

Pollinator declines, international trade and global food security: Reassessing the global economic and nutritional impacts

Arndt Feuerbacher

Ecological-Economic Policy Modelling Research Group, University of Hohenheim, Schwerzstr. 46, 70599 Stuttgart, Germany

ABSTRACT

The decline in biodiversity is threatening the provision of vital ecosystem services such as animal-mediated pollination services. While about 17 % of the global crop production value depends on pollination services, these crops make up an even larger share—28 %—of global agricultural trade. This reflects their strong international demand and higher tradability compared to other agricultural commodities. Hence, global trade needs to be considered when assessing how pollinator population declines affect the availability of micronutrient-rich foods and economic welfare in net-importing and exporting regions. This paper critically reviews and extends a global partial equilibrium model covering about 120 edible crops across 22 regions while also capturing international trade. The replication efforts reveal significant methodological and empirical flaws in an earlier, comparable study. Most recent bioeconomic data on crop yield dependence on pollination services are used to simulate a global pollinator collapse. Crop prices are projected to rise by 30 %, leading to a global welfare loss of 729 billion USD, or 0.9 % of global GDP and 15.6 % of global agricultural production value used for human food in 2020. The revised model also reports substantial declines in food production and micronutrient availability such as an 8 % reduction in global Vitamin A availability. These estimates by far surpass previous estimates that were based on earlier bioeconomic data. The findings highlight the critical need for more robust modeling frameworks to inform policy decisions regarding the sustainability of agri-food systems.

1. Introduction

Terrestrial biodiversity is experiencing significant declines due to various human pressures such as direct exploitation and land-use changes (Díaz et al., 2019; Jaureguiberry et al., 2022). An increasing number of studies report declining insect populations (Dicks et al., 2021; Forister et al., 2019; Thompson et al., 2022; Wagner et al., 2021), particularly concerning the abundance of terrestrial insects on a global scale (Van Klink et al., 2020). Pollinators are crucial for the global agri-food system, as approximately 75 % of food crops rely on pollination services, including a large share of nutrient-dense crops (Chaplin-Kramer et al., 2014; Klein et al., 2007). According to the most recent bioeconomic data on dependence ratios on pollination services (Siopa et al., 2024), approximately 17 % of the global crop production value relies on pollination services, while these crops account for an even larger share—28 %—of the global agricultural trade value. Pollinator declines, whether partial or total, could severely impact crop yields, leading to economic losses (Gallai et al., 2009; Lippert et al., 2021) and significant human health consequences, particularly through reduced access to nutrient-rich foods (Smith et al., 2015).

The effects of pollinator declines extend beyond producing countries through trade, influencing economic welfare and nutrition in consuming regions. As a result, the consequences for welfare and nutrition can arise in locations distinct from where crop yield losses occur (Kevan and

Phillips, 2001). However, the role of trade has so far been understudied by the economic literature in this context. Most economic analyses of global pollinator declines (Gallai et al., 2009; Lippert et al., 2021; Smith et al., 2015; Southwick and Southwick, 1992) do not explicitly capture the role of international trade and, if at all, only account for it implicitly through their model parameters. Bauer and Sue Wing (2016) were the first to consider pollinator declines in a global economic model capturing international trade, but their analysis did not focus on the role of trade and the model database used highly aggregated commodity data.

Analyzing the impacts of pollinator declines through the lens of trade is crucial, as countries vary significantly in their reliance on animal-pollinated crops. While agricultural net exporters of these crops may seem particularly vulnerable, Lippert et al. (2021) demonstrated that in the short term, producers could benefit from a pollinator decline if consumer demand is inelastic, consistent with the 'King-Davenant law,' which describes the relationship between price elasticity and revenue. In the long term, however, welfare losses are largely driven by declines in consumer welfare, as consumers face higher prices for pollination-dependent crops and reduced intake of nutrient-dense foods. To determine who bears the costs of pollinator declines, models must explicitly account for the international trade of these crops.

A recent study by Uwingabire and Gallai (2024), published in *Ecological Economics*, investigates the potential impacts of global

E-mail address: a.feuerbacher@uni-hohenheim.de.

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pollinator declines on the supply and demand of food crops, with a focus on human nutrition and food security. To this end, Uwingabire and Gallai (henceforth UG) employ a global partial equilibrium model that covers 22 regions and approximately 120 edible crops. Given the relatively limited literature in this field and the inclusion of numerous pollination-dependent crops with varying economic significance, this detailed model provides valuable insights into how pollinator declines affect food security across regions when consumption and trade adjustments are considered.

The empirical findings are potentially highly relevant for society and policymakers, especially as the UG study claims that “the average global crop price will increase by about 187% if pollinators go extinct at a global scale” (Uwingabire and Gallai, 2024). However, reporting such a substantial crop price increase prompts questions, as no previous study has suggested impacts of this magnitude. If accurate, such a result would indicate far more severe consequences for global food security than previously thought. However, the UG study does not fully discuss the assumptions and mechanisms driving this extreme outcome.

This paper has three objectives. First, it replicates the UG study by repeating the pollinator decline scenarios using a reconstructed version of its underlying model. Second, it modifies the UG model to evaluate how sensitive its results are to changes in key assumptions. Third, it updates the model’s underlying data, including crop production, prices, and—most importantly—bioeconomic estimates of dependence on animal-mediated pollination services. These updates provide new empirical insights into the effects of hypothetical pollinator declines.

The paper is structured as follows: Section Two describes the replicated and extended model setups. Section Three presents the main results for welfare, prices, and food security under a full decline of pollinators. Section Four discusses the key methodological and empirical insights from replicating the UG study, interprets the updated empirical findings, and provides an outlook for future research on modeling pollinator population changes in international agricultural markets. Finally, Section Five concludes the paper.

2. Replicating and extending the model approach of Uwingabire and Gallai (2024)

The model documented in UG is a comparative-static, net-trade global partial-equilibrium model.¹ The UG model is based on 2010 data from FAOstat (FAO, 2024) and covers about 120 edible crops in the 22 FAO sub-regions.

The first sub-section of this chapter reconstructs the UG partial-equilibrium model, referred to as model A. The detailed reconstruction makes the underlying mechanisms of model A explicit and elucidates why the replication of the UG analysis leads to different results. Model setup B is an extension of model A and is introduced in the second sub-section of this chapter. The main difference is that it relaxes the restrictive assumption of model A of identical preferences (equal budget shares) across crops and regions, which distorts the estimation of demand and trade balances. Model setups C and D share the same theoretical basis as model B² but incorporate updated data (from 2020) on crop production and prices. Additionally, model D further integrates updated data on dependence ratios on animal-mediated pollination services.

¹ The UG study states that it is based “on the traditional international trade theory and the Heckscher-Ohlin-Samuelson (HOS) model, which posits that” international trade is explained by differences in relative factor endowments (Uwingabire and Gallai, 2024, p. 2). However, the UG model does not (explicitly) represent relative factor endowments nor consequently factor scarcity.

² For brevity, this study refers to variations of the partial equilibrium model as “models,” though all setups share the same underlying framework and differ only in assumptions, data, and parameters.

2.1. Model A – Replicating the UG model

The UG model is based on the following key assumptions. It relies on the law of one price, meaning there is a single world market price that clears both global and national markets. It does not account for transaction costs like trade or transportation costs, quality differences, trade policies and the like, which would drive wedges between prices in different markets. The model is limited to edible crops implicitly assuming that other sectors, specifically the livestock sector, are subject to the *ceteris paribus* assumption, i.e., they remain unaffected. On the demand side, the UG model assumes that all countries have identical preferences and therefore spend identical fractions of their budget on all edible crops. On the supply side, it assumes that the supply behavior is governed by an “adjustment index”, which we refer to as supply slope in the following. Next, I reconstruct the mathematical calibration and formulation of the UG model.

The model’s supply function is derived from a quadratic cost function, which yields:

$$Q_{ij} = \frac{P_{ij}^*}{a_{ij}} (1 - \alpha_i D_j) \quad (1)$$

where Q_{ij} represents the supply of edible crops j in region i , P_{ij} is a crop’s equilibrium price, a_{ij} is a crop- and region-specific calibrated slope parameter, α_i denotes the extent of pollinator population declines, and D_j is the crop-specific dependence ratio on pollination services. The supply function has a unitary supply elasticity ($\epsilon=1$), meaning the percentage change in quantity supplied equals the percentage change in price (i.e., a direct, proportional relationship between price and quantity supplied). The supply function’s y-axis intercept is zero, meaning the first unit is supplied at negligible cost.

The consumers in each region maximize their utility subject to a budget constraint, R_i , which is equal to the sum of the product of crop prices, P_{ij} , and their demand quantity, X_{ij} :

$$R_i = \sum_{j=1}^J P_{ij} X_{ij} \quad (2)$$

The total food budget constraint is exogenously determined and thus fixed. The demand function for crop j is derived from a Cobb-Douglas utility function. Here, the UG model assumes that all regions i have identical preferences for crops j . This indicates that the budget share in model A, b_{ij}^A , is identical across all crops and regions, and equals the global budget share of a crop, bg_j .

$$bg_j = b_{ij}^A = \frac{1}{J} \quad (3)$$

where J represents the total number of all crops j . The model’s corresponding demand function for edible crops j in region i is:

$$X_{ij} = \frac{b_{ij}^A R_i}{P_{ij}} \quad (4)$$

A key property of a demand function derived from a Cobb-Douglas utility function is that its own-price elasticity equals -1 . Thus, both the supply and demand in the UG model follow unit elastic behavior. The UG model does not rely on external data to determine the base values of crop specific demand, X_{ij} , or the world market prices, PW_j . Instead, these values are derived based on the assumption of identical preferences, which implies equal budget shares, b_{ij} , for all crops in all regions (as stated in Eq. (3) above), along with an exogenously determined total food budget constraint R_i . Consequently, the base values for both X_{ij} and PW_j are initially unknown. The region-specific base production quantity, Q_{ij} , is known and based on FAOstat data (see Section 2.5 for an overview of data sources). This approach yields the following equation to determine the base world market prices:

$$PW_j = \frac{\sum_{i=1}^I R_i b_{ij}^A}{\sum_{i=1}^I X_{ij}} \Leftrightarrow PW_j = \frac{\sum_{i=1}^I R_i b_{ij}^A}{\sum_{i=1}^I Q_{ij}} \text{ with } \sum_{i=1}^I X_{ij} = \sum_{i=1}^I Q_{ij} \quad (5)$$

Even though X_{ij} is unknown, Eq. (5) can still be solved. This is because total global demand must equal total global supply, which is determined by summing region-specific production quantities. The interpretation is straightforward: a crop's world market price equals its global consumption value divided by its global consumption quantity. When losses and stock changes are neglected, global consumption must equal global production. Eq. (5) is used to calibrate the base world market prices, but it is not explicitly included in the model. In the model, world market prices are represented as a variable. The model is solved by finding a vector of prices that clears the (implicit) global market, which occurs when the sum of net exports equals zero (see also Eq. (8) below).

Under the law of one price, the model assumes that all national market-clearing prices are equal to the world market-clearing price. Consequently, after determining the world market price PW_j , we can calibrate the national demand quantities in the base as follows:

$$X_{ij} = \frac{R_i b_{ij}^A}{P_{ij}} = \frac{R_i b_{ij}^A}{PW_j} \text{ with } PW_j = P_{ij} \quad (6)$$

Eqs. (5) and (6) show that the budget shares are key parameters in determining global world market prices and demand quantities. In the UG study, these parameters are not derived from data or behavioral differences but are instead a byproduct of the assumption of identical preferences. Unlike Eq. (5), the UG study reports an 'approximation' of the world market price. However, this approximation appears to be a key reason for flaws in the UG model (see Appendix A).

The last model equation reported in the UG study is the calculation of the region and crop-specific trade balance, TB_{ij} :

$$TB_{ij} = (Q_{ij} - X_{ij})PW_j \quad (7)$$

Finally, the UG model seems to lack an essential equation that ensures that global crop markets clear. Market clearing requires that the sum of net exports across all regions equals zero:

$$\sum_{i=1}^I Q_{ij} - X_{ij} = 0 \quad (8)$$

Eq. (8) also allows solving for the market-clearing world prices, making Eq. (5) redundant and thus unnecessary in model A (and its extensions).

If model A is set up correctly, we should not expect any changes in TB_{ij} , since both the supply and demand equations are unit elastic across all regions and crops, as described above. Thus, the value of regions' supply and demand remains unchanged, as any increase in prices is offset by a proportional decrease in quantities, and vice versa. In contrast, the UG study reports regional changes in the trade balance, whereas models A and B do not.

2.2. Model B - model setup with heterogenous preferences

Model B is an extension of model A. It is also based on 2010 FAOstat data and relies on the same model equations, but differs in the calibration of parameters and base variables.

Model B uses FAOstat trade data (FAO, 2024) to estimate regional demand as follows:

$$X_{ij} = Q_{ij} - E_{ij} + M_{ij} \quad (9)$$

where E_{ij} denotes a region's crop exports and M_{ij} is equal to the region's crop imports.

For many crops, the available trade data also reports exports or imports of processed forms of the crop (e.g., shelled almonds instead of almonds in shell; or orange juice instead of oranges). To ensure consistency, I convert trade data of processed crops into raw equivalents. The

conversion ratios are documented in the model code and are largely based on FAO (2025). A well-known issue is that trade data inconsistencies arise when importers report different quantities than exporters for the same trade flows. Moreover, in some regions reported export quantities exceed their production quantities, which is possible due to stock changes or re-exports. However, data for these flows are often missing. To ensure consistency, an algorithm limits regional exports to a maximum of 99 % of that region's production. Given the lack of data on re-exports and stock changes, failing to impose this constraint could result in infeasible negative demand values. As a second step, region-specific imports and exports are adjusted to ensure that total global imports equal total global exports. This procedure is repeated until no cases remain where exports exceed production and until global exports match global imports.³

The base world market price, PW_j , is initialized using the global average of country-specific producer prices, PP_{cj} , retrieved from the FAOstat database:

$$PW_j = \frac{1}{C_j} \sum_{c=1}^C PP_{cj} \quad (10)$$

where c is an index for countries and C_j is the number of countries reporting a producer price. Like model A, model B also follows the law of one price: there is one world market price that clears both global and national markets.

The regional food budget is subsequently determined by the sum product of world market prices, PW_j , and the region-specific crop demand, X_{ij} , as described in Eq. (2). Consequently, the budget shares for model B, b_{ij}^B , are determined as:

$$b_{ij}^B = \frac{PW_j X_{ij}}{\sum_{j=1}^J PW_j X_{ij}} = \frac{PW_j X_{ij}}{R_i} \quad (11)$$

2.3. Model setups C and D

Model C relies on the same model equations and calibration procedure as model B, but is calibrated based on 2020 FAOstat data. Model D further extends model C by incorporating the most recent dependence ratios on animal-mediated pollination services from a recent review by Siopa et al. (2024). Models A, B and C rely on the dependence ratios taken from Klein et al. (2007), allowing for a direct comparison with the UG study. Unlike Klein et al. (2007), which report broad dependence categories translated into quantitative values, Siopa et al. (2024) provide point estimates for mean dependence ratios. In general, the Siopa et al. data show a substantially higher level of dependence for most crops. For example, papayas, lemons, or palm oil were all characterized with a low dependence ratio (0.05 or 5 % of crop yield) in Klein et al. (2007), but Siopa et al. (2024) now report much higher dependence ratios of 0.91, 0.80 and 0.81, respectively. A comparison of dependence ratios in both studies is provided in Appendix B.

2.4. Scenarios, model implementation and ex-post model analysis

The UG study reports results for three hypothetical scenarios in which a_{ij} represents a decline in pollinators of 5 %, 50 % or 100 %, with the latter indicating the complete extinction of both managed and wild pollinators. All three scenarios were replicated across all model setups. However, for brevity, I focus on replicating the most extreme shock: a 100 % decline in pollinators. The models are implemented in GAMS as mixed-complementarity-problems using the PATH solver. The model data and code, including data preparation, model structure, and solution

³ The subsequent model results are very insensitive towards changes in method of trade data reconciliation. For instance, using 90 % instead of 99 % of production as limits for exports did only change key results by less than 0.1 %.

procedures, are provided in the electronic supplementary materials and can be found on github (<https://github.com/ArndtFeuerbacher/PollinatorCropMarketModel>).

The UG study assesses the changes in regional per capita micronutrient availability, $\Delta NA_{i,n}$, ex-post by multiplying the changes in food demand with the crop-specific micronutrient content $NC_{j,n}$:

$$\Delta NA_{i,n} = \frac{\sum_{j=i}^J (X_{ij}^{0 < \alpha \leq 1} - X_{ij}^{\alpha=0}) NC_{j,n}}{Pop_i} \quad (12)$$

where n represents the set of six micronutrients: Vitamin A, Vitamin C, Vitamin B6, folate, iron and protein. The superscript denotes whether the value corresponds to the reference scenario ($\alpha = 0$) or a scenario in which pollinator populations decline ($0 < \alpha \leq 1$). Pop_i is a parameter representing the population of region i .

Changes in consumer surplus ΔCS_{ij} and producer surplus ΔPS_{ij} are calculated ex-post as follows.

$$\begin{aligned} \Delta CS_{ij} &= \left(\int_0^{X_{ij}} \frac{b_{ij} R_i}{X_{ij}} dX_{ij} - P_{ij} X_{ij} \right) - \left(\int_0^{X_{ij}^0} \frac{b_{ij} R_i}{X_{ij}^0} dX_{ij} - P_{ij}^0 X_{ij}^0 \right) \\ &= [b_{ij} R_i \log(X_{ij}) - b_{ij} R_i \log(X_{ij}^0)] - [P_{ij} X_{ij} - P_{ij}^0 X_{ij}^0] \\ &= b_{ij} R_i [\log(X_{ij}) - \log(X_{ij}^0)] - [P_{ij} X_{ij} - P_{ij}^0 X_{ij}^0] \end{aligned} \quad (13)$$

$$\begin{aligned} \Delta PS_{ij} &= \left(P_{ij} Q_{ij} - \int_0^{Q_{ij}} \frac{Q_{ij}}{(1 - \alpha_i D_i)} a_{ij} dQ_{ij} \right) - \left(P_{ij}^0 Q_{ij}^0 - \int_0^{Q_{ij}^0} \frac{Q_{ij}^0}{(1 - \alpha_i D_i)} a_{ij} dQ_{ij} \right) \\ &= (P_{ij} Q_{ij} - P_{ij}^0 Q_{ij}^0) - \left(\frac{a_{ij} Q_{ij}^2}{2(1 - \alpha_i D_i)} - \frac{a_{ij} Q_{ij}^0{}^2}{2(1 - \alpha_i D_i)} \right) \\ &= (P_{ij} Q_{ij} - P_{ij}^0 Q_{ij}^0) - \left(\frac{P_{ij} Q_{ij} - P_{ij}^0 Q_{ij}^0}{2} \right) \\ &= \frac{P_{ij} Q_{ij} - P_{ij}^0 Q_{ij}^0}{2} \end{aligned} \quad (14)$$

Producer surplus can also be derived geometrically, given the linear form of the supply function and its resulting triangular shape.

2.5. Data sources

The underlying data used to simulate the pollinator decline scenarios are shown in Table 1. Like the UG model, models A and B use FAOstat data (FAO, 2024) from 2010, while models C and D use data from 2020 allowing an assessment of how sensitive the model results are to the choice of the base year. As in the UG study, models A, B and C use bioeconomic data from Klein et al. (2007) data, while model D uses the most recent data from Siopa et al. (2024).

The UG study provides no supplementary materials, which complicates replicating it. The study states that its model relies on 122 edible crops, but does not provide a list of them. According to personal communication with the corresponding author of the UG study, the list of crops corresponds to appendix 2.3, as reported in Uwingabire (2021, p. 236). This appendix lists 118 crops and is based on Chaplin-Kramer et al. (2014), which reports data on the micronutrient content of 115 crops. Here, I add sugarcane and sugar beet to the Chaplin-Kramer list of

edible crops and match the resulting 117 crops with the FAOstat database. Since various single crops on the Chaplin-Kramer list correspond to multiple FAOstat items (e.g., plantains and cooking plantains), this results in a possible list of 136 edible crops (Appendix D). However, only crops with available production data can be included in model A; this applies to 121 edible crops in the year 2010. In addition to production quantity data, model B, C, and D also require price data, which are available for 2010 and 2020 for 119 crops of the 121 edible crops⁴ included in model A. An overview of the total number of crops and their distribution across crop categories in the respective models is provided in Appendix C.

2.6. Comparison of model input data

One main driver of differences in the absolute magnitude of model results is the variation in data sources for estimating crop prices and food budget. The UG study uses data from “revenue spent on food and beverages in US dollar” as labeled in table 4 of the UG study, which lists various databases (Uwingabire and Gallai, 2024, p. 5). For several reasons, I consider this approach somewhat problematic approach for estimating the value of edible crops. First, expenditure data on food and beverages include more than just edible crops, most notably livestock products as well as synthetic and alcoholic beverages. Second, in many countries processed foods dominate food consumption and raw inputs only constitute a small fraction of the total consumption value. Third, using food expenditure data is also problematic for unprocessed edible crops, as they are valued at purchaser prices, which include various

mark-ups such as transportation and trade margins but also taxes. For these reasons, the value of pollination-dependent crops is likely to be substantially inflated when using total food budget data. Arguably, a pollinator decline predominantly impacts production costs, which, in turn, affects producer prices. Like previous studies (Gallai et al., 2009; Lippert et al., 2021), models B to D also rely on producer prices, which are certainly not a perfect proxy, but provide a more conservative estimate for the reasons mentioned above.

Table 2 presents the food budget for the 22 FAO sub-regions, as reported by the UG study, and as estimated in models B to D, using producer prices for the years 2010 and 2020. The food budget in the UG study—and thus its implicit prices, derived from expenditures—is 92 % higher than the food budget estimated using producer prices in model B for the same year. The per capita food budget reported by UG exhibits significant variation (see Appendix E), partly due to an outlier in Southern Asia, where the reported expenditure corresponds is only 11 USD per capita per year. Despite the region’s high prevalence of food insecurity, the actual annual food budget per capita in Southern Asia is at least twenty times higher than the UG estimate (Appendix E). This discrepancy is also reflected in the UG study’s per capita welfare results for Southern Asia (see also Table 3 below). Correcting this error would amplify welfare changes in both the UG model and model A.

⁴ The two crops not included in model B are “Brazil nuts” and “Cashewapples”, for which the FAOstat database reports production quantities but no producer prices. These crops play a minor role in terms of production quantity among pollination-dependent crops.

Table 1

Sources for the underlying data to calibrate model A and B.

Symbol	Indicator	Units considered	Year (if applicable)	Data source	Comment
Q_{ij}	Production quantity	In metric tons	2010 and 2020	FAOstat	UG study uses only 2010
P_{ij}	Producer prices	In USD per metric ton	2010 and 2020	FAOstat	Calibrated to real-world data. UG instead impute these.
E_{ij}	Exports of crops	In metric tons	2010 and 2020	FAOstat	
M_{ij}	Imports of crops	In metric tons	2010 and 2020	FAOstat	
Pop_i	Population	Persons per FAO sub-region	2010 and 2020	FAOstat	UG study uses only 2010
R_i	Food budget	Expenditures spent on food and beverages in USD	2010 for model B and 2020 for model C and D	Documented as World Bank database, Eurostat, United nation Stat database" in Table 4 Uwingabire and Gallai, 2024	Model A uses same data. Models B to D estimate expenditure based on producer prices and demand derived from FAO data
D_j	Dependence ratio	% of crop yield dependent on animal-mediated pollination services	NA	Klein et al., 2007 and Siopa et al., 2024 – see appendix B	Model A, B and C use Klein et al. and Model D uses Siopa et al.
NC_{nj}	Micronutrient content of crops	Vitamin A in International Units per 100 g, Vitamin C, Vitamin B6, Folate and Iron in milligram per 100 g and Protein in gram per 100 g of food intake	NA	Chaplin-Kramer et al., 2014 – see appendix D	Same data source across all models

Source: Adapted from [Uwingabire and Gallai \(2024\)](#).**Table 2**

Comparison of the exogenous food budget data for different model setups and years across FAO sub-regions.

		Food budget - total (in billion USD)		
	FAO sub-regions	UG model – 2010/ Model A – 2010	Model B - 2010	Model C & D - 2020
Africa	Northern Africa	107.5	96.0	126.4
	Western Africa	83.5	163.3	332.9
	Eastern Africa	84.3	81.4	137.2
	Middle Africa	46.8	49.4	81.8
	Southern Africa	27.4	17.5	20.7
Americas	Northern America	726.1	267.4	337.1
	Central America	70.1	75.5	95.2
	Caribbean	47.8	16.8	18.6
	South America	347.9	326.2	329.5
	Eastern Asia	2704.2	952.3	1354.9
Asia	Southern Asia	19.1	493.2	697.0
	South Eastern Asia	243.5	308.6	416.9
	Central Asia	52.0	23.8	39.8
	Western Asia	309.9	109.5	153.6
	Eastern Europe	536.7	142.8	175.0
Europe	Northern Europe	220.9	42.3	51.4
	Western Europe	508.6	124.4	154.6
	Southern Europe	379.3	120.6	137.0
	Australia and New Zealand	76.9	19.7	17.8
	Melanesia	13.4	4.7	7.9
Oceania	Micronesia	1.4	0.1	0.2
	Polynesia	2.3	0.3	0.3
	World	6609.4	3435.9	4685.9

Source: Author's compilation based on [FAO \(2024\)](#) and [Uwingabire and Gallai \(2024\)](#).

3. Model results

In this section, I report the results from simulating a complete pollinator loss using models A and B with 2010 data and models C and D with 2020 data. Where applicable, I compare the results from these simulations with those reported in the UG study. The analysis focuses on changes in welfare, prices, quantities and micronutrient availability. Unlike the UG study, these results do not show changes in the monetary trade balance due to the unit elastic behavior of supply and demand equations.

3.1. Welfare results

[Table 3](#) presents the declines in net welfare per capita reported by the four model setups. They are consistently and substantially lower than those reported by the UG study – even when considering only the changes in consumer surplus. Models A to D do not report any changes in producer surplus, which makes up a third of the net welfare declines in the UG study. However, since all model setups considered assume unit elastic demand and supply, we should not expect any changes in the producer surplus. For a more thorough exploration of welfare changes across different ranges of demand elasticities the interested reader may refer to [Lippert et al. \(2021\)](#). Assuming no cost reductions from lower harvest volumes, Lippert et al. show that if there is an exogenous shift (e. g., due to a pollinator decline), producer surplus remains unchanged when demand elasticity equals one. Lippert et al. demonstrated this for both infinitely inelastic and elastic supply curves, which naturally extends to unit elastic supply curves. The UG model exhibits theoretical inconsistencies, as indicated by the missing market-clearing equation and incorrect calibration of the supply slope (see also Appendix A). This inconsistency likely explains the unexpected changes in regional producer surplus and trade balance.

The model A is a direct replication of the UG study and uses the same food budget data. Here, the consumer surplus changes are largely structurally aligned with those reported by the UG study ([Table 3](#)). Yet, the average global consumer surplus change is 29 % lower in model A, and the total welfare decline is 52 % lower than in the UG study. Hence, even when replicating the same approach with similar data, the magnitude of welfare changes differs substantially. Notably, the consumer surplus changes reported for Southern Asia in both the UG model and model A column in [Table 3](#) stand out. This extremely low welfare decline is likely due to the beforementioned incorrect data entry for this region's food budget per capita in the UG study.

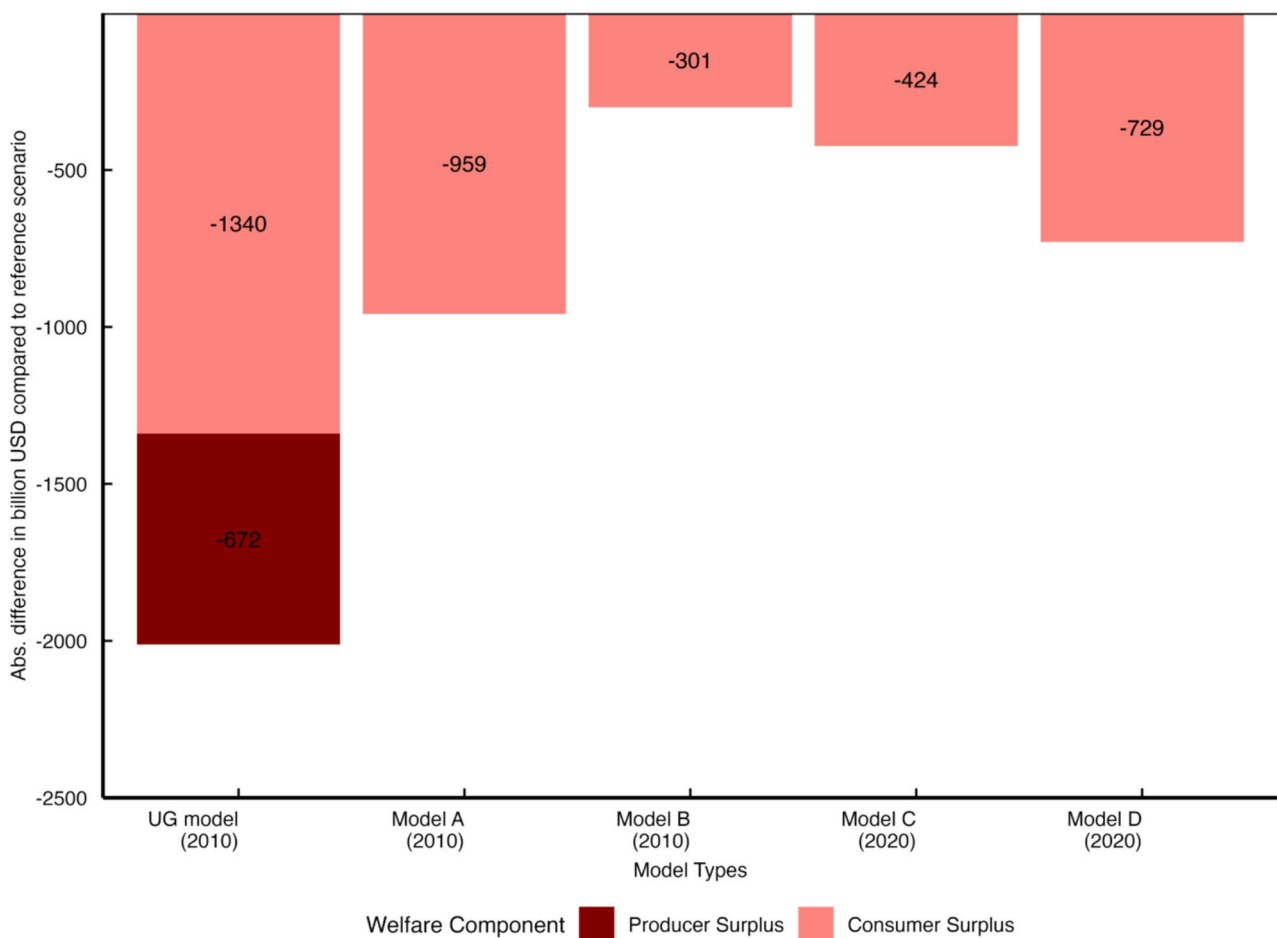
In the following, I focus only on changes in consumer surplus to examine how model setup differences account for result discrepancies. Model B, which allows for heterogenous preferences and uses different food budget data, reports consumer surplus changes that are 78 % lower than in the UG study ([Table 3](#)), despite both models being based on 2010 data. Adjusting model B to the same food budget magnitude as the UG model (and model A) increases the consumer surplus change per capita from 43.0 to 82.8 USD. Thus, 42 % of the difference in consumer surplus between models A and B result from the difference in the food budget magnitude, while the remaining 58 % must be due to other differences, such as the oversimplified assumption of uniform expenditure shares.

Comparing the per capita welfare results between model C and D, it becomes clear that the more recent bioeconomic data leads to higher

Table 3

Welfare changes in USD per capita across FAO sub-regions resulting from a 100 % pollinator decline as reported by the UG study and simulated by model setups A to D.

	FAO sub-region	UG model - 2010			Model A	Model B	Model C	Model D
		Consumer surplus change	Producer surplus change	Net welfare change	Consumer surplus change = Net welfare change			
Africa	Northern Africa	-100	-67	-167	-72	-49	-54	-83
	Western Africa	-54	-257	-311	-28	-20	-18	-68
	Eastern Africa	-51	-68	-119	-37	-8	-14	-23
	Middle Africa	-71	-41	-112	-38	-13	-10	-29
	Southern Africa	-94	-12	-106	-47	-17	-17	-28
Americas	Northern America	-427	-147	-574	-288	-52	-73	-111
	Central America	-91	-110	-201	-74	-39	-49	-100
	Caribbean	-232	-29	-261	-109	-40	-53	-107
	South America	-180	-125	-305	-156	-37	-44	-82
	Eastern Asia	-347	-89	-436	-270	-80	-109	-157
Asia	Southern Asia	-2	-105	-107	-2	-23	-28	-46
	South Eastern Asia	-82	-20	-102	-43	-23	-29	-136
	Central Asia	-166	-132	-298	-103	-58	-99	-122
	Western Asia	-263	-52	-315	-199	-62	-77	-121
	Eastern Europe	-369	-133	-502	-242	-47	-66	-91
Europe	Northern Europe	-448	-4	-452	-170	-19	-27	-38
	Western Europe	-548	-27	-575	-365	-51	-66	-102
	Southern Europe	-501	-98	-599	-380	-77	-96	-148
Oceania	Australia and New Zealand	-581	-364	-945	-370	-47	-55	-83
	Melanesia	-275	-370	-645	-120	-35	-35	-76
	Micronesia	-269	-9	-278	-36	-29	-46	-77
	Polynesia	-452	-1902	-2354	-268	-78	-72	-131
	World	-192	-96	-288	-137	-43	-54	-93

**Fig. 1.** Absolute changes in total global welfare changes following a 100 % pollinator collapse. Note: The result of the UG study has been calculated based on the reported per capita welfare changes.

welfare losses across all regions. This is particularly pronounced in West Africa and South Eastern Asia, where per capita welfare losses increase severalfold.

Differences in welfare changes reported by the models become clearer at the aggregate level (Fig. 1). The UG study does not report aggregate welfare changes directly, but they can be calculated based on per capita welfare change results. This calculation suggests a total welfare decline of 2012 billion USD in the UG study, compared to a decline of 959 billion USD as reported by model A, the direct replication attempt. The arguably more realistic setup in model B, with heterogeneous preferences, reports a decline of 301 billion USD for the same year.

Using 2020 instead of 2010 data leads to a 41 % larger welfare decline in model C compared to model B. The choice of the underlying year affects the results, however, model assumptions (e.g., homogenous expenditure shares versus heterogeneous preferences) have an even greater impact, as shown by the comparison between models A and B. Compared to models B and C, model D reports substantially higher welfare declines due to its use of updated dependence ratios. In model D, global welfare declines by 729 billion USD in 2020, which is 72 % higher than the welfare decline in model C for the same year. This highlights the sensitivity of results to the choice of the dependence ratio data, as Siopa et al. (2024) arguably provide the most accurate estimates currently available.

3.2. Price changes

Changes in consumer surplus result from changes in prices and quantities. Any pollinator decline scenario leads to lower production quantities and higher prices, causing a decline in consumer surplus. The UG study does not report any changes in production quantities; however, it does report price changes for crop groups (see table 3 in the UG study). Model A reports an average price increase of 37.4 % across all agricultural crops (Table 4), while the weighted average price change in models B and C is approximately 16 % in 2010 and 2020, respectively. This indicates that the assumption of equal expenditure shares across regions and crops in model A overstates the value of pollination-dependent crops, leading to an overestimation of price changes. In contrast, this assumption does not hold in models B and C, resulting in lower price estimates. The price changes in model D are nearly as high on average as in model A, which, however, is solely due to the updated dependence ratios underlying model D.

All price changes reported by models A to D differ significantly from the price changes reported by the UG study (Table 4). This discrepancy

can, to some extent, be attributed to differences in crop categorization. However, this does not apply to the average price change of agricultural crops. The UG study reports an exceptionally high 186 % price increase, which is also emphasized as a key result in its abstract. The simulated models A to D deviate significantly from this finding, with price increases at least five times lower.

The UG study does not report information for the categories cereals, roots and tubers, and, sugar crops. The price changes in models A to D are zero for these categories because neither roots and tubers nor sugar crops depend on animal-mediated pollination services. However, one crop within the cereals category, buckwheat (a pseudo-cereal categorized as a vegetable in the UG study), has a low dependency on pollination services. This explains why models A to D report slight price changes in this category.

3.3. Impacts on global food security

The changes in micronutrient availability and crop production at the global level are the same in models A and B in 2010 (Fig. 2). This is not surprising, because at the global level – at least for pollination-dependent crops – they rely on identical aggregate production and demand data. They hardly differ from model C, which uses 2020 data, because models A, B and C are all based on the same dependence ratio from Klein et al. (2007). Using the same dependence ratios results in similar production changes, while monetary results differ due to variations in prices and preferences. Compared to models A, B and C, the UG study reports slightly higher declines for Vitamin A but lower declines for other micronutrients. In relative terms, the discrepancy is particularly high for Vitamin B6 and folate, where the UG study reports 67 % and 40 % lower availability following a pollination decline.

Across all models, model D shows the largest declines by far in micronutrient availability and crop production. In model D, which is based on substantially higher dependence ratios, the decline in the production and demand of pollination-dependent crops is about twice as high as in all other models (Table 5). This is particularly evident in the changes in the availability of Vitamin C, Vitamin B6, iron and protein (Fig. 2). Thus, the impacts on food security are highly sensitive to dependence ratio data, and previously assessed impacts on food security are likely understated.

Regional relative changes in overall food demand and Vitamin A availability for models A to D are reported in Table 5. The UG study does not report regional food demand or Vitamin A availability. Globally, the mean changes are nearly identical for models A to C, because they use the same dependence ratio data (Klein et al., 2007). In model A, regional changes for both indicators remain constant across all regions due to the assumption of equal budget shares across all crops and regions. In the models B, C and D, substantial variation in these indicators occurs across regions because they account for heterogeneous preferences and demand patterns based on observed empirical data. Model D is arguably most realistic, given the update in the underlying dependence ratio data. In this model, most regions in Asia and Oceania experience above-average declines in food demand. In contrast, notably, regions in Sub-Saharan Africa as well as South America report below-average declines.

The change in Vitamin A availability does not directly correspond to the change in food demand. For instance, in Southern Asia, food demand declines by only 4.5 % in model D, but Vitamin A availability drops by 19.5 % (Table 5). This discrepancy is explained by the extent to which Vitamin A availability relies on pollination-dependent crops. A considerable share, 25 %, of total Vitamin A intake in Southern Asia depends on the consumption of pumpkins, melons, papayas, and mangos. The dependence ratios for these crops are high, especially according to recent data from Siopa et al. (2024). A contrasting case is Micronesia. Here, Vitamin A availability stays almost constant even though overall food demand declines by 4 % to 19 % across models B to D (Table 5). This seemingly paradox result occurs because approximately 95 % of Vitamin A intake in this region comes from sweet potatoes, which are

Table 4

Price changes after a full pollinator collapse at the crop category and agricultural level in % across the different model setups.

Crop category	UG model (2010)	Model A (2010)	Model B (2010)	Model C (2020)	Model D (2020)
Cereals	NA	6.3	0.1	0.1	0.0
Roots and tubers	NA	0.0	0.0	0.0	0.0
Oil crops	2	35.6	13.2	10.7	32.5
Sugar crops	NA	0.0	0.0	0.0	0.0
Pulses	3	2.6	2.4	2.2	14.7
Vegetables	26	19.1	13.1	13.7	32.3
Treenuts	212	62.6	7.8	26.7	108.4
Fruits	48	59.9	53.6	51.0	78.6
Stimulants	57	60.4	106.2	60.8	155.8
Spices	288	97.6	25.2	29.8	84.6
Agricultural crops (Average across all crops)	186	37.4	15.5	15.6	30.4

Source: Based on Uwingabire and Gallai (2024) and own results. Note: Average price changes are weighted by the value of crops. As all crops in the UG study and in model A have equal expenditure and production shares, the simple and weighted averages results are identical.

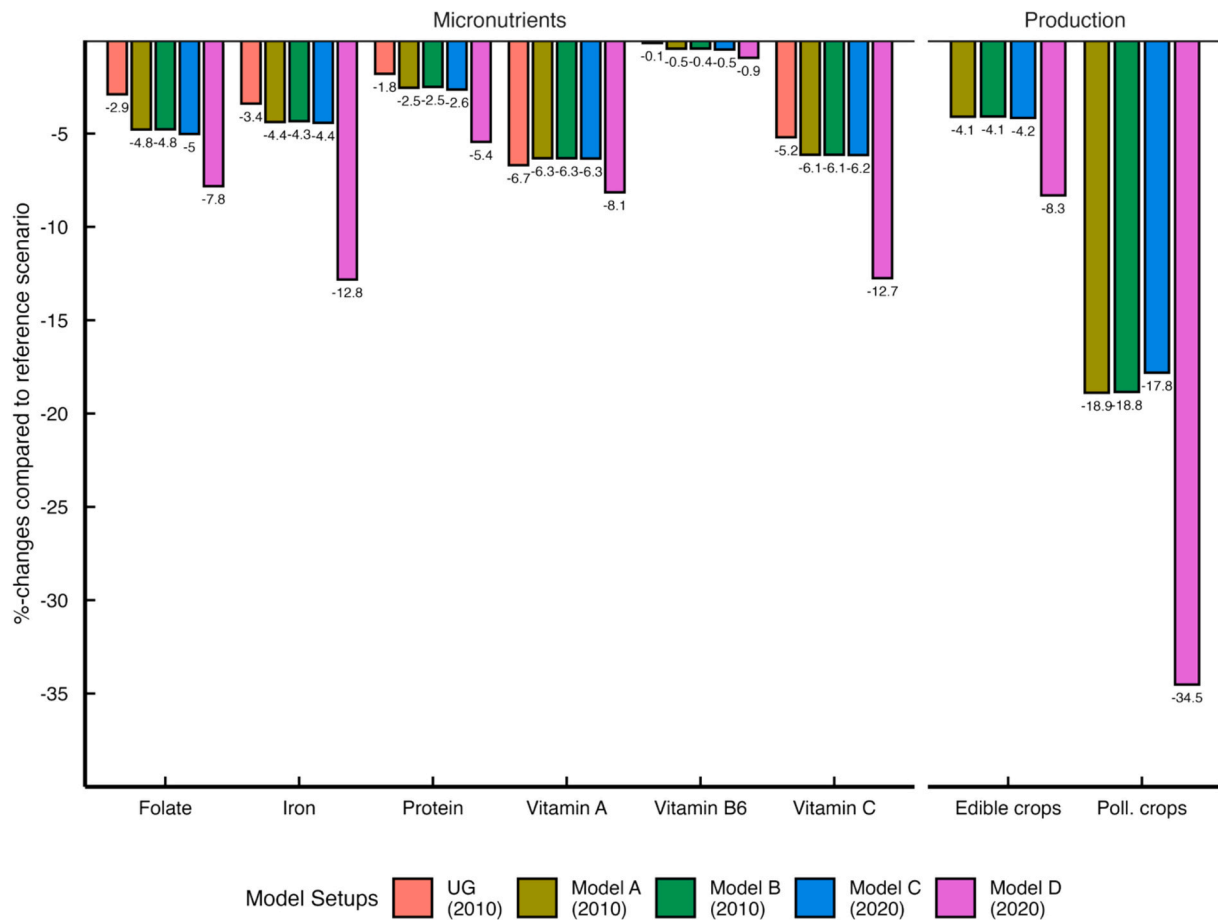


Fig. 2. Changes in global micronutrient availability and crop production after a 100 % collapse in pollination services. Note: Aggregate crop production changes are reported based on physical quantities not weighted by value. The UG study does not contain results for global crop production changes and reports the changes in micronutrient availability as a bar chart (See figure 4 in the UG study). The exact percentage changes were provided as data labels, except for protein and Vitamin B6, for which the changes were visually estimated.

Table 5

Regional % changes in food demanded (quantity) and Vitamin A availability at the FAO sub-region level.

		Food Demand (Quantity)				Vitamin A availability			
	FAO sub-region	Model A (2010)	Model B (2010)	Model C (2020)	Model D (2020)	Model A (2010)	Model B (2010)	Model C (2020)	Model D (2020)
Africa	Northern Africa	-4.1	-5.3	-4.9	-7.0	-6.3	-17.1	-12.1	-15.9
	Western Africa	-4.1	-1.5	-1.5	-6.3	-6.3	-1.7	-2.7	-4.7
	Eastern Africa	-4.1	-1.0	-1.7	-2.7	-6.3	-0.7	-1.2	-1.4
	Middle Africa	-4.1	-1.0	-1.0	-4.4	-6.3	-2.4	-1.8	-2.7
	Southern Africa	-4.1	-2.2	-1.9	-2.7	-6.3	-9.1	-7.4	-9.1
Americas	Northern America	-4.1	-3.3	-3.5	-4.5	-6.3	-5.6	-5.2	-6.7
	Central America	-4.1	-2.5	-2.5	-6.2	-6.3	-12.6	-12.4	-17.7
	Caribbean	-4.1	-3.1	-3.9	-7.6	-6.3	-8.2	-11.0	-18.6
	South America	-4.1	-1.4	-1.5	-2.6	-6.3	-8.8	-7.9	-11.0
Asia	Eastern Asia	-4.1	-8.8	-8.8	-11.2	-6.3	-4.8	-5.5	-6.7
	Southern Asia	-4.1	-2.8	-2.6	-4.5	-6.3	-18.5	-15.3	-19.5
	South Eastern Asia	-4.1	-2.3	-2.4	-22.8	-6.3	-5.2	-5.6	-8.3
	Central Asia	-4.1	-8.3	-9.1	-10.2	-6.3	-6.1	-6.5	-7.5
Europe	Western Asia	-4.1	-7.4	-7.3	-10.3	-6.3	-19.3	-18.2	-23.7
	Eastern Europe	-4.1	-4.1	-4.4	-6.2	-6.3	-8.1	-10.4	-13.3
	Northern Europe	-4.1	-4.2	-4.2	-5.8	-6.3	-3.7	-4.0	-6.0
	Western Europe	-4.1	-4.2	-4.4	-6.2	-6.3	-5.6	-6.2	-8.3
	Southern Europe	-4.1	-5.4	-5.3	-7.4	-6.3	-12.3	-13.4	-17.3
Oceania	Australia and New Zealand	-4.1	-2.1	-2.2	-2.9	-6.3	-10.3	-10.1	-12.5
	Melanesia	-4.1	-3.4	-3.1	-17.8	-6.3	-0.1	-0.1	-0.1
	Micronesia	-4.1	-11.9	-12.2	-18.7	-6.3	0.0	-0.1	-0.8
	Polynesia	-4.1	-12.8	-13.1	-20.8	-6.3	-21.3	-22.5	-27.4
Global		-4.1	-4.1	-4.2	-8.3	-6.3	-6.3	-6.3	-8.1

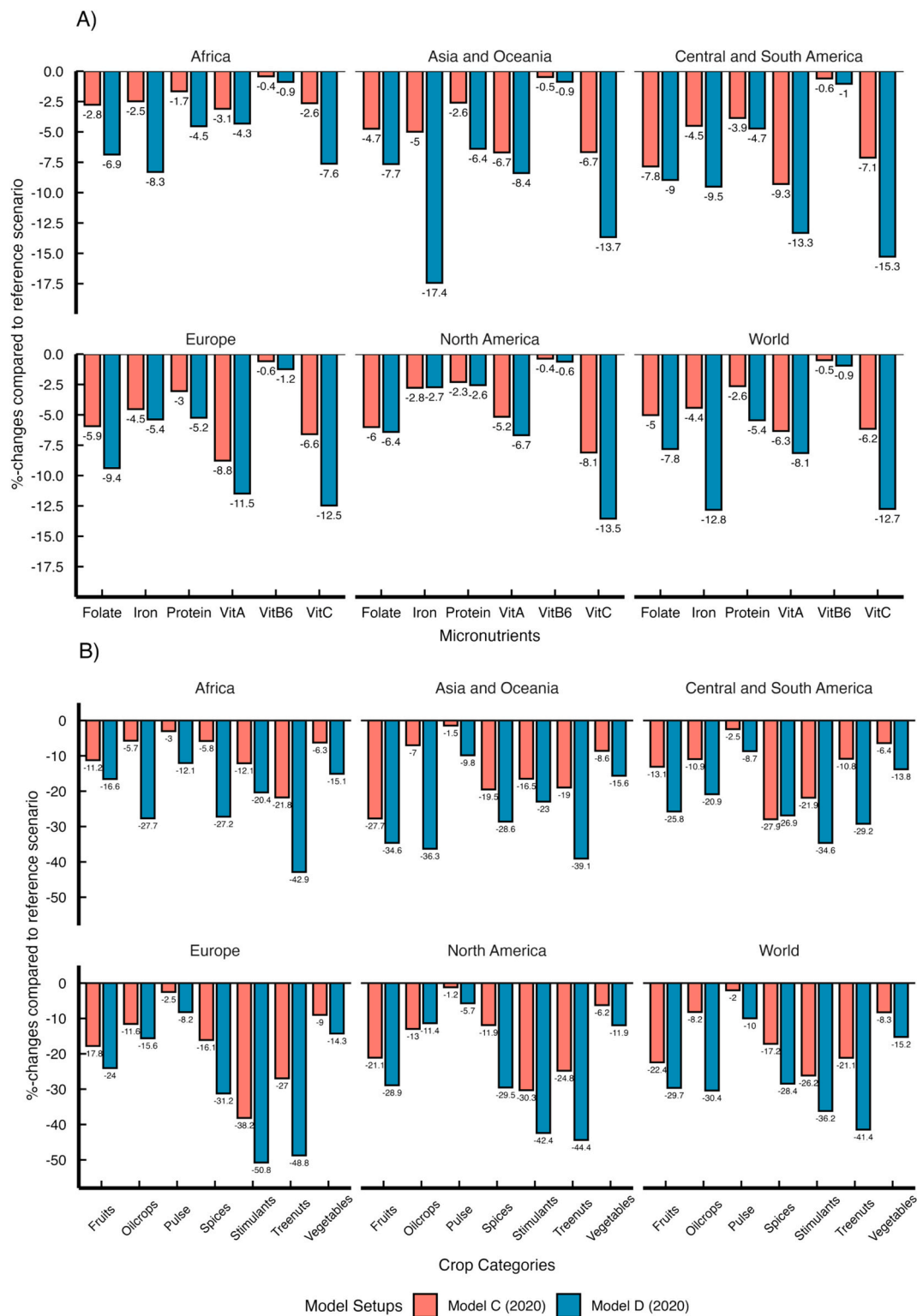


Fig. 3. Relative changes in A) Regional micronutrient availability; and B) Regional food demand in 2020 according to model setups C and D. Note: Dependence ratios in model setup C are based on [Klein et al. \(2007\)](#) and in model setup D are based on [Siopa et al. \(2024\)](#). Source: Own analysis.

unaffected by a pollinator decline.

The relevance of updated and more accurate data on dependence ratios becomes evident when comparing the impacts on micronutrient availability and food demand from models C and D. [Fig. 3](#) illustrates changes at both global and regional levels in micronutrient and food availability. The regional classifications are aggregated FAO sub-regions at the continental level. Compared to model C, model D shows a greater

decline in micronutrient availability across almost all regions and nutrients. Globally, the availability of iron and Vitamin C declines the most, by almost 13 % in model D, while in model C they decline by only about half that amount. Asia and Oceania as well as Central South America report particularly high declines, while Africa and North America experience only moderate declines. Changes in food demand vary substantially across crop categories and regions. Globally, food

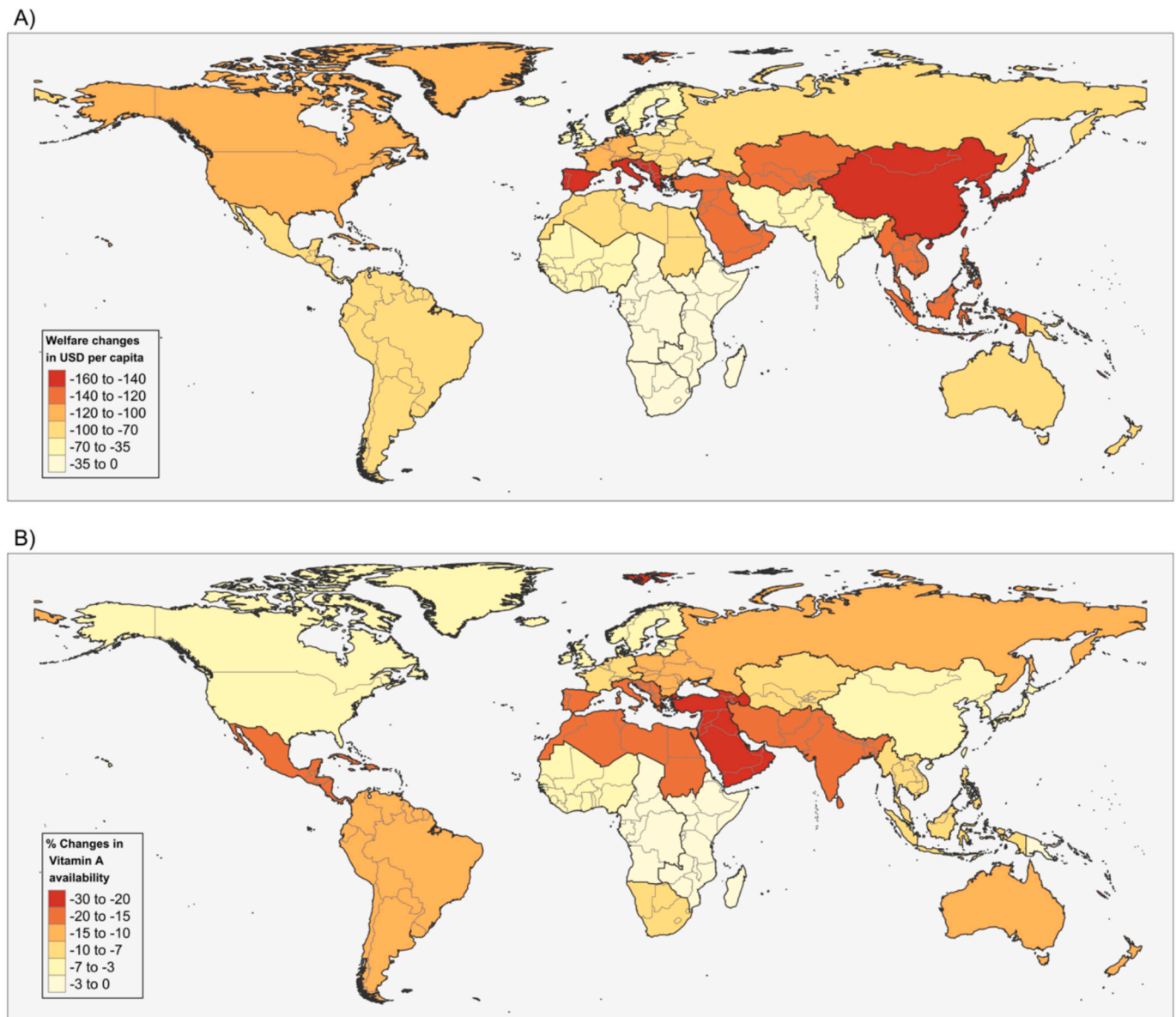


Fig. 4. Map A) shows the welfare changes in USD per capita; and B) the relative change in Vitamin A availability. Both maps present results from model setup D, which simulates a 100 % pollinator collapse in 2020 with dependence ratios from [Siopa et al. \(2024\)](#). Detailed numerical results are provided in [Tables 3 and 5](#) for welfare and Vitamin A availability changes, respectively.

demand declines are consistently higher across crop categories in model D compared to model C. In model D, global availability of tree nuts and stimulants declines the most, by 41 % and 36 %, respectively. Notably, Europe experiences the greatest decline in demand for these two crop categories, followed by North America. In particular, stimulants (mostly coffee and cocoa) are crops for which both regions almost exclusively rely on imports. In model D, demand changes for pulses and vegetables are relatively uniform across regions, whereas fruit demand declines the most in Asia and Oceania, followed by Central and South America.

The spatial divergence of changes in welfare and micronutrient availability at the FAO sub-region level from model D under a 100 % pollinator decline is illustrated in [Fig. 4](#). Globally, the mean welfare decline is 93 USD per capita ([Table 3](#)) and is highest in East Asia (−157 USD per capita) and Southern Europe (−148 USD per capita). However, even low absolute welfare changes, as seen in most Africa regions, may be critical given their low GDP per capita. Welfare changes do not directly correspond to changes in Vitamin A availability. Vitamin A availability decline the most in Polynesia (27.4 %), Western Asia (23.7

%), and Southern Asia (19.5 %). As [Uwingabire and Gallai \(2024\)](#) also note, these changes should be interpreted in the context of existing micronutrient deficiencies, particularly Vitamin A, which are especially high in the Global South.

4. Discussion

Changes in pollinator populations, whether partial declines or complete collapses, can significantly impact crop yields. These effects propagate through trade linkages from producing countries to importing countries where the affected crops are consumed. Consequently, welfare and nutritional impacts may occur in regions far removed from the initial production losses. Assessing the effects of such events on food security and economic welfare across world regions requires a model that accounts for international trade and the economic behavior of producers and consumers within each region. Additionally, the productivity shock—and thus the supply shock—of pollination-dependent crops must be estimated, typically using dependence ratios.

The first section of the discussion examines the insights gained from replicating and extending the study by [Uwingabire and Gallai \(2024\)](#). The second section presents empirical findings using the extended model, calibrated with the most recent bioeconomic data on dependence ratios and agricultural production, demand, and trade data from 2020, to simulate a global pollinator collapse.

4.1. Insights from replicating and extending the UG study

The multi-market model (and its variants) presented in here, which derive from [Uwingabire and Gallai \(2024\)](#), can be described as “simple”⁵ for at least three reasons. First, it employs basic functional forms, such as Cobb-Douglas demand and unitary supply elasticity. Second, it assumes zero cross-price elasticities, meaning it does not account for cross-market interactions. Third, it omits market distortions caused by policies such as tariffs, subsidies, or taxes.

Despite its simplicity, the model remains defensible for at least three reasons. First, it avoids the risk of becoming a “black box,” a common critique of more complex economic simulation models. Second, it allows for highly detailed coverage of edible crops and regions. Third, in the context of modeling pollinator declines, it addresses a significant research gap by explicitly incorporating international trade – even though there are many avenues of how trade can be modeled in a more sophisticated manner (see below). Previous studies have often relied on even simpler approaches ([Murphy et al., 2022](#); [Smith et al., 2015](#)) or considered trade only indirectly, if at all ([Gallai et al., 2009](#); [Lippert et al., 2021](#)). A notable exception is [Bauer and Sue Wing \(2016\)](#), although their global general equilibrium model features a high degree of crop aggregation.

Regardless of a model’s simplicity or complexity, it should be applied rigorously, with its mechanisms clearly understood and critically evaluated. Through the reconstruction of the UG model, I identified several methodological issues. Model A, designed to replicate the UG model as closely as possible, reveals fundamental differences in the underlying equations, which account for a significant portion of the discrepancies in the results with the UG study. Furthermore, a comparison with model B suggests that the assumptions underpinning the UG model (and model A) further amplify distortions in the estimated economic impacts. These findings are elaborated upon in the following discussion.

4.1.1. Methodological discrepancies

The UG study employs a price equation that appears to estimate price changes directly, rather than allowing prices to be determined endogenously within the model. This approach is potentially problematic as it seems to rely on a closed-economy calibration of the supply slope parameter, despite using production data derived from an observed open-economy setting. In contrast, model A adopts a straightforward and interpretable price equation to calibrate initial price levels, with prices being implicitly determined by global market-clearing conditions within the model. Notably, the UG model does not appear to incorporate market-clearing conditions. In addition, the UG model reports changes in regional trade balances and a global producer surplus loss of USD 672 billion. This outcome appears inconsistent with the assumption of unit elastic supply and demand behavior. I acknowledge the possibility that I have misinterpreted the UG model and that any errors may be due to my own understanding.

The UG study reports a significantly higher global welfare decline (USD 2012 billion) than model A (USD 959 billion). This discrepancy appears to result from the differences in producer surplus changes and the remarkable agricultural crop price increase of 186 %, which is five

times higher than the price increase (37 %) observed in model A. These discrepancies between the UG model and model A are likely due to differences in model equation derivation and calibration, since both rely on similar (if not identical) data or assumptions.

4.1.2. Sensitivity of results to changes in underlying assumptions and data

A comparison of model B with the UG model and model A reveals that results are highly sensitive to changes in assumptions and data. The Heckscher-Ohlin model uses homothetic demand for theoretical simplicity, focusing on factor endowments and trade while disregarding heterogeneous preferences. It is unclear why the UG model, which significantly departs from a Heckscher-Ohlin framework, adopts the assumption of homogenous preferences in the form of equal budget shares for all crops. This assumption disproportionately inflates the importance of pollination-dependent crops. A more reasonable approach would be to use global production shares to approximate crop-specific preferences, which could then be uniformly applied across all regions. Additionally, the UG model (and model A) derives crop values from total food expenditure data, further overestimating the value of pollination-dependent crops. The UG study provides insufficient detail on how food budget data was estimated and the exact data sources used, complicating replication. Nevertheless, I commend the authors for their responsiveness in sharing data and clarifying information through personal communication upon request.

Model A is extended in models B to D by incorporating heterogeneous rather than homogeneous preferences and by using FAOStat producer prices and trade data to estimate each region’s food budget. These models report price changes that are relatively consistent with those found in [Bauer and Sue Wing \(2016\)](#) and [Feuerbacher et al. \(2024b\)](#). Direct comparisons with other models are challenging due to differences in model approaches and features. For example, none of the models analyzed here include cross-price effects, while the cited studies do. However, even considering these differences, the UG study’s reported average price increase of 186 % appears unprecedented. The price changes in crops are driven by the productivity shocks, which are identical for the UG study and models A to C. Only model D relies on different productivity shocks, which are on average much higher.

Compared to the UG model and model A, the total global welfare declines reported by models B and C are significantly lower, at USD 301 billion and USD 424 billion, respectively. These estimates align relatively well with studies that assume a medium- to long-term adjustment horizon (e.g., [Bauer and Sue Wing, 2016](#); [Feuerbacher et al., 2024b](#); [Lippert et al., 2021](#)). In contrast, the welfare changes reported by the UG study and model A are striking. In case of the UG study, they even exceed the welfare estimate by [Lippert et al. \(2021\)](#) for a short-term horizon—a scenario typically considered the most extreme because it assumes no supply-side adjustments. Notably, the UG model’s (implicit) time horizon allows for supply adjustments, a factor that should be carefully considered when interpreting its results.

4.2. Reflection on empirical findings and outlook

The extended model D uses the most recent bioeconomic data on crop yields’ dependence on pollination services from [Siopa et al. \(2024\)](#) to simulate a global pollinator collapse. According to the mean dependence ratios of this data, about 17 % of global crop production value depends on pollination services,⁶ while the share in global value of agricultural trade is even 28 %. This reflects their strong international demand and higher tradability compared to other agricultural commodities. Using the mean dependence ratios from [Klein et al. \(2007\)](#), which was so far commonly used by previous studies, only 11 % and 20

⁵ Models are always an abstraction of reality, and in the spirit of Occam’s razor, they should not be made more complex than necessary. Thus, describing this model as “simple” is not meant in a pejorative sense but rather acknowledges its deliberate design for key economic mechanisms.

⁶ This calculation is analogous to the ratio of vulnerability which divides the fraction of production value dependent on animal-mediated pollination by the total production value (see [Gallai et al., 2009](#)).

% of global crop production and trade value depends on pollination services (Appendix F). These relative shares indicate already that the global agri-food system is much more dependent on pollination services than previously thought, which is also reflected in the model results.

Model D uses the Siopa et al. data to simulate a global pollinator collapse in 2020, reporting a decline in total welfare of 729 billion USD, representing 0.9 % of global GDP and 15.6 % of global agricultural production value used for human food in 2020. This compares to 424 billion USD (0.5 % of global GDP and 9.0 % of global agricultural production value for human food in 2020) reported by model C using the Klein et al. data. The welfare estimate from model D is also substantially higher than those from comparable simulation model-based studies that allow for market adjustments. The magnitude of welfare effects reported by Bauer and Sue Wing (2016) and Feuerbacher et al. (2024b) represent 0.3 % and 0.4 % of global GDP in 2004 and 2017, respectively.

Model D projects crop prices to rise by 30.4 %, compared to just 15.6 % in model C. This discrepancy is entirely due to the updated data on dependence ratios. The price change estimate from model D exceeds the few available results from other studies. Similar to model C, Feuerbacher et al. (2024b) report a 15.3 % increase in crop prices using the Klein et al. (2007) data in combination with the global partial equilibrium model CAPRI. Bauer and Sue Wing (2016), also using the Klein et al. data, does not explicitly report an aggregated change in crop prices, but a graph with region and commodity specific price changes suggests that the average price change is below 20 %.

Model D reports substantially higher negative impacts on food security than previously known. Smith et al. (2015) used the Klein et al. (2007) data to assess the health impacts from a hypothetical total collapse in pollinators and found Vitamin A and folate declined by 2 % and 6 % across all WHO regions. Model D instead reports declines ranging from 4 % to 13 % across all world regions (Fig. 3). For Africa specifically, the most vulnerable region, Smith et al. (2015) reported declines of about 3 % for both Vitamin A and folate, respectively. These results for Africa are strikingly similar to those of model C, whereas model D shows substantially higher declines of 4 % for Vitamin A and 7 % for folate.

Hence, it becomes clear that based on the new data on dependence ratios from Siopa et al. (2024), the impact of pollinator declines on economic welfare and food security is substantially higher than previously assessed. However, the analysis presented here, like previous analyses, is subject to various limitations. Beyond questions on modeling international trade and determining the most suitable scale of data aggregation, there are also valid concerns about the actual scope and likelihood of a catastrophic pollinator collapse and the role of adaptation measures.

While the scenario of a global pollinator collapse may be considered hypothetical and unlikely (Melathopoulos et al., 2015), alarming rates of decline have been reported for various insect taxa (Hallmann et al., 2021; Möller, 2019; Seibold et al., 2019; Van Klink et al., 2020). However, data on population trends for pollinators remain scarce, and to the author's knowledge, no comprehensive global dataset is available. Furthermore, simulating a global partial decline in pollinator populations ideally requires detailed knowledge of the agro-ecological relationships between pollination service provision and yield changes. Unfortunately, such information is limited to a small number of crops and regions (Groeneveld et al., 2010; Reilly et al., 2020a).

The model considers adaptations by consumers and producers within regions and across regions through trade. Feuerbacher et al. (2024b) show that cross-price effects and expansion of agricultural land are crucial mechanisms buffering the direct effects of pollinator declines. Melathopoulos et al. (2015) rightly point out that the ecological data on dependence ratios is often based on a few field studies and that it is often unclear to what extent pollination is provided by managed or wild pollinators, even though the data foundation is steadily improving (Allen-Perkins et al., 2022; Siopa et al., 2024). They further note that beyond the crops included in the Klein et al. (2007) review, there are

many other crops such as alfalfa or clover that depend on animal-mediated pollination services which would indirectly impact the livestock sector (Feuerbacher et al., 2024a; Melathopoulos et al., 2015). For these forage crops and many vegetables, a collapse of pollination services would substantially decrease the seed yield resulting in additional and substantial implications for welfare and food security, which so far have been understudied (Feuerbacher et al., 2024a). Moreover, the knowledge on how declines in animal-mediated pollination services can be mitigated is growing, for example through the cultivation of less pollination-dependent crops and varieties, manual pollination (Wurz et al., 2021), and even the use of robots or drones (Shukla et al., 2022). These aspects are often overlooked in economic assessments of pollinator population changes but should be discussed and acknowledged.

The model replicated and extended here (model setups A to D) offers easily interpretable mechanisms. It can also be readily updated to more recent data, as demonstrated by using publicly available FAOstat data from 2010 and 2020. The model is parsimonious in terms of parameter requirements, which is often a criticism of more sophisticated agro-economic market models. However, the model's relatively simple design also entails various limitations. The model's representation of trade assumes perfect substitution between imports and exports, which does not sufficiently reflect reality, here economies simultaneously import and export the same commodities. This could be rectified using the Armington assumption, as employed by more sophisticated agro-economic market models like CAPRI or MAGNET, which also consider policy distortions through tariffs, subsidies, and taxes.

Moreover, the model assumes constant food expenditure with fixed, exogenous budget shares for each crop. Alternative functional forms, for example, using nested constant-elasticity-of substitution functions, would allow for more realistic model behavior but would require substantially more parameters. In a similar fashion, an advanced version of the model could incorporate households' trade-offs between food and non-food consumption to endogenize the total expenditure on food.

A strength of the model presented in here is that it covers all edible crops. This lowers the risk of aggregation bias as welfare effects change nonlinearly with the magnitude of dependence on pollination services (Lippert et al., 2021). However, the assumption of unit elastic demand and supply fails to capture cross-price effects. This is a limitation given the wide variation in pollination service dependence across crops, making non-pollination-dependent crops relatively more attractive, as found by studies using models that capture cross-price effects, such as Feuerbacher et al. (2024b). While the model's depiction of consumer behavior is overly restrictive, it arguably overestimates the adaptive capacity on the supply side, which is also governed by unit elastic supply and not limited by land constraints, especially for crops that require very specific agro-climatic conditions, as already highlighted by Lippert et al. (2021).

This paper reported, by building on the UG study, a detailed global partial equilibrium model. This model could be further extended in various forms to address the above mentioned limitations. Future research could also explore the impacts on different household types, or the role of land markets. The UG study briefly suggests that pollinators could be modeled as an explicit (quasi-market based) input or production factor—an idea also explored in Bauer and Sue Wing (2016). Ideally, data would be available to model managed and wild pollinators as separate production factors. Such an approach would enable investigating of differences in pollinator endowments, which could be incorporated into a trade model with explicit treatment of production factors (e.g., applied general equilibrium models). In addition, future assessments of pollinator declines could focus on simulating gradual pollinator declines, which requires better data on pollinator trends and agro-ecological relationships between partial pollinator declines and yield changes (Lippert et al., 2021; Reilly et al., 2020b).

5. Conclusions

Animal-mediated pollination services are essential for global food production, particularly for micronutrient-rich crops such as tropical fruits, coffee, and cocoa. These crops are predominantly exported from the Global South to consumers in the Northern Hemisphere. Approximately 17 % of global crop production value and 28 % of global agricultural trade depend on pollination services, making international trade a critical factor in how pollinator declines affect food availability, nutrition, and economic welfare across regions.

This study replicated and extended the global partial equilibrium model reported by Uwingabire and Gallai (2024). The replication identified several methodological and empirical flaws in the original analysis, notably an overestimation of the impacts of pollinator declines on crop prices and economic welfare. These findings highlight the need to refine modeling frameworks for accurate assessments of pollinator dependence and its consequences. Building on the replication, the model setup D updates crop production and trade data to 2020 and also incorporates the latest bioeconomic data on pollination dependence. Using model D, simulations of a hypothetical global pollinator collapse estimate a 30 % increase in crop prices, resulting in a global welfare loss of 729 billion USD (0.9 % of global GDP in 2020 or 15.6 % of the value of global agricultural production used for human food in 2020). The analysis shows significant reductions in essential micronutrients, including an 8 % decline in global Vitamin A availability, with severe implications for food and nutrition security. The findings emphasize the need to account for international trade and regional heterogeneity when assessing the impacts of pollinator declines. While the model relies on relatively simple assumptions about market and trade mechanisms, it provides an initial framework for incorporating international trade with detailed crop coverage. Future research should refine and advance this approach.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used chatGPT in order to improve language and readability of the manuscript. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CRedit authorship contribution statement

Arndt Feuerbacher: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolecon.2025.108565>.

Data availability

The underlying data and model code are available as an electronic supplement and on github (<https://github.com/ArndtFeuerbacher/PollinationCropMarketModel>).

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