pairs with a log correlation of 0.80, but much of that reflects the scale of output, which the calibration pins: output per hectare,

which removes it, correlates at 0.37. The agricultural employment share tracks the data across countries with a correlation of 0.80 (Table 5). Four untargeted margins fit less well, each for a reason the model's structure makes explicit (Appendix F): the level of agricultural employment, 2.6% of world employment against 27%, because average earnings are equalized across sectors; the division of cropland among crops, which follows revenue; the split of India's farmland between crops and pasture; and the livestock imports of the rest-of-world aggregate, which bear most on the headline.

Input intensity. I evaluate whether the calibrated model reproduces untargeted moments that capture cross-country variation in agricultural input intensity. Appendix Figure F.2 shows the fit of these indicators (cost share of agricultural inputs, labor per unit of land, fertilizer per unit of land, and fertilizer per unit of labor) across quartiles of GDP per capita. The same moments correlate with their empirical counterparts at 0.79 for labor per hectare, 0.65 for fertilizer per hectare, 0.72 for fertilizer per worker, and 0.42 for the purchased-input cost share (Table 5); none is targeted.

Price elasticity of land supply. Because θ_1 is estimated from a single population moment, I check what the model implies for the response of agricultural land to its own price. Raising the upper-tier food taste shifter by 10% in every country shifts land demand outward and so traces the supply curve: the elasticity of agricultural land to the agricultural price index is 1.17 for the United States, 1.40 for Brazil and 0.87 in the world. In the world it is less than half of the partial-equilibrium value 1.96: general-equilibrium adjustment of wages and prices lowers it to 1.40, and the convertible-land ceiling to 0.87.[17] It remains above static estimates, which Barr et al. (2011) put at 0.007 to 0.029 for the United States and 0.20 to 0.245 for Brazil. The counterfactuals compare equilibria nearly four decades apart, over which land supply is more elastic; the long-run U.S. cropland elasticity of Scott (2014) is 0.30, for cropland alone, whereas the model's elasticity includes pasture. It moves less than proportionally with θ_1: a 12% increase raises it by 8%. With a single land-supply elasticity, the model generates cross-country differences in this response only through how much of each country's land is already farmed, so it compresses them: Brazil's elasticity is 1.20 times that of the United States, where the static estimates differ by

[17] In partial equilibrium the model's own-crop acreage elasticity has the closed form $\sum_f \sum_\tau (L_{fi}^{k\tau}/L_i^k)(1/\gamma_L^{k\tau})\left[\theta_1 \alpha_{fi}^k (1-\alpha_{fi}^a) + \theta_2 (1-\alpha_{fi}^k)\right]$ (Appendix B.4), whose two terms are the extensive and the across-crop margins. Land is a fifth of costs under the modern technique, so the pass-through $1/\gamma_L^{k\tau}$ from an output price to the bid for land is large, and the partial-equilibrium elasticity of U.S. maize acreage is 8.0, against short-run micro estimates of 0.01 to 0.95 (Gouel and Laborde, 2021). That distance reflects the Fréchet allocation structure and holds wages and input prices fixed.

roughly a factor of ten. Country-specific elasticities would require a country-level moment, which the cross-country population regression does not provide.[18]

Response to a shock. The moments above compare levels. Appendix F.1 checks a response instead, raising Chinese demand for livestock products as after WTO accession: Brazil and Indonesia expand cropland and lose forest, monotonically in the size of the shock, because Chinese demand draws largely on imported feed rather than on Chinese cropland. China itself also converts land in the model, by more than it plausibly would. The land share of intensive livestock is a single value, kept because the model then reproduces the world's grazing-land extent, and it is too high for a sector made largely of confined pigs and poultry; with a smaller share, more of China's demand would be met by imported feed, so the overstatement works against the exporter response the check validates.

Biodiversity. I check the ecological module against two external benchmarks. The first applies the per-ecoregion characterization factors of Chaudhary and Brooks (2018), which give committed bird extinctions per unit of cropland from the same ecological inputs the model uses, to the model's baseline cropland.[19] Across the 712 ecoregions containing cropland the two agree well: the Spearman rank correlation of committed extinctions is 0.82, the log–log Pearson correlation 0.74, and the realms' shares of the total differ by at most 5 percentage points (Appendix Table F.1). Because both rest on a species–area relation and the same vulnerability weighting, this validates the implementation rather than the species–area framework itself.

The second benchmark does not share that framework, and is harder to pass: *observed* endangerment, the IUCN-threatened bird species present in each ecoregion, built from the BirdLife range maps (BirdLife International and Handbook of the Birds of the World, 2025) with marine species excluded. Because the vulnerability scores carry the Red List threat level, the model side of this comparison is the number of species committed to local extinction, unweighted. Appendix Figure F.4 maps both. Against all threatened birds the rank correlation is 0.38, and 0.09 once total bird richness is netted out, so much of the association runs through richness. Splitting threatened

[18] In $d\ln\alpha/d\ln H^a = (1-\alpha)\theta_1$, the unfarmed share $1-\alpha$ differs between the two countries by a factor of 1.6 (0.59 against 0.36) before general-equilibrium damping compresses it. The convertible-land ceiling encodes a closed frontier and binds even for a 10% demand shock, lowering the elasticity from 1.54 to 1.17 in the United States and from 1.40 to 0.87 in the world, but it is a hard constraint rather than a rising marginal cost; a supply curve whose elasticity declines as headroom is exhausted is left to future work. The compression mainly affects where a given expansion lands, and likely understates how concentrated the response is at the tropical frontiers (Appendix D).

[19] The two constructions share the vulnerability weighting but differ in aggregator, a linear characterization factor against the countryside species–area relation solved here, and in land use, which is imposed in theirs and an equilibrium outcome here.

birds by the cause the Red List records shows where it comes from. It holds for birds threatened by crops or livestock, three-quarters of the total (0.35, and 0.10 net of richness), while for birds threatened only by other causes the correlation is −0.12, and −0.03 net of richness (Appendix Figure F.5). The model measures the extinctions committed by agricultural land use, while observed endangerment also reflects hunting, invasive species, pollution, climate, and centuries of conversion already complete at the baseline.[20] The counterfactuals therefore measure agriculture's marginal contribution to extinction risk; they do not predict which ecoregions will lose birds next.

5 Measuring the biodiversity effects of agricultural trade

This section describes the counterfactuals and reports their results; Appendix H collects robustness checks and additional results.

5.1 Counterfactual design

I evaluate how agricultural trade policies affect biodiversity by implementing a set of counterfactual simulations, following the approach of Farrokhi and Pellegrina (2023): all model parameters are held at their 2017 values, while the trade costs for both agricultural inputs and outputs are reset to the 1980 levels.[21] This generates alternative land-use patterns, which are then fed into the ecological sub-models. The resulting species-richness outcomes are compared with the baseline 2017 scenario, allowing me to isolate the net impact of reduced trade barriers on biodiversity. To disentangle the separate contributions, I run two additional scenarios. In the first, only the input trade costs are set to their 1980 levels while output costs remain at 2017 values, isolating the effect of input liberalization. In the second, only the output trade costs are set to 1980 levels while input costs stay at 2017 levels, revealing the impact of output liberalization alone. By contrasting these three outcomes with the baseline, I can identify how changes in trade costs, both jointly and individually, shape bird biodiversity outcomes. Alongside ecoregion-level outcomes, I report a single global measure of committed extinctions: each ecoregion's regionally lost species are weighted by its vulnerability score, the endemism- and threat-based share of those losses that translate into

[20] Oceania is the clearest illustration: it holds a twelfth of the world's agriculture-threatened birds but almost none of the model's committed extinctions, because its island endemics are threatened by introduced predators on land areas too small to matter in any land-conversion accounting.

[21] Changes in bilateral trade costs between 1980 and 2017 are measured with the symmetric index of Head and Ries (2001), from trade and domestic absorption in 1979–1981 and 2016–2018. As in Farrokhi and Pellegrina (2023), input trade costs move with manufacturing trade costs, because 1980 gross output is not available by input category. Technology, preferences, population and endowments stay at their 2017 values, so the counterfactual isolates trade costs; it is not a simulation of the 1980 economy.

global extinctions (Chaudhary and Brooks, 2018), and summed across ecoregions, converting spatially heterogeneous regional losses into a policy-relevant count of bird species committed to global extinction. I also report three trade shutdowns: complete agricultural autarky, and the elimination of trade in livestock feed or in livestock products alone (Section 5.4). Each counterfactual is solved starting from the baseline equilibrium (Appendix E.4), which also selects among equilibria should there be several (Appendix E.5).

The counterfactuals reported below are computed with the biodiversity–productivity feedback active. Section 5.2 isolates its contribution by re-running them with it switched off: the aggregate effects are essentially unchanged, because the productivity losses it causes are small relative to the gains from trade, but its incidence is spatially concentrated.

Convertible-land ceiling. Because the agricultural frontier is elastic (Section 3), I restrict counterfactual expansion to land that is physically available for conversion. For each field f I cap the agricultural share at its 2017 level plus a convertible fraction,

$$\text{conv}_f = \text{suit}_f \times \max\big(\text{natural}_f - \text{pasture}_f,\, 0\big) \times \big(1 - \text{prot}_f\big), \tag{55}$$

where suit_f is agro-climatic suitability from FAO-GAEZ (Fischer et al., 2021); natural_f the share of the field under natural vegetation (forest, shrub, grassland, savanna) from ESA-CCI land cover (ESA, 2017); pasture_f grazing land from HYDE 3.5 (Klein Goldewijk et al., 2025), subtracted because it is already agricultural; and prot_f the protected share from the World Database on Protected Areas (UNEP-WCMC and IUCN, 2011). The ceiling opens genuinely unused, suitable, unprotected land (Brazil's Cerrado, for instance) while keeping arid, cold, or protected land off-limits. It is imposed only in the counterfactuals, binds only under expansion, and plays no role in the baseline or in the estimation of θ_1. A second restriction bounds *where* new agriculture can go: each field is split into the part that GAEZ rates suitable for crops and a part that can only be grazed, and each part converts natural land only if it is farmed in the baseline data (Appendix B.1). Crops can expand onto 42.6% of convertible land and grazing onto a further 39.3%. The restriction likely biases the counterfactuals toward understating loss.[22]

Table 6: Impact of resetting agricultural trade costs from the 2017 baseline to their 1980 levels

		Changes in agricultural trade costs		
	Baseline (2017)	Output and input (1)	Only input (2)	Only output (3)
	A. Biodiversity			
Bird species committed to global extinction	237.2	+26.4	+12.9	+14.5
same change, equally weighted (presences)	20,988	+2169	+1001	+1246
Insectivorous-bird abundance (% of natural)	90.19	−0.48	−0.23	−0.30
	B. Agricultural production and land use			
Agricultural land (% change)	–	+7.08	+3.97	+3.69
cropland	–	+2.55	+2.67	−0.80
pasture	–	+8.61	+4.41	+5.22
Modern (high-input) cropland share (pp)	58.77	−1.14	−2.11	+1.02
	C. Welfare			
Real income (%)	–	−1.09	−0.45	−0.59
Farm revenue, biodiversity feedback ($bn/yr, net)	–	−5.52	−1.90	−3.68

Notes: The baseline column reports 2017 levels; columns (1)–(3) report changes under counterfactuals that reset agricultural trade costs to their 1980 levels, both input and output costs in (1), input costs only in (2), and output costs only in (3), following the decomposition of Farrokhi and Pellegrina (2023). A positive species entry is species lost, so signs reverse when the result is read in the direction of the historical liberalization. "Bird species committed to global extinction" weights each regionally lost species by its global vulnerability and sums across the 760 ecoregions (Chaudhary and Brooks, 2018). The row beneath weights ecoregions equally, so a species present in k ecoregions is counted k times and its level is not comparable to the row above. Insectivorous-bird abundance is the area-weighted mean across ecoregions, as a share of its level under natural vegetation; the area weighting assumes uniform pristine density, so a square kilometer of tundra counts as one of rainforest. Land-use rows are percentage changes in world-total area, except the modern cropland share, which is in percentage points. Real income is the population-weighted generalized mean. All rows are computed with the biodiversity–productivity feedback active, through insectivorous-bird abundance at $\beta = 0.15$ (Noack, Engist, and Larsen, 2025); Appendix Table H.3 compares them with the same counterfactuals run without it. "Farm revenue" values the feedback's effect on output as $\mathrm{d}R = (f^{bio} - 1)R$, anchored to global agricultural output; Appendix Table H.2 splits it into gross losses and gains across countries.

5.2 Aggregate effects

Table 6 summarizes the biodiversity, land-use, and welfare outcomes. In the 2017 baseline, current agriculture has already committed about 240 bird species to global extinction (vulnerability-score weighted), and the world retains 90.2% of its pristine insectivorous-bird abundance. Agriculture occupies 36.3% of the land the model covers, of which pasture accounts for 27.1 percentage points, and 59% of cropland is farmed with modern, high-input technology. Resetting both input and output trade costs to their 1980 levels, a de-liberalization (column 1), commits a further 26.4 bird

[22] Fields with no observed agriculture, which are closed to conversion, hold more natural land than average (a mean convertible fraction of 0.35 against 0.27 elsewhere), so to the extent that they are also species-rich the restriction understates potential loss. Conversion of natural habitat is possible on 81.9% of convertible land; pasture on land unsuitable for crops cannot become cropland (Appendix G).

species to global extinction. Relative abundance falls as well, by 0.48 points.

Global, local and revenue measures. The three valuations of Table 6 agree on what happened and differ only in what it is worth. Weighting each lost species by its global vulnerability gives the 26.4 headline. Weighting every species equally gives a net loss of 2,169 local species-presences,[23] 10.3% of the 20,988 already committed, against 11.1% on the vulnerability-weighted measure: the two agree on magnitude, so the headline's share of the stock does not depend on the weights. Valuing the change in insectivorous-bird abundance by the farm revenue it supports puts the loss at $6.0 billion a year in forgone farm revenue in the 48 countries that lose, against $0.5 billion gained in the other 18. The equally weighted measure is the more conservative of the two species counts.

Extensive and intensive margins. The mechanism operates through both margins of land use. At the extensive margin, world agricultural area expands by 7.1%, with pasture expanding faster than cropland (+8.6 against +2.6%). At the intensive margin, costlier traded inputs make modern, high-input cultivation less profitable, so the modern share of cropland *falls* by 1.1 percentage points, a modest extensification toward traditional methods. The spatial distribution of these land-use changes is mapped in Appendix Figure H.1, and Appendix Figures H.4 and H.5 split it between the input and output channels. Read in the direction of the historical liberalization between 1980 and 2017, these results imply that trade liberalization spared roughly 26 bird species from global extinction: it shrank the global farming footprint even as it intensified the land remaining in cultivation, and the land-sparing effect dominates the lower per-hectare habitat quality of modern farming.

Input versus output trade costs. Columns (2) and (3) of Table 6 isolate the effects of resetting input and output trade costs separately; the biodiversity and welfare rows are nearly additive. Both forms of liberalization raise the return to farming, which on its own draws land into agriculture. What differs between them is the offsetting force that releases land, and whether it operates on technique or on the location of production. For inputs, that force works through prices. Appendix B.5 shows that agricultural land moves with farm revenue and with the share of it paid to land, so cheaper inputs spare land when farm-gate demand is inelastic, as it is in the calibration (an elasticity of 0.17), and when farms shift to the input-intensive technique, which pays land a

[23] A species-presence is one species in one ecoregion: a species lost from three ecoregions counts three times. The count measures local losses; its level is not comparable to the vulnerability-weighted count of global extinctions.

smaller share of revenue. *Output*-cost liberalization is the larger of the two, though only just: resetting output costs alone commits 14.5 bird species to extinction against 12.9 for input costs, and the two expand world agricultural land by similar amounts (3.7 and 4.0%). They do so by different routes. Costlier traded inputs make modern, high-input farming less profitable, so the modern share of cropland falls by 2.1 percentage points as farmers substitute toward traditional, land-hungry methods, and cropland and pasture both expand (2.7 and 4.4%). Resetting *output* costs works differently: higher trade barriers shift production toward domestic livestock, so pasture expands (5.2%) while cropland *contracts* (0.8%), with intensity barely moving (a 1.0-point rise in the modern share).

Net and gross land reallocation. Because land expands in some ecoregions and retreats in others, the net and gross land movements diverge sharply. The input channel clears 193.3 million hectares and abandons only 8.3, so its net and gross footprints nearly coincide; the output channel clears 220.7 million hectares while abandoning 48.4, so its net expansion of 172.3 million hectares hides the 48.4 million it abandons. This matters because abandonment does not undo clearing. Agriculture retreating in one ecoregion restores habitat for the species of that ecoregion, not for the species committed to extinction where land is cleared in another; the output channel's 48.4 million hectares of abandonment recover 3.3 species against the 17.7 it destroys, an offset of 18%. Measured gross, the output channel is therefore the *more* destructive of the two, committing 17.7 species against 13.5, while clearing 14% more land.

Species loss per hectare cleared. Per hectare actually cleared, the output channel is about 15% more damaging than the input channel, at 0.080 species per million hectares against 0.070, and the difference comes from where the clearing happens. The output channel's expansion is the more tropical of the two, 51% of hectares against 43, and within the tropics it clears more vulnerable land: per million hectares cleared it commits 0.30 species in the Neotropics and 0.24 in Indo-Malaya, against 0.15 and 0.18 for the input channel. Higher trade barriers push Southeast Asian importers back onto their own land while releasing land in South America, and that exchange is unfavorable species for species. The output channel's net footprint thus understates what it moves, and per hectare it is the more damaging. Read forward as liberalization, opening output markets *expands* world cropland by 0.8%, toward the countries whose agro-climatic conditions favor it, while contracting pasture by 5.0%: agriculture occupies slightly less land, but a substantially different set of hectares. Resetting output costs is also the larger source of the *welfare* loss (-0.59% versus

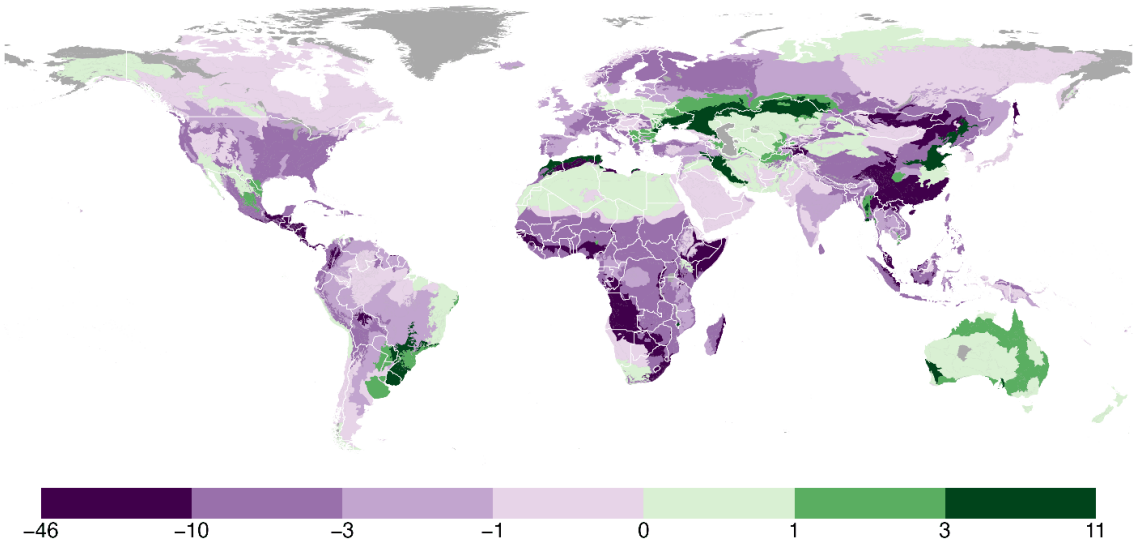
-0.45%)[24]: forcing countries to produce crops in which they lack comparative advantage is costly even though it spares cropland. Output trade thus matters as much as input trade for how much habitat agriculture clears, and more for where the loss falls. Most of the output channel's cost runs through pasture: with grazing land held at its baseline, resetting output trade costs commits 2.3 species rather than 14.5, and the model of Farrokhi and Pellegrina (2023), which has no pasture, gives 2.8 (Appendix I).

The biodiversity–productivity feedback. Every counterfactual reported above is computed with the biodiversity–productivity feedback of Eqs. (18)–(20) active, so that biodiversity loss feeds back into farm productivity and land use adjusts again. This paragraph asks what the loop contributes, by comparing those numbers with the same counterfactuals run with it switched off; Appendix Table H.3 reports the comparison for all six. Following Noack, Engist, and Larsen (2025), I set the elasticity of farm productivity with respect to local insectivorous-bird abundance to $\beta = 0.15$, their estimated elasticity of agricultural yields with respect to bird-provided ecosystem services under high species substitutability, the case their evidence favors for agricultural landscapes; a richness channel with $\beta = 0.08$ serves as a robustness check.

The quantitative impact of the feedback on aggregate welfare is modest. Resetting trade costs both relocates production and expands it, and the expansion lowers insectivorous-bird abundance on net, so the feedback does not net out: the mean of f_{fi}^{bio} across fields is 0.999, with field-level values in $[0.966, 1.025]$. The welfare effects are accordingly almost identical with and without the feedback: the de-liberalization loss is -1.090% without it and -1.095% with it, the feedback *adding* 0.004 percentage points to the loss and costing \$5.5 billion a year in farm revenue. The biodiversity outcomes move as little: de-liberalization commits 26.4 species with the feedback against 26.6 without it, and autarky 117.8 against 118.0. Activating the loop therefore neither rescues nor worsens the headline; Appendix Figure H.10 maps where it bites. Autarky, which expands agriculture far more (world cropland rises by a third), is where the drag is largest: the feedback costs \$27.0 billion a year in farm revenue and 0.03 percentage points of real income, with field-level productivity down to 0.937. Ecosystem-service losses from trade-induced biodiversity change are thus too small to alter the gains from trade materially, although larger biodiversity shocks, or a higher β, could generate substantial productivity losses. The estimates value one taxon through one channel, the pest control that birds provide; insects, bats and soil organisms

[24] World real income aggregates country changes $\hat{C}_n$ with a population-weighted generalized mean, $\left(\sum_n \pi_n \hat{C}_n^{1-\rho}\right)^{1/(1-\rho)}$ with $\rho = 2$, where π_n is country n's population share. With $\rho = 2$ this is a harmonic mean, so a loss weighs more than a gain of the same size.

Figure 5: Change in the number of bird species per ecoregion under de-liberalization



Notes: Change in the number of bird species each ecoregion supports under de-liberalization (agricultural input and output trade costs reset to their 1980 levels), relative to the 2017 baseline: the ecoregion's species pool times the change in its species-remaining share. A species present in several ecoregions is counted in each, so the map corresponds to the equally weighted row of Table 6: 607 ecoregions lose species and 139 gain, −2,362 against +178. Solved without the biodiversity–productivity feedback (net −2,184, against −2,169 with it). Purple: loss; green: gain. Appendix Figure H.2 maps the vulnerability-weighted change and the species-remaining share.

deliver services this model does not price. The elasticity itself is identified on U.S. agriculture, a chemically intensive setting in which purchased pesticides substitute readily for natural pest control; where that substitution is harder, as in the low-input tropical systems that absorb most of the biodiversity loss in the counterfactuals, the same decline in bird populations could cost more output than β implies.

5.3 Incidence

The aggregate hides two distributions, one ecological and one economic. Read in the direction of the historical liberalization, 139 of the 760 ecoregions in the model lose species even as the global count improves, and nearly three-quarters of countries gain farm revenue through the biodiversity feedback while the rest lose it. This subsection takes them in turn: first where the species are lost, then where the revenue consequences fall.

Figure 5 maps these changes as counts of species per ecoregion, and the ecoregion averages conceal wide dispersion. Without the feedback, as mapped, the joint de-liberalization changes the number of bird species an ecoregion supports by between −11.7 and +1.3 (5th to 95th percentiles across ecoregions), the extremes reaching −45.6 in the Yunnan Plateau subtropical evergreen

forests and +11.1 in the Irrawaddy dry forests; expressed as a share of each ecoregion's own species pool, the shift runs from −3.5 to +0.6 percentage points (5th to 95th percentiles), with extremes of −8.0 and +4.2 (Appendix Figure H.2). Land use is more dispersed still: the modern share of cropland falls in about half of the ecoregions, by as much as 13.6 points.

Ecological incidence. The two trade channels write the geography mapped in Figure 5. De-liberalization commits species above all where it pushes economies that import their staples back onto their own land: China, Indonesia, the Philippines and the economies of the rest-of-world aggregate, all net importers of rice, wheat, maize, soybeans and livestock products, together account for two-thirds of the headline. It spares species among the agricultural exporters that lose markets, Brazil, Australia, Paraguay, New Zealand, Argentina and Uruguay above all when only output costs are reset. Read forward as liberalization the pattern reverses: the global footprint shrinks, the staple-importing regions gain, and the ecoregions that lose are concentrated in the exporting countries. Of the 139 ecoregions that lose species under liberalization, 46 are Australasian (35 in Australia, 11 in New Zealand), 41 Palearctic (16 in the former Soviet Union) and 26 Neotropical (15 in Brazil), against 15 in the Afrotropics and Indo-Malaya combined. Ecoregions whose dominant country is a net agricultural exporter are twice as likely to lose species as the others, 25% against 13%. Conditional on a tropical-realm indicator, the baseline agricultural share, the land still available for conversion, the vulnerability score and the species pool, the gap in that probability is no longer significant, but exporters' ecoregions lose 0.4 percentage points more of their species pool (s.e. 0.2); the strongest predictor is the land still available for conversion, which goes with smaller losses (Appendix Table H.4). Agricultural trade liberalization therefore curbs global biodiversity loss on average, mostly in the tropics, at the expense of the exporters' own ecoregions. The spatial decomposition of the species-remaining change into the input- and output-cost channels is mapped in Appendix Figure H.6.

Farm revenue. Because the feedback scales output, it can be valued in revenue units. I value it as the output gained or lost through the biodiversity–productivity margin, at counterfactual prices, $\mathrm{d}R_{fi} = (f_{fi}^{bio} - 1)\, R_{fi}$, and aggregate it to countries; anchoring the model's farm revenue to global crop-and-livestock output (about $3.9 trillion in 2017)[25] expresses it in dollars. Appendix Table H.2 reports the result, in the same de-liberalization direction as the counterfactuals above. Losses dominate: de-liberalization would cost the 48 countries that lose about $6.0 billion a year in farm revenue, against $0.5 billion gained by the other 18, and autarky would cost the 49 that

[25] FAOSTAT gross production value of crops and livestock, world, 2017, in current US dollars ($3.93 trillion).

lose $28.5 billion, 0.73% of world farm revenue, against $1.5 billion gained elsewhere. The losses are concentrated. Under autarky they reach 1.8% of national farm revenue in Malaysia and 1.6% in Indonesia, and 1.3 to 1.4% in the United States, the former Yugoslavia, Sri Lanka and Czechia, while 17 countries gain, led by Paraguay, the United Kingdom and the Netherlands. Under deliberalization the losses are smaller: the most exposed countries are Portugal, Greece, Sri Lanka, the former Yugoslavia and Malaysia, at 0.36 to 0.59% of national farm revenue, and the largest loss in dollars is that of China, $1.8 billion. Expressed as lost farm revenue, then, the biodiversity externality of trade policy is minor as a share of world farm income but materially concentrated, the revenue counterpart to the committed extinctions above.

5.4 Autarky, feed and livestock trade

The counterfactuals above reset trade costs to their 1980 level. Three narrower experiments shut trade down outright: in all agriculture, in livestock feed alone, and in livestock products alone (Table 7). The first closes agricultural trade altogether; the other two separate the roles of shipping the *feed* and shipping the *animal product*, the two ways livestock demand in one country can clear habitat in another.

Autarky. Column (1) is the limiting case. Autarky commits 117.8 further bird species to global extinction, expands world agricultural land by 22.7%, and costs 14.2% of world real income. Cropland grows by 33.0% and pasture by 19.2%, while the modern share of cropland falls by only 1.8 percentage points. Because pasture expands as well, none of the cropland gain comes, on net, from converted pasture: all of it is natural habitat. A closed world must grow at home what it used to import, on land less suited to it. Appendix Figures H.9 and H.8 map the resulting species and land-use changes.

Feed trade versus livestock-product trade. Columns (2) and (3) are far from symmetric. Eliminating trade in livestock feed costs 0.80% of world real income, about three-quarters of the cost of resetting every agricultural trade cost to its 1980 level; eliminating trade in livestock products costs 0.09%. Against the like-for-like benchmark of autarky in column (1), feed trade accounts for about 6% of the total gains. Feed is an input of the intensive livestock technology, so without imported feed that technology retreats: world cropland *contracts* by 27.6% as the feed-grain belt retires, while pasture expands by 23.8% as production reverts to grazing. That re-grazing is the largest shift in livestock intensity in the paper, and the two ecological metrics split on it exactly as the sparing–sharing logic predicts: relative abundance rises by 1.9 points, the only gain in any

Table 7: Narrower trade shutdowns: all agriculture, feed, and livestock products

		Shutting down trade in		
	Baseline (2017)	All agriculture (1)	Livestock feed (2)	Livestock products (3)
		A. Biodiversity		
Bird species committed to global extinction	237.2	+117.8	+33.0	+3.7
Insectivorous-bird abundance (% of natural)	90.19	−1.99	+1.91	−0.03
		B. Agricultural production and land use		
Agricultural land (% change)	–	+22.67	+10.79	+0.14
cropland	–	+32.95	−27.62	−0.71
pasture	–	+19.20	+23.80	+0.43
Modern (high-input) cropland share (pp)	58.77	−1.80	+0.76	+0.88
		C. Welfare		
Real income (%)	–	−14.18	−0.80	−0.09
Farm revenue, biodiversity feedback ($bn/yr, net)	–	−27.01	+15.45	−1.24

Notes: As Table 6. Column (1) eliminates all cross-country agricultural trade by raising off-diagonal trade costs prohibitively. Column (2) requires livestock feed to be sourced domestically, leaving food-crop and livestock-product trade costs at baseline. Column (3) eliminates trade in the livestock good only, leaving crop trade costs unchanged. Changes are relative to the 2017 baseline; welfare is the generalized mean of real income across countries with $\rho = 2$.

counterfactual, while 33.0 additional bird species are committed to extinction, because the pasture arrives disproportionately on species-rich land. Shutting down trade in livestock *products* moves far less land: world pasture rises by 0.4% and cropland falls by 0.7%, and 3.7 species are committed at a welfare cost of 0.09%. World livestock output falls by 2%, which on its own would release pasture, but production relocates from the exporters (New Zealand, the Netherlands, Poland, the United States and Brazil) to the importers, and where those herds graze extensively, as in the rest of the world, the relocation clears more pasture than the fall in output releases (Section 6). The asymmetry is a direct consequence of the pasture margin: feed trade sustains a land-sparing technology, whereas meat trade moves the grazing itself.

5.5 Species richness versus abundance

The species–area metric counts how many species an ecoregion retains; relative abundance instead measures how many *individuals* remain: the abundance of insectivorous birds, weighting each land use by its abundance relative to primary vegetation (Eq. (17)). The two metrics agree on the headline: de-liberalization costs species richness 2,169 species-presences and 26.4 species committed to global extinction, and lowers insectivorous-bird abundance by 0.48 points, area-weighted across ecoregions (Table 6). The extensification that could offset a larger footprint is small here, the

modern share of cropland falling by only 1.1 points, so more farmland means fewer birds as well as fewer species. The metrics part ways only where extensification is large. Shutting down feed trade re-grazes the livestock sector, and relative abundance rises by 1.9 points while 33 species are committed (Table 7): lower-input farmland retains more individuals per hectare than high-input farmland, enough to more than offset the larger footprint, whereas species richness depends mainly on the total area of natural habitat. It is the land-sparing–land-sharing trade-off (Green et al., 2005; Phalan et al., 2011) surfacing as a property of the world trading system rather than of field-scale management: feed trade enables sparing (less land, farmed harder), which favors habitat and species richness, while cutting it imposes sharing (more land, farmed less intensively), which favors abundance per hectare. Weighted by farm revenue rather than by vulnerability, the same land-use change is a gain under the headline specification: shutting down feed imports raises net farm revenue by $15.5 billion (the richness specification gives a $1.5 billion loss), because pasture replaces the retiring feed-grain belt on species-rich land where agriculture is economically small, while the revenue gains accrue in the large producers that give up cropland. For de-liberalization the two specifications of the feedback carry the same sign in revenue terms: it costs farmers $3.5 billion a year through species richness, the robustness specification, and $5.5 billion through insectivorous-bird abundance, the headline. Richness is a commitment discharged over decades, abundance a stock that responds within years. Every counterfactual except the feed shutdown is negative on both. The spatial pattern of the abundance response is mapped in Appendix Figure H.3, and Appendix Figure H.7 covers the remaining counterfactuals.

5.6 Robustness

Four ingredients could move these numbers: the mapping from land use to species, the land-supply elasticity that governs how much land the frontier gives up, the elasticity of food demand, and the productivity feedback. The feedback is examined above (Section 5.2); Appendix Table H.1 varies the other three. The pattern is the same in all three cases. The *level* of committed extinctions moves, sometimes a great deal, while the quantities the paper reads off it do not. Nor does its geography: across ecoregions, each variant's contributions to the de-liberalization effect correlate with the benchmark's at 0.93 or more (column 7).

Species–area mapping. Panel A rescores the same equilibrium land allocations under three alternatives to the benchmark exponents, substituting the continent-specific bird exponents of Storch, Keil, and Jetz (2012) for the ecoregion-specific ones of Chaudhary and Brooks (2018): first in the area–richness mapping alone, then together with the flat cropland affinities of Scherer et al.

(2023), and finally recomputing every habitat affinity at the alternative exponent so that a single z governs both. The level moves with the exponent: the baseline stock of committed extinctions falls by up to 31%, from 237.2 species to 164.4, because the Storch exponents are lower and a given conversion therefore destroys fewer species; the de-liberalization effect falls with it, from +26.4 to between +18.5 and +19.3. The two ratios the paper draws from the table move little. The input channel accounts for 48.9% of the total at the benchmark and for 47.8, 47.0 and 47.5% in the alternatives, and de-liberalization is 11.1% of the baseline stock at the benchmark against 11.0 to 11.4% in the alternatives. Every sign survives; the livestock-trade shutdown commits species under every mapping (+3.7 to +4.0).

Extinction weights. The vulnerability scores that convert regional losses into global extinctions combine the share of each species' range that an ecoregion holds with the species' Red List threat level. I keep them as the benchmark for three reasons. They are the standard measure of land-use impacts on biodiversity in the life-cycle literature, where the UNEP–SETAC Life Cycle Initiative provisionally recommended the method (Chaudhary and Brooks, 2018). They come from the same source as the benchmark's species–area exponents, habitat affinities and species pools, and are defined on the same ecoregions, so the mapping from land use to extinctions is internally consistent. And the threat level carries information a range share does not: the same loss of habitat is more likely to complete the extinction of a species that is already threatened. The threat level has two drawbacks. It is held at its 2017 value, which agriculture itself helped set, and it reflects every driver of endangerment, not land use alone. The last row of Panel A drops it and weights each ecoregion by endemism alone, using the BirdLife range maps (BirdLife International and Handbook of the Birds of the World, 2025). The level nearly triples, to 650.6 species, because species of least concern now count in full, but de-liberalization remains 11.5% of the baseline stock, against 11.1% at the benchmark, and the input channel 49.5% of the total, against 48.9%. Every sign survives.

Land-supply elasticity. Panel B recalibrates the model at $\theta_1 = 3.73$ and $\theta_1 = 6.21$, the two ends of the ± 1 standard-error band of Section 4, and re-runs the counterfactuals from scratch. The baseline stock is invariant by construction, since the calibration reproduces observed land use whatever θ_1 is (237.2 species at both ends). Committed extinctions under de-liberalization range from +23.3 to +29.6 around the benchmark's +26.4: a change of −12 and +12% for a −22 and +29% change in the elasticity, so the headline scales with θ_1 at between two-fifths and a little over a half of the proportional rate. Autarky ranges from +108 to +125. The division between the two trade-cost channels barely moves (the input channel's share is 49.4, 48.9 and 48.3%), and the

welfare cost barely moves, from -1.10% at the low end to -1.09% at the benchmark and the high end, because θ_1 governs how the land margin absorbs the shock rather than the gains from trade themselves.

Food demand elasticity. Panel C raises η from 0.5 to 1.2, roughly doubling the farm-gate demand elasticity: consumers then absorb more of a trade-cost increase by eating less, and the headline falls to 20.4 species. Welfare and the division between the two channels barely move (-1.04%, with inputs at 51% and outputs at 54% of the joint effect).

6 Bilateral trade costs and biodiversity

The counterfactuals of Section 5 show that liberalization spared about 26 bird species on net. A net figure sums over every bilateral flow and can conceal offsetting parts. This section examines it flow by flow: which flows carry the biodiversity consequences, in which direction, and at what cost to act on them.

6.1 Method

I differentiate rather than optimize. Countries are grouped into nine regions and goods into three classes.[26] A block $\mathcal{B}$ is the set of hub-to-hub trade costs d_{in}^{g} of Eq. (14) with exporter i in one region, importer $n \neq i$ in one region, and good g in one class. Let Λ denote vulnerability-weighted committed global bird extinctions and W world real income. Starting from the baseline equilibrium, I multiply the trade costs of block $\mathcal{B}$ by $e^{0.1}$ and by $e^{-0.1}$, re-solve the model in general equilibrium each time, and compute the central difference

$$\frac{\mathrm{d}\Lambda}{\mathrm{d}\ln d_{\mathcal{B}}} \approx \frac{\Lambda\big(e^{0.1} d_{\mathcal{B}}\big) - \Lambda\big(e^{-0.1} d_{\mathcal{B}}\big)}{0.2}, \tag{56}$$

and likewise for W. The biodiversity–productivity feedback is active throughout. Of the 243 possible blocks, the 122 that carry at least 0.1% of world agricultural trade are evaluated.

The gradient requires no weight of species against consumption, no search over a policy space of many thousands of dimensions and no assumption on how tariff revenue is recycled. It delivers,

[26] The regions are four tropical groups, South America (Brazil, Argentina, Paraguay, Uruguay), Southeast Asia (Indonesia, Malaysia, Thailand, Vietnam, the Philippines, Sri Lanka), Sub-Saharan Africa and other Latin America (the remaining Latin American economies); three rich temperate groups, the temperate exporters (the United States, Canada, Australia, New Zealand), Europe (with the former Soviet and Yugoslav composites) and East Asia (China, Japan, Korea); and two others, South Asia with the Middle East and North Africa, and the rest of the world. Goods are livestock products, feed crops (those with a world feed-absorption share above one third) and food crops.

for each block, the sign of the effect, its rank among blocks and the welfare cost of acting on it, which are the elements an optimal policy would be built from.

6.2 Direction of trade and class of goods

Figure 6 maps the gradients. Most of the map is green: for 92 of the 122 blocks, raising trade costs adds to committed extinctions, so liberalizing them helps biodiversity. The exceptions turn on the direction of trade and on the class of goods.

Trade from the rich temperate regions into the tropics is unambiguous. Of the 12 evaluated blocks running from the rich temperate regions into tropical regions, none has a negative gradient, and together they account for +12.4 species per log point: every restriction on these flows costs species.

Trade out of the tropics is mixed, and the split is by good. Of the 20 blocks running from tropical to rich temperate regions, 10 have negative gradients, summing to −5.8, against +4.0 for the other ten. Raising the cost of tropical crop exports mostly costs species (8 of the 10 positive blocks are food crops), while raising the cost of tropical livestock exports saves them (five of the ten negative blocks, led by South American meat and dairy into East Asia, −2.8, and into Europe, −1.5). Exports to Europe illustrate the split: of the six tropical blocks into Europe, South American livestock is the only one whose restriction would save species, while restricting South American feed crops, the largest of the six flows, would cost 1.9 species per log point.

The livestock pattern extends beyond the tropics and turns on the importer. Livestock flowing into East Asia and Europe from outside them carries the most negative gradients on the map, all nine such blocks being negative: the temperate exporters into East Asia (−5.2) and the rest of the world into Europe (−5.0). Livestock traded within Europe, the largest block on the map, is the exception, at +3.7. Livestock flowing into the rest of the world carries the most positive, led by Europe (+10.9). Restricting a livestock flow moves production to the importer's own herds. Where those herds are intensive, as in East Asia and Europe, this spares pasture in the exporting region; where they graze extensively, as in the rest of the world, it clears more. The livestock-trade shutdown of Table 7 pools both kinds of block, which is why it nets to a small loss.

Summed over all 122 blocks, the gradients give +43.8 species per log point for a uniform increase in trade costs: +64.9 from the positive blocks and −21.1 from the negative ones.[27] To first order, the gradients also rank whole schedules: moving every block in the direction its gradient favors,

[27] The sum is the first-order effect of raising the trade costs of every evaluated block, 97% of world agricultural trade, by one log point. It differs from the +26.4 of Table 6, which resets input as well as output trade costs, by amounts that differ across trade flows, to their 1980 levels; the two agree in sign and order of magnitude.

cheapening the 92 with positive gradients and raising the cost of the 30 with negative ones, spares 86.0 species per log point, twice the 43.8 of uniform liberalization, while world real income still rises by 0.71% against 0.95%. Livestock accounts for 17 of the 30 restrictions and 93% of the species they save. Uniform liberalization is therefore not the trade policy that spares the most species. The room for an asymmetric policy lies in livestock trade into intensive importers, not in tropical exports as such.

6.3 Marginal abatement cost per block

Combining species and real income into a single objective requires a value per species, a judgment the model can inform but not make. Uniform liberalization raises world real income and spares species at once, so it involves no such trade-off; the trade-off arises only for the restrictions that save species. Pairing each gradient with its welfare counterpart turns the map into a schedule of the terms of that choice: species saved per unit of welfare forgone, block by block. Table 8 reports the cheapest.

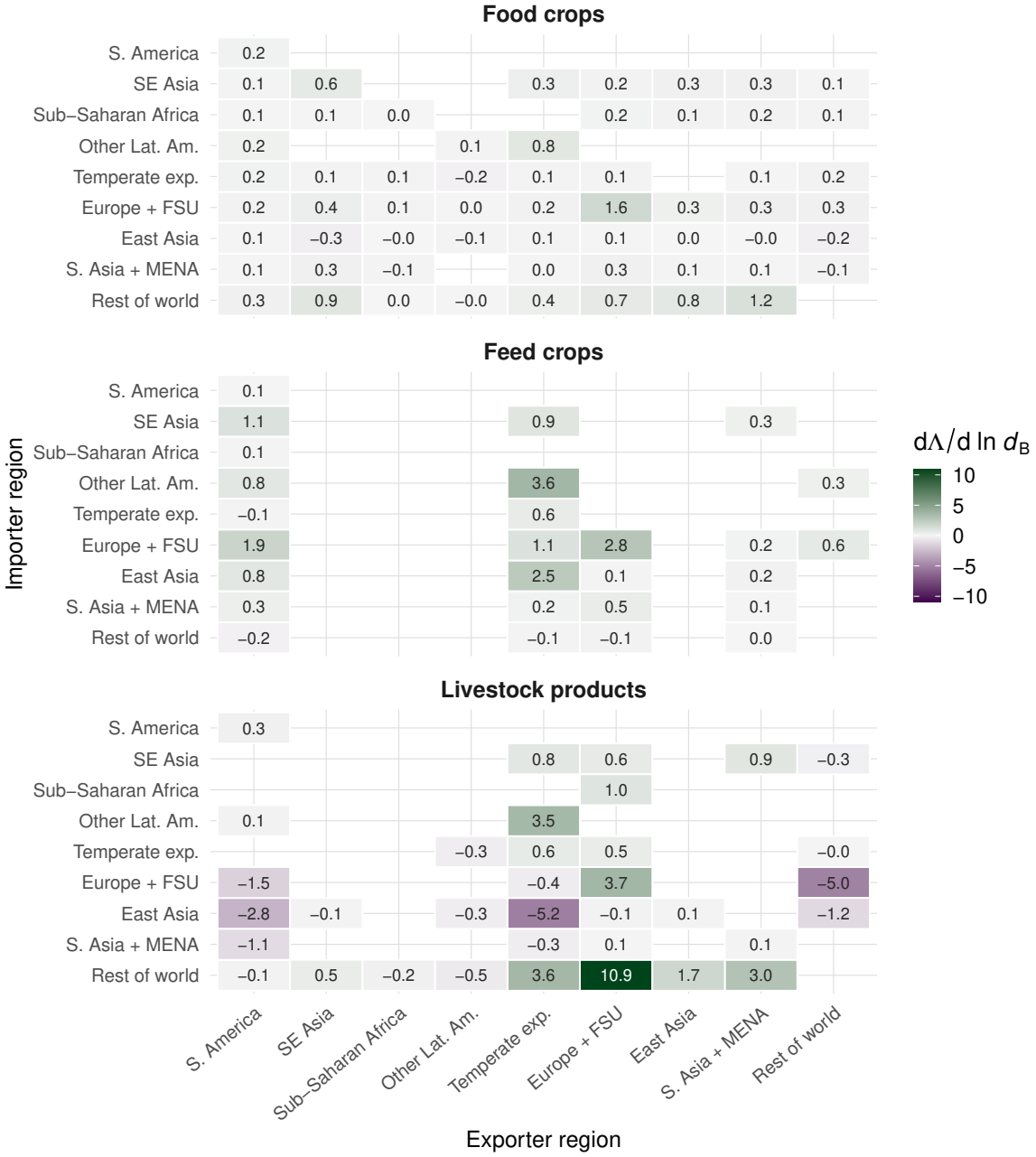
The cheapest restriction of material size is on livestock trade from the temperate exporters into East Asia: raising its cost by one log point avoids 5.2 committed extinctions at a welfare cost of 0.0035%, about 0.0007% per species, on a block carrying about 3% of world agricultural trade. Livestock from the rest of the world into Europe (5.0 species, 0.009%) and from South America into East Asia (2.8 species, 0.006%) follow. One food-crop block is cheaper per species but avoids only a fifth of a species. Restricting two blocks would both avoid extinctions and raise measured welfare, temperate feed exports to the rest of the world and other Latin American food crops to East Asia, but each avoids less than a tenth of a species, so the map offers no material restriction that is also a welfare gain.

6.4 Limitations

Three qualifications bound what the map establishes. First, trade policy is second-best here by construction. The externality is attached to land use, through conversion and through the intensity of farming, and instruments aimed at those margins would address it more directly; the map ranks blocks within one instrument class. Trade costs are studied because they are the instrument that importing countries control unilaterally, whereas a consumer country cannot legislate another country's land use.

Second, trade costs here are of the iceberg form, so a wedge is dissipated rather than collected. For the biodiversity side the difference is second order: both forms move relative prices, and through them land use, in the same direction, although an iceberg wedge also uses up output and

Figure 6: Marginal effect of bilateral trade costs on committed extinctions



Notes: Each cell is $\mathrm{d}\Lambda/\mathrm{d}\ln d_{\mathcal{B}}$ (Eq. (56)), the change in vulnerability-weighted committed bird extinctions when the trade costs of one exporter–importer block are raised, at the baseline equilibrium with the biodiversity–productivity feedback active. Panels separate food crops, feed crops and livestock products. Purple: raising the cost lowers extinctions, so liberalizing that block harms biodiversity; green: the reverse. Regions are ordered tropical regions first, then the rich temperate regions, then the rest. Blank cells carry less than 0.1% of world agricultural trade and are not evaluated. Table 8 reports the gradients with their welfare counterparts.

Table 8: Marginal abatement cost per trade block

Exporter → importer	Class	Trade share (% world ag.)	Species avoided	dW (%)	MAC
A. Biodiversity gain at no welfare cost					
Temperate exp. → Rest of world	Feed crops	0.28	0.09	+0.0011	–
Other Lat. Am. → East Asia	Food crops	0.13	0.08	+0.0007	–
B. Cheapest abatement					
Other Lat. Am. → Temperate exp.	Food crops	0.96	0.20	−0.0001	0.0006
Temperate exp. → East Asia	Livestock products	2.86	5.16	−0.0035	0.0007
Temperate exp. → Europe + FSU	Livestock products	0.44	0.37	−0.0004	0.0011
Other Lat. Am. → East Asia	Livestock products	0.14	0.35	−0.0005	0.0015
Rest of world → East Asia	Livestock products	0.34	1.20	−0.0020	0.0016
Rest of world → Europe + FSU	Livestock products	1.98	5.04	−0.0093	0.0018
S. America → East Asia	Livestock products	0.83	2.81	−0.0056	0.0020
Other Lat. Am. → Temperate exp.	Livestock products	0.22	0.33	−0.0008	0.0025

Notes: Effect of raising the trade costs of one block by one log point, by central difference (Eq. (56)) at the baseline equilibrium, with the biodiversity–productivity feedback active. "Species avoided" is the reduction in vulnerability-weighted committed bird extinctions; dW is the change in world real income, the population-weighted generalized mean of Section 5. MAC is welfare forgone per species avoided. Panel A lists blocks where restricting trade raises both; the welfare gains there are close to zero. Because dW aggregates over all countries, an entry can reflect effects on third countries rather than on the two trading regions.

a tariff returns income to the importer. It matters for welfare on the blocks the map would *raise*, where the iceberg form overstates the cost by burning revenue a tariff would return. That bias runs against the instrument: the welfare costs in Table 8 likely overstate what a tariff would cost.

Third, welfare is world real income, the population-weighted generalized mean of real consumption used throughout. On a single block, it combines the effects on the two trading regions with those on every third country, and its weights favor the most populous regions: East Asia and South Asia with the Middle East and North Africa together carry about half of the total. The two welfare gains in Panel A of Table 8, about a thousandth of a percent each, therefore do not show that the importing region itself gains from the restriction.

7 Conclusion

Agriculture is the leading cause of biodiversity loss on land (IPBES, 2019), and a large share of the land it clears supplies consumers in other countries: roughly a quarter of agriculture-driven deforestation in the tropics has been traced to goods consumed abroad (Pendrill et al., 2019). Governments have begun to respond through trade policy, most prominently with the European Union's Deforestation Regulation.

This paper provides a framework for evaluating such policies. It combines a quantitative Ricardian model of agricultural trade with global data on agro-climatic potential, land cover, protected areas and bird species pools, resolved at the level of 5-arcminute fields. The model separates the two margins through which trade moves habitat, the conversion of natural land and the intensity at which farmland is used, and lets the species that survive feed back into farm productivity. Because birds control pests across plots, this feedback is a production externality: a landowner who clears habitat lowers yields on other farms without bearing that cost. The framework can be used to evaluate protected-area expansion, taxes on land conversion, agricultural productivity growth and shifts in diets.

In this paper, I use it to study whether agricultural trade liberalization erodes biodiversity or helps preserve it. I find that the liberalization of 1980 to 2017 spared about 26 bird species from global extinction, 11% of the 240 that agriculture has committed. It did so because habitat is cleared to obtain land, and cheaper trade lowered the demand for land. Cheaper inputs and cheaper outputs contribute about equally, the first by intensifying farming, which spares land, the second by letting countries import livestock and feed, which contracts pasture even as cropland moves to where it grows best. The gain is unevenly shared, as losses concentrate in the ecoregions of exporting countries. Through the pest control that birds provide, liberalization also raised farm revenue in most countries, though by sums small relative to the world total. The effect of restricting trade depends on the direction of trade and on the good traded. Restricting trade from rich temperate regions into tropical regions costs species, and so does shutting down trade in feed or in livestock products, while raising the cost of livestock shipped into the intensive producers of East Asia and Europe from outside those regions saves them.

Trade restrictions are a natural response to habitat loss abroad, but applied across the board they cost species. A trade policy that serves biodiversity sets trade costs block by block, and, to first order, can prevent extinctions that neither uniform liberalization nor uniform restriction avoids.

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Appendix

A Motivating facts: data and additional results

This appendix describes the data behind the five facts of Section 2 and reports additional results: the maps and the threat ranking behind Facts 1 and 3, and the robustness, timing and species translation of the price response in Fact 5.

A.1 Data

Biodiversity. The Red List Index is the EPI's country-year score of range-weighted extinction risk, built from the IUCN Red List and rescaled so that 100 means that no evaluated species is threatened and 0 corresponds to the 5th percentile of index values or below. I use the 2000 to 2023 window, since earlier country values are backfilled. Threat prevalence is computed from the species-level assessments themselves: I download the current assessments for all globally threatened birds (categories CR, EN and VU; 1,256 species, assessed between 2016 and 2025) and retrieve each assessment's coded threats from the IUCN Red List API (IUCN, 2025; BirdLife International, 2025). A species counts as affected by a threat if that threat is coded ongoing or future under the IUCN Threats Classification Scheme. Agriculture is class 2, which comprises crop farming (2.1), wood and pulp plantations (2.2), livestock farming (2.3) and aquaculture (2.4); crop or livestock farming alone affects 70% of the species. Logging is 5.3, hunting and trapping 5.1, invasive and problematic species class 8, and climate change class 11. Shares therefore sum to more than 100%, since a species may face several threats. Ecoregion boundaries are from Olson et al. (2001) and ecoregion bird pools and vulnerability weights from the countryside species–area repository of Chaudhary and Brooks (2018); these are the same ecological objects the model uses, described in Section 4.4.

Agricultural output, land use and trade. Production, land use and trade come from FAOSTAT. The two margins in Figure 1 decompose the change in log gross production value (constant 2014 to 2016 international dollars) between the 1993 to 1997 and 2016 to 2020 averages into the change in log cropland area and the change in log value per hectare, for the 139 countries above the 25th percentile of initial output with data for both margins. Input intensity is world fertilizer use per hectare of cropland (nitrogen, phosphate and potash nutrients, from 1961) and pesticide use per hectare (from 1990). Trade openness is the sum of agricultural exports and imports over the value of agricultural production, and net exporter status is net agricultural exports over total

agricultural trade, both built from the FAOSTAT detailed trade matrix and averaged over 2018 to 2022, as is the Red List Index in Fact 4. Production is valued at constant 2014 to 2016 prices: in current dollars, the value of production collapses in some countries late in the window, Argentina's with the peso.

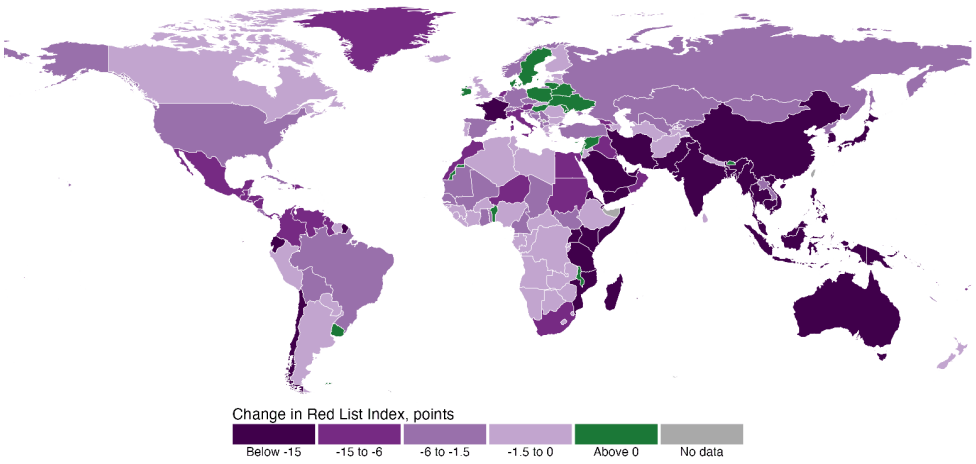
Land-cover change. Cropland expansion by ecoregion is from the GLAD global land-use-change product for 2000 to 2019 (Potapov et al., 2022). Tree-cover loss in Table 1 is from the Global Forest Change data (Hansen et al., 2013): column 1 is the variable of Berman et al. (2023), from their replication package, and the 10% to 25% canopy band of column 2 is summed from the 30 m pixels of version 1.13 over the same half-degree cells, an extraction that reproduces their 25% variable on all but 5 of 221,310 cell-years. Natural-land loss and cropland gain are built from ESA-CCI 300 m annual land cover (ESA, 2017), aggregating classes 40 to 153 (natural land) and 10 to 30 (cropland) to the half-degree grid as exact area fractions; this is the same natural-land definition the convertible-land ceiling of Section 5 uses.

Prices and suitability. The price regressor P_{ct} of Eq. (1), the grid, sample, fixed effects and clustering are taken unchanged from the replication package of Berman et al. (2023): an international crop price index weighted by GAEZ crop suitability (Fischer et al., 2021), on 12,295 half-degree tropical cells in 93 countries over 2001 to 2018. Only the dependent variable changes, and, for the ESA-CCI outcomes, the year window, which runs to 2014 and excludes 2004 for the reasons set out in the notes to Appendix Table A.3.

A.2 Additional results

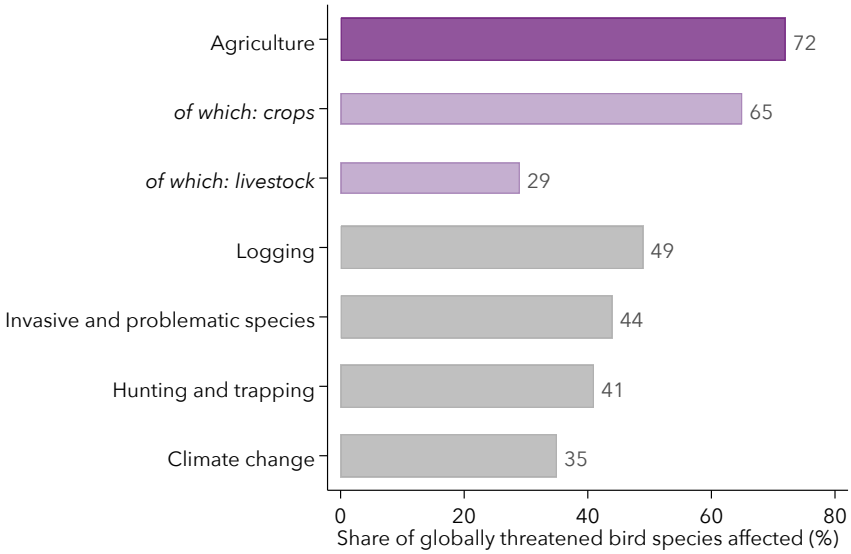
Timing. Adding the previous year's price and the next two years' prices to Eq. (1) gives, for forest loss, 0.22, 0.82, 1.41 and 0.36 (for $t-1$, t, $t+1$ and $t+2$), of which only the coefficients on t and $t+1$ are significant with standard errors clustered by country; for wooded-savanna loss, -0.20, 0.78, 1.14 and 0.49, with the same pattern; and for cropland gain, 0.05, 1.15, -0.47 and 0.44, of which only the coefficient on t is significant. The response of tree loss to the next year's price survives cell-specific linear trends (0.70 for forest, 0.77 for wooded savanna), which a trend shared by cells with similar crop suitability would remove, and it fades two years out. Tree loss thus runs a year ahead of the price, consistent with land being cleared before the crop it is cleared for is sold, whereas cropland gain is recorded once the land is farmed. Because the species counterfactual uses the contemporaneous coefficient alone, it leaves out the response to expected prices. Cell-specific trends also lower the contemporaneous coefficients, to 0.52, 0.73 and 0.62, as expected when prices

Figure A.1: Change in the Red List Index, 2000 to 2023



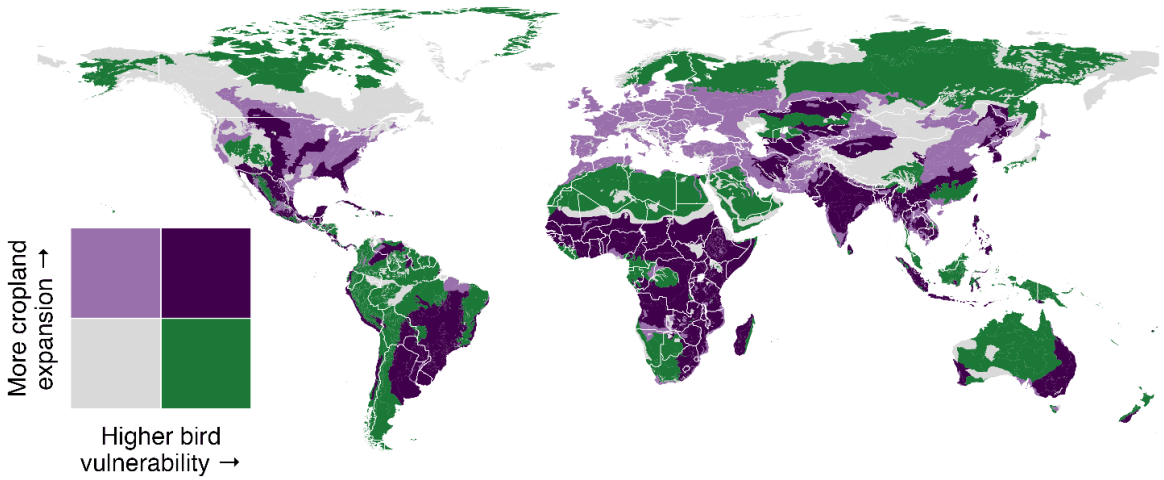
Notes: The Red List Index (EPI/IUCN indicator, 0 to 100) is higher where aggregate extinction risk is lower; the map shows the change in the index between the 2000 to 2004 and 2019 to 2023 averages, in index points; purple denotes decline, green improvement, and grey missing data.

Figure A.2: Threats to globally threatened birds



Notes: Share of the 1,256 globally threatened bird species (IUCN categories CR, EN, and VU) with at least one ongoing or future threat coded in each class, computed from the species-level assessments by BirdLife for the IUCN Red List (IUCN, 2025). Agriculture is threat class 2, which comprises crops (2.1), wood and pulp plantations (2.2), livestock (2.3) and aquaculture (2.4); crops or livestock alone affect 70%. Logging is 5.3, invasive and other problematic species class 8, hunting 5.1, and climate change class 11. Species facing several threats are counted under each class, so shares do not sum to 100.

Figure A.3: Cropland expansion and bird vulnerability across ecoregions



Notes: The bivariate shading combines cropland expansion between 2003 and 2019 (GLAD land-use change, Potapov et al., 2022; the vertical axis of the legend) with the bird-community vulnerability score (Chaudhary and Brooks, 2018) (the horizontal axis). Each axis is split in two: vulnerability at its median across ecoregions, and expansion at the median of those ecoregions that expanded at all. Dark purple marks conversion on high-vulnerability land, medium purple conversion on low-vulnerability land, green high-vulnerability land with little conversion, and grey neither.

Table A.1: Crop prices and natural-land conversion in ESA-CCI land cover

	(1) Forest loss (Hansen)	(2) Natural-land loss (ESA-CCI)	(3) Natural-land loss (ESA-CCI, natural cover ≥1%)	(4) Cropland gain (ESA-CCI)
A. asinh of the outcome				
Log crop price	0.616***	0.203	0.207	1.284***
	(0.102)	(0.212)	(0.214)	(0.196)
	[0.386]	[0.665]	[0.674]	[0.581]
B. Percent of cell area				
Log crop price	0.310***	0.111***	0.111***	0.126***
	(0.027)	(0.017)	(0.017)	(0.017)
	[0.160]	[0.039]	[0.040]	[0.042]
C. Poisson pseudo-maximum likelihood, levels				
Log crop price	1.457***	0.142	0.134	0.638
	(0.134)	(0.359)	(0.360)	(0.421)
	[0.778]	[1.002]	[1.002]	[1.351]
Observations (panels A and B)	159,744	159,744	158,132	159,744

Notes: As Table 1, on the common window 2001 to 2014 excluding 2004. Column 1 is forest loss on that window, for comparison. Column 3 keeps only the cells with at least 1% natural cover in ESA-CCI in 2000, 12,172 of the 12,295 cells of Berman et al. (2023); the natural-land estimate is unchanged (0.21 against 0.20). Panel B divides each outcome by cell area; panel C estimates its level by Poisson pseudo-maximum likelihood. Natural-land loss rises with prices in panel B, also with standard errors clustered by country, but not in panels A and C, so these data do not settle whether the price response reaches open natural land. Standard errors clustered by cell in parentheses and by country in brackets; stars refer to the cell-clustered errors; $^{*}\,p<0.1$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table A.2: Tree-cover loss by canopy density

Canopy cover in 2000	(1) 10–25%	(2) 25–50%	(3) 50–75%	(4) ≥75%
A. asinh of pixels lost				
Log crop price	0.908***	1.282***	1.381***	1.688***
	(0.092)	(0.092)	(0.091)	(0.096)
	[0.383]	[0.389]	[0.354]	[0.412]
B. Percent of the band's 2000 cover lost				
Log crop price	0.414***	0.744***	1.313***	1.713***
	(0.036)	(0.055)	(0.111)	(0.202)
	[0.110]	[0.202]	[0.324]	[0.460]
C. Poisson pseudo-maximum likelihood, pixels lost				
Log crop price	0.918***	0.479***	0.919***	1.743***
	(0.266)	(0.158)	(0.154)	(0.166)
	[1.157]	[0.409]	[0.497]	[0.876]
Mean annual loss, % of band cover	0.206	0.376	0.734	1.106
Observations (panels A and B)	221,130	221,166	220,086	213,786

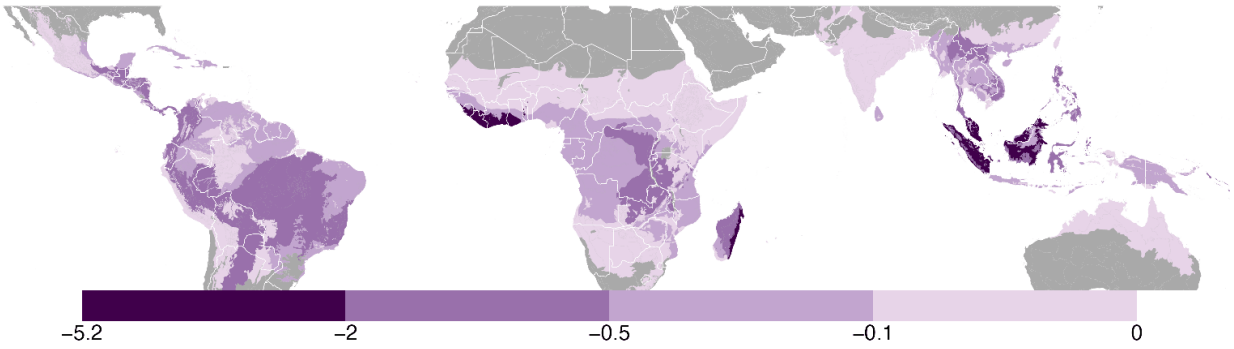
Notes: Tree-cover loss on the cells of Berman et al. (2023), 2001 to 2018, by canopy cover in 2000, with the specification of Table 1. Columns 2 to 4 difference their 25%, 50% and 75% variables; column 1 is summed from the 30 m pixels (Appendix A.1). Each column uses the cells with some cover in its band. Panel B divides the pixels lost by the band's cover in 2000, so that its coefficient divided by the mean annual loss gives the response relative to the band's baseline rate: 2.0 for canopy of 10% to 25%, and 2.0, 1.8 and 1.5 for the denser bands. Standard errors clustered by cell in parentheses and by country in brackets; stars refer to the cell-clustered errors; $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table A.3: Sensitivity of the conversion estimates to two faults in the ESA-CCI panel

	2001–2015		2001–2014	
	all years	excl. 2004	all years	excl. 2004
Forest loss (Hansen)	0.801***	0.936***	0.477***	0.616***
	(0.102)	(0.101)	(0.103)	(0.102)
Natural-land loss (ESA)	0.763***	-0.082	1.150***	0.203
	(0.207)	(0.206)	(0.212)	(0.212)
Cropland gain (ESA)	1.618***	1.119***	1.849***	1.284***
	(0.188)	(0.189)	(0.194)	(0.196)
Observations	184,320	172,032	172,032	159,744

Notes: The specification of Table 1, estimated on the same cells (the Berman et al. (2023) final sample) across four year windows. Two faults affect the ESA-CCI outcomes and not the forest outcome, which is built from different data. First, ESA-CCI v2.0.7b is truncated in 2015: the mean of asinh natural-land loss is 0.58 against 1.75 in 2014, and only 16% of cells register any loss. Second, 2004 carries a reclassification confined to the Americas: the share of cells recording positive natural-land loss moves 0.44, 0.64, 0.33 across 2003 to 2005 in the Americas while Africa (0.42, 0.43, 0.39) and Asia (0.42, 0.43, 0.39) are flat, and 2004 is the only year of the fifteen in which the median cell registers any loss at all. Because country×year fixed effects absorb country-level shifts, what enters the estimate is the within-country pattern of which cells were reclassified, which is correlated with agro-climatic suitability in the same way the price regressor is. 2004 is uniquely influential: dropping any one of the other fourteen years leaves the natural-land coefficient in [0.47, 1.15], each with $t > 2.0$, whereas dropping 2004 alone gives -0.08 ($t = -0.40$). The last column is the window used for the ESA-CCI outcomes in Tables 1 and A.1. Standard errors clustered by cell in parentheses; $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Figure A.4: Price-driven forest loss: committed global extinctions by ecoregion



Notes: The change of Figure 4, weighted by the global vulnerability of each ecoregion's birds (Chaudhary and Brooks, 2018) and expressed as a share of the total, in percent, as in Appendix Figure H.2: 14 species committed to global extinction. Grey: ecoregions with no cell in the sample.

themselves trend over the 2000s boom; with standard errors clustered by country, the first two remain significant and the cropland coefficient does not ($p = 0.47$).

Price-driven forest loss in species. The counterfactual of Section 2 holds each cell's price index at its 2001 level, as in Berman et al. (2023), and reads β as an elasticity: loss in the counterfactual is $Y_{ct} \exp[-\hat{\beta}(\ln P_{ct} - \ln P_{c,2001})]$, and the difference from observed loss, summed over 2001 to 2018, is the loss attributable to the rise in prices. The share is 42% with the Poisson estimate of β, and 58% with the procedure of Berman et al. (2023), which inverts the predictions of their specification with forest-cover deciles. Each cell's attributable loss is allocated to ecoregions in proportion to land area and converted into committed global extinctions with the measure of Section 5, evaluated at the model's baseline land use with cleared land counted as no habitat. Range losses use the BirdLife range maps (BirdLife International and Handbook of the Birds of the World, 2025), with each cell's loss spread evenly over its land; for species with very small ranges, such as island endemics, the even spread is a coarse approximation. Figure A.4 weights the change mapped in Figure 4 by global vulnerability.

B Model derivations

This appendix derives the equations of Section 3: the allocation of land across uses and techniques (Appendix B.1), demand at the farm gate (Appendix B.2), the ecosystem services that birds provide to farms (Appendix B.3), the comparative statics used to estimate the land-supply elasticity (Appendix B.4), how agricultural land responds to farm revenue and input prices (Appendix B.5),

and a sufficient statistic for the species effect of any shock (Appendix B.6).

B.1 Land allocation

The conversion margin and Eq. (12). Each plot ω of field f in country i is put to agricultural use when the field's expected agricultural return exceeds the plot's idiosyncratic conversion cost,

$$H^a_{fi} \;\geq\; a^0_{fi}\, P^0_{fi}\, z^0_{fi}(\omega). \tag{57}$$

The conversion draw $z^0_{fi}(\omega)$ is log-logistic with unit scale and shape θ_1, $\Pr\big(z^0 \leq x\big) = x^{\theta_1}/(1+x^{\theta_1})$, drawn independently of the product-technology draws $\mathbf{z}_{fi}(\omega)$. A log-logistic variable is the ratio of two independent Fréchet draws of common shape θ_1, one on the plot's value in agriculture and one on its value left natural, so the conversion margin compares two extreme-value draws of equal dispersion, as the product margin compares Fréchet draws across products. The converted share of the field is

$$\alpha^a_{fi} = \Pr\!\left(z^0 \leq \tfrac{H^a_{fi}}{a^0_{fi}P^0_{fi}}\right) = \frac{\left(H^a_{fi}\right)^{\theta_1}}{\left(a^0_{fi}P^0_{fi}\right)^{\theta_1} + \left(H^a_{fi}\right)^{\theta_1}}, \tag{58}$$

which is Eq. (12).

The convertible-land ceiling. In the counterfactuals the agricultural share of each field is also bounded by the ceiling q_{fi} of Section 5, the observed agricultural share plus the field's convertible fraction. With the field split into the two parts described below, the ceiling applies to the field total: the solver finds a common cap c_{fi} on the converted share of both parts such that their land-weighted sum equals q_{fi} wherever the unconstrained shares would exceed it, and leaves the conversion law unchanged wherever the ceiling is slack. With a single part this is equivalent to replacing $\left(a^0_{fi}P^0_{fi}\right)^{\theta_1}$ in Eq. (12) with $\max\!\left\{\left(a^0_{fi}P^0_{fi}\right)^{\theta_1},\, \left(H^a_{fi}\right)^{\theta_1}(1-q_{fi})/q_{fi}\right\}$. The ceiling is slack everywhere at the baseline, because q_{fi} exceeds the observed share by construction.

Output under the nested Fréchet. Because the conversion draw is independent of $\mathbf{z}_{fi}(\omega)$, converted plots are a random sample of the field, and within them the nested Fréchet allocates land as in Farrokhi and Pellegrina (2023): product k receives the share α^k_{fi} of agricultural land and technology τ the share $\alpha^{k\tau}_{fi}$ of product k's land, and the average productivity of the plots that

select (k,τ) is

$$\mathbb{E}\Big[z_{fi}^{k\tau}(\omega)\,\Big|\,(k,\tau)\text{ chosen}\Big] = a_{fi}^{k\tau}\left(\alpha_{fi}^{k}\right)^{-1/\theta_2}\left(\alpha_{fi}^{k\tau}\right)^{-1/\theta_3}, \tag{59}$$

where the normalizing constant $\bar{\phi}$ removes the Gamma-function term. Plots that choose a product or technology held by a small share of the field are selected on high draws, so their average productivity is high. Multiplying the land in (k,τ), $L_{fi}\,\alpha_{fi}^{a}\alpha_{fi}^{k}\alpha_{fi}^{k\tau}$, by Eq. (59) and by output per efficiency unit of land, $(\gamma_L^{k\tau})^{-1}\tilde{h}_{fi}^{k\tau}$, gives the field output in Section 3,

$$Q_{fi}^{k\tau} = L_{fi}\left(\gamma_L^{k\tau}\right)^{-1}\tilde{h}_{fi}^{k\tau}a_{fi}^{k\tau}\,\alpha_{fi}^{a}\left(\alpha_{fi}^{k}\right)^{(\theta_2-1)/\theta_2}\left(\alpha_{fi}^{k\tau}\right)^{(\theta_3-1)/\theta_3}. \tag{60}$$

No selection into conversion. The agricultural share α_{fi}^{a} enters this expression linearly, because conversion does not select on the product draws: the plots converted are a representative sample, so average yields conditional on conversion equal unconditional ones. Under the nested alternative discussed next, plots with high agricultural draws would convert first, field output would rise less than proportionally with the converted share, as $\left(\alpha_{fi}^{a}\right)^{(\theta_A-1)/\theta_A}$, and yields would carry a selection term $\left(\alpha_{fi}^{a}\right)^{-1/\theta_A}$. Selection of the best land first is not lost by removing it within fields; it operates across fields, where it is measured. The calibration inverts Eq. (12) field by field and so assigns a high conversion cost a_{fi}^{0} to sparsely farmed fields; as returns rise, the frontier advances into progressively costlier fields. Within a field, GAEZ supplies a single potential yield per product and technology, so within-field selection on agricultural productivity would be a property of the assumed distribution rather than of the data.

Why the nested alternative caps the land-supply elasticity. The alternative draws the conversion option jointly with the product productivities, as one more branch of the nested Fréchet of Farrokhi and Pellegrina (2023): an outer nest with dispersion θ_A over natural use and agriculture, and an inner nest with dispersion θ_2 over products. The nested distribution is a valid joint distribution only if $\theta_A \le \theta_2$: the within-nest correlation of log productivities is $1-(\theta_A/\theta_2)^2$, which must lie in $[0,1]$. The restriction makes moving land into or out of agriculture no more elastic than moving it across products. Section 4 puts θ_1 at three times θ_2, and above twice it at the lower end of its ±1 standard-error band, so the data reject the nested structure in its admissible region, and the independent draw removes the constraint.

Fields split by crop feasibility. Crops cannot grow on all of a field's land: steep, arid or cold land can be grazed but not cropped. Each field is therefore split into a crop-usable part, of

share s_{fi}, and a grazing-only part, of share $1 - s_{fi}$. The usable share is the share of the field that FAO-GAEZ rates suitable or very suitable for at least one food crop, and never less than the field's observed cropland. Observed grazing land is placed on the grazing-only part first and on the usable part only when it exceeds that part's area, which gives each part an observed agricultural share, $\alpha_{fi}^{a,S}$ and $\alpha_{fi}^{a,U}$, with $s_{fi}\alpha_{fi}^{a,S} + (1 - s_{fi})\alpha_{fi}^{a,U} = \alpha_{fi}^{a}$. On the usable part, crops and livestock compete through the nested Fréchet of Section 3; on the grazing-only part livestock is the only product. Each part has its own conversion margin, Eq. (12) with its own return H^a and its own cost shifter a^0, both calibrated to the observed shares, so the baseline is reproduced exactly. A part with no observed agriculture stays unconverted, as does a field with none.

The split determines which convertible land the counterfactuals can reach. Of the 1,648 million hectares the ceiling opens, 42.6% lies where crops can expand, on usable parts already farmed; 39.3% can only be grazed; 8.5% lies in fields with no observed agriculture; and 9.6% exceeds the natural land of the parts that can convert. Conversion of natural habitat is therefore possible on 81.9% of convertible land, and crop expansion on less than half of it.

The conversion-cost bill. The converted share α_{fi}^{a} is the probability that a plot converts; the resource cost is the partial mean of the draw over the plots that do. Writing $\bar{z} = H_{fi}^{a}/(a_{fi}^{0}P_{fi}^{0})$, the log-logistic density is $f(z) = \theta_1 z^{\theta_1 - 1}/(1 + z^{\theta_1})^2$ and

$$\mathbb{E}[z\,\mathbf{1}\{z \le \bar{z}\}] = \int_0^{\bar{z}} z\, f(z)\,\mathrm{d}z = \int_0^{\bar{z}} \frac{\theta_1 z^{\theta_1}}{(1 + z^{\theta_1})^2}\,\mathrm{d}z. \tag{61}$$

Substituting $u = z^{\theta_1}$ gives $\int_0^U u^{1/\theta_1}(1+u)^{-2}\mathrm{d}u$ with $U = \bar{z}^{\theta_1} = \alpha^a/(1-\alpha^a)$ by Eq. (12), and the further substitution $t = u/(1+u)$, which maps U to α^a, gives

$$\mathbb{E}[z\,\mathbf{1}\{z \le \bar{z}\}] = \int_0^{\alpha^a} t^{1/\theta_1}\,(1-t)^{-1/\theta_1}\,\mathrm{d}t = B\Big(\alpha^a;\, 1 + \tfrac{1}{\theta_1},\, 1 - \tfrac{1}{\theta_1}\Big), \tag{62}$$

the incomplete Beta function of Eq. (38). The integrand vanishes at $t = 0$, so the first plots converted are almost free and the marginal cost rises from zero; as $\alpha^a \to 1$ the bill tends to $B(1 + \frac{1}{\theta_1}, 1 - \frac{1}{\theta_1}) = (\pi/\theta_1)/\sin(\pi/\theta_1)$, which exceeds one because the log-logistic has unbounded support.

A Pareto conversion cost with shape θ_1 and minimum $(\theta_1 - 1)/\theta_1$, so that its mean is one, would give $1 - (1 - \alpha^a)^{(\theta_1 - 1)/\theta_1}$ instead. Its marginal cost, $\frac{\theta_1 - 1}{\theta_1}(1 - \alpha^a)^{-1/\theta_1}$, is bounded away from zero at $\alpha^a = 0$. The two bills agree in the upper tail, since the log-logistic is Pareto-tailed, and differ on lightly farmed fields, where the Pareto minimum charges for plots that the log-logistic makes almost free.

B.2 Demand at the farm gate

Equation (27) follows from the upper tier. Hold expenditure E_{fi} and the outside-good price fixed and let P^a_{fi} change. Food is Leontief in the farm bundle and marketing services with baseline-price weights, so C^a_{fi} moves one for one with C^F_{fi}, and the food price index of Eq. (24) responds as

$$\frac{\partial \ln P^F_{fi}}{\partial \ln P^a_{fi}} = \frac{\mu_i P^a_{fi}/\bar{P}^a_i}{P^F_{fi}} \equiv \mu^F_{fi}, \tag{63}$$

the farm share of the food dollar at current prices. With real consumption $C_{fi} = E_{fi}/P_{fi}$ and $\partial \ln P_{fi}/\partial \ln P^F_{fi} = s^F_{fi}$, the food share of spending, the food demand of Eq. (21) gives

$$\partial \ln C^F_{fi} = -\eta \left(\partial \ln P^F_{fi} - \partial \ln P_{fi}\right) - \partial \ln P_{fi} = -\left[\eta \left(1 - s^F_{fi}\right) + s^F_{fi}\right] \partial \ln P^F_{fi}, \tag{64}$$

and multiplying by μ^F_{fi} gives Eq. (27). The first term is substitution away from food, the second the income effect of a higher price level. With μ^F_{fi} at 0.21 in the median country, from 0.06 in Czechia to 1 in Burkina Faso, Cameroon, Ghana and Mali, farm-gate demand is several times less elastic than the demand for food.

B.3 Ecosystem services

Services aggregate the abundances x_s of the S species present with a CES function, $ES = \left(\sum_{s=1}^{S} x_s^{\rho}\right)^{1/\rho}$, $\sigma_{ES} = 1/(1-\rho)$. If the species share total abundance A evenly, $x_s = A/S$, and

$$ES = \left(S\,(A/S)^{\rho}\right)^{1/\rho} = A\,S^{(1-\rho)/\rho} = A\,S^{1/(\sigma_{ES}-1)}, \tag{65}$$

since $(1-\rho)/\rho = 1/(\sigma_{ES}-1)$. Taking the ratio of a counterfactual to the baseline, and measuring A by the abundance index and S by the species–area index of the field, gives Eq. (19). Any proportional rescaling of either index cancels in the ratio, which is why the feedback inherits the elasticities of Noack, Engist, and Larsen (2025) without inheriting the units of their indices.

B.4 Comparative statics used in estimation

The odds elasticity and the area elasticity. Let p scale output prices, wages and input prices together, holding P^0_{fi} fixed. Since the factor and input shares of each technology sum to one, each

product-technology return $h_{fi}^{k\tau}$ is then proportional to p, so $H_{fi}^{a} \propto p$ and Eq. (12) gives, exactly,

$$\frac{d\ln\big(\alpha_{fi}^{a}/(1-\alpha_{fi}^{a})\big)}{d\ln H_{fi}^{a}} = \theta_1, \qquad \frac{d\ln\alpha_{fi}^{a}}{d\ln H_{fi}^{a}} = (1-\alpha_{fi}^{a})\,\theta_1. \tag{66}$$

θ_1 is the elasticity of the conversion odds; the elasticity of agricultural area is $(1-\alpha_{fi}^{a})\theta_1$, which differs across fields and vanishes as a field approaches full conversion. Averaged over agricultural land, $1-\alpha_{fi}^{a}$ is 0.41 at the baseline, so the area elasticity is about 1.96; general-equilibrium price responses damp it further (Section 4). The second expression holds field by field; it does not carry over to countries, whose agricultural share averages over fields with different shares (Appendix D).

Own-price acreage elasticity of a product. Raising the price of product k alone, with factor prices held fixed, raises each return $h_{fi}^{k\tau}$ in proportion to p^k to the power $1/\gamma_L^{k\tau}$, since land is the residual claimant on a Cobb-Douglas technology. Writing the land of (k,τ) as $L_{fi}\alpha_{fi}^{a}\alpha_{fi}^{k}\alpha_{fi}^{k\tau}$ and differentiating the three shares,

$$\frac{d\ln L_{fi}^{k}}{d\ln p^{k}} = \Big[\theta_1\,\alpha_{fi}^{k}\left(1-\alpha_{fi}^{a}\right) + \theta_2\left(1-\alpha_{fi}^{k}\right)\Big]\sum_{\tau\in\mathcal{T}}\frac{\alpha_{fi}^{k\tau}}{\gamma_L^{k\tau}}, \tag{67}$$

where L_{fi}^{k} is the field's land in product k. The first term in brackets is the extensive margin, weighted by product k's share of the field's agriculture, and the second the margin across products; the technology margin θ_3 reallocates land between techniques within k and drops out of the total. The country elasticity is the L_{fi}^{k}-weighted mean over fields. With the crop-feasibility split, α_{fi}^{a} and α_{fi}^{k} are the agricultural share of the field's usable part and product k's share of that part's farmland. For U.S. maize at the baseline the elasticity is 8.0, of which 2.5 is the extensive margin and 5.5 the product margin: land is a fifth of costs under the modern technique, which 95% of U.S. maize land uses, so the pass-through $1/\gamma_L^{k1}$ from the output price to the return on land is almost five.

Saturation of the aggregate statistic and the small-shock limit. A larger θ_1 makes each field more responsive, but it also concentrates the response on fewer fields: only those whose return-to-cost ratio is close to one are near their conversion margin. Aggregate the field-level share to a country, $\alpha_c = \int \alpha^{a}(u)\,dF(u)$, where $u = \ln H^{a} - \ln(a^{0}P^{0})$, F is the country's distribution of log return-to-cost ratios, and $\alpha^{a}(u) = \Lambda(\theta_1 u)$ with Λ the logistic function. Substituting $v = \theta_1 u$,

$$\frac{d\alpha_c}{d\ln p} = \theta_1\int \alpha^{a}(1-\alpha^{a})\,dF(u) = \int \Lambda'(v)\,f(v/\theta_1)\,dv \xrightarrow[\theta_1\to\infty]{} f(0), \tag{68}$$

where f is the density of u. The aggregate land response converges to the density of fields at the margin, so raising θ_1 without limit does not raise a country's land response without limit. Two consequences follow. The cross-country coefficient of land growth on population growth is bounded above and flattens in θ_1, so the moment is less informative at large values. And because the aggregate response is concave in the shock, the model's coefficient declines with the size of the shock fed into it, whereas its empirical counterpart is stable across windows (between 0.32 and 0.38 from 1961–2020 to 2000–2020) that span a fourfold range of population changes. The estimation therefore evaluates the model's statistic in its small-shock limit, where Eq. (66) is the exact local counterpart (Appendix D).

B.5 Agricultural land, farm revenue and input prices

On every product-technology pair, land is the residual claimant of a Cobb-Douglas technology, and under the nested Fréchet the plots that choose each pair earn, on average, the same gross rent per hectare. A field's agricultural land therefore moves with its farm revenue and with the share of that revenue paid to land, which gives a simple condition for when cheaper inputs spare land.

Proposition B.1 (Land follows revenue)**.** *Let field f of country i have a slack ceiling, farm revenue $R_{fi} = \sum_{k,\tau} p_{fi}^{k} Q_{fi}^{k\tau}$ and land share of revenue $\bar{\gamma}_{fi}^{L} = \sum_{k,\tau} \gamma_{L}^{k\tau}\, p_{fi}^{k} Q_{fi}^{k\tau} / R_{fi}$. Then*

$$L_{fi}\, \alpha_{fi}^{a}\, H_{fi}^{a} = \bar{\gamma}_{fi}^{L}\, R_{fi}, \qquad \bar{\gamma}_{fi}^{L} = \left[\sum_{k,\tau} \frac{\alpha_{fi}^{k}\, \alpha_{fi}^{k\tau}}{\gamma_{L}^{k\tau}} \right]^{-1}, \tag{69}$$

and, to first order, for any change in prices, wages or productivity,

$$d\ln\!\left(L_{fi}\alpha_{fi}^{a}\right) = \frac{e_{fi}}{1+e_{fi}} \Big(d\ln R_{fi} + d\ln \bar{\gamma}_{fi}^{L} - d\ln P_{fi}^{0} \Big), \qquad e_{fi} \equiv \theta_1 \left(1 - \alpha_{fi}^{a}\right). \tag{70}$$

Proof. Multiply the output of (k,τ) in Appendix B.1 by $\gamma_{L}^{k\tau}\, p_{fi}^{k}$ and use $p_{fi}^{k} \tilde{h}_{fi}^{k\tau} = h_{fi}^{k\tau}$. Equation (30) gives $a_{fi}^{k\tau} h_{fi}^{k\tau} = H_{fi}^{k} \left(\alpha_{fi}^{k\tau}\right)^{1/\theta_3}$, and the product share gives $H_{fi}^{k} = H_{fi}^{a} \left(\alpha_{fi}^{k}\right)^{1/\theta_2}$, so

$$\gamma_{L}^{k\tau}\, p_{fi}^{k} Q_{fi}^{k\tau} = L_{fi}\, \alpha_{fi}^{a}\, a_{fi}^{k\tau} h_{fi}^{k\tau} \left(\alpha_{fi}^{k}\right)^{\frac{\theta_2-1}{\theta_2}} \left(\alpha_{fi}^{k\tau}\right)^{\frac{\theta_3-1}{\theta_3}} = L_{fi}\, \alpha_{fi}^{a}\, \alpha_{fi}^{k}\, \alpha_{fi}^{k\tau}\, H_{fi}^{a} :$$

the land in every pair earns the same average rent per hectare, H_{fi}^{a}. Summing over (k,τ) gives the identity in Eq. (69). The revenue of each pair is therefore proportional to $\alpha_{fi}^{k}\alpha_{fi}^{k\tau}/\gamma_{L}^{k\tau}$, so the land share is the harmonic mean shown. Differentiating the identity gives $d\ln(L_{fi}\alpha_{fi}^{a}) + d\ln H_{fi}^{a} = d\ln R_{fi} + d\ln \bar{\gamma}_{fi}^{L}$, and Eq. (12), with L_{fi} and a_{fi}^{0} fixed, gives $d\ln(L_{fi}\alpha_{fi}^{a}) = e_{fi} \left(d\ln H_{fi}^{a} - d\ln P_{fi}^{0} \right)$. Eliminating $d\ln H_{fi}^{a}$ gives Eq. (70). □

The identity is exact; only the land-supply step is local. With the crop-feasibility split it holds part by part, and where the ceiling binds agricultural land cannot rise, so e_{fi} is zero for increases.

Corollary B.1 (When cheaper inputs spare land)**.** *Let the fields of country i be identical and produce one farm product, or let all products move together, so that Proposition B.1 holds for the country with its farm revenue R_i. Let R_{in} be the part of R_i earned in market n, σ the elasticity of substitution between origins, P_n the farm price index of market n and ε_n^F the farm-gate demand elasticity of Eq. (27). Holding expenditure in every market and the outside-good price fixed,*

$$d\ln R_i = -(\sigma-1)\sum_n \frac{R_{in}}{R_i}\left(d\ln p_i + d\ln d_{in} - d\ln P_n\right) + \sum_n \frac{R_{in}}{R_i}\left(1-\varepsilon_n^F\right) d\ln P_n. \tag{71}$$

Consider a fall in input prices that lowers country i's output price and raises its modern share, so that $d\ln \bar{\gamma}_i^L \le 0$.

1. *If the fall is common to all origins, $d\ln p_i = d\ln P_n \equiv d\ln P$, it lowers country i's agricultural land if and only if $\varepsilon^F < 1 + \left|d\ln \bar{\gamma}_i^L\right| / \left|d\ln P\right|$, where $\varepsilon^F = \sum_n (R_{in}/R_i)\,\varepsilon_n^F$.*

2. *If it is specific to country i, and country i is small in its markets so that $d\ln P_n = 0$, it raises country i's agricultural land if and only if $(\sigma-1)\left|d\ln p_i\right| > \left|d\ln \bar{\gamma}_i^L\right|$.*

Proof. Spending in market n on the product of origin i is $R_{in} = b_{in}\left(p_i d_{in}/P_n\right)^{1-\sigma} X_n$, where X_n is farm spending in n, so $d\ln R_{in} = (1-\sigma)\left(d\ln p_i + d\ln d_{in} - d\ln P_n\right) + d\ln X_n$. With expenditure and the outside-good price fixed, Eq. (27) gives $d\ln X_n = \left(1-\varepsilon_n^F\right) d\ln P_n$, and weighting by R_{in}/R_i gives Eq. (71). By Proposition B.1, with $d\ln P^0 = 0$, agricultural land falls if and only if $d\ln R_i + d\ln \bar{\gamma}_i^L < 0$. In the first case the first sum in Eq. (71) vanishes and $d\ln R_i = (1-\varepsilon^F)\, d\ln P$ with $d\ln P < 0$; in the second the second sum vanishes and $d\ln R_i = (\sigma-1)\left|d\ln p_i\right|$. □

The first case is the condition of Hertel (2012) for a global change in farm productivity, inelastic farm-level demand, with one term added. Cheaper inputs move land to the input-intensive technique, which pays land a smaller share of revenue ($\gamma_L^{k1} = 0.206$ against $\gamma_L^{k0} = 0.551$ for crops), so they can spare land even where farm-gate demand is elastic; with a single technique and a common land share the term vanishes and the threshold is one. The second case is the mechanism through which market integration can turn a regional yield gain into cropland expansion (Hertel, Ramankutty, and Baldos, 2014). A change in input trade costs combines the two. Its part common to all origins faces farm-gate demand, whose elasticity averages 0.17 in the calibration, weighted by farm spending (0.30 at $\eta = 1.2$); its part specific to each country faces trade-elastic demand, $\sigma - 1 = 4.4$. Input liberalization can therefore spare land in aggregate while expanding it in the countries whose input costs fall most relative to their competitors, and the species it spares depend

on where that land goes. The input-only reset of Table 6 behaves as the first case predicts, in reverse: input prices rise by 14.4% and crop prices by 10.2% (weighted by cropland), the modern share falls and raises land's share of crop revenue from 0.278 to 0.283, which puts the threshold at 1.18, far above the farm-gate elasticity of 0.17, and world agricultural land expands by about 4%.

B.6 A sufficient statistic for the species effect of a shock

Fields differ in their land, yields and distance to the hub, but within a country they face the same proportional changes in prices: domestic trade costs are fixed, so $\hat{p}^k_{fi} = \hat{p}^k_i$ and $\hat{P}^j_{fi} = \hat{P}^j_i$, where $\hat{x} \equiv x'/x$. The land allocation of Section 3 is an explicit function of these prices, and the species counts an explicit function of land. The species a shock commits therefore depend on it only through 41 prices in each country, its product prices, farm wage, three input prices, feed price and outside-good price, and, with the feedback, each field's productivity multiplier. Once a shock's effect on those prices is known, from this model or any other, the land allocation and the species count follow from explicit formulas. Let $E = \sum_e v_e \left(S^0_e - B^{SAR}_e\right)$ denote committed global extinctions, where v_e is the vulnerability score of ecoregion e (Chaudhary and Brooks, 2018).

Proposition B.2 (Country prices are sufficient)**.** *Take the baseline allocation as given. For each country i, let the shock change product prices by $\hat{p}^k_i$, the farm wage by $\hat{w}^1_i$, the price index of intermediates by $\hat{m}^k_i$ (for crops $\prod_j (\hat{P}^j_i)^{\gamma^{kj}_M}$, for livestock the feed price $\hat{P}^{feed}_i$) and the outside-good price by $\hat{P}^0_i$, and let it change field productivity by $\hat{a}^{k\tau}_{fi}$ (the feedback multiplier $\hat{f}^{bio}_{fi}$). Then each field's counterfactual allocation is*

$$\begin{aligned}
\hat{h}^{k\tau}_{fi} &= \left(\hat{p}^k_i\right)^{1/\gamma^{k\tau}_L} \left(\hat{w}^1_i\right)^{-\gamma^{k\tau}_N/\gamma^{k\tau}_L} \left(\hat{m}^k_i\right)^{-\gamma^{k\tau}_M/\gamma^{k\tau}_L}, \\
\alpha^{k\tau\prime}_{fi} &= \frac{\alpha^{k\tau}_{fi}\left(\hat{a}^{k\tau}_{fi}\hat{h}^{k\tau}_{fi}\right)^{\theta_3}}{\left(\hat{H}^k_{fi}\right)^{\theta_3}}, \qquad \alpha^{k\prime}_{fi} = \frac{\alpha^k_{fi}\left(\hat{H}^k_{fi}\right)^{\theta_2}}{\left(\hat{H}^a_{fi}\right)^{\theta_2}}, \\
\frac{\alpha^{a\prime}_{fi}}{1-\alpha^{a\prime}_{fi}} &= \frac{\alpha^a_{fi}}{1-\alpha^a_{fi}} \left(\frac{\hat{H}^a_{fi}}{\hat{P}^0_i}\right)^{\theta_1},
\end{aligned} \tag{72}$$

with $\left(\hat{H}^k_{fi}\right)^{\theta_3} = \sum_\tau \alpha^{k\tau}_{fi}\left(\hat{a}^{k\tau}_{fi}\hat{h}^{k\tau}_{fi}\right)^{\theta_3}$ and $\left(\hat{H}^a_{fi}\right)^{\theta_2} = \sum_k \alpha^k_{fi}\left(\hat{H}^k_{fi}\right)^{\theta_2}$, and the agricultural share then capped at q_{fi}. The change in E follows from Eqs. (15) and (16). To first order,

$$dE = \sum_i \sum_{f\in\mathcal{F}_i} L_{fi}\Big[\sum_{k,\tau} \pi^{k\tau}_{fi}\,\omega^{k\tau}_{fi}\; d\ln\!\left(a^{k\tau}_{fi}h^{k\tau}_{fi}\right) - \theta_1\,\alpha^a_{fi}\left(1-\alpha^a_{fi}\right)\bar{\mu}_{fi}\; d\ln P^0_i\Big], \tag{73}$$

$$\omega^{k\tau}_{fi} = \theta_1\left(1-\alpha^a_{fi}\right)\bar{\mu}_{fi} + \theta_2\left(\bar{\mu}^k_{fi} - \bar{\mu}_{fi}\right) + \theta_3\left(\mu^{k\tau}_{fi} - \bar{\mu}^k_{fi}\right), \tag{74}$$

where $\mu_{fi}^{k\tau} = \sum_e \lambda_{fe}\, v_e\, z_e\, S_e^0\, b_e^{z_e-1}\big(1-\chi_e^{k\tau}\big)/L_e$ *is the number of species committed per hectare of field* f *converted from natural habitat to* (k,τ)*,* b_e *is the bracket of Eq. (16),* $\bar{\mu}_{fi}^{k} = \sum_\tau \alpha_{fi}^{k\tau}\mu_{fi}^{k\tau}$ *and* $\bar{\mu}_{fi} = \sum_k \alpha_{fi}^{k}\bar{\mu}_{fi}^{k}$*. Where the ceiling binds, the term in* θ_1 *is zero for increases.*

Proof. The hat expressions follow from the definition of $h_{fi}^{k\tau}$, whose factor and input shares sum to one, and from the three nests of Section 3, with a_{fi}^0 fixed. For the first-order form, $dE = \sum_f \sum_{k,\tau} L_{fi}\,\mu_{fi}^{k\tau}\,d\pi_{fi}^{k\tau}$ with $\pi_{fi}^{k\tau} = \alpha_{fi}^{a}\alpha_{fi}^{k}\alpha_{fi}^{k\tau}$. Writing $x^{k\tau} = d\ln(a_{fi}^{k\tau}h_{fi}^{k\tau})$, the nests give $d\ln H_{fi}^{k} = \sum_\tau \alpha_{fi}^{k\tau}x^{k\tau}$, $d\ln H_{fi}^{a} = \sum_k \alpha_{fi}^{k}\,d\ln H_{fi}^{k}$, $d\alpha_{fi}^{k\tau} = \theta_3\,\alpha_{fi}^{k\tau}\big(x^{k\tau} - d\ln H_{fi}^{k}\big)$, $d\alpha_{fi}^{k} = \theta_2\,\alpha_{fi}^{k}\big(d\ln H_{fi}^{k} - d\ln H_{fi}^{a}\big)$ and $d\alpha_{fi}^{a} = \theta_1\,\alpha_{fi}^{a}\big(1-\alpha_{fi}^{a}\big)\big(d\ln H_{fi}^{a} - d\ln P_i^0\big)$. Substituting and collecting the coefficient of each $x^{k\tau}$ gives Eqs. (73)–(74). □

Each pair's weight is its land times its marginal species cost, weighted by the elasticity of the margin that moves it. Conversion draws land from natural habitat at the field's average cost $\bar{\mu}_{fi}$, with elasticity $\theta_1(1-\alpha_{fi}^{a})$; reallocation moves land between products at elasticity θ_2, and costs species only to the extent that product k costs more than the field's average; the choice of technique does the same within the product at elasticity θ_3. Because $d\ln(a_{fi}^{k\tau}h_{fi}^{k\tau}) = (1/\gamma_L^{k\tau})\,d\ln p_i^k - (\gamma_N^{k\tau}/\gamma_L^{k\tau})\,d\ln w_i^1 - (\gamma_M^{k\tau}/\gamma_L^{k\tau})\,d\ln m_i^k + d\ln f_{fi}^{bio}$ is common to the fields of a country apart from the feedback, Eq. (73) aggregates to one weight per country and pair, $\Omega_i^{k\tau} = \sum_{f\in\mathcal{F}_i} L_{fi}\pi_{fi}^{k\tau}\omega_{fi}^{k\tau}$: the species a country commits per percent rise in the return to (k,τ). The trade model determines the price changes; the land margins and the ecology determine the weights. With the crop-feasibility split, the proposition holds part by part, and the off-grid placement of land beyond a field's cell (Appendix C) enters through the weights λ_{fe}. In the three counterfactuals of Table 6, the explicit formulas reproduce the solved counts of committed extinctions to within 0.001 species, with or without the feedback, whether they are fed the prices the solver uses in its last land allocation or the equilibrium prices it reports. The first-order form of Eq. (73) is less accurate, because the ceiling binds on 280,000 to 350,000 fields in these counterfactuals: ignoring the ceiling, it overstates the counts by 57 to 62%; imposing it, it recovers 81 to 92% of them. In that first-order form, nearly the whole change runs through conversion; reallocation across products contributes less than 0.1 species, and the choice of technique subtracts 0.7 to 1.4.

C Quantitative data

Tables C.1 and C.2 list every dataset the quantitative model uses, the year and resolution at which it enters, and the object it identifies or validates. Table C.3 describes the calibration inputs at each of the model's three spatial scales.

Farmland outside the grid. The model's fields are the 822,053 five-arcminute cells with a GAEZ potential yield for some crop (Farrokhi and Pellegrina, 2023). They hold 91% of the world's cropland in HYDE 3.5 (2017) but only 45% of its grazing land, most of the rest lying in cells where no crop has potential, such as arid rangeland. The economic model scales each country's field areas so that they add up to its FAOSTAT land area, and its land-use shares are shares of these scaled areas; the ecological module needs physical hectares by ecoregion instead. It places them as follows, identically at the baseline and in every counterfactual. A field's cropland enters its own cell at the model's hectares, and any excess over the cell's area joins a country pool. A field's grazing land enters its own cell at its share of the cell's physical area, and the part due to the scaling joins a second country pool; where cropland and grazing together exceed the cell, grazing moves to the pool first. The grazing pool is spread over the country's cells outside the grid in proportion to their HYDE grazing land, and the cropland pool in proportion to their HYDE cropland, then their HYDE grazing land, each cell filling up to its area and passing any excess on. At the baseline, 3.4 million hectares, 0.07% of farmland, cannot be placed. The resulting ecoregion areas enter the species–area and abundance measures of Section 4.4.

Table C.1: Data sources: countries

Data	Source	Year	Resolution	Use
Country level				
Bilateral trade and gross output, outside good and agricultural inputs	BACI-CEPII, OECD Inter-Country Input-Output tables, STAN, UNIDO	2017	Country pair	Demand shifters $b_{ni}^g (d_{ni}^g)^{1-\sigma_g}$, productivities A_i^g
Value added, agricultural and non-agricultural	OECD Inter-Country Input-Output tables; World Development Indicators where missing	2017	Country	Expenditure E_i
Food share of household spending	International Comparison Program (COICOP 01–02)	2017	Country	Upper-tier shifters b_i^0, b_i^F
Output and producer prices, by product	FAOSTAT	2017	Country × product	Productivity levels $\delta_{0,i}^k$
Bilateral agricultural trade	FAOSTAT Detailed Trade Matrix, farm-gate value, primary equivalents	2016–2018	Country pair × product	Lower-tier shifters; farm share μ_i (farm-gate absorption)
Feed use by crop	FAOSTAT Food Balance Sheets	2017	Country × crop	Feed shifters $b_i^{k,feed}$
Livestock production by system	FAO-GLEAM v3	2015	Country	Intensive share of livestock output
Labor force and agricultural employment	World Development Indicators (ILO-modeled estimates)	2016–2018	Country	Labor endowment N_i; model fit
Fertilizer production (N, P_2O_5, K_2O)	FAOSTAT	2016–2018	Country	Raw fertilizer endowment V_i
Land area, agricultural land	FAOSTAT land use	2017	Country	Land endowment L_i; model fit
Agricultural land, forest, population	FAOSTAT	1990–2020 (1961–2020 in robustness)	Country	Target for θ_1 (Table 3)
Youth share of population	World Development Indicators	1990	Country	Instrument for population growth
Predicted mortality decline	Acemoglu and Johnson (2007)	1940–1980	Country	Second instrument (overidentification)

Notes: Years are those of the data as used; ranges are averaged unless the row is a long difference. "Use" names the parameter the data identify, or "model fit" for data used only to evaluate the calibrated model (Section 4). The 66 country units are 63 countries, the former Soviet Union, the former Yugoslavia and a rest-of-world aggregate; aggregates are built by summing member countries in every source.

Table C.2: Data sources: ecoregions and fields

Data	Source	Year	Resolution	Use
Ecoregion level				
Ecoregion boundaries	Olson et al. (2001)	–	Polygon	Ecoregions; field weights λ_{fe}
Original bird species, vulnerability scores, broad habitat affinities	Chaudhary and Brooks (2018)	–	Ecoregion	S_e^0, vulnerability weights, $\chi_{e,T}^{broad}$
Species–area exponents	Drakare, Lennon, and Hillebrand (2006); Storch, Keil, and Jetz (2012) (robustness)	–	Habitat type; continent	z_e
Bird richness by land use and intensity	Newbold et al. (2015) (PREDICTS)	–	Land use × intensity	Intensity split $f_{RR}^{T,\tau}$ of the affinities
Insectivorous bird abundance	PREDICTS (Hudson et al., 2017); diet traits from SAviTraits (Murphy et al., 2023)	–	Study site	Abundance weights δ_u^{low}, δ_u^{high}
Yield elasticity to bird-provided services	Noack, Engist, and Larsen (2025)	–	–	β, σ
Bird range maps	BirdLife International and Handbook of the Birds of the World (2025)	2025	Species polygon	Model fit (IUCN benchmark); endemism weights (robustness)
Red List category and threats	IUCN Red List (IUCN, 2025)	2025	Species	Model fit (IUCN benchmark)
Field level				
Potential yields, low and high input	FAO-GAEZ v4 (Fischer et al., 2021), rain-fed	1961–1990	5′	Yields $y_{fi}^{k\tau}$; suitability index of the convertible-land ceiling
Cropland and grazing-land shares	HYDE 3.5 (Klein Goldewijk et al., 2025)	2017	5′	Conversion-cost shifters a_{fi}^0; placement of farmland outside the grid
Crop suitability (suitable and very suitable share)	FAO-GAEZ v4, high input, rain-fed	1981–2010	5′	Crop-usable part of each field (Appendix B.1)
Natural vegetation	ESA-CCI land cover (ESA, 2017)	2017	300 m	Convertible-land ceiling
Protected areas	WDPA (UNEP-WCMC and IUCN, 2011)	–	Polygon	Convertible-land ceiling
Ruminant density	Gridded Livestock of the World v4	2010	5′	Grazing feasibility of extensive livestock
Domestic trade costs	Farrokhi and Pellegrina (2023), method of Allen and Arkolakis (2014)	–	5′	d_{fi}
Country boundaries	geoBoundaries	–	Polygon	Field-to-country assignment

Notes: As in Table C.1. Fields are 5-arcminute grid cells; ecoregion-level data enter fields through the area shares λ_{fe}.

Table C.3: Descriptive statistics

	Mean	SD	Min	Median	Max
Panel A. Countries ($n = 66$)					
Land area (million ha)	197	479	3	38	2,934
Agricultural land (million ha)	71	178	1	16	1,203
Agricultural share of land	0.41	0.19	0.03	0.43	0.86
Value added (billion US$)	1,139	2,830	8	243	18,899
Agricultural share of value added	0.10	0.09	0.01	0.07	0.41
Agricultural share of employment	0.21	0.19	0.01	0.14	0.72
Food share of household spending	0.29	0.14	0.08	0.25	0.68
Farm-gate absorption (billion US$)	48	119	1	14	835
Net agricultural exports / absorption	0.07	0.50	-0.38	-0.05	3.00
Panel B. Ecoregions ($n = 759$)					
Area (thousand km^2)	169	339	0	67	4,650
Original bird species, S_e^0	281	144	20	245	847
Vulnerability score	0.012	0.019	0.000	0.006	0.205
Species–area exponent, z_e	0.28	0.06	0.21	0.26	0.34
Affinity, annual cropland, low input	0.19	0.12	0.05	0.13	0.74
Affinity, annual cropland, high input	0.11	0.07	0.03	0.09	0.43
Affinity, pasture, extensive	0.33	0.33	0.07	0.14	1.00
Affinity, pasture, intensive	0.17	0.19	0.03	0.07	0.64
Cropland share, baseline	0.11	0.13	0.00	0.06	0.88
Pasture share, baseline	0.26	0.21	0.00	0.23	0.98
Panel C. Fields ($n = 822{,}053$)					
Area (thousand ha)	7.12	1.25	3.39	7.39	8.55
Cropland share	0.25	0.25	0.00	0.16	1.00
Pasture share	0.24	0.25	0.00	0.17	1.00
Natural share	0.50	0.32	0.00	0.46	1.00
Convertible share	0.28	0.32	0.00	0.14	1.00
Crop-suitable share	0.56	0.39	0.00	0.64	1.00
Crops with positive high-input potential yield	21.1	5.0	0.0	22.0	30.0
Domestic trade cost to hub, d_{fi}	1.19	0.26	1.00	1.11	3.73

Notes: Statistics are unweighted across units. Panel A: land from FAOSTAT around 2017 (land area averaged over 2016–2018); value added and employment from the sources in Table C.1; farm-gate absorption is the value of agricultural goods, at farm-gate prices, that each country absorbs (production less exports plus imports); net agricultural exports are at the same prices. Panel B: area from Olson et al. (2001); species pools, vulnerability scores and exponents as in Section 4.4, with affinities for the low- and high-input technologies of Eq. (54); land-use shares are those of the baseline equilibrium, which reproduces the HYDE 3.5 field shares. One ecoregion with no species-pool estimate in Chaudhary and Brooks (2018) is omitted. Panel C: one observation per 5-arcminute field; land-use shares from HYDE 3.5 (2017), with the natural share their complement; the convertible share is the ceiling of Section 5; crop-suitable share and potential yields from FAO-GAEZ v4; the domestic trade cost is the iceberg cost to the field's hub.

D Estimating the land-supply elasticity

This appendix details the estimation of the land-supply elasticity θ_1 summarized in Section 4: the reduced form and its instruments, the targeted estimate and how it compares with Farrokhi et al. (2025), what θ_1 implies for the dispersion of conversion costs, and the binding function that maps the model's coefficient into θ_1, with the joint fixed point of estimation and calibration.

Reduced form. Agricultural land is FAOSTAT's agricultural area (arable land, permanent crops, and permanent meadows and pastures), a physical stock; population is FAOSTAT's total population. The regression of Eq. (53) is a single long difference over 1990–2020, estimated on the model's country units, so that the target and its model counterpart are computed on the same units. It uses the 61 units with a continuous FAOSTAT series over the window: the former Soviet Union, the former Yugoslavia, Czechia and Ethiopia are excluded because their borders changed in the early 1990s. China is not in the sample either; including it moves the IV estimate from 0.446 to 0.447 and the OLS estimate from 0.376 to 0.378. On the 189 individual countries the OLS coefficient is 0.33 against 0.38 on the aggregates. Table D.1 reports the coefficient across estimation windows.

Instruments. Population growth is instrumented with the country's youth share (population aged 0–14, World Bank) dated at the start of the window and entered as a cubic. Age structure predicts subsequent growth through demographic momentum and is predetermined with respect to later land conversion. The robust first-stage F is 120.4 (69.9 under homoskedasticity). A second instrument, predicted mortality decline from the 1940 disease environment of Acemoglu and Johnson (2007), is restricted to airborne diseases (tuberculosis, pneumonia, influenza); vector-borne diseases are excluded because their control opens frontier land directly. On its own it is weak on this window (first-stage $F = 2.9$), but it supports an overidentification test, which does not reject (Hansen $J = 2.56$, $p = 0.46$).

Which estimate is targeted. The IV estimate exceeds OLS, 0.446 against 0.376, the opposite of the bias that frontier-pull endogeneity would produce and consistent with attenuation in long-difference growth rates. θ_1 is set so that the model matches the IV coefficient; the OLS coefficient is carried through the binding function as an alternative.

Comparison with Farrokhi et al. (2025). Their agricultural area is total harvested area plus grazing land imputed at 0.75 hectares per head of cattle; on it they report elasticities of agricultural area to population between 1.04 and 1.21 across 150 countries (their Table 1, panel b). Rebuilding

Table D.1: Window invariance of the population–land coefficient

Window	1961–2020	1980–2017	1990–2020	2000–2020
OLS coefficient	0.378	0.352	0.376	0.323
	(0.049)	(0.056)	(0.065)	(0.077)
Mean $\Delta \ln$ population	0.95	0.54	0.39	0.24
Country aggregates	61	61	61	65

Notes: Long-difference regressions of $\Delta \ln$ agricultural land on $\Delta \ln$ population across the model's country aggregates, by window. Heteroskedasticity-robust (HC1) standard errors in parentheses. The coefficient is stable across a fourfold range of shock sizes, whereas the model's counterpart declines with shock size (Appendix B.4), which motivates matching in the small-shock limit.

their measure on this paper's country aggregates over 1961–2020, instrumented with the 1961 youth share, gives an IV coefficient of 0.93 (OLS 0.98), against 0.48 (0.38) for the physical measure used here on the same window, aggregates and instrument. The gap is one of measurement: harvested area rises with multiple cropping when no land is converted, and imputed pasture moves with herd size rather than hectares. Because the model's land variable is a physical area share, the physical measure is the one whose model counterpart is computed identically.

What θ_1 means: cost dispersion. Because the conversion draw is log-logistic with shape θ_1, the parameter is a dispersion statistic. The ratio of the 90th to the 10th percentile of conversion costs among the plots of one field is

$$c_{90}/c_{10} \;=\; 81^{1/\theta_1},$$

so $\theta_1 = 4.80$ says that conversion costs vary by a factor of 2.5 within a 5-arcminute field, about 9 kilometers across at the equator. Heterogeneity between fields is carried by a^0_{fi}, which is calibrated separately, so this is a statement about local variation.

French farmland transactions give an outside reading of the same statistic (Table D.2). Among parcels sold on their own, the 90th-to-10th percentile ratio of the price per hectare within 4.6 kilometers, half the width of a field, is 2.2, which the identity maps to $\theta_1 = 5.5$; the ratio rises with the radius, to 5.0 at 150 kilometers. Price dispersion also reflects soil quality and parcel characteristics, so 5.5 is a lower bound at the model's own scale; netting out agronomic suitability, parcel size and land type raises it slightly, to 5.8. The estimate lies below it: it implies more dispersion of conversion costs within a field than French farmland prices show, and since committed extinctions rise with θ_1, the estimate is conservative on this reading. Including sales that bundle the parcel with buildings or other land raises the ratio to 3.8 within 4.6 kilometers, because their price includes property other than farmland.

Table D.2: Dispersion of farmland values by spatial scale

Neighborhood radius	4.6 km	9 km	20 km	50 km	150 km
Parcels sold on their own					
p_{90}/p_{10} of price per hectare	2.21	2.55	3.00	3.59	5.00
Implied θ_1	5.53	4.70	4.00	3.44	2.73
Implied θ_1, net of suitability, size and land type	5.76	5.00	4.29		
Parcels per neighborhood (median)	15	28	112	599	4,167
Including sales with buildings or other land					
p_{90}/p_{10} of price per hectare	3.83	5.43	7.20	9.31	11.89
Implied θ_1	3.27	2.60	2.23	1.97	1.78

Notes: French agricultural land transactions (*Demandes de valeurs foncières*, geolocated, 2021–2025), arable and meadow parcels of at least one hectare. The upper panel keeps the 32,643 parcels sold on their own; the lower panel adds the 13,473 sold together with buildings or other land. Parcels below one hectare are excluded as amenity and building-adjacent land: among parcels sold on their own, dispersion falls monotonically with parcel size, from $p_{90}/p_{10} = 22.1$ below half a hectare to 5.1 above 20 hectares. Each cell is the median, across neighborhoods centered on 4,000 randomly drawn parcels and holding at least 12 parcels, of the ratio within the neighborhood. The implied θ_1 inverts $c_{90}/c_{10} = 81^{1/\theta_1}$. The third row first nets the log price of the GAEZ suitability of the parcel's field, log parcel size and land type, on the parcels matched to the model's grid.

How much cross-country variation the structure generates. Since the area elasticity is $(1-\alpha^a_{fi})\theta_1$ field by field and θ_1 is common, all cross-country variation runs through the agricultural-land-weighted mean of $1-\alpha^a_{fi}$: 0.27 in India, 0.36 in the United States and 0.59 in Brazil, and from 0.09 (Uruguay) to 0.94 (Egypt) across the 66 units. The partial-equilibrium elasticity is therefore 1.3 in India, 1.7 in the United States and 2.8 in Brazil, a ratio of 1.6 between Brazil and the United States, and ranges from 0.4 to 4.5 across the 66 units. Barr et al. (2011) report static agricultural-land elasticities of 0.007 to 0.029 for the United States and 0.20 to 0.245 for Brazil, an order of magnitude apart, although from separate estimations. The one-parameter specification thus compresses cross-country heterogeneity: it lets a frontier economy and a fully converted one differ in responsiveness only through their current conversion shares. The calibration targets the aggregate response, so the compression affects where a given expansion lands rather than its size, and because frontier ecoregions are the most species-rich, it likely understates the concentration of losses in the tropics. Letting θ_1 vary across countries would require moments that the single population regression does not provide.

The binding function. The model counterpart of the reduced-form coefficient is computed by simulation: from the baseline, scale each country's population by $\exp(s\,\Delta \ln \mathrm{Pop}_c)$ with the observed 1990–2020 changes, re-solve without the convertible-land ceiling, and run the same unweighted regression on the 61 aggregates. The model's land response is concave, so the coefficient falls with the shock scale s (Table D.3). The estimation uses the small-shock limit, extrapolated linearly to $s = 0$ from $s = 0.25$ and $s = 0.10$, which is the model's exact local counterpart of a

Table D.3: The model's auxiliary statistic by shock scale, at $\theta_1 = 4.80$

Shock scale s (fraction of the 1990–2020 changes)	1	0.25	0.10	limit
Model coefficient	0.346	0.430	0.440	0.448

Notes: The regression of Eq. (53) on model output when each country's population is scaled by its observed 1990–2020 growth times s. The limit extrapolates linearly to $s = 0$ from the two smallest scales; the IV target is 0.446.

coefficient that the data show to be invariant to the size of the shock (Table D.1).

Across the four values of θ_1 at which the limit statistic has been computed (3.83, 4.79, 4.80 and 9.10), it is well approximated by $b(\theta_1) = A - B/\theta_1$ with $A = 0.73$ and $B = 1.32$. The moment is informative but not sharp: the elasticity of b with respect to θ_1 is about 0.6 at the estimate. The heteroskedasticity-robust standard error of the target, 0.071, maps through the fitted function to a ± 1 standard-error band of [3.7, 6.2], and the OLS target maps to 3.7. The band is approximate: at the estimate the fitted function lies 0.007 above the exact statistic, and it would place the IV target at 4.66 rather than 4.80.

The arc convention. Matching the coefficient at the full observed shock instead of its limit gives a larger estimate. The arc statistic is 0.346, 0.402, 0.443 and 0.474 at $\theta_1 = 4.80$, 6.73, 8.65 and 10.57, and crosses the IV target at $\theta_1 \approx 8.9$ (OLS: 5.8), a factor of 1.8 above the limit estimate. The limit convention is the conservative one for what the paper concludes: committed extinctions rise with θ_1, from 23.3 to 26.4 and 29.6 under de-liberalization at $\theta_1 = 3.73$, 4.80 and 6.21 (Appendix Table H.1), so matching the arc would raise the headline.

The interacted regression. The conversion law implies that a field's land response, $(1-\alpha^a_{fi})\theta_1$, falls with the share already farmed and vanishes at full conversion. Column 4 of Table 3 shows a cross-country counterpart in the data: the response of agricultural land to population falls with the initial agricultural share of land, with an interaction (-0.61) close to minus the main effect ($+0.59$). I do not use this as a test of the model, because the calibrated model does not imply it across countries. Run on model output at $\theta_1 = 4.80$, in the small-shock limit and with the 1990–2020 population changes that the binding function uses, rather than the 1961–2020 window of column 4, the same specification gives a main effect of 0.54 and an interaction of -0.20. A country's initial share averages over fields whose own shares differ widely, so in a country that is mostly farmed, the fields that are not keep responding, and general-equilibrium price responses differ across countries.

Joint fixed point of estimation and calibration. The binding function is evaluated through a reference calibration, which is itself computed at a value of θ_1; the reported estimate is the fixed point of alternating the two. The productivity shifters do not depend on θ_1, because the converted share is held at the data during calibration and output is linear in it (Appendix B.1), and the conversion-cost shifters a^0_{fi} rescale in closed form. A new reference therefore moves the estimate only through general-equilibrium income effects, which are small: starting from a reference at 7.51, the sequence of estimates was 4.84, 4.79 and 4.79, so a move of 2.7 in the reference moved the next estimate by 0.05. Recalibrating at the final value of θ_3 moved it to 4.80, a step of 0.01, about a hundredth of the target's standard error mapped into θ_1; the procedure stops at a tolerance of 0.05 and verifies that the converged calibration reproduces the baseline.

E Computation

This appendix describes the algorithms that solve, calibrate and simulate the model. Appendix E.1 gives the algorithm that solves for a general equilibrium, Appendix E.2 the fixed point that adds the biodiversity–productivity feedback, and Appendix E.3 the calibration algorithm, which is the inner problem of the estimation of θ_1 in Appendix D. Appendix E.4 describes how each counterfactual is computed, and Appendix E.5 how equilibria are selected and what the search for other equilibria returns. The algorithms follow those of Farrokhi and Pellegrina (2023) and depart from them where the model does. All computations run in MATLAB R2025b on a laptop (Apple M5, 10 cores, 24 GB of memory).

E.1 Solving for an equilibrium

The algorithm takes endowments $\mathcal{D}$, supply parameters Ω_S and demand parameters Ω_D as given (Definition 1) and solves for each country's two wages $\{w^0_i, w^1_i\}$, the price of processed fertilizer $\{p^v_i\}$ in each producing country, and the price $\{p^k_i\}$ of each agricultural product in each country that produces it: about 2,100 unknowns at the baseline. Every other variable follows in closed form from these prices. Field-level prices follow from their national counterparts through domestic trade costs, $p^k_{fi} = p^k_i / d^k_{fi}$ for products at the origin field and $P^j_{fi} = d^j_{fi} P^j_i$ for agricultural inputs at the destination field, so the algorithm solves for national variables and recovers field-level ones from them. The U.S. non-agricultural wage is the numeraire.

1. Guess wages, fertilizer prices and product prices. Rescale both wages of every country by the factor that sets the U.S. non-agricultural wage to its normalized value.

2. Compute the prices of the outside good, pesticides and machinery at the origin, $p_i^0 = w_i^0/A_i^0$ and $p_i^j = w_i^0/A_i^j$.

3. For every good, compute the price index at each destination, Eq. (26), and the expenditure share of each destination on each origin, Eq. (44). Compute the feed price index P_i^{feed}, the price index of agricultural goods P_i^a, the food price index and the upper-tier index, Eq. (24), and the price of the intermediate bundle m_{fi}^k of each crop.

4. Compute the returns $h_{fi}^{k\tau}$ of every product and technology in every field, Eq. (28), and the aggregate returns H_{fi}^k and H_{fi}^a, Eq. (33).

5. Allocate land. Within each field, compute the technology shares, Eq. (30), and the product shares. Each field has a crop-usable part, on which crops and livestock compete, and a grazing-only part (Appendix B.1); compute the agricultural share of each part from the conversion margin, Eq. (12), with the part's own shifter a_{fi}^0. A part with no farmland at the baseline stays unconverted. In the counterfactuals, the convertible-land ceiling caps the field total: a common cap on the two parts is found by bisection, 60 halvings, so that their farmland sums to the ceiling.

6. Compute output in each field and each country, Eq. (36), and the conversion bill, Eq. (38).

7. Compute the labor-supply shares n_i^s and the efficiency units $\tilde{N}_i^s$ supplied to each sector, and labor income $w_i^s \tilde{N}_i^s$.

8. Compute the value of output, $Y_i^k = p_i^k Q_i^k$ and $Y_i^v = p_i^v V_i$; land rents R_i, net of the conversion bill valued at the price of the outside good; and expenditure E_i, Eq. (51).

9. Compute world demand for every good: final demand for farm goods from Eqs. (21) and (22), at the farm share μ_i of the food dollar; feed demand of intensive livestock, Eq. (39); demand for fertilizer, pesticides and machinery by the modern crop technology; and demand for the outside good, which includes the conversion bill and the non-farm share of food spending. Compute labor demand in each sector, ND_i^0 and ND_i^1, from the labor shares of production.

10. *Update prices.* With X world demand for a country's output and Y its supply,

$$\tilde{p}_i^k = p_i^k \left(\frac{X_i^k}{Y_i^k} \right)^{\rho_p}, \qquad \tilde{p}_i^v = p_i^v \, \frac{X_i^v}{Y_i^v}, \qquad p \leftarrow 0.2\,\tilde{p} + 0.8\,p,$$

with $\rho_p = 0.2$. While the largest excess demand exceeds one, ρ_p is lowered for each product so that no price moves by more than a factor of 100 in one step. The price loop returns

to Step 2 until the largest excess demand is below 10^{-3}, measured relative to the product's mean output across countries for crops, to the country's own output for livestock, and to mean output across producers for fertilizer, or until 50 iterations.

11. *Update wages.* At the prices of Step 10, compute excess labor demand $\epsilon_i^s = ND_i^s - w_i^s \tilde{N}_i^s$. Where the slope of ϵ_i^s in w_i^s across the last two wage steps is negative, take the secant step $\tilde{w}_i^s = w_i^s - \epsilon_i^s \, \Delta w_i^s / \Delta \epsilon_i^s$; elsewhere take the fixed-point step $\tilde{w}_i^s = ND_i^s / \tilde{N}_i^s$. Cap each move at 50% and set $w_i^s \leftarrow 0.5\,\tilde{w}_i^s + 0.5\,w_i^s$. Return to Step 1.

The algorithm stops when the largest excess demand in goods markets and the largest excess labor demand, relative to labor demand and excluding the numeraire's market, are both below 10^{-3}. It reports a failure if it reaches 100 wage steps without converging; none of the solutions reported in the paper does.

Wages and prices are updated in nested loops rather than together, because updating them together makes them oscillate in this model. Wages move only at prices that clear goods markets, so the secant measures the slope of excess labor demand at cleared prices.

Re-solving the baseline from its calibrated prices takes one wage step, 13 or 14 price iterations and under 20 seconds. A counterfactual takes 18 to 27 wage steps.

E.2 The biodiversity–productivity feedback

With the feedback, an equilibrium is also a fixed point in the field modifiers f_{fi}^{bio} of Eq. (18), which enter Step 4 above through the productivities $a_{fi}^{k\tau}$.

1. Solve the counterfactual without feedback, $f_{fi}^{bio} = 1$.

2. Given the current modifiers, solve for the equilibrium with the algorithm of Appendix E.1, starting from the previous iteration's wages and prices.

3. Compute land use in each field and ecoregion, the biodiversity indices, Eqs. (16) and (17), and the implied modifiers $\hat{f}_{fi}$, Eqs. (19) and (20).

4. Set $f_{fi}^{bio} \leftarrow 0.5\,\hat{f}_{fi} + 0.5\,f_{fi}^{bio}$ and return to Step 2 until $\max_f |\hat{f}_{fi}/f_{fi}^{bio} - 1| < 10^{-3}$.

The loop reports a failure after 40 iterations. The headline feedback, on the abundance index of Eq. (19), converges in 5 to 8 iterations, and the richness-only feedback of the robustness check in 3 to 6.

E.3 Calibration

Estimation has two tiers. The calibration is the inner problem: it takes the dispersion parameters $\Theta = \{\theta_1, \theta_2, \theta_3\}$ and the parameters set outside the model (Table 4) as given, and sets the calibrated parameters

$$\Gamma = \left\{\delta^k_{0,i},\ \delta^k_1,\ \delta^\ell_{0,i},\ \delta^\ell_{1,i},\ s_i,\ a^0_{fi},\ b^0_i,\ b^F_i\right\}$$

so that the general equilibrium matches the targets below, where s_i is the share of country i's income spent on farm goods. The outer problem, the estimation of θ_1 (Appendix D), re-runs the calibration at each candidate value.

Targets. Each block of Γ has its own target:

- $\delta^k_{0,i}$, one productivity level per producer and crop: the producer's observed output, 1,524 pairs;
- δ^k_1, one modern-technology factor per crop (34): the modern share of the crop's land at its anchor country, from farm micro data (Section 4);
- $\delta^\ell_{0,i}$ and $\delta^\ell_{1,i}$, one livestock productivity level and one technology factor per country (66 each): livestock output and the intensive share of FAO-GLEAM;
- s_i: each country's farm-gate absorption, in all 66 countries;
- a^0_{fi}, one conversion-cost shifter per part of each field: the observed agricultural share of the part (HYDE 3.5, 2017);
- b^0_i and b^F_i: the food share of household spending (International Comparison Program).

Productivities follow from GAEZ potential yields as $\tilde{a}^{k0}_{fi} = \delta^k_{0,i}\, y^{k0}_{fi}$ and $\tilde{a}^{k1}_{fi} = \delta^k_{0,i}\, \delta^k_1\, y^{k1}_{fi}$, and likewise for livestock with country-specific factors.

Algorithm. Given Θ:

1. Guess Γ, wages and prices; the guess is the previous calibration when one exists.
2. Set the productivities $\tilde{a}^{k\tau}_{fi}$ from the current δ's.
3. Solve for the general equilibrium with the algorithm of Appendix E.1, with two differences. First, the conversion margin is inverted rather than solved: at the current returns, each

part's shifter is set so that Eq. (12) returns the observed agricultural share $\alpha_{fi}^{a,\text{data}}$,

$$a_{fi}^{0} = \frac{H_{fi}^{a}}{P_{fi}^{0}} \left(\frac{1 - \alpha_{fi}^{a,\text{data}}}{\alpha_{fi}^{a,\text{data}}} \right)^{1/\theta_1},$$

so field land shares are matched at every iteration. Second, each country spends the share s_i of its income on farm goods. The number of wage steps per iteration rises with progress: 5 in the first five iterations, 10 while the largest error of the calibration exceeds one, and 25 afterwards.

4. Update each block once, with damping weight λ and step exponent 0.5; each ratio is clipped at a factor of 1,000 for productivity levels and 100 for technology factors:

   (a) productivity levels, for each producer the model reaches, $\delta_{0,i}^{k} \leftarrow \lambda\, \delta_{0,i}^{k} \big(Q_i^{k,\text{data}}/Q_i^{k}\big)^{0.5} + (1-\lambda)\, \delta_{0,i}^{k}$. Prices absorb most of a move common to all producers of a crop, so every producer of crop k is then scaled by the square of the crop's world output ratio, clipped to $[0.5, 2]$;

   (b) modern-technology factors, by the ratio of target to model odds of the modern share, $\delta_1^{k} \leftarrow \lambda\, \delta_1^{k} \big[(o^{k,\text{data}}/o^{k})^{1/\theta_3}\big]^{0.5} + (1-\lambda)\, \delta_1^{k}$, where $o = \alpha^{k1}/(1-\alpha^{k1})$ at the anchor country. These steps wait until 95% of producers are within 25% of their output target, because the technology choice responds strongly to crop prices, which move until outputs settle;

   (c) livestock, by the same rules country by country: the level on the output ratio, the technology factor on the odds of the intensive share, with smaller steps once within 5% of target;

   (d) farm spending shares, by $s_i \leftarrow s_i\, (s_i^{\text{target}}/s_i)^{0.5}$, each step capped at 10%, where s_i^{target} is the share at which absorption matches the data.

   The weight λ is 0.5 in a first pass that holds wages fixed, which produces a guess consistent with θ_1 in at most 150 iterations, and 0.7 in the second pass, which clears labor markets at every iteration.

5. Return to Step 2 until every market error and every target error is below 10^{-3}.

6. Recover the upper-tier shifters: with $b_i^{0} = 1$, iterate $b_i^{F} \leftarrow 0.5\, b_i^{F} (\beta_i^{\text{data}}/\beta_i)^{0.5} + 0.5\, b_i^{F}$ on the food share β_i of Eq. (21) to a tolerance of 10^{-12}, where β_i^{data} is the food share of household spending β_i^{ICP}, or s_i where farm spending exceeds it. The farm share of the food dollar is $\mu_i = \min(s_i/\beta_i^{ICP}, 1)$.

On a first calibration, world spending on farm goods starts at the level of food spending in the International Comparison Program and is lowered to the farm-gate level, 4.2% of world value added, in equal logarithmic steps, each country moving along its own path; each step is taken once the other blocks have settled at the current level, or after 15 iterations. The final calibration, started from the previous one, converges in 43 iterations after 60 iterations of the first pass, in about an hour.

Fit. At the calibrated baseline, the 1,484 producer–product outputs the model produces match the data with a median gap of 0.004% and a maximum of 0.11%; livestock output, the intensive and modern shares, and farm-gate absorption are within 0.08%; and field land shares are within 10^{-4}. Forty producer–product pairs, 0.8% of world crop output by value, are produced in the data but not in the model and are left out of the targets: most are crops for which rain-fed GAEZ yields give the producing country no potential, such as irrigated rice in Egypt, or that are grown outside the grid, such as bananas in France's overseas departments. Demand for them falls on other origins. Each is below 0.2% of world output of its crop except flax in Ethiopia (3.1%), buckwheat in Tanzania, other pulses in Poland, rice in Egypt and olives in Peru (0.5 to 0.8%).

E.4 Counterfactuals

Each counterfactual changes trade costs and holds every other primitive at its calibrated value. A change $\hat{d}^g_{ni}$ scales the bilateral demand shifter $b^g_{ni}(d^g_{ni})^{1-\sigma_g}$ by $(\hat{d}^g_{ni})^{1-\sigma_g}$.

- *De-liberalization* (Table 6) resets trade costs to 1980: output trade costs move by their estimated change, and input trade costs by the change in manufacturing trade costs. The changes are winsorized at their 5th and 95th percentiles across country pairs, separately for outputs and inputs. The input and output experiments apply one set of changes each.
- *Autarky* multiplies every international trade cost of agricultural outputs and inputs by 10^3.
- *Feed autarky* sources every country's feed from its own production, at domestic crop prices; all other trade is unchanged.
- *The livestock-trade shutdown* multiplies the international trade costs of the livestock good alone by 10^3.

The convertible-land ceiling binds only in the counterfactuals (Step 5 of Appendix E.1). Every counterfactual starts from the baseline wages and prices, and each feedback run from the solution of the same counterfactual without feedback. A trade-cost experiment, solved without feedback and then with each feedback, takes 20 to 30 minutes; autarky takes about an hour.

E.5 Equilibrium selection

No uniqueness result covers this model. Demand across agricultural products and between food and other goods is complementary ($\kappa, \eta < 1$); crops, feed and livestock form a loop in which scarce pasture raises feed demand and so cropland; and the convertible-land ceiling makes land supply vertical where it binds. The biodiversity feedback adds a further loop, from land use to ecosystem services to productivity and back to land use. I therefore select equilibria by continuation from the data: every counterfactual is solved starting from the observed baseline equilibrium, so the solver returns the equilibrium reached by continuation from it, and the feedback starts from the counterfactual without feedback. I check this choice by restarting each loop far from its solution.

The general equilibrium without feedback. I re-solve the de-liberalization without feedback from six starting points, each drawing every country's two wages independently from a lognormal distribution around the baseline with a standard deviation of 10%; a uniform rescaling would be absorbed by the numeraire. Every start returns to the benchmark solution: the largest relative gap in any of the 2,089 positive prices and wages is 4.3×10^{-3}, below ten times the solver's tolerance.

The feedback loop. Iterating $f \leftarrow 0.5\,\hat{f}(f) + 0.5\,f$ converges only if the gain of the loop, the response of $\hat{f}$ to f through the equilibrium, is below one. Its size follows from the iteration itself: the ratio of successive errors is $0.5\,(1+g)$, where g is the gain. In the de-liberalization experiment the measured gain is 0.02 for the headline feedback and below 0.01 for the richness-only feedback: a change in productivity returns, one iteration later, as a change about 50 times smaller. To check for a second fixed point, I restart the loop with every modifier at 0.9, a 10% loss of productivity on all farmland, far outside the range of the solution ([0.966, 1.025]). The loop returns to the same fixed point: the modifiers differ from the benchmark by at most 7×10^{-4}, within the solver's tolerance, field land shares by at most 8×10^{-4}, and world real income by at most 0.002 percentage points.

F Model fit and validation: additional results

This appendix complements the assessment of model fit in Section 4.6: it explains the margins the model fits less well, reports the fit of pasture area, input intensity and committed extinctions in more detail, and traces the model's response to a rise in Chinese livestock demand (Appendix F.1).

Untargeted margins. Four untargeted margins fit less well than those of Table 5, for reasons the model's structure makes explicit.

First, the model places 2.6% of world employment in agriculture, against 27% in the data. With average earnings equalized across sectors, a sector's employment share equals its share of labor income, so matching farm income at farm-gate prices, which is what determines land rents, cannot also match the farm workforce; the difference is the agricultural productivity gap of Gollin, Lagakos, and Waugh (2014). Valuing farm demand at retail prices would raise the share only by overstating farm revenue about fivefold. Land decisions depend on the farm wage rather than on the number of farm workers, so the gap leaves the baseline allocation of land unchanged and affects how much labor moves between sectors in the counterfactuals.

Second, under the Fréchet allocation a crop's land follows its revenue, so staples, which earn little per hectare, receive too little land (rice and wheat in India at about a quarter of their FAOSTAT area) and vegetables and tree crops too much. Habitat affinities and abundance weights differ between annual crops, permanent crops and pasture, and by intensity, but not across annual crops, so this misallocation moves the biodiversity measures only through the intensity mix and the area of tree crops.

Third, India's farmland is matched, but the model places 110 million hectares of it in grazing against 10 million of FAOSTAT permanent pasture (Figure F.1). Livestock occupies its own land in the model, whereas India's 301 million cattle and buffalo, the world's largest bovine herd, are raised almost entirely in mixed crop–livestock systems (97% of their feed intake in FAO-GLEAM v3), which draw 40% of their feed from crops, crop residues and by-products, against 27% worldwide; the grass and leaves that make up the rest, 470 million tonnes of dry matter, would require 45 tonnes per hectare of FAOSTAT pasture, so most of it comes from land that FAOSTAT does not classify as pasture. India accounts for under 2% of the headline. Worldwide the model places 1,184 million hectares in crops against 1,568 in FAOSTAT, and 3,498 in pasture against 3,115, while matching total farmland; pasture definitions themselves differ widely, FAOSTAT and other rangeland-inclusive sources running about four times larger than HYDE's managed-pasture measure.

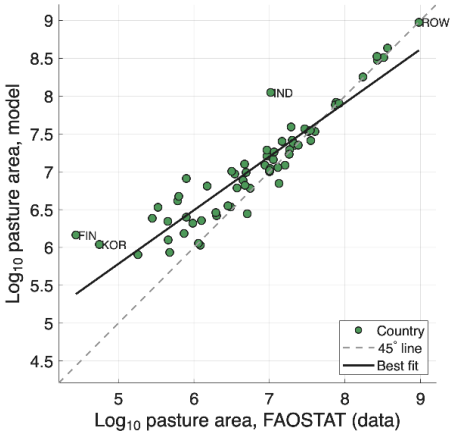
Fourth, the rest-of-world aggregate, which accounts for 40% of the headline, matches its net agricultural imports in the data, but its imports of livestock products are about twice those observed, so when trade costs rise it must find more grazing land than it otherwise would: under de-liberalization its grazing land expands by 120 million hectares, against 7 million for cropland. If the excess imports doubled that response, correcting them would lower the headline by about five species, to 21. Irrigation is not a separate technology: heavily irrigated agricultures such as Egypt's are fitted through their productivity shifters, because their rain-fed potential understates their yields.

Table F.1: Committed bird extinctions by biogeographic realm: model vs. external benchmark

Realm	Model (% of world total)	Chaudhary and Brooks (2018) (% of world total)	IUCN, threatened by agriculture (%)	Ecoregions
Neotropic	36.4	31.4	35.9	165
IndoMalay	19.9	23.6	22.0	104
Afrotropic	25.1	27.2	19.6	107
Palearctic	7.0	7.4	4.9	177
Australasia	7.4	5.3	7.2	68
Nearctic	4.0	4.6	2.3	87
Oceania	0.2	0.4	8.2	4

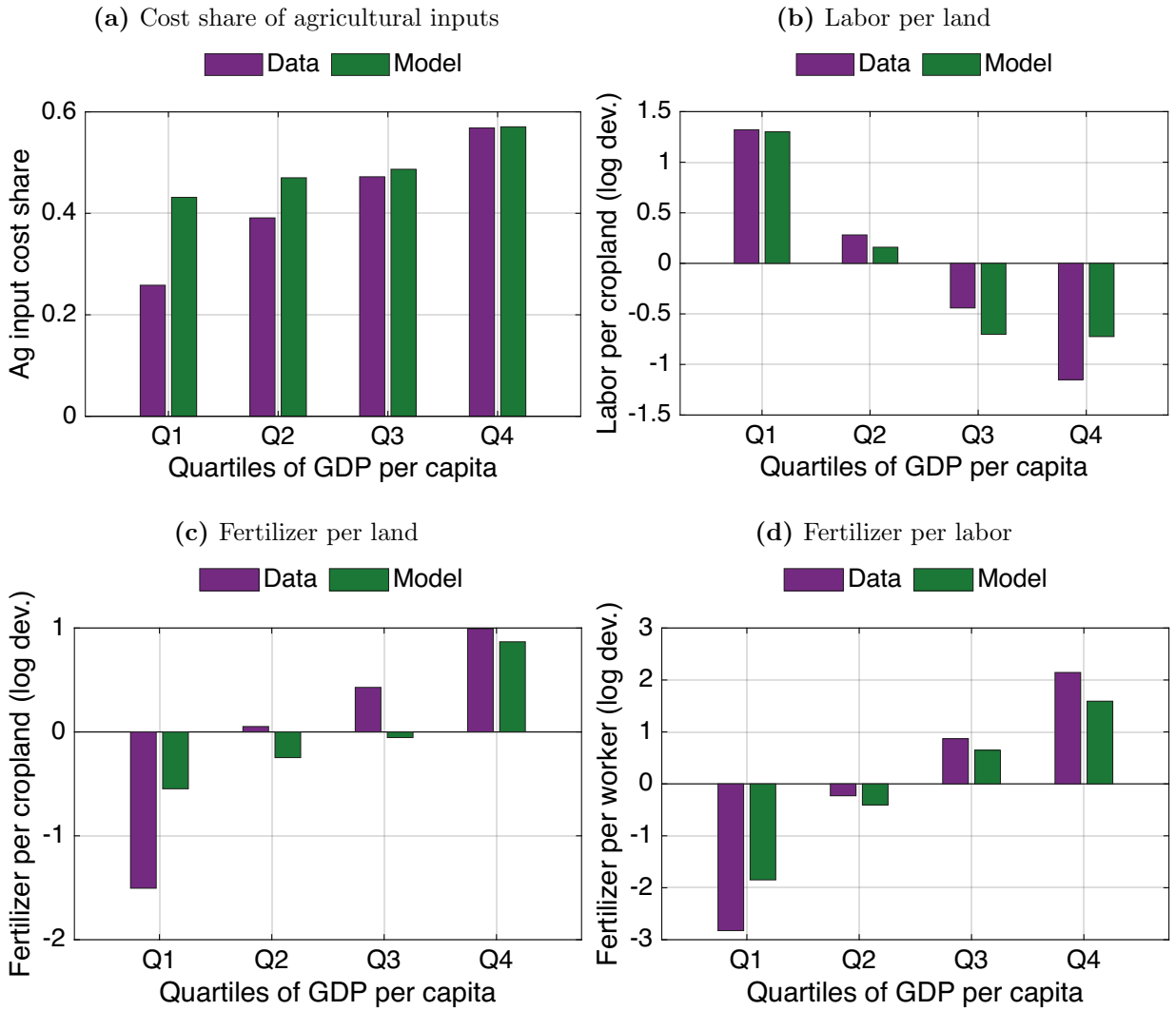
Notes: Each column reports a realm's share of world committed bird extinctions. The model column is the vulnerability-weighted countryside species–area loss at the calibrated 2017 land use; the benchmark column applies the cropland characterization factors of Chaudhary and Brooks (2018) to the same baseline cropland, and the rank correlation across the 712 ecoregions with cropland is 0.82. The model's total includes pasture and permanent crops, which the cropland-only benchmark omits; the largest gaps are in the Neotropic (+5.0 points) and the IndoMalay realm (−3.7), followed by the Afrotropic (−2.1) and Australasia (+2.1); the model is higher where pasture is extensive. The third column is each realm's share of the world's IUCN-listed birds threatened by crops or livestock (Red List classes 2.1 and 2.3, ongoing or future; marine species excluded), splitting multi-realm species evenly. It is descriptive rather than a test: the model column is vulnerability-weighted, and the vulnerability scores carry Red List threat levels. Figure F.5 gives the test. Oceania is an outlier by construction, its island endemics being threatened mainly by invasive predators rather than land conversion.

Figure F.1: Pasture area, model vs. data



Notes: Each point is a country: grazing-land area in the model against FAOSTAT permanent pasture, in base-10 logarithms. Only livestock output is targeted, so the allocation of grazing land across countries is untargeted. Dashed line: 45°; solid line: least-squares fit. Correlation 0.99 in levels and 0.92 in logs, rank correlation 0.93, model-to-data ratio 1.12. Labels mark the rest-of-world aggregate and the three largest log residuals; India's is also the largest gap in hectares (110 against 10 million): its herd is raised in mixed crop–livestock systems and draws most of its grass from land FAOSTAT does not classify as pasture.

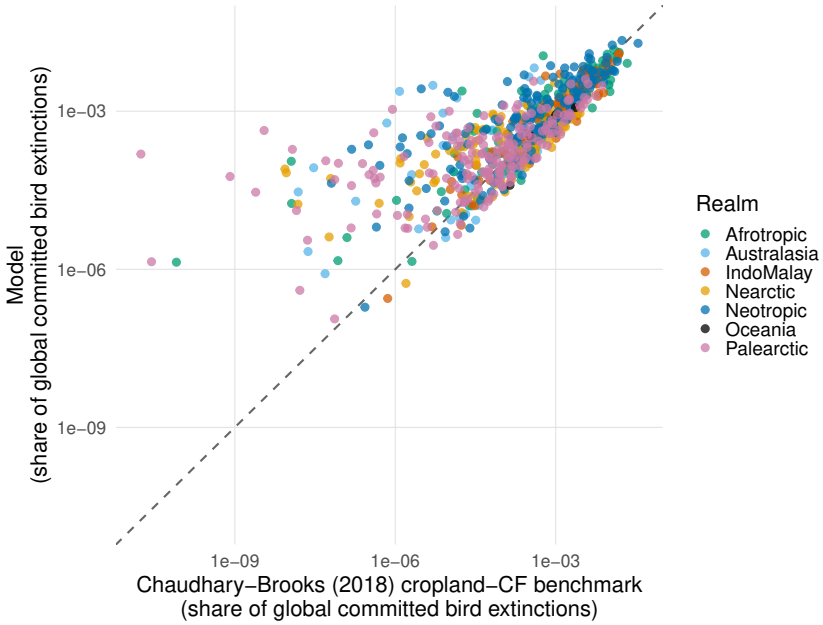
Figure F.2: Model fit on measures of input intensity



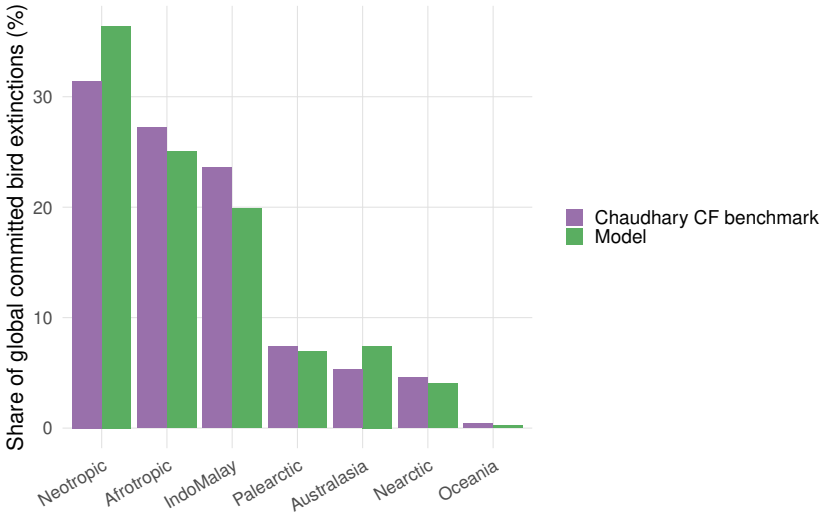
Notes: Observed (purple) and model (green) input intensity by quartile of GDP per capita at the 2017 baseline. Panel (a) is in levels; panels (b) to (d) are log deviations from the world average. None of the four moments is targeted. Across the 66 countries, model and data correlate at 0.42 (cost share), 0.79 (labor per hectare), 0.65 (fertilizer per hectare) and 0.72 (fertilizer per worker).

Figure F.3: Committed extinctions: model vs. the Chaudhary and Brooks (2018) benchmark

(a) Each ecoregion's share of world committed extinctions



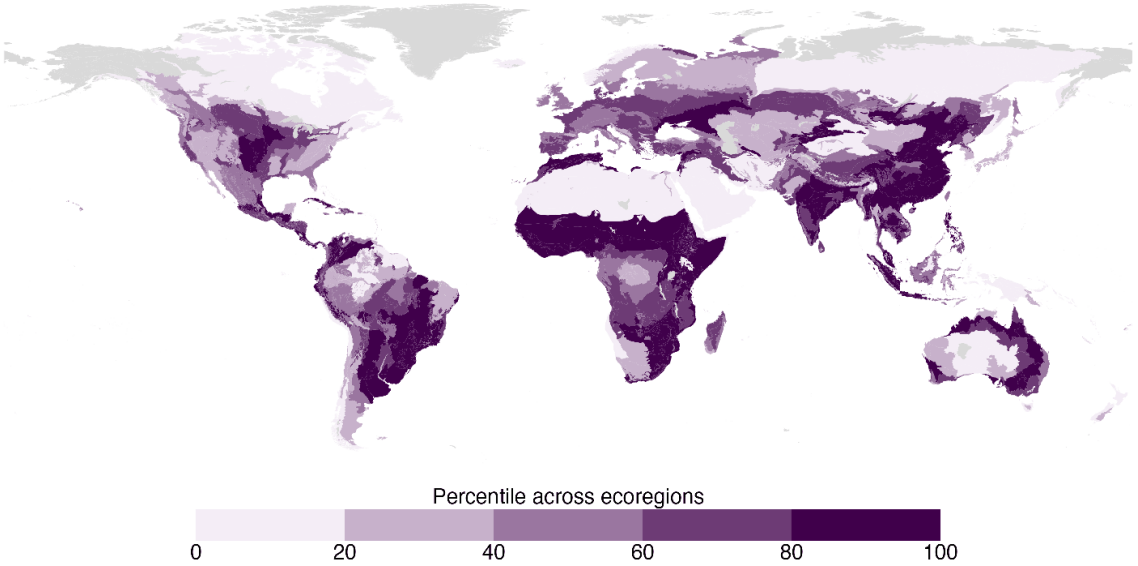
(b) Shares by biogeographic realm



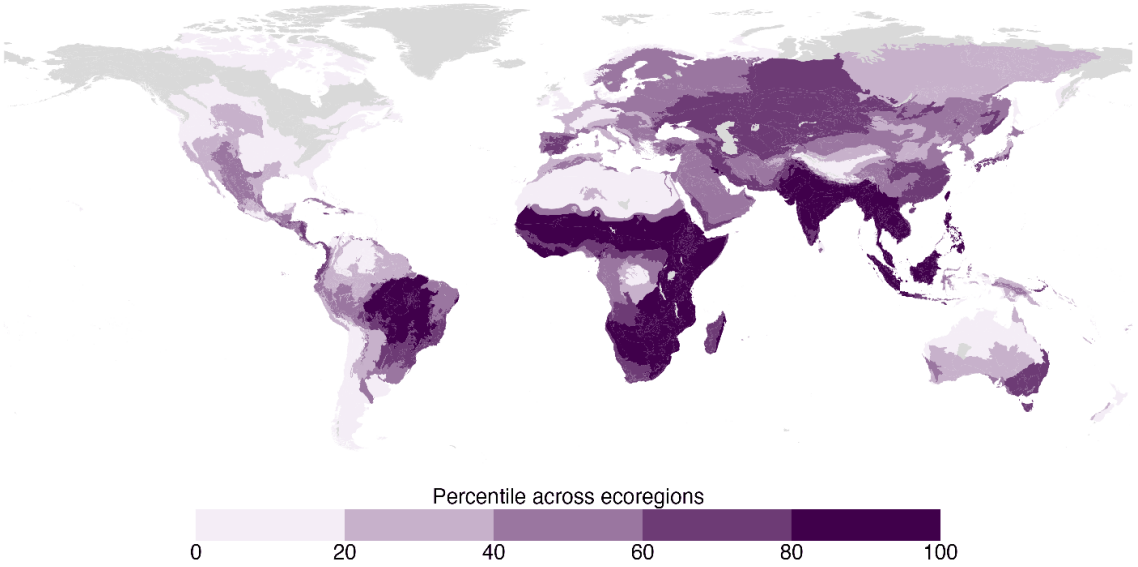
Notes: The model's vulnerability-weighted committed bird extinctions by ecoregion against those implied by the cropland characterization factors of Chaudhary and Brooks (2018) applied to the same baseline cropland, as shares of the world total. The 45-degree line marks equal shares. Rank correlation 0.82 and log–log correlation 0.74 across the 712 ecoregions with cropland. See Table F.1.

Figure F.4: Committed bird losses and observed endangerment by ecoregion

(a) Model: bird species committed to local extinction

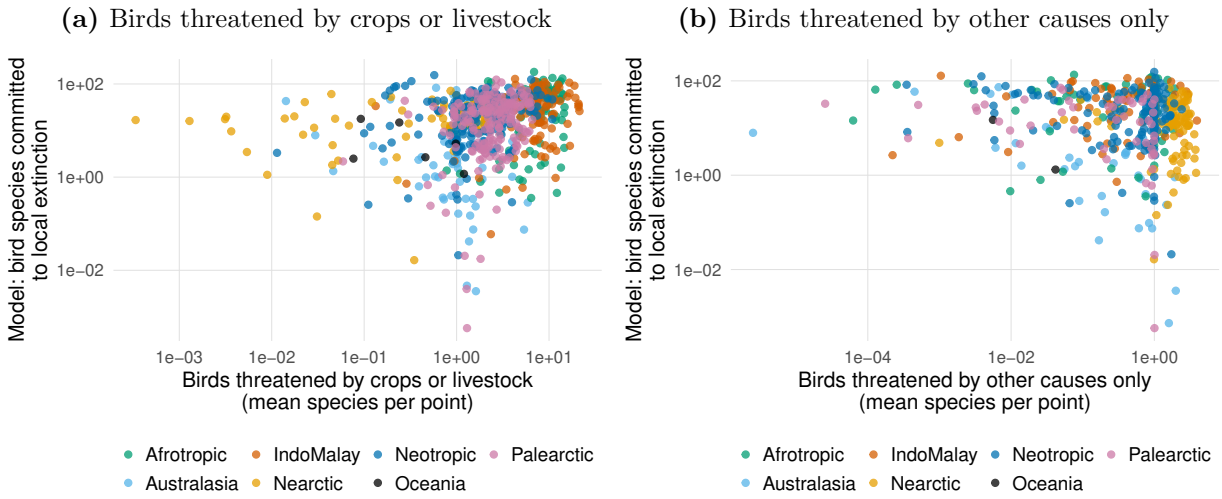


(b) IUCN: birds threatened by crops or livestock



Notes: The comparison with observed endangerment discussed in Section 4.6. Each ecoregion is shaded by its percentile across ecoregions, in quintiles: (a) the number of the ecoregion's bird species that the model commits to local extinction at the 2017 land use, unweighted; (b) the mean number of IUCN-threatened birds whose Red List threats include crops or livestock (classes 2.1 and 2.3, ongoing or future), from the BirdLife range maps (BirdLife International and Handbook of the Birds of the World, 2025), marine species excluded. Darker purple is higher. Light grey: ecoregions without both measures. Figure F.5 plots the two against each other.

Figure F.5: Committed bird losses vs. observed endangerment, by cause of threat



Notes: Each point is an ecoregion. Vertical axis: the number of its bird species the model commits to local extinction, unweighted, since the vulnerability scores carry the Red List threat level. Horizontal axis: the mean number of IUCN-threatened birds present, from the BirdLife range maps (BirdLife International and Handbook of the Birds of the World, 2025), marine species excluded; (a) those whose Red List threats include crops or livestock (classes 2.1 and 2.3, ongoing or future), (b) those with no agricultural threat of any kind. Rank correlations: 0.35 in (a) ($n = 712$; 0.10 controlling for total bird richness) and -0.12 in (b) ($n = 441$; -0.03). Both axes on log scales.

F.1 Response to a rise in Chinese livestock demand

Every moment in Table 5 compares a *level* in the model to the same level in the data. None shows how the model *responds* to a shock, which is what the counterfactuals ask of it. This subsection traces one such response, using a well-documented episode: the surge in Chinese demand for animal protein that followed WTO accession. It checks internal consistency. No moment of the episode enters the calibration, so nothing here is fitted, and the response is not compared against an independent causal estimate of the same object. The exercise establishes that the model transmits demand to land coherently, in the direction and with the composition its mechanism implies, not that it does so at a rate the data confirm.

Design. The experiment raises China's middle-tier preference for the livestock good, d^{ℓ}_{CHN}, by a factor s, renormalizing the demand row so that only the *composition* of Chinese agricultural demand changes and not its level. Nothing else moves: trade costs, productivities and preferences everywhere else are held at their calibrated values, and demand for feed crops is never shocked directly. Any expansion of soybean or maize demand in the counterfactual therefore arises endogenously, through Chinese livestock production drawing on the feed nest, exactly as the mechanism in Section 3 describes. The parameters were fixed before the experiment was run.

Table F.2: Response to a rise in Chinese livestock demand

	Δ ln cropland			Δ ln forest			China	
Shock s	Brazil	Argentina	Indonesia	Brazil	Argentina	Indonesia	Δ ln crop	imports
0.5	+0.112	−0.001	+0.037	−0.039	−0.066	−0.014	+0.016	×2.75
1.0	+0.233	−0.026	+0.075	−0.106	−0.147	−0.029	−0.013	×5.97
2.0	+0.401	+0.026	+0.131	−0.191	−0.205	−0.054	−0.078	×14.3
4.0	+0.518	+0.051	+0.186	−0.224	−0.221	−0.085	−0.162	×29.2
Observed, 1990–2020								
	+0.117	+0.530	+0.305	−0.208	−0.165	−0.197	–	×10–25

Notes: Each row raises China's middle-tier livestock preference by the factor s, holding all else at calibrated values and renormalizing the demand row so only composition changes. Feed demand is not shocked; it responds through livestock production. The final row reports observed changes over 1990–2020 (FAOSTAT land use; Chinese agricultural imports), shown for direction and relative magnitude, not as a target: the observed changes reflect three decades of many shocks, of which Chinese demand is one.

Exporter land use. Table F.2 reports the response at four shock sizes. In every one, Brazil and Indonesia expand cropland and lose forest, and the effect grows monotonically with the shock: Brazil's cropland rises by 0.11 to 0.52 log points and its forest falls by 0.04 to 0.22. Argentina loses forest at every shock size while its cropland barely moves. China's own cropland contracts at every shock above the smallest. That configuration is the signature of the mechanism rather than of a general expansion: Chinese meat demand is met by importing feed rather than by growing it, which releases Chinese cropland and clears land at the frontiers that supply the feed. Nothing in the calibration asks for this.

Conversion versus reallocation. Cropland can grow two ways, and only one of them destroys habitat: a field converts natural land, or crops displace pasture within land the field already farms. The distinction matters here because the crop-feasibility split confines new cropland to crop-suitable parts of fields already farmed (Appendix G), which could in principle route the entire response through composition. It does not. Decomposing each country's cropland change into the part attributable to a rising converted share, holding the crop share of agriculture fixed, and the part attributable to a rising crop share, holding agriculture fixed, conversion of natural land accounts for 69 to 80% of Brazil's response across the four shock sizes; in Argentina, where cropland barely moves, conversion adds 2 to 5 million hectares that a falling crop share of farmed land offsets. This is the quantitative counterpart of the forest column in Table F.2, and it establishes that the exporter response is an extensive-margin phenomenon rather than a reallocation of crops across land already in use.

Transmission elasticity. The natural summary of the experiment is not any single row but the ratio between them. Dividing Brazilian cropland growth by the growth in Chinese agricultural imports gives 0.11, 0.13, 0.15 and 0.15 at the four shock sizes. This elasticity of frontier cropland to importer demand rises by a third while the shock grows eightfold, and levels off at the two largest shocks, although the convertible-land ceiling and the curvature of the conversion margin could have made it drift. The transmission rate is thus mostly a property of the calibrated structure rather than of the size of the experiment.

The experiment spans the size of the historical episode: Chinese agricultural imports grew roughly 10- to 25-fold over the period, within the range that shocks of 1 to 4 produce here ($\times$6.0 to $\times$29.2). The observed changes in the final row of Table F.2 are not a causal benchmark, however: Brazilian cropland grew over three decades for many reasons, so the ratio of raw changes attributes to Chinese demand what other forces also caused. What the experiment establishes on its own is therefore the internal coherence of the transmission mechanism and the sign pattern across exporters.

Limitations. The model's Chinese response does not test the mechanism. China's forest area *rose* over this period, and that recovery was driven substantially by afforestation and forest-protection policy, namely the Natural Forest Protection Program and the Grain-for-Green conversion program, neither of which has a counterpart in this model. A framework containing no afforestation subsidy and no logging ban cannot produce reforestation in response to a demand shock, so the discrepancy is a limit on the model's scope rather than evidence against its structure.

The *magnitude* of the predicted Chinese forest loss is overstated, and the experiment shows why. Decomposing China's land response, grazing land on the extensive technology contracts at every shock above the smallest ($\Delta \ln$ of $+0.04$ to -0.76 across the four shocks) while total livestock land rises by a third or more (0.29 to 0.39), and the share of the convertible ceiling in use rises from 75 to 94%. The margin clearing China's forest is therefore operation land for *intensive* livestock, not pasture. That land requirement is governed by $\gamma_L^{\ell 1} = 0.33$, a single value for all countries, kept because the livestock land shares reproduce the world's grazing-land extent rather than taken from cost accounts; applied to a livestock sector composed largely of confined pigs and poultry, it overstates how much land Chinese production needs. Separating confined pigs and poultry, which need almost no land of their own, from grazing livestock would remove the overstatement; it requires production, demand and trade data by species and a new calibration of the livestock block, which I leave to future work. A smaller land requirement in China would shift more of its response onto imported feed, so the overstatement works against the exporter response. The

validation claim here is accordingly the exporter pattern and its monotonicity, which the model reproduces without having been asked to, and not the magnitudes.

G Restrictions on the production possibility set

Two restrictions bound where the counterfactuals can put new agriculture. The convertible-land ceiling of Section 5 caps each field's agricultural share, and the crop-feasibility split of Appendix B.1 determines which land use can expand into it: each part of a field converts natural land only if it is farmed in the baseline data. Of the convertible land the ceiling opens, 42.6% lies where crops can expand, on crop-suitable parts already farmed; 39.3% can only be grazed; 8.5% lies in fields with no observed agriculture, which are closed to conversion entirely; and 9.6% exceeds the natural land of the parts that can convert. Habitat conversion, which is what the ecological module registers, is therefore possible on 81.9% of convertible land.

Two implications follow. First, the fields with no observed agriculture are more natural than average, with a mean convertible fraction of 0.35 against 0.27 elsewhere. To the extent that they are also species-rich, the restriction makes the counterfactuals understate potential loss rather than overstate it. Admitting them would require conversion costs for fields where no conversion has ever been observed, which the calibration cannot identify. Second, the restriction binds on composition as well as on conversion: pasture on the grazing-only part of a field cannot become cropland, and in a field that is grazed but not cropped, crops can enter only where its pasture extends onto crop-suitable land, as in 2,431 of the 26,655 such fields with convertible land. The model therefore reproduces the conversion of cerrado pasture to soybeans only where that pasture lies on land GAEZ rates suitable for crops. Because a field spans about 85 square kilometers at the equator, and less toward the poles, and expansion at a frontier overwhelmingly occurs at the edge of existing agriculture rather than in wholly uncultivated terrain, this displaces where new cropland appears at the margin without preventing it from appearing.

H Counterfactuals: robustness and additional results

This appendix collects the robustness checks and additional results of Section 5. Table H.1 varies the ecological mapping, the land-supply elasticity and the elasticity of food demand; Tables H.2 and H.3 report the biodiversity–productivity feedback, and Table H.4 which ecoregions lose species. Figures H.1 to H.10 map land use, bird species and the abundance of insect-eating birds under de-liberalization, its two trade-cost channels and autarky, and where the biodiversity–productivity feedback changes them.

Table H.1: Sensitivity to the ecological mapping, the land-supply elasticity and the elasticity of food demand

	Baseline	Trade costs reset to 1980			Shutting down trade in			Corr.
	(2017)	Output and input (1)	Only input (2)	Only output (3)	All agriculture (4)	Livestock feed (5)	Livestock products (6)	(7)
A. Ecological mapping (same allocations, rescored)								
Chaudhary–Drakare z (benchmark)	237.2	+26.4	+12.9	+14.5	+117.8	+33.0	+3.7	1.00
Storch z, exponent only	169.5	+19.3	+9.2	+10.8	+81.8	+21.3	+3.9	0.97
Storch z + Scherer cropland ratios	164.4	+18.5	+8.7	+10.6	+82.1	+22.3	+3.8	0.97
Storch z, affinities recomputed	167.7	+18.5	+8.8	+10.4	+79.0	+15.8	+4.0	0.97
Endemism weights, no threat level	650.6	+75.1	+37.2	+40.0	+321.2	+84.8	+10.3	0.93
B. Land-supply elasticity θ_1 (recalibrated, counterfactuals re-run)								
$\theta_1 = 3.73$ (band, lower)	237.2	+23.3	+11.5	+12.6	+108.1	–	–	1.00
$\theta_1 = 4.80$ (benchmark)	237.2	+26.4	+12.9	+14.5	+117.8	+33.0	+3.7	1.00
$\theta_1 = 6.21$ (band, upper)	237.2	+29.6	+14.3	+16.4	+125.4	–	–	1.00
C. Food demand elasticity η (recalibrated, counterfactuals re-run)								
$\eta = 0.5$ (benchmark)	237.2	+26.4	+12.9	+14.5	+117.8	+33.0	+3.7	1.00
$\eta = 1.2$	237.2	+20.4	+10.4	+11.0	–	–	–	0.99

Notes: Committed bird extinctions; positive entries are species lost. *Panel A* varies the ecological mapping while holding the equilibrium land allocation fixed, so the rows are an ex-post rescoring of the same counterfactuals. Row 2 substitutes the continent-specific exponents of Storch, Keil, and Jetz (2012) in the area–richness mapping alone; row 3 adds the flat global cropland ratios of Scherer et al. (2023), leaving permanent crops and pasture at the benchmark; row 4 recomputes all six habitat affinities at the Storch exponent as $\chi_T = \chi_T^{\text{base}} \, f_T^{RR\,1/z}$ for $T \in \{$annual crops, permanent crops, pasture$\}$, where f_T^{RR} are the intensity multipliers of Newbold et al. (2015). Row 5 keeps the benchmark mapping but weights each ecoregion's losses by endemism alone: the vulnerability score of Chaudhary and Brooks (2018) without its Red List threat level, that is, the mean share of each bird species' range that lies in the ecoregion, computed from the range maps of BirdLife International and Handbook of the Birds of the World (2025). *Panel B* varies the land-supply elasticity θ_1; each band end is a full recalibration with columns (1)–(4) re-run; columns (5)–(6) are not available there. *Panel C* raises the elasticity of substitution between food and other goods from $\eta = 0.5$ to 1.2, which roughly doubles the price elasticity of demand at the farm gate (Eq. (27)); the model is recalibrated and columns (1)–(3) re-run. Column (7) correlates, across ecoregions, each ecoregion's contribution to the column-(1) change with its contribution at the benchmark (Pearson), so it tests the geography of the effect rather than its total; the rows for θ_1 and η apply the benchmark mapping to the land allocations of their re-runs. Section 5.6 discusses what moves and what does not.

Table H.2: Farm revenue gained and lost through the biodiversity–productivity feedback

	Trade costs reset to 1980		Shutting down trade in					
	Output and input		All agriculture		Livestock feed		Livestock products	
	$bn/yr	% of ag. rev.	$bn/yr	% of ag. rev.	$bn/yr	% of ag. rev.	$bn/yr	% of ag. rev.
Net change	−5.52	−0.140	−27.01	−0.687	+15.45	+0.393	−1.24	−0.032
Lost revenue (gross)	−6.02	−0.153	−28.52	−0.726	−0.87	−0.022	−3.45	−0.088
Gross gains	+0.50	+0.013	+1.52	+0.039	+16.32	+0.415	+2.21	+0.056

Notes: Value of the biodiversity–productivity feedback, $\mathrm{d}R = (f^{bio} - 1)\,R$, through insectivorous-bird abundance at $\beta = 0.15$, under each counterfactual, aggregated to countries and anchored to global agricultural output (about $3.9 tn in 2017). "Net change" sums gains and losses across countries; "lost revenue" sums only the countries with revenue *losses* and "gross gains" only those with gains. The second column of each pair expresses the same figure as a share of world farm revenue and is independent of the dollar anchor. The first pair of columns, de-liberalization, resets both trade costs to their 1980 level; read in the direction of liberalization, it reverses in sign.

Table H.3: Counterfactuals with and without the biodiversity–productivity feedback

	Trade costs reset to 1980			Shutting down trade in		
	Output and input (1)	Only input (2)	Only output (3)	All agriculture (4)	Livestock feed (5)	Livestock products (6)
	A. Bird species committed to global extinction					
Without feedback	+26.57	+13.00	+14.56	+118.04	+33.39	+3.79
With feedback	+26.42	+12.91	+14.48	+117.84	+33.01	+3.74
Difference	−0.14	−0.08	−0.08	−0.20	−0.38	−0.05
	B. Insectivorous-bird abundance (change, pp)					
Without feedback	−0.48	−0.23	−0.30	−1.99	+1.91	−0.04
With feedback	−0.48	−0.23	−0.30	−1.99	+1.91	−0.03
Difference	−0.000	+0.001	−0.000	−0.004	+0.004	+0.001
	C. Real income (change, %)					
Without feedback	−1.09	−0.45	−0.59	−14.14	−0.81	−0.09
With feedback	−1.09	−0.45	−0.59	−14.18	−0.80	−0.09
Difference	−0.004	−0.002	−0.003	−0.034	+0.008	−0.002

Notes: Columns (1)–(3) are the trade-cost counterfactuals of Table 6; columns (4)–(6) the trade shutdowns of Table 7. "With feedback" runs the model with the biodiversity–productivity feedback active (insectivorous-bird abundance, $\beta = 0.15$), as in the main tables; "without feedback" holds farm productivity at its baseline level; "difference" is the former minus the latter. Species are birds committed to global extinction (a positive entry is species lost), abundance is the area-weighted mean across ecoregions in percentage points, and real income is the population-weighted generalized mean.

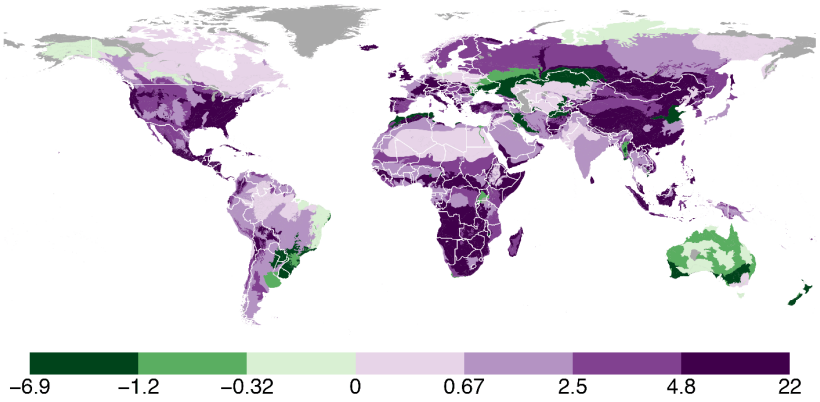
Table H.4: Which ecoregions lose species under liberalization?

	Loses species (0/1) (1)	Share lost (pp) (2)
Net agricultural exporter	+0.097	+0.396**
	(0.080)	(0.201)
Tropical realm	−0.130*	−0.194
	(0.075)	(0.201)
Baseline agricultural share	+0.039	−0.407***
	(0.029)	(0.101)
Convertible headroom	−0.103***	−0.514***
	(0.026)	(0.079)
Vulnerability score	+0.041	+0.099*
	(0.030)	(0.059)
Species pool	+0.000	−0.005
	(0.017)	(0.069)
Mean of outcome	0.183	−0.967
R^2	0.163	0.144
Ecoregions	694	694
Clusters (countries)	53	53

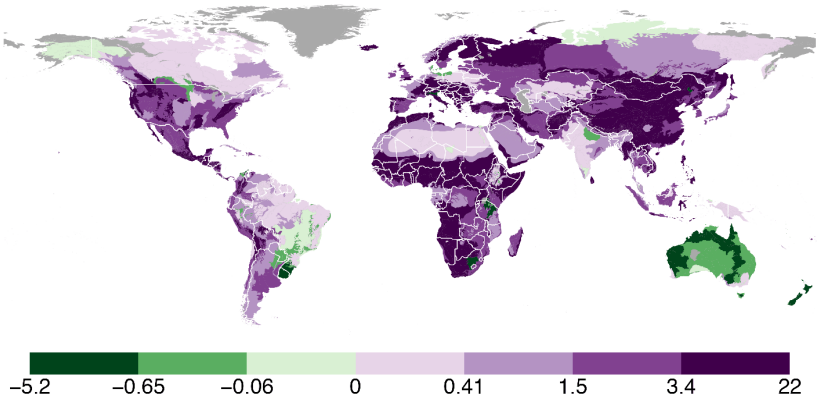
Notes: OLS across ecoregions, in the direction of the historical liberalization: the joint de-liberalization of Table 6, with the biodiversity–productivity feedback active, read with its sign reversed. Column (1): an indicator for an ecoregion that loses species; column (2): the share of its species pool lost, in percentage points (negative values are gains). Net agricultural exporter: the ecoregion's dominant country exported more agricultural output than it imported in 2017. Tropical realm: Neotropic, Afrotropic or Indo-Malaya. The remaining regressors are standardized: the ecoregion's baseline agricultural share, its convertible headroom (the mean convertible fraction of its land, Section 5), its vulnerability score and its species pool. The sample excludes ecoregions without a dominant model country or without model fields. Standard errors clustered by dominant country in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure H.1: Land use under de-liberalization

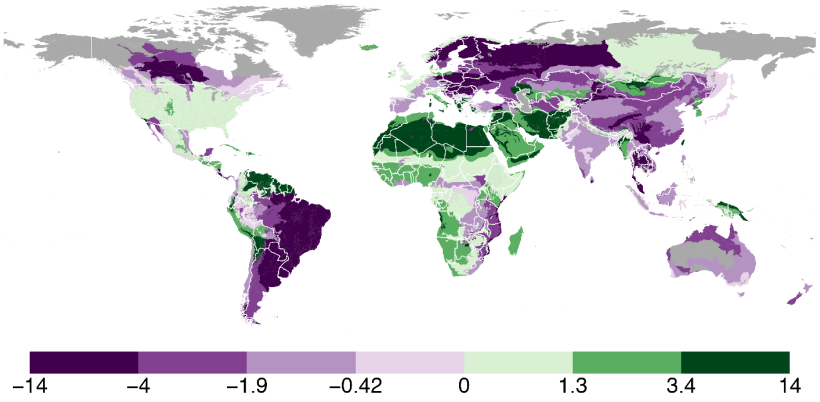
(a) Agricultural share



(b) Pasture share



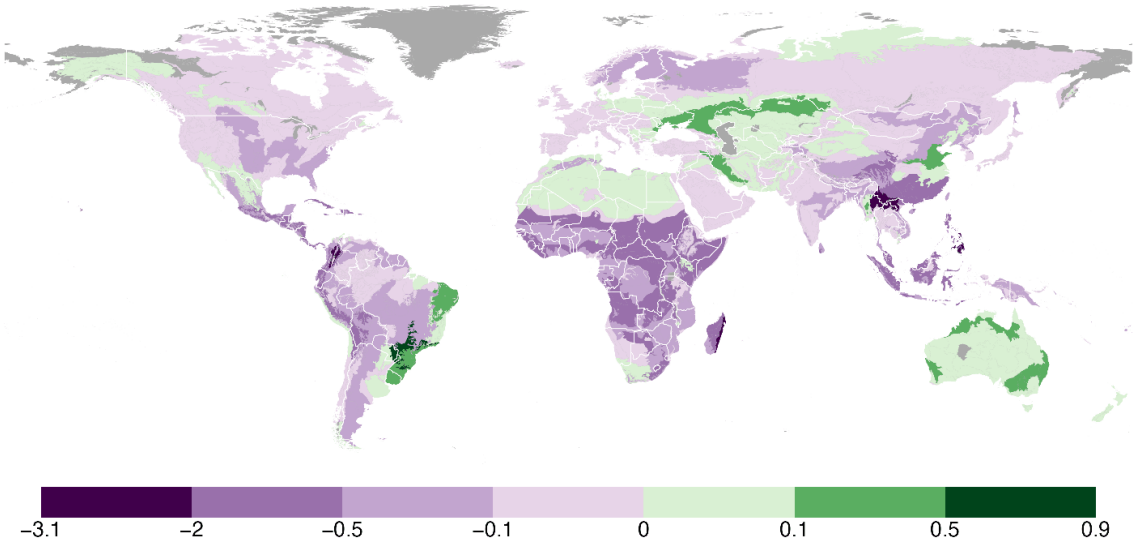
(c) Modern share of cropland



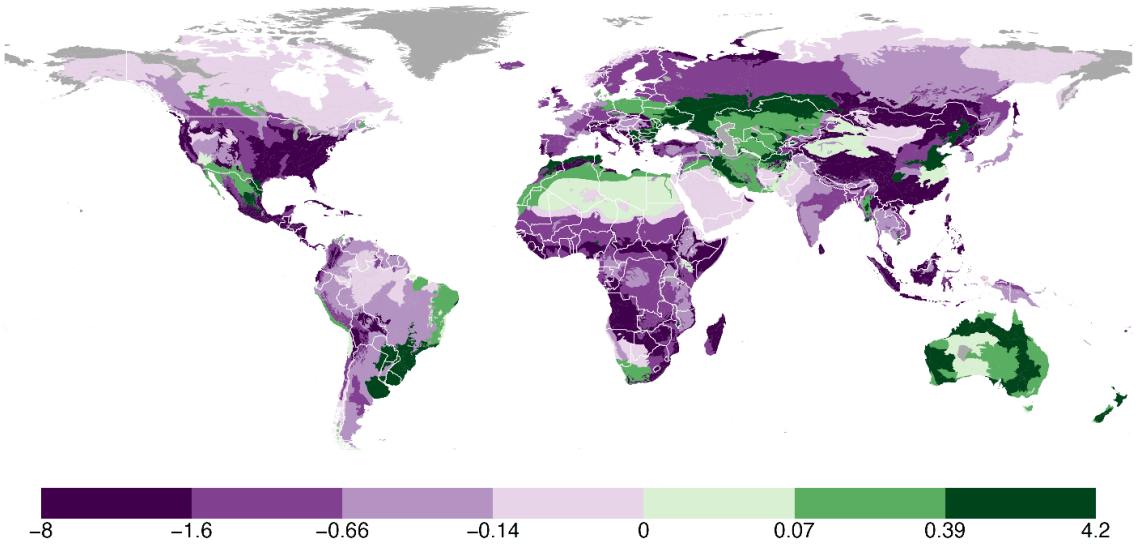
Notes: Change in each ecoregion's agricultural (crop and pasture) share (a), pasture share (b) and modern share of cropland (c), in percentage points, under de-liberalization (agricultural input and output trade costs reset to their 1980 levels), relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Panels (a) and (b), purple: expansion; green: contraction. Panel (c), purple: decrease; green: increase. Grey: ecoregions without data, and in panel (c) without cropland.

Figure H.2: Bird species under de-liberalization: alternative measures

(a) Share of the global extinction total (vulnerability-weighted)

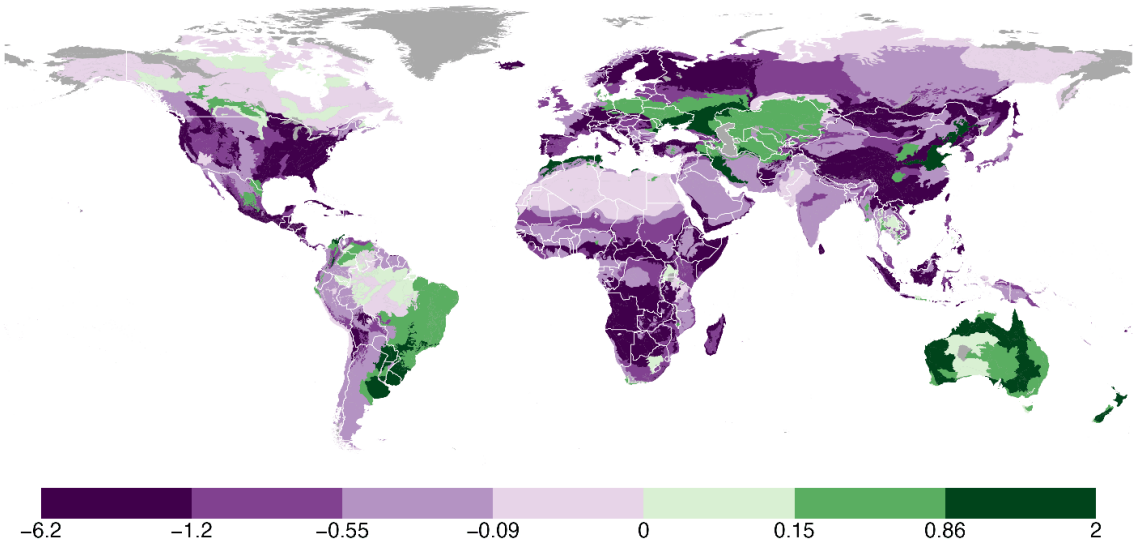


(b) Change in the species-remaining share (percentage points)



Notes: The counterfactual of Figure 5. Panel (a) weights each ecoregion's species change by global vulnerability and expresses it as a share of the total, in percent, 26.6 species committed to global extinction without the feedback (26.4 with it, Table 6); the Neotropics, the Afrotropics and Indo-Malaya account for 81% of it. Panel (b) is the change in each ecoregion's species-remaining share, in percentage points, a measure of local severity that does not depend on the size of the species pool. Solved without the biodiversity–productivity feedback. Purple: loss; green: gain.

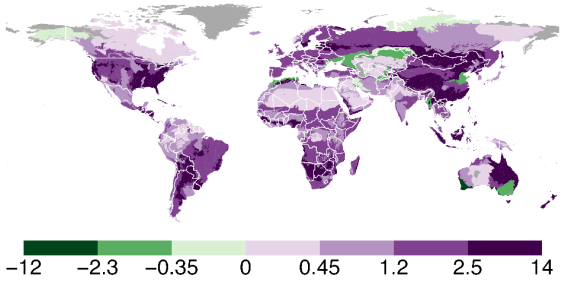
Figure H.3: Insectivorous-bird abundance under de-liberalization



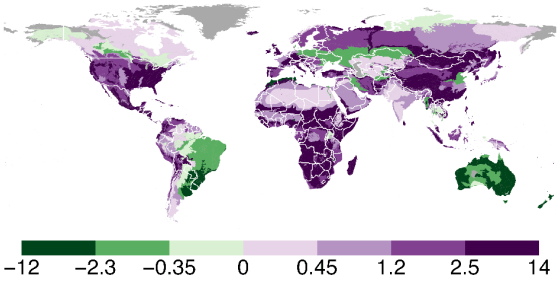
Notes: Change in each ecoregion's insectivorous-bird abundance, as a percentage of its level under natural vegetation (Eq. (17)), in percentage points, under de-liberalization (agricultural input and output trade costs reset to their 1980 levels), relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Purple: loss; green: gain.

Figure H.4: Land-use change by trade-cost channel

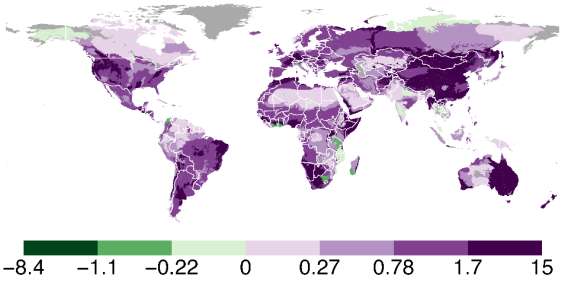
(a) Agricultural share, only input trade costs



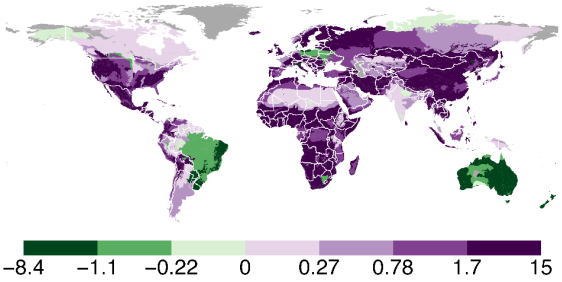
(b) Agricultural share, only output trade costs



(c) Pasture share, only input trade costs



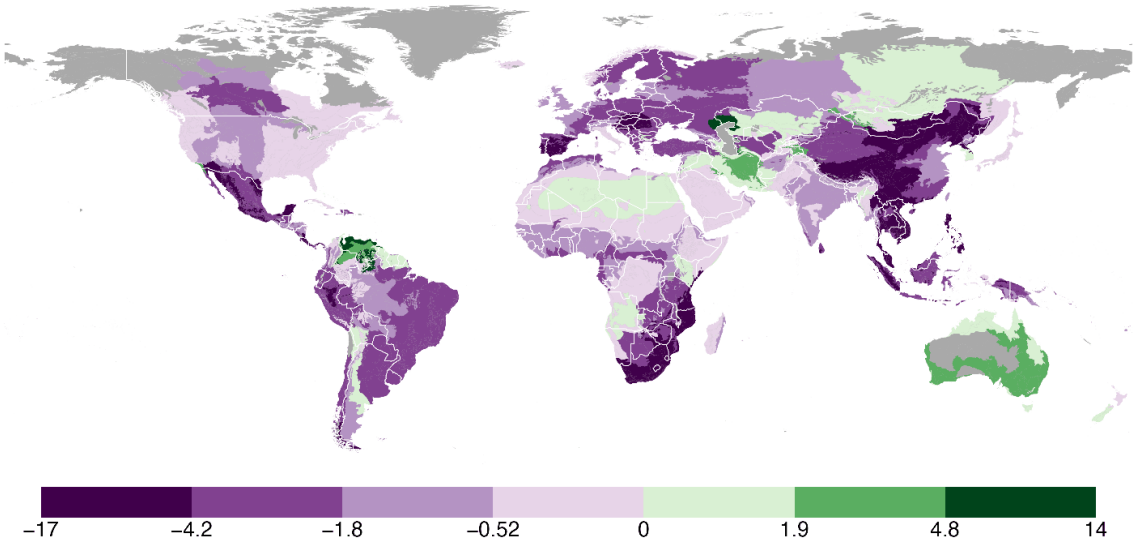
(d) Pasture share, only output trade costs



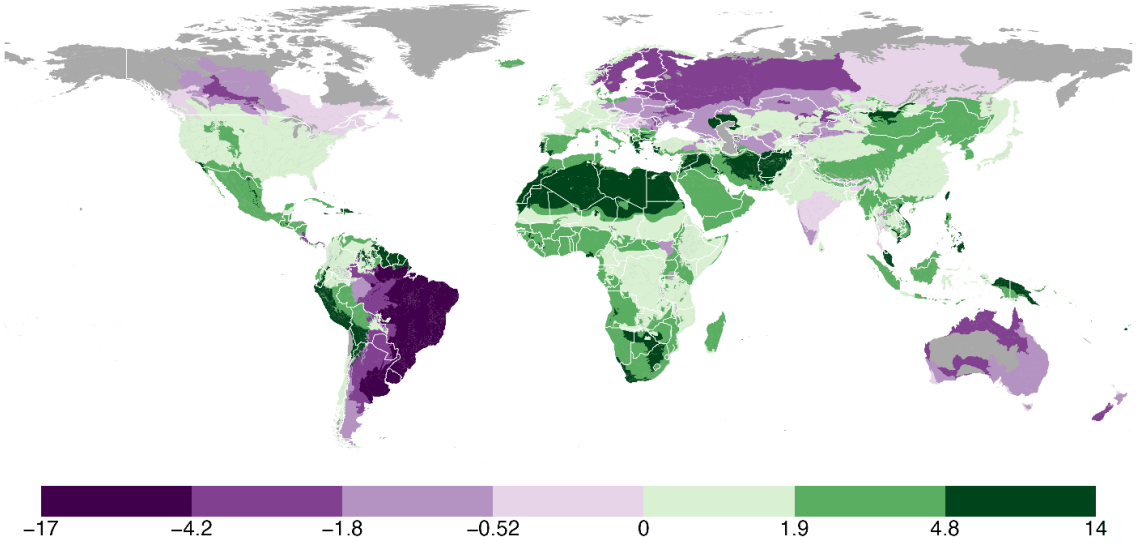
Notes: Change in the agricultural (panels a, b) and pasture (c, d) share of each ecoregion, in percentage points, when only input (a, c) or only output (b, d) trade costs are reset to their 1980 levels, relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Purple: expansion; green: contraction. The input and output panels of each row share one color scale. Where output costs contract cropland, pasture usually expands, so the agricultural share understates the land reallocated (Section 5).

Figure H.5: Modern share of cropland by trade-cost channel

(a) Only input trade costs



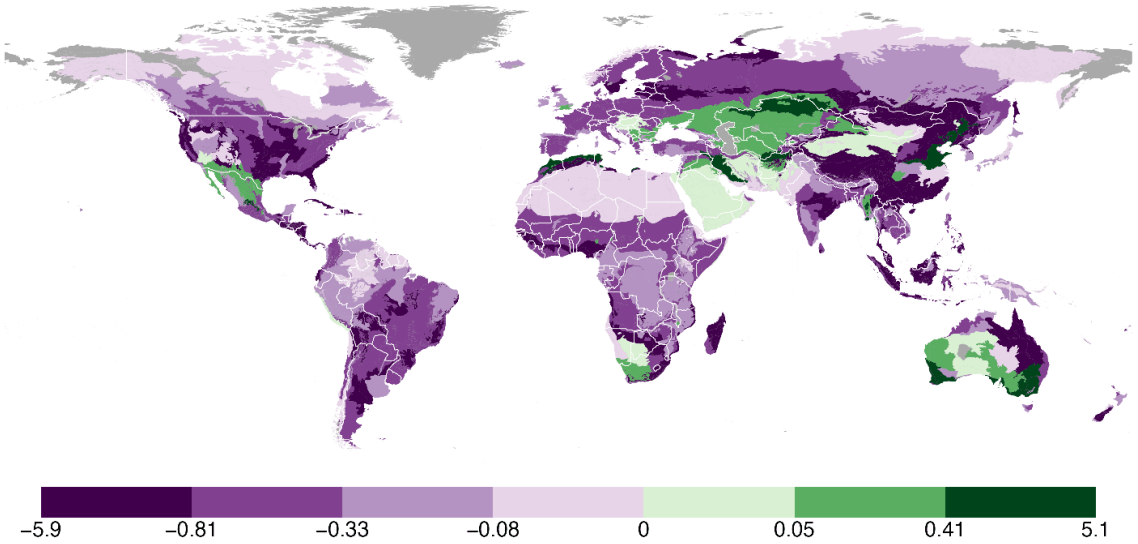
(b) Only output trade costs



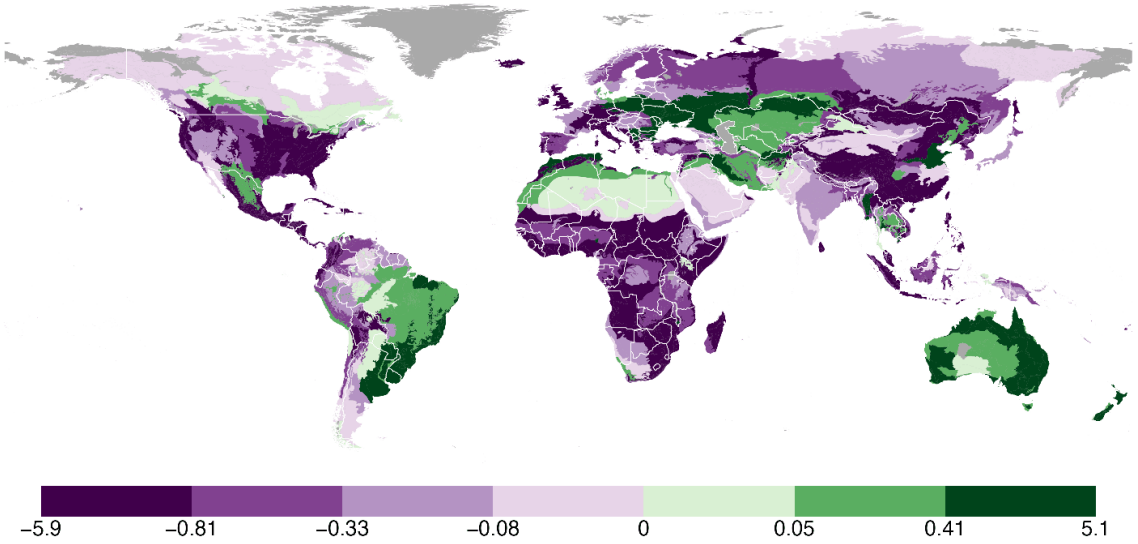
Notes: Change in each ecoregion's modern (high-input) share of cropland, in percentage points, when only input (a) or only output (b) trade costs are reset to their 1980 levels, relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Purple: decrease; green: increase. Both panels share one color scale; grey: ecoregions without cropland. Costlier inputs lower the modern share in most ecoregions and costlier outputs raise it.

Figure H.6: Species-remaining share by trade-cost channel

(a) Only input trade costs



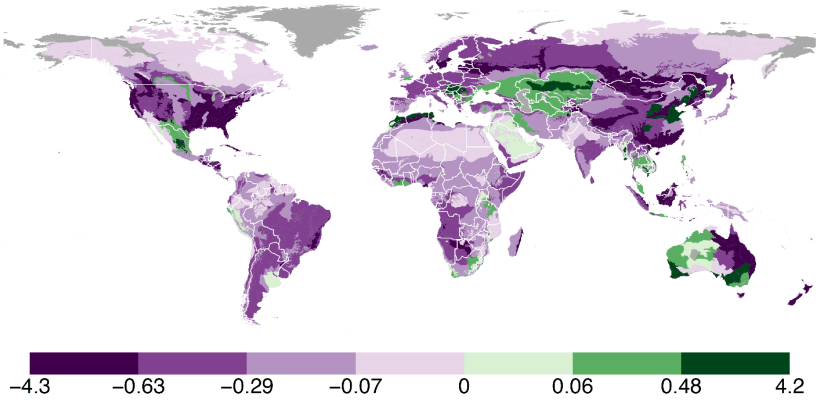
(b) Only output trade costs



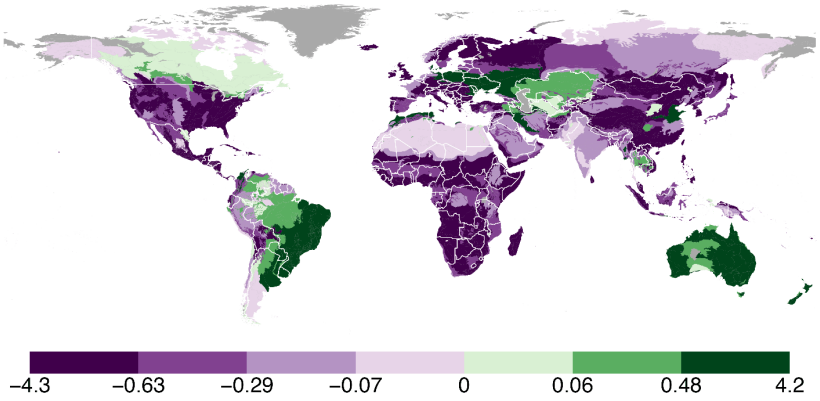
Notes: Change in each ecoregion's species-remaining share, in percentage points, when only input (a) or only output (b) trade costs are reset to their 1980 levels, relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Purple: loss; green: gain. Both panels share one color scale.

Figure H.7: Insectivorous-bird abundance under the other counterfactuals

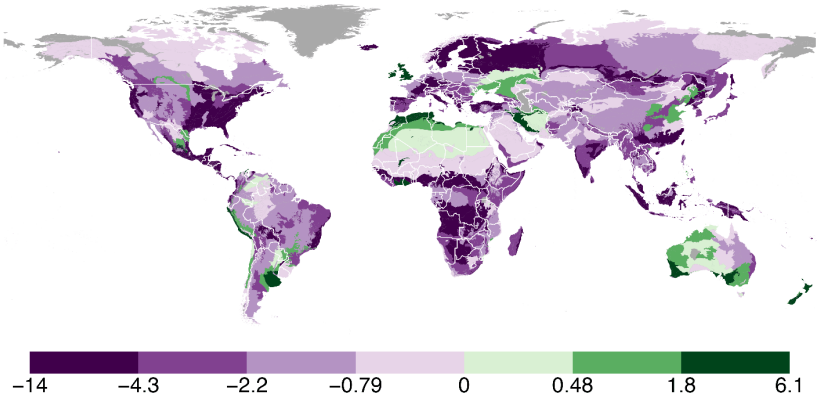
(a) Only input trade costs



(b) Only output trade costs



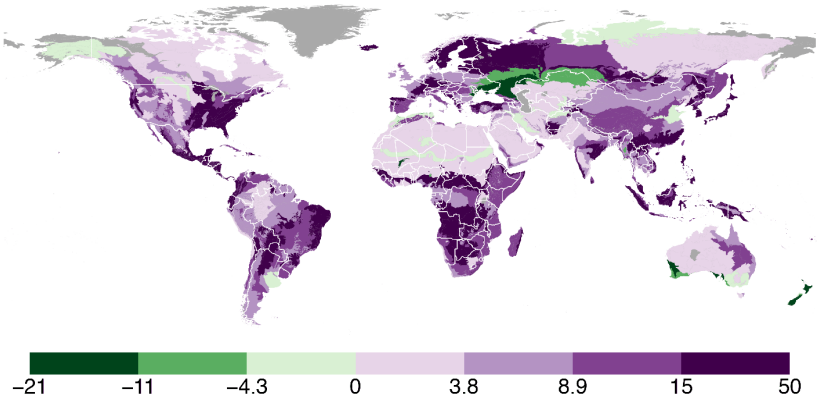
(c) Complete agricultural autarky



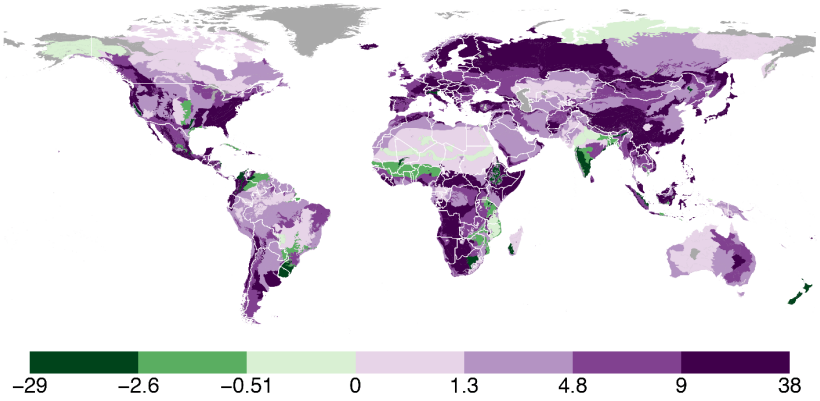
Notes: As Figure H.3, when only input (a) or only output (b) trade costs are reset to their 1980 levels, and under complete agricultural autarky (c). Solved without the biodiversity–productivity feedback. Purple: loss; green: gain. Panels (a) and (b) share one color scale; panel (c) has its own.

Figure H.8: Land use under autarky

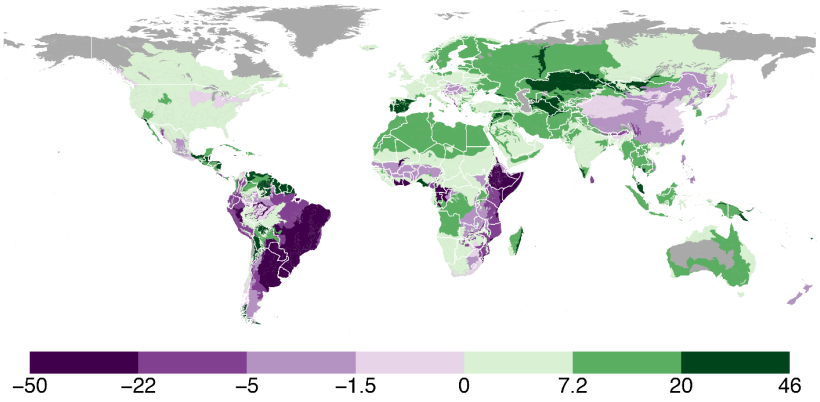
(a) Agricultural share



(b) Pasture share

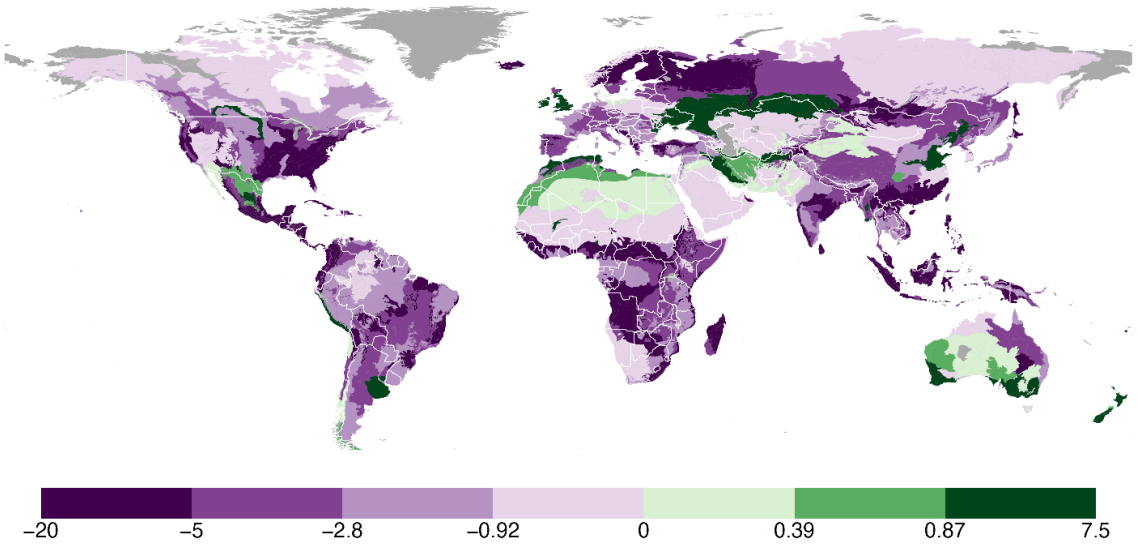


(c) Modern share of cropland



Notes: Change in each ecoregion's agricultural (crop and pasture) share (a), pasture share (b) and modern share of cropland (c), in percentage points, under complete agricultural autarky, relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Panels (a) and (b), purple: expansion; green: contraction. Panel (c), purple: decrease; green: increase. Grey: ecoregions without data, and in panel (c) without cropland.

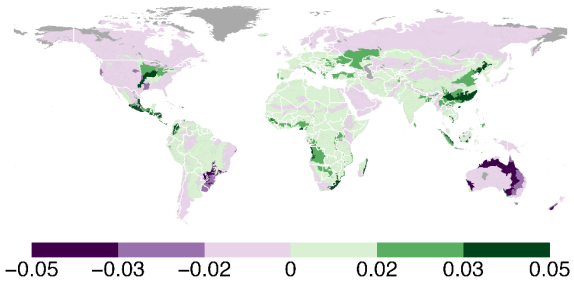
Figure H.9: Species-remaining share under autarky



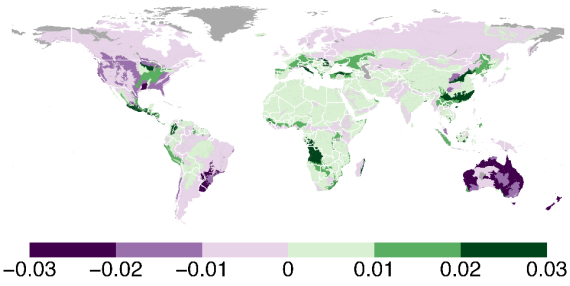
Notes: Change in each ecoregion's species-remaining share, in percentage points, under complete agricultural autarky, relative to the 2017 baseline. Solved without the biodiversity–productivity feedback. Purple: loss; green: gain.

Figure H.10: Where the biodiversity–productivity feedback bites

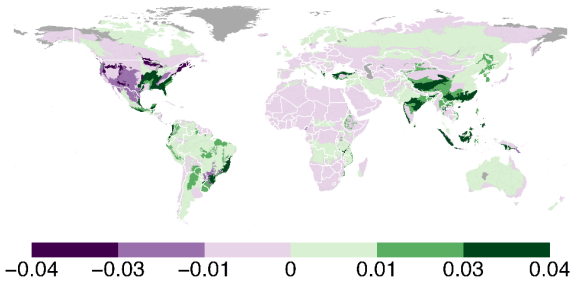
(a) Species richness, de-liberalization



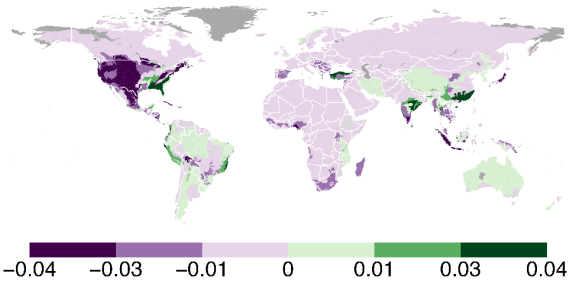
(b) Insectivorous-bird abundance, de-liberalization



(c) Species richness, autarky



(d) Insectivorous-bird abundance, autarky



Notes: Counterfactual solved with the biodiversity–productivity feedback minus the same counterfactual solved without it, by ecoregion, in percentage points of species remaining (richness panels) or of insectivorous-bird abundance (abundance panels). The aggregate wedge is negligible (Table H.3) but not uniform: the feedback raises some ecoregions and lowers others. Purple: the feedback lowers the outcome; green: it raises it. End bins include the ecoregions beyond the 2nd and 98th percentiles.

I Departures from Farrokhi and Pellegrina (2023)

The model of Section 3 departs from Farrokhi and Pellegrina (2023) in four ways: livestock holds land; conversion has its own elasticity; households buy food, a composite of farm goods and marketing services; and biodiversity is endogenous. This appendix asks how much the biodiversity results depend on these departures. The replication package of Farrokhi and Pellegrina (2023) solves the counterfactuals of Table 6 on the same 822,053 fields: agricultural trade costs reset to their 1980 levels for outputs and inputs, for inputs only, and for outputs only. I re-solve their baseline and counterfactual equilibria with their code, data and estimates, which reproduces the equilibria stored in the package, and pass the cropland of each field through the ecological component of Section 3, mapped to ecoregions as in the main text. Their model has no livestock, and therefore no pasture.

Table I.1 reports the results. Under the same shocks, their model commits 8.4 bird species to global extinction, a third of the 26.4 in this paper. The pasture margin accounts for the difference. On cropland alone the two models are close: holding pasture at its baseline, the cropland changes of this paper commit 7.3 species. Pasture changes commit 18.9, including 12.1 of the 14.5 species committed by resetting output trade costs alone. Without pasture, the output channel commits about half as many species as the input channel, in this paper (2.3 against 4.8) as in theirs (2.8 against 5.1); with it, the output channel is the larger of the two. Leaving out the pasture margin therefore understates the species cost of output trade by about four-fifths, in either comparison, and misplaces it: the Afrotropics account for 7.2 species in this paper, 5.4 of them through pasture, and for 0.35 in theirs.

Hectares and species also diverge. Their model expands world cropland by 7.7%, three times as much as this paper (2.6%), yet commits about as many species through it, 8.4 against 7.3. Across ecoregions, its changes correlate at 0.43 with the benchmark (column 4). This is why the paper counts species ecoregion by ecoregion, weighted by vulnerability, rather than hectares converted.

The comparison changes several things at once. Their economy is that of 2007, with 10 crops; their trade costs change from 1980 to 2007; and their parameters are their own estimates, with one dispersion parameter, 1.38, governing both the choice between crops and the conversion of land to agriculture. It therefore does not isolate a single departure, and the other three are examined within this paper's model. Across the estimated band of the conversion elasticity θ_1, de-liberalization commits 23.3 to 29.6 species (Table H.1, Panel B). Raising the elasticity of food demand from $\eta = 0.5$ to 1.2, which roughly doubles the price elasticity of demand at the farm gate, lowers the count to 20.4 (Panel C). The biodiversity–productivity feedback moves the count

Table I.1: The model of Farrokhi and Pellegrina (2023) scored with this paper's ecological component

	Baseline	Trade costs reset to 1980			Corr.
	level	Output and input (1)	Only input (2)	Only output (3)	(4)
A. Bird species committed to global extinction					
This paper (benchmark)	237.2	+26.4	+12.9	+14.5	1.00
cropland changes only	–	+7.3	+4.8	+2.3	0.67
pasture changes only	–	+18.9	+8.2	+12.1	0.89
Farrokhi and Pellegrina (2023)	99.6	+8.4	+5.1	+2.8	0.43
with this paper's 2017 pasture, held fixed	263.8	+10.1	+6.4	+3.1	0.43
B. Agricultural land (% change)					
This paper, cropland	–	+2.6	+2.7	−0.8	–
This paper, pasture	–	+8.6	+4.4	+5.2	–
Farrokhi and Pellegrina (2023), cropland	–	+7.7	+5.2	+1.9	–

Notes: Committed bird extinctions; positive entries are species lost. Columns (1)–(3) reset agricultural trade costs to their 1980 levels, as in Table 6. *This paper*: the benchmark of Table 6; "cropland changes only" holds pasture at its 2017 baseline in each counterfactual, and "pasture changes only" holds cropland at its baseline. *Farrokhi and Pellegrina (2023)*: their baseline (2007) and counterfactual equilibria, re-solved with their code, data and estimates, which uses their own trade-cost changes from 1980 to 2007. Their model has 10 crops and no livestock, so its baseline level counts cropland alone; the next row adds this paper's 2017 pasture, held fixed in every scenario. All rows use the same fields, the same mapping to ecoregions and the same species–area relationships and vulnerability weights. Column (4) correlates, across ecoregions, each row's contribution to the column-(1) change with the benchmark's (Pearson). Panel B: change in mapped agricultural land.

by 0.14 species (Table H.3); its role is to value the loss in farm revenue, about $6.0 billion a year for the countries that lose (Table H.2), rather than to change the land allocation.