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Mapping potential conflicts between global agriculture and terrestrial conservation

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Demand for food products, often from international trade, has brought agricultural land use into direct competition with biodiversity. Where these potential conflicts occur and which consumers are responsible is poorly understood. By combining conservation priority (CP) maps with agricultural trade data, we estimate current potential conservation risk hotspots driven by 197 countries across 48 agricultural products. Globally, a third of agricultural production occurs in sites of high CP (CP > 0.75, max = 1.0). While cattle, maize, rice, and soybean pose the greatest threat to very high-CP sites, other low-conservation risk products (e.g., sugar beet, pearl millet, and sunflower) currently are less likely to be grown in sites of agriculture–conservation conflict. Our analysis suggests that a commodity can cause dissimilar conservation threats in different production regions. Accordingly, some of the conservation risks posed by different countries depend on their demand and sourcing patterns of agricultural commodities. Our spatial analyses identify potential hotspots of competition between agriculture and high-conservation value sites (i.e., 0.5° resolution, or ~367 to 3,077km^2, grid cells containing both agriculture and high-biodiversity priority habitat), thereby providing additional information that could help prioritize conservation activities and safeguard biodiversity in individual countries and globally. A web-based GIS tool at https://agriculture.spatialfootprint.com/biodiversity/ systematically visualizes the results of our analyses.

conservation risk hotspots | agricultural trade | biodiversity footprint

Significance

Despite efforts to promote sustainable agriculture, food and agricultural production remain the main driver of global biodiversity loss. However, where food production conflicts with biodiversity conservation and which products and countries contribute the most has not been as comprehensively assessed. Based on spatial models of farming and conservation priority areas, we estimate how production and consumption of 48 agricultural commodities driven by 197 countries may conflict with conservation priorities for 7,143 species. This study provides a quantitative basis to better understand and manage the large-scale transformative changes between humanity and nature through decisions concerning food consumption, production, and trade.

Conversion of terrestrial habitats to farmland is the primary driver of human-induced species loss (1, 2). Risks to ecosystems and biodiversity are imposed within and beyond country borders, through domestic production and imports of food, fiber, and fuel in the developed world (3–6). Reversing this trend requires a comprehensive understanding of where competition between biodiversity conservation and agriculture is likely to occur and which downstream consumers are responsible (7). However, disentangling these linkages is difficult due to the lack of integration between agricultural, consumption, and species risk data (8).

Conflicts between agriculture and biodiversity have been a focal subject of concern in environmental footprinting of consumption. Yet, compared to greenhouse gas emissions, water demand, and land use, consumption impacts on biodiversity remain a nascent topic of analysis (9). Current knowledge on the drivers of biodiversity threats in agriculture stems from two lines of inquiry and modeling: i) integration of species, ecosystem, and habitat richness data into global macroeconomic databases, and ii) detailed case studies of high-impact products or countries which employ supply chain data of high sectoral or spatial resolution. Lenzen and colleagues offer a remarkable study of country and sector biodiversity footprints by integrating information on nationally threatened species with a global supply chain database (10). This provided a theoretical basis to examine how nations impose risks to biodiversity within a global context. Subsequent studies have employed a similar approach, making use of more detailed sectoral and biodiversity risk data to advance understanding of the products, species, and geographies implicated in the biodiversity footprints of countries.

An early advancement in global biodiversity footprinting resulted from the use of global supply chain databases with a greater diversity of agricultural sectors to better distinguish drivers of biodiversity threats (11). Physical, commodity-level agricultural trade data have further enriched the sectoral resolution of assessment to this end (4, 12–17). Characterization factors of biodiversity risks driven by consumption have also advanced in several ways when compared to earlier, count-based biodiversity metrics. Noteworthy developments within this context include the calculation and use of fractional loss of species (18), species vulnerability (19–21), thresholds for species intactness (21), and species–area relationships within biodiversity footprinting (4, 20, 22–24). While linkage of geospatial species occurrence

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information to global supply chain databases has offered the capability to construct spatially explicit maps of species threat hotspots driven by remote consumption activities (3), global spatially explicit biodiversity footprinting models do not currently capture the location and extent of agricultural production and its competition with species hotspots within countries, nor offer a detailed picture of the products responsible.

Recent case studies have sought to integrate spatially explicit agricultural production maps with species and ecosystem hotspot data. These include assessments of high-risk products [soy (25), beef (26), palm oil (27), timber (24, 28)], high-impact consumers [EU (29), Switzerland (28, 30), the United States (31, 32)], species hotspots [e.g., in South America (26, 33) and South East Asia (12)], and studies of broad land-use categories (11, 34). Although instructive, we lack a systematic overview of the location, scale, and drivers of biodiversity threats in agricultural and livestock product supply chains. As a result, there remains a mismatch between the evidence base on consumption drivers of biodiversity loss and the local, product-level data needed by governments and industry to monitor, implement, and further develop policy commitments to reverse this trend. To address this gap, we integrate conservation priority (CP) area sites based on modeling the distributions of 7,143 species, land-use maps for 48 agricultural commodities, and trade data for 197 countries, to capture how crop and animal products conflict with high-CP areas and where these implicated commodities are produced and finally consumed.

Results

A CP score for each grid cell in the model is calculated worldwide using the Zonation algorithm that produces a hierarchical ranking of CP via a strategy of minimization of marginal loss (35, 36). The CP index ranges from 0 to 1, where a higher index means a greater degree of structural connectivity within a habitat for multiple species simultaneously. Areas with CP < 0.5 are referred to as lower CP sites, sites with CP > 0.5 are referred to as medium-high value, sites with CP > 0.75 as high value, and sites with CP > 0.9 as very high CP. The potential conflict or risk between agricultural production and conservation is estimated by linking agricultural land-use area and CP values within a pixel unit (0.5 decimal degrees). We assume a higher degree of conflict is associated with i) increased land-use share in a pixel and ii) greater CP value of a pixel. While we acknowledge the uncertainty of our analysis (e.g., not accounting fully for differences in cultivation practices, habitat fragmentation, hunting pressures, and unmeasured land clearing for each commodity over time; see *SI Appendix*, *Appendix 1* for a full discussion of limitations), this spatially explicit approach allows us to provide comparable, comprehensive, and detailed assessment of agriculture–biodiversity footprints of many commodities and countries at a pixel level.

Globally, over three-quarters of agricultural land use is estimated to occur in sites of medium-very high CP (CP > 0.5) and over a third exclusively in high-CP sites (CP > 0.75). Although 23.4% of agricultural land use occurs in low-CP sites, only 5 of 48 commodities modeled (barley, other cereals, sugar beet, sunflower, and wheat) are primarily sourced (>50%) in these areas. These findings imply potentially widespread conflict between agricultural land use and conservation of biodiversity (37–39). However, such risk hotspots vary among commodities and production sources and so might be minimized by purchasing of low-conservation risk products, which we identify using the high-resolution mapping of agricultural production, species distributions, and their flows to consumers through global trade networks. The maps and data underlying this study are available online at https://agriculture.spatialfootprint.com/biodiversity/ and can also be found in *SI Appendix*. For production activity as shown in Figs. 1 and 2, land use represents the actual area where a crop is grown or an animal is raised. To link biodiversity risks to final consumer in Figs. 3 and 4, land use of crop commodities does not include croplands used for livestock feed, and land use of livestock commodities is the sum of physical area for livestock raising (housing, exercise yards, pasture, etc.) and feed croplands.

Risk Hotspots between Agricultural Production and Conservation. The degree and location of potential risk hotspots between agricultural land use and high value ecosystems and biodiversity varies substantially among commodities, as shown in Fig. 1*A*. Coffee, cocoa, plantain, and oil palm are produced almost exclusively in sites of very high CP (CP > 0.9), but cattle, maize, rice, and soybean occupy the most abundant land-use areas in those sites and pose the highest conservation risk of the commodities analyzed. Other cash crops, produced mostly for export markets, such as coconut and sugarcane, are similarly risky. However, not all cash crops are linked to biodiversity pressure; the relationship between crop export ratio and conservation risk varies widely across cultivation areas (*SI Appendix*, Fig. S11).

Our analysis also suggested key agricultural commodity sources which occupy significant land area in very high-CP areas (Table 1 and *SI Appendix*, Table S4). Brazilian cattle, soybean, maize, and sugarcane are grown on the largest areas of land at potential conservation risk hotspots. Other conservation risk commodity sources included wheat, cattle, and sheep in Australia, where humans and wild species often compete for water; cattle in Colombia, where pasture expansion for extensive grazing in the departments of Caquetá, Guaviare, and Meta occurs within high-CP tropical moist broadleaf forests; palm oil in Indonesia and Malaysia, where many endemic species are threatened with extinction; and cocoa from Côte d'Ivoire, a country rich in biodiversity and the world's largest exporter of cocoa for chocolate. These findings corroborate and expand insights from previous literature (3, 10, 17, 25, 28, 40).

In contrast, sugar beet, pearl millet, sunflower, cotton, and certain pulses, such as pigeon peas, lentils, chickpeas, and cowpeas, pose the lowest conservation risk (Fig. 1*A*). Differences in conservation risk are also observed between agricultural commodities of the same commodity group (Fig. 1*A*), such as sugarcane (high risk) and sugar beet (low-medium risk); tropical fruit (high risk) and temperate fruit (medium risk); and sweet potato (high risk) and potato (medium risk). We also find that the same commodities can pose a different conservation threat depending on their production region (Figs. 1*B* and 2). For example, soybean and cattle production in Central and South America occurs in high-CP areas (such as the state of Mato Grosso in Brazil, Chihuahua in Mexico, and the Chaco region of Paraguay), but poses a lower conservation risk in North America and Africa (Fig. 1*B*). Wheat grown in Eastern Europe has a lower biodiversity risk than wheat grown in Western Europe. For other commodities, such as maize, production occurs in low-, medium-, and high-CP areas within the same region, Asia and Pacific, preventing a simple distinction of production regions as low and high risk (Fig. 1*B*).

Conservation Risks of National Consumption. Our measure of the conservation risk posed by national demand for agricultural commodities varies between countries based on consumption and sourcing patterns. Fig. 3*A* highlights these differences for major centers of consumption. (Equivalent analysis for all 197 countries analyzed can be found in *SI Appendix*, Fig. S9.) China is responsible for the greatest agricultural land area (114,258 km^2) in very high-CP

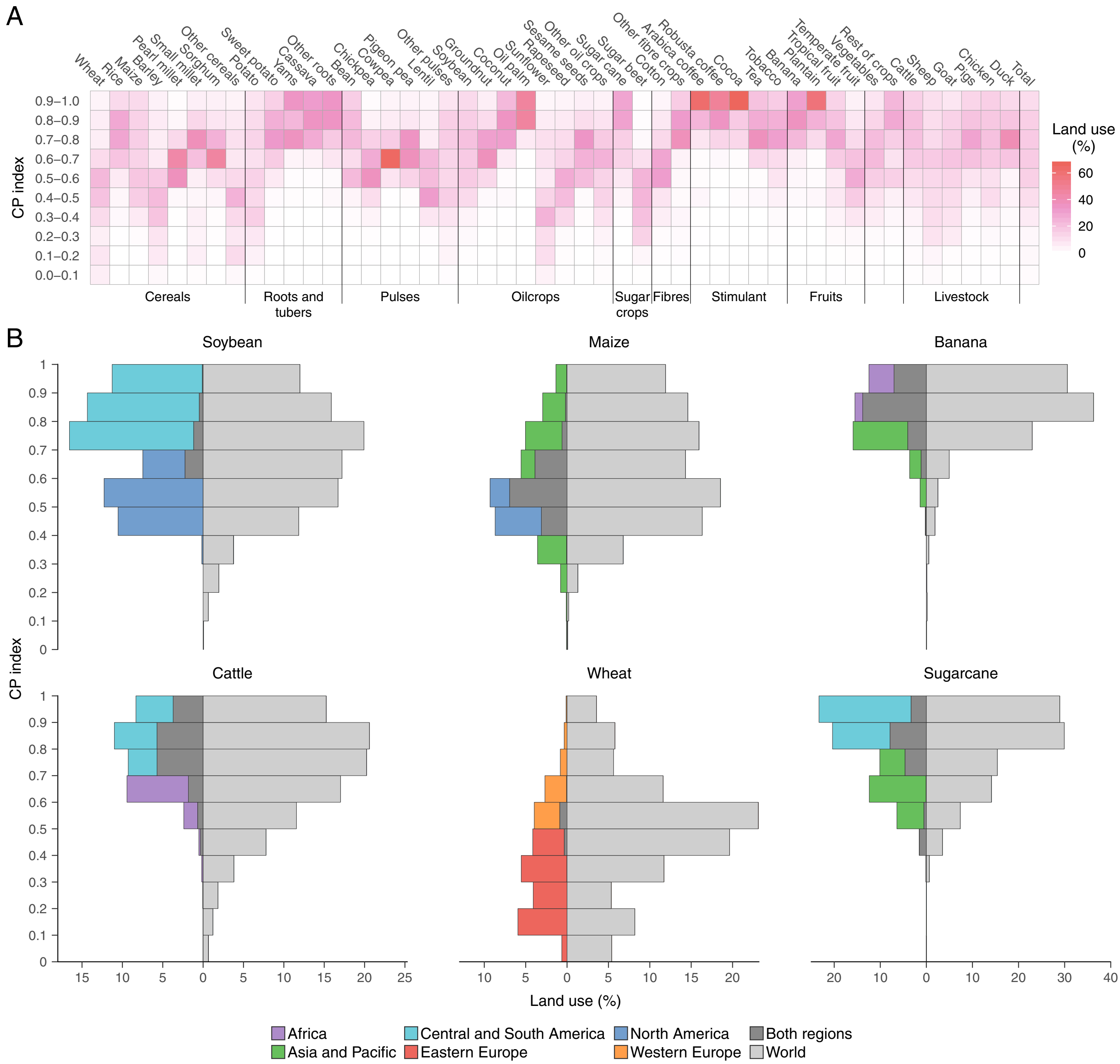

Fig. 1. Agricultural land use in conservation priority sites. (*A*) Heatmap of land-use proportions per conservation priority (CP) index interval for 48 analyzed agricultural commodities in 2010. (*B*) Distribution of regional land use (*left*) and global land use (*right*) in 2010 for major agricultural commodities by CP intervals. For each commodity, a pair of world regions (following the UN region groupings) is selected to highlight the difference in distributions of conservation priority embedded in land use. Regional land use is represented as a proportion of the total global production area.

areas due primarily to its consumption of oil crops—mainly from outside the country (74%)—and livestock. In contrast, stimulant (coffee, cocoa, tobacco, and tea) consumption in the United States and the EU-27 economic bloc is responsible for a greater share of their land use in very high-conservation areas (Fig. 3*A*). As a proportion of its overall land use, Japan has one of the highest dependencies (18.9% of total) on agricultural land use in areas of very high CP, mainly as a result of imports of cattle, stimulants, and rest of crops (e.g., rubber and tree nuts). While Japan consumes just 2.7% of Ghana's cocoa, 98% of cocoa in the country is grown on very high-CP sites. Although the EU-27's land footprint within the EU region is mostly imposed in low-medium CP areas, its agricultural sourcing beyond the EU is far riskier (from 18.2% in low-CP areas to 86.1% in very high-CP areas) (*SI Appendix*, Fig. S2). Conversely, India's land use in low-CP areas constitutes just 1.3% of its overall footprint, and its agricultural consumption is generally satisfied by domestic production. A noticeable feature of these country land-use profiles is their sourcing of the same agricultural products from high-, medium-, and low-CP locations, highlighting opportunities for derisking supply chains based on existing consumption patterns (Fig. 3*A*). For example, Japan's beef and cow's milk consumption is significantly (25.3%) from very high-CP areas, but the same risk is not associated with beef consumption in the United States, EU-27, and China. However, the scale and nature of risk hotspots between agricultural land use and CP areas will also change as a result of climate-induced shifts in species distributions, demanding adaptive governance of such risks.

Viewed within the context of economic development, high- and upper-middle-income countries are found to bear primary responsibility (60%) for land use in high-very high-CP sites based on

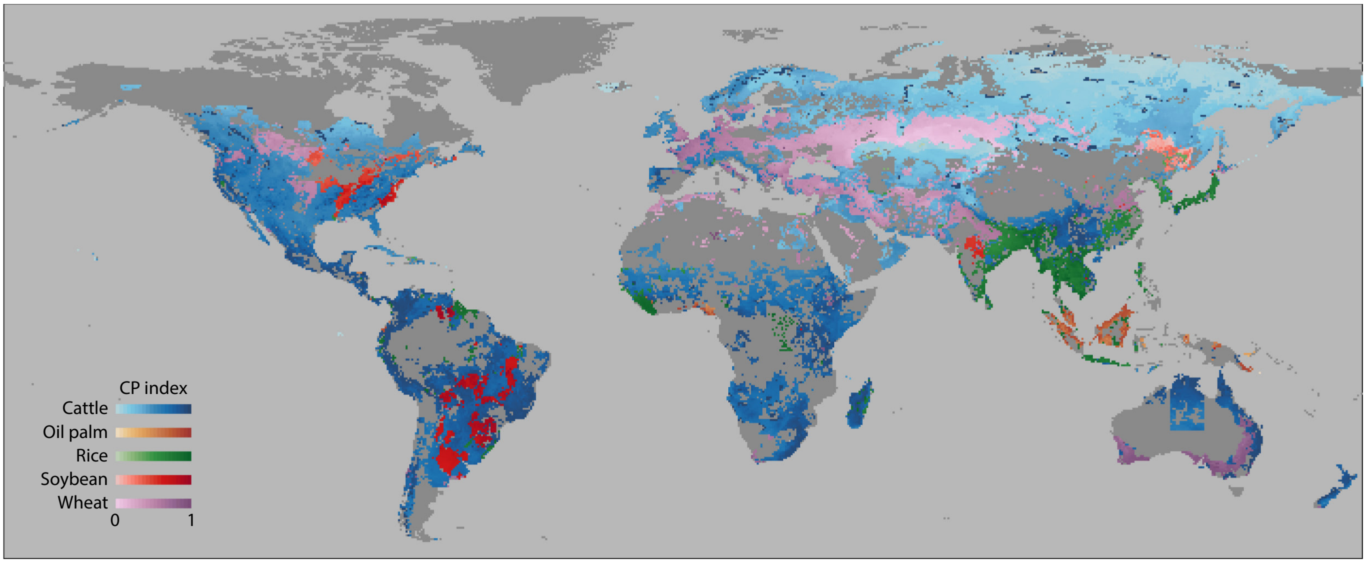

Fig. 2. Map of land use and conservation priority index for major agricultural commodities. Spatial distribution of land use for five major agricultural commodities colored according to conservation priority (low = light, high = dark) index in 2010. For each pixel, the land-use commodity with the greatest share of the five preselected commodities is shown.

the scale and sources of their consumption (Fig. 3*B*). In addition to the impact of international trade, domestic consumption poses a significant threat to biodiversity conservation in the tropics, mainly by low- and lower-middle-income countries. For certain high-conservation risk products, such as cocoa and coffee, high-income countries do not contribute to production (<0.2%) but are the major centers of consumption (>50%). After adjusting for population size, a large variation in the relative conservation risk of individual consumers in high-, middle-, and low-income countries is also evident (Fig. 3*C*). For example, high-very high-CP land use related to cattle consumption is nearly three times higher for consumers in upper-middle-income countries when compared with lower-middle-income countries and 1.7 times as large as consumers in high-income countries, but for all income groups, cattle consumption accounts for 20-42% of total consumers' high-conservation risk land use (CP > 0.75). Overall, the highest per capita land use in high-very high-CP sites is found in low-income and upper-middle-income countries, suggesting a complex and nonlinear relationship between economic development, diet, and food consumption impacts. While high-income countries have 50% higher per capita land use in high-very high CP, when comparing their consumption and production footprints, other income groups have approximately the same level of such land use for production and consumption.

National consumption of agricultural commodities is met by both domestic production and imports. As a result, nations impose risks to biodiversity within and beyond their borders. Since data availability limitations preclude our analysis from tracing the sub-national supply chain, it is not possible to identify and link the exact land use in sub-national areas to national or remote consumption of agricultural products. Yet, by combining land-use maps and the physical trade model, we can estimate the potential land-use footprint at a pixel level using a consumption-weighted approach. For 124 countries, imported agricultural commodities posed a greater risk to areas of very high CP than domestic agricultural land use. As shown in Fig. 4*A*, land use in very high-CP areas (CP > 0.9) driven by consumption in several major countries is mostly nondomestic and geographically concentrated in South-East Asia, West Africa, and the Neotropics. However, the main production regions implicated in these trade-related biodiversity risks vary by country. Chinese consumers threaten species in the Brazilian highlands for cattle and soybeans; Malaysia for palm oil; Vietnam and Thailand for rubber, cassava, and fruits; and the southern part of Australia by importing barley, sheep meat, and hides. While risk hotspots in Western African very high-CP areas are driven by European cocoa consumption, consumption across the EU-27 nations drives conservation risk hotspots in Vietnam, Brazil, Honduras, El Salvador, Guatemala, and Peru for coffee; in Indonesia and Papua New Guinea for palm oil and coffee; and in the Philippines for coconuts. US imports of agricultural commodities also risk hotspots with several very high-CP areas: beef from Australia, Mexico, Nicaragua, and New Zealand; coffee from Brazil, Colombia, Peru, Ecuador, Vietnam, Indonesia, and Central America; rubber from Indonesia, Côte d'Ivoire, Thailand, Liberia, Brazil, and Vietnam; cocoa from Western African, Indonesia, Ecuador, and Brazil; and sheep from Australia (Fig. 4*B*). For countries which are located in regions of high CP, such as Brazil and Indonesia, their biodiversity footprint falls mostly domestically rather than abroad. Commonalities between the sources of conservation risk hotspots in national supply chains highlight the need for greater transboundary cooperation to monitor, regulate, and incentivize (via certification, subsidies, and pricing) biodiversity-friendly forms of production for high-risk agricultural commodities (41). Conservation risk hotspots are associated with both domestic and export-bound production, underlining the need for mitigation efforts at both scales (*SI Appendix*, Figs. S2 and S10).

We identify major commodity export flows driving conservation risk hotspots where interventions should be prioritized (Table 2). Australian beef exported to Japan; Brazilian beef, soybeans, and pork exported to China; and Ivorian cocoa exported to the United States were responsible for the greatest land use in very high-CP areas. Overall, high-risk trade flows are dominated by traditional primary commodities: trade in cattle, palm oil, coffee, wheat, and cocoa comprises 75 of the top 100 at-risk trade flows (Table 2); see *SI Appendix*, Table S5 for complete listing. Major trading partners implicated in such high-risk trade includes Malaysia and Indonesia which export palm oil to China and India (#12, #18), respectively, Brazil and Colombia which export coffee to the United States (#11, #24), and Brazil and Paraguay which export beef to Russia (#8, #45). We develop software to

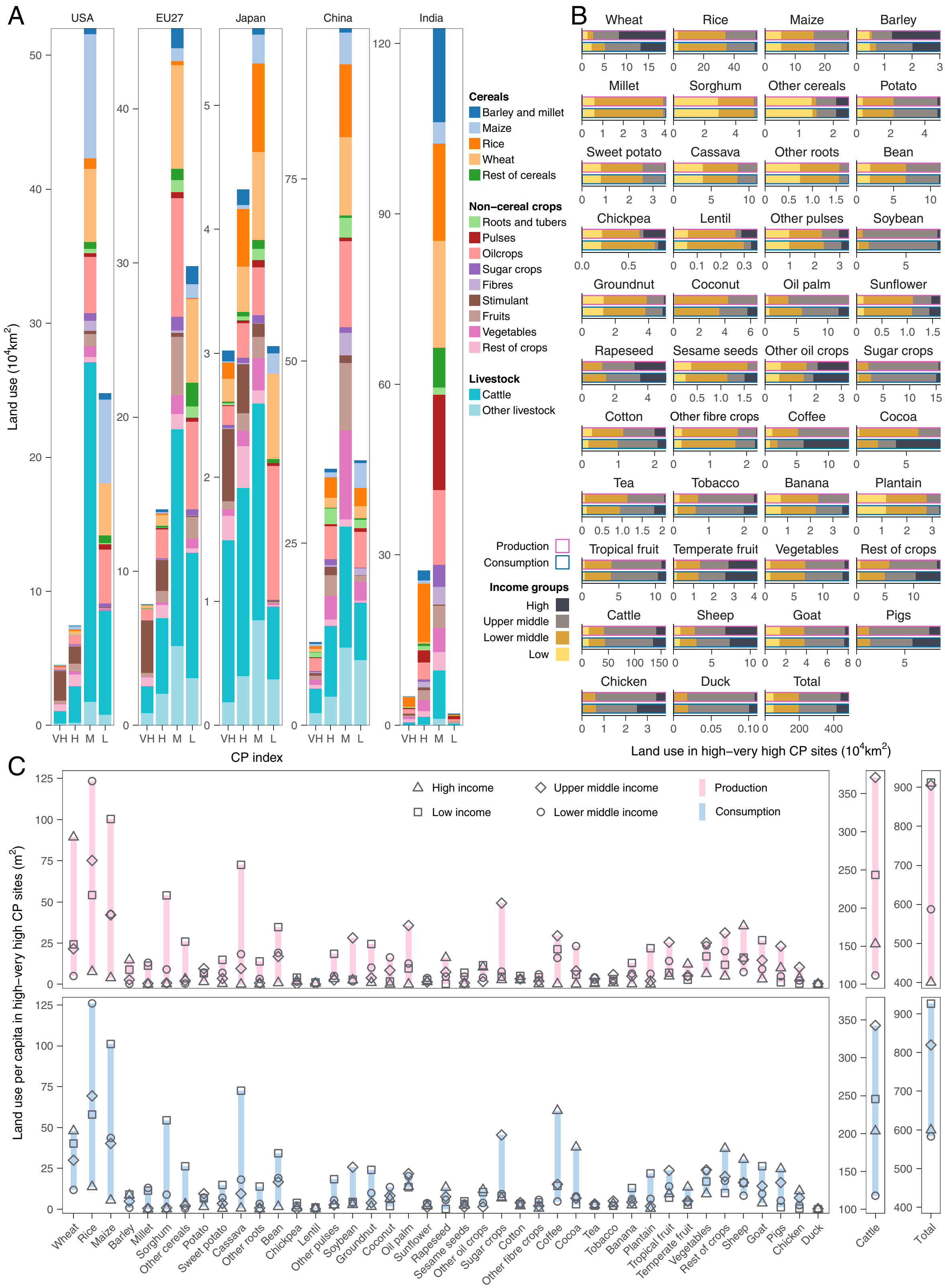

Fig. 3. Country and regional profiles of agricultural commodity demand by conservation priority level in 2010. (*A*) Land-use area embodied in consumption of all agricultural commodities by CP levels in 2010. CP levels are classified by four CP index ranges: VH (very high, 0.9 to 1.0), H (high, 0.75 to 0.9), M (medium, 0.5 to 0.75), and L (low, 0 to 0.5). EU27 refers to the European Union (EU) excluding the United Kingdom because of its withdrawal in 2020. (*B* and *C*) Overall land use (*B*) per capita land use (*C*) in high-very high-CP sites (CP > 0.75) linked to production and consumption of every agricultural commodity for four country groups, following World Bank country classifications by income level. Land use of crop commodities does not include croplands used for livestock feed. Land use of livestock commodities is the sum of physical area for livestock raising (housing, exercise yards, pasture, etc.) and feed croplands.

visualize trade flows of land use embodied in international trade for every analyzed commodity, of which an example for cocoa is shown in Fig. 4*C*.

In the past decade, sustainable procurement policies have sought to reduce commodity sourcing from high-CP areas, via zero deforestation commitments, certified commodities, and

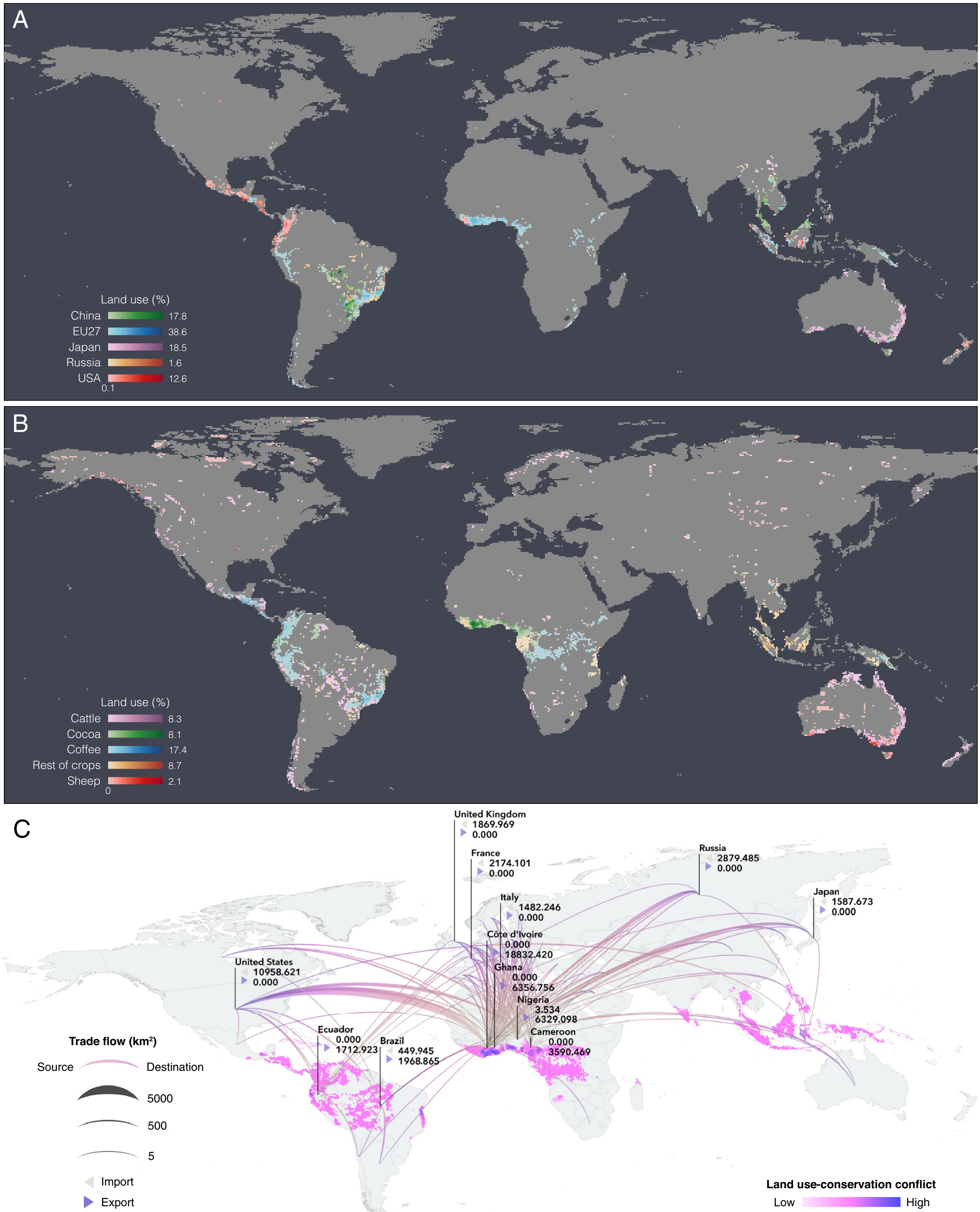

Fig. 4. Conservation risk hotspots embodied in traded agricultural commodities in 2010. (*A*) Total land use associated with agricultural commodity trade from the highest conservation priority areas (CP > 0.9) to the top five importing countries. Pixels are colored by the land-use percentage of the top importer in the entire pixel area (only where land-use ratio of an importer ≥0.1%). (*B*) Land use in the highest conservation priority areas (CP > 0.9) linked to consumption of five major agricultural commodities in the United States. Pixels are colored by the percentage of agricultural land use in the entire pixel area. (*C*) Trade flows of high-very high-CP's land use (CP > 0.75) embodied in international trade for cocoa in 2010. The countries selected on the map represent either top consumers or top producers.

supply chain screening. While these zero deforestation policies are mainly focused on cattle, soybean, and palm oil, our results suggest a need to cover other high-risk commodities, such as maize, sugarcane, coconut, and rubber. Although effective in certain contexts, such as Brazil's Amazon Soy Moratorium (42), lax enforcement, loopholes, and nonstringent environmental demands of

Table 1. Top 15 potential risk hotspots between CP (CP > 0.9) and agricultural land use per commodity and country in 2010

Country	Commodity	Used area in high-CP sites (km^2)	Share of production area in high-CP sites (%)
Brazil	Cattle	113,902	33.7
Brazil	Soybean	99,977	44.1
Brazil	Maize	62,599	48.9
Brazil	Sugarcane	44,062	49.1
Australia	Wheat	42,008	32.1
Australia	Cattle	37,949	57.5
Colombia	Cattle	32,906	60.2
Vietnam	Rice	22,623	63.1
Côte d'Ivoire	Cocoa	21,379	92.2
Malaysia	Oil palm	20,581	53.6
China	Cattle	19,871	10.0
Australia	Sheep	18,381	44.8
South Africa	Cattle	18,272	34.5
Indonesia	Oil palm	18,197	33.5
Tanzania	Cattle	17,898	35.5

such measures have failed to fully mitigate ecosystem and biodiversity risks in legally protected areas, and such areas seldom constitute the full range of CP areas being threatened by agriculture (43). As such, these areas were not excluded from our modeling.

Table 2. Top 15 potential risk hotspots between CP (CP > 0.9) and agricultural land use per commodity and trade flow in 2010

Producer	Consumer	Commodity	Area in very high-CP sites (km^2)	Area in very high-CP sites, as fraction of total (%)
Australia	Japan	Cattle	11,071	47.9
Brazil	China	Cattle	8,771	42.0
Brazil	China	Soybean	6,988	40.5
Brazil	China	Pigs	5,451	42.3
Côte d'Ivoire	United States	Cocoa	5,446	92.2
Australia	Indonesia	Wheat	4,838	34.6
Australia	United States	Cattle	4,744	49.0
Brazil	Russia	Cattle	4,392	36.9
Brazil	Iran	Cattle	3,949	40.7
Australia	South Korea	Cattle	3,874	48.2
Brazil	United States	Coffee	3,791	83.0
Malaysia	China	Oil palm	3,357	53.4
Brazil	France	Cattle	2,771	42.0
Côte d'Ivoire	India	Rest of crops	2,418	80.2
Brazil	Germany	Coffee	2,387	83.0

Equally, changes in the scale of global agri-food production and trade have compounded risk hotspots in other areas (e.g., the growth in soy imports to China, cattle ranching in Brazil, and oil palm plantations in Southeast Asia). Accounting for the dynamic temporal shifts in risks to CP areas requires further sharing of up-to-date economic and production data.

Discussion

Decisions made in relation to consumption, production, and trade of agricultural products can help protect or further endanger ecosystems and biodiversity. By investigating the spatial overlap between agricultural land use and species habitats, it is possible to estimate how, where, and what products and countries threaten CP areas (44). The findings from this study indicate that consumption of certain key products, such as coffee, cocoa, and palm oil, by a subset of countries drives land use in very high-CP areas. This corroborates prior research which also identified these crops as key biodiversity threats (45). In this study, we also identify lower conservation risk products, countries, and regions which avoid such risk hotspots, which suggests that judicious import and export policies for food, fiber, and food goods can be one factor to help minimize species threats.

The degree of spatial overlap can help identify potential conflicts between agricultural land use and species distributions at high resolution. While spatial colocation is only an approximate method for identifying potential conflict (*SI Appendix*, *Appendix 1*), this approach offers several benefits over prevailing, national-level, count-based approaches to species risk assessment (4, 10, 22, 23). Spatially explicit assessment makes it possible to map geography and scale of species threats posed by agricultural production activity. This specificity can support a triage-based approach to conservation, helping to invest scarce regulatory and governance resources into protecting high-conservation areas at greatest threat where they have not been effectively targeted to date (1, 46, 47). The ability to distinguish where commodities are produced in areas of high or very high CP can help companies define criteria and regions for screening their supply chains to avoid such potential conflicts. Such information is becoming increasingly needed in order for companies to meet sustainable procurement legislation, such as the French Loi de Vigilance, UK Environmental Bill, and recent decision of the European Union to mandate deforestation-free imports, as well as corporate sustainability initiatives, such as the Global Reporting Initiative, Roundtables for sustainable palm oil, beef, and soy, and company-level biodiversity targets. Since localized species threats are often driven by economic activity beyond the territories in which they occur, cooperation and risk sharing between supply chain actors across agricultural supply chains (e.g., producers, processors, manufacturers, supermarkets, and consumers) is needed to moderate land use in high-conservation areas. While zero-deforestation policies have succeeded in reducing deforestation, transparent monitoring of the supply chain should be improved to ensure no further agricultural expansion into natural forests and avoid laundering and leakage (40–42).

Our spatial approach has several limitations. One limitation arises because selecting a larger (or smaller) grid cell size would lead to more (or less) seeming overlap between the farming and CP layers, making our predicted area of "potential conflict" be a scale-dependent approximation. Our approach does not consider other agriculture–biodiversity conflicts including habitat fragmentation, pollution, and resource and water use, and is limited by the current accuracy of both the MapSPAM spatial crop model and of data on international agricultural trade and the actual within-country crop production locations of exported crops.

While it is recognized that conservation and agriculture activities may coexist in certain pixels that this study cannot capture (see *SI Appendix*, *Appendix 1* for more), the current resolution (0.5 decimal degrees) of CP maps enables us to update the maps easily over time and predict the potential conflicts under climate change scenarios (presented in *SI Appendix*, *Appendix 5*).

Our findings highlight the need to consider i) sourcing, ii) substitution, iii) sufficiency, and iv) transparency in order to minimize risk hotspots between agriculture and conservation. For commodities which can be cultivated in low-CP sites, such as wheat, soybeans, and maize, shifting sourcing from high- to low-conservation sites will be most effective (Fig. 2). Practically, for regions that have a large, remote land footprint in high-CP areas, such as China, the United States, India, Japan, and the EU, domestic production and regional import of staple crops could help to mitigate conservation conflicts. Such a shift in sourcing could be a likely prospect owing to geopolitical and climate-related shocks stemming from remote sourcing of agricultural products of OECD countries. Geopolitically, the COVID-19 pandemic, war in Ukraine, and conflicts in sub-Saharan Africa have exposed the instability of globally integrated food markets and the need for greater adaptiveness of local markets to respond to these shocks. Climate-induced yield shifts are predicted to result in lower agricultural productivity of staple crops in the Global South and moderate gains in the Global North (48, 49), indicating a potential for price competitiveness of staple food production in areas of low CP. Yet, in the case of China, declining domestic water availability has led to outsourcing of soybean production to Brazil, indicating a more complex relationship between environmental change and sourcing from high-CP areas (50). Understanding the geographical "stickiness" of agricultural supply chains is key to assess the scope and speed of changes to sourcing and other measures. Observations of soybean supply chains suggest that stickier traders tend to pose higher deforestation risk by maintaining sourcing and signing zero-deforestation commitments which are less effective at curbing threats to habitats (51, 52). Hence, there is a necessary role for monitoring and regulation of corporate sustainability commitments. Moreover, land sparing and land-sharing strategies must be explored within the context of sourcing to ensure restoration of habitats, ecosystems, and biodiversity through conservation areas and agro-ecological farming practices (53).

Where changes to sourcing are not feasible or only partially effective, substitution in the consumption and use of agricultural products which meet a similar nutritional and functional role is desirable, such as switching from livestock to pulses, sugarcane to sugar beet, and tropical to temperate fruit. However, if increased consumption of such products is not accompanied by significant "disadoption" of high-impact products, the total biodiversity risk of food consumption may increase (54). Limiting consumption of agricultural commodities which pose a high-conservation risk, such as coffee, cocoa, and oil palm, is also key to reconciling agriculture and conservation activities. Alexander et al. (55) show that just marginal shifts in food consumption habits; reduced food waste; switches from ruminant to plant-based, insect, and monogastric protein sources; and replacing marine-sourced seafood with aquaculture products help to significantly reduce agricultural land use which in turn can alleviate pressures on conservation priority areas. Several barriers and opportunities exist in shifting consumption and production patterns away from high-CP sites and products. The case of livestock products is an opposite example to understand these owing to the high risk it poses to high-conservation priority areas and its role as a widely studied product in behavioral and policy studies. Empirical observation indicates a strong relationship between per capita income and meat consumption (56) which signals the need for policy interventions to curb livestock production. Restructuring physical microenvironments to improve the availability and accessibility of meat alternatives offers an effective and publicly acceptive measure within this context (57). While negative labeling of products has been shown to be more effective than positive labeling at shifting consumption patterns (58), as well as arguing shifts on the grounds of health rather than environmental benefits (59), there is also a positive, potentially causal link between perceived effectiveness of interventions and public acceptability, suggesting a role for education and public information campaigns in shifting awareness of biodiversity-(un)friendly products to open space for acceptable and effective interventions (60). However, several barriers remain to demand-side dietary interventions. First, there is a need to better distinguish high- and low-impact consumers within countries where policy measures should be targeted (61). This relies on using micro-consumption data instead of nationally averaged consumption accounts to profile biodiversity footprints of consumers by sociodemographic groups. Such data could be integrated into the framework of analysis presented in this study. Second, dietary shifts call for wide-scale changes to production systems and potential land sparing which may negatively impact farmer livelihoods. Within this context, agri-environmental policies are needed to support, financially and technically, farmers to transition toward agro-ecological farming methods and production. However, we must also carefully monitor deforestation due to farmland expansion from declining agricultural productivity (62). The uptake of such schemes relies on communication to and engagement of farmers at the early stages of policy development (63), but may face continued resistance from large-scale farmers who are less willing or able to change their production (64). Nevertheless, the widespread availability of synthetic animal protein within the next decade also signals an inevitable decline in the competitiveness of intensive livestock production (65). Third, consideration of nutritional parity in dietary transitions remains a concern within low-income countries and requires modeling both the ecological and health outcomes of policy and scenarios (66).

Although not explored within this study, closing yield gaps through improvements in agricultural productivity are important to consider alongside alternative sourcing and dietary change to mitigate pressures on conservation priority areas (67). Improvements in agricultural productivity may lead to greater food self-sufficiency of countries currently outsourcing their agricultural production to areas of high conservation priority (68). However, cropland expansion and intensification in Central and South America, sub-Saharan Africa, India, and China also present a latent threat to high conservation priority areas if current food consumption patterns continue (69). Evaluating the scale and drivers of potential conflicts between agricultural land use and conservation priorities is subject to several sources of uncertainty. These concern i) the characterization of conservation threats posed by agricultural commodities, ii) their traceability to final consumption sectors, and iii) how they might evolve over time. Within this study, we assume that the threat of agricultural commodities to ecosystems and biodiversity corresponds only to the proportion of their cultivation in high-conservation priority sites. However, such proxy does not account fully for differences in cultivation practices (e.g., farming intensity, land conversion, and fertilizer application) between commodities which influence the disturbance of habitats in different ways (70). In addition, agricultural production and biodiversity conservation can coexist through sustainable farming practices (71). While a commodity can be produced in certified production areas (e.g., by Soy

Moratorium, Roundtable on Sustainable Palm Oil) or managed pasturelands instead of in unadopted areas or native grasslands, it is not possible to distinguish such different areas in our analysis because land management practices are absent from the input land-use data. Areas of abandoned, degraded, or underutilized land where land restoration can enhance crop production and avoid encroachment on high-conservation areas were also not identifiable. As more data become available, commodity-specific cultivation methods and their relative threats could be weighted in future analyses. Meanwhile, the final products and countries of demand responsible within this context are not fully identified due to data gaps which limit the traceability of agricultural commodities through complex, globalized supply chains. Improved linkage of big data on environmental and economic flows at high sectoral and spatial resolution can help toward this end and is an active area of development in life cycle analysis and economy-wide environmental footprinting (40, 72–75). Similarly, future developments in remote sensing techniques and spectral downscaling (76) could enable detailed mapping of cropland and commodity-level land clearing, offering the capability to monitor conservation conflicts in response to land-use change.

Bottom-up supply chain modeling approaches (25, 77, 78) which combine farm-level data and track trade using customs declarations offer great promise within this context, particularly for company goal setting and regulatory monitoring around sustainable procurement. For example, Trase (https://www.trase.earth/) maps company-level supply chains for major forest-risk commodities from different production areas in several tropical countries. However, such an approach often relies on proprietary data which limit its applicability globally, across many producers and commodities. Hence, there is a continued need for both comprehensive global studies, as presented here, and research based on bottom-up data collection and ground truthing. Yet, the opaque nature of agri-commodity trader and processor activities, which command majority control of this system, remains a key challenge in tracing supply chains and their impacts. Our study identifies individual case studies and high-risk commodities where such advancements should be targeted. However, understanding how the biodiversity risks highlighted within this study will change under given policies or scenarios requires dynamic and coupled modeling of the socioeconomic and environmental system and a departure from prevailing static methods of environmental footprinting and forecasting.

This study uses one selected method for evaluating conservation value, though many others are available. Although agriculture and conservation practices can coexist within a pixel, deforestation, agricultural encroachment, and hunting still occur in some protected areas worldwide due to illegal activities (79, 80). Indeed, the latest satellite-based analyses reveal a recent accelerated cropland expansion, with a significant proportion encroaching on natural forests and protected areas (81, 82). Moreover, unless protected areas are securely fenced, animal species that leave the protected area may be killed for food or to protect crops. As such, a state of potential conflict can occur where sites of high conservation priority and agriculture co-occur in a pixel, even if such a site has protected status. The conservation priority maps derived from the Zonation method will tend to prioritize tropical areas and hotspots with high richness or endemicity, but do not take into consideration other possible conservation priorities such as preserving a certain mix of biomes or hotspots worldwide. Additionally, we note that there is a structural bias, present across many studies on biodiversity, to assign lower biodiversity protection value to developed areas in Europe and North America because those areas are assessed based on their current, rather than historical or potential, biodiversity. Additionally, measuring the conservation value of land is difficult, and the results presented in this study are subject to the accuracy of the selected methods for estimating the indexed conservation priority of land. While our global CP map focuses on species richness, it could undermine the conservation of other dimensions, such as phylogenetic diversity and trait diversity. Since the overlap of key areas across different biodiversity dimensions can be low (83), careful consideration must be given to the other dimensions when shifting agricultural production or supply chains to low-CP areas. It is crucial to emphasize that this study does not account for landscape connectivity, spatial continuity of ecosystems, or ecological fragmentation within each pixel.

Climate change is likely to change the scale and nature of interactions between species and agricultural land use. Consequently, managing existing risk hotspots between agriculture and conservation priority sites will not necessarily safeguard species from future, climate-induced threats. Understanding how these tensions will evolve, alongside nonagricultural drivers of habitat degradation and loss, such as urbanization, extractive industries, and direct overexploitation, is essential to anticipate future conservation needs (3, 84–86). Conservation gains will also need to be achieved in a manner consistent with other environmental limits (climate, water, energy, and nutrient) and social goals (e.g., protection of land rights, poverty alleviation, and good nutrition) (87–91). By meeting the increasing scope and spatial resolution of assessments in other domains (92–94), the analysis developed within this study can serve as part of a broader assessment of meeting human needs within planetary boundaries. Here, our study emphasizes a crucial piece of the puzzle needed to evaluate options for sustainable food systems, which have had limited sub-national spatial coverage of biodiversity threats to date.

Methods

This study shows at a global level which recent agricultural production and consumption activities across 197 countries potentially conflict with biodiversity conservation. This is achieved by linking detailed agricultural production maps, trade data, and final consumption statistics for 48 commodities with a high-resolution map of conservation priority sites based on an ecological niche model (ENM) of over 7,000 species. This analysis extends the scope of previous studies by country coverage, spatial resolution, commodity-level detail, and integration of species threats.

Our analysis consists of two main steps to expose the location and drivers of potential conflict between conservation priority sites and agricultural products. First, we assess the level of co-occurrence between agricultural production activities and conservation priority sites. Second, we link agricultural commodity production in conservation priority sites to countries and sectors of final consumption using trade and final use data to attribute responsibility for the drivers of these potential conflicts. The data, methods, and limitations pertaining to these steps are outlined in the remainder of this section.

Overlaps between Agricultural and Conservation Value. Risk hotspots between agricultural production and conservation priorities were analyzed by measuring their spatial extent and co-occurrence in a pixel unit. Conservation risk hotspots are estimated and classified by comparing the percentage of land use for each agricultural commodity within a pixel and its CP index. Increasing land-use proportions in a high-CP value pixel causes more risk hotspots between agricultural production and biodiversity conservation. This produced a profile for each agricultural commodity which captured its production in sites of varying conservation priority. Since such profiles were built from 2010 data, we refer to sites of agricultural production in high-conservation priority areas as potential conflicts between agriculture and conservation, or "risk hotspots," accepting that the scale or severity of these conflicts may have evolved due to shifting production, consumption, trade, and land-based conservation measures. For instance, the risk level may be overestimated in some high-CP sites where agricultural expansion took place long before 2010 and existing native habitats are still intact or well managed.

A CP index ranged from 0 to 1 (*SI Appendix*, Fig. S12), which is assigned to each pixel, is identified using the Zonation conservation planning tool detailed in the studies by Moilanen et al. (35) and Moilanen (36). The Zonation is one of the most widely used tools in the field of systematic conservation planning. While biodiversity hotspots can be determined from the International Union for Conservation of Nature (IUCN) Red List of Threatened Species maps (3), we adopt the Zonation with input data generated by ENM for the following reasons. First, ENM allows us to predict future species distributions under climate change scenarios. Second, ENM can equilibrate omission errors (when a species is mistakenly thought to be present) and commission errors (when a species is mistakenly thought to be absent). The Zonation method generates a hierarchy of landscape prioritization based on the degree to which areas support connectivity for multiple species synchronously. It starts from the full landscape, and then stepwise removes all cells one by one in such a way that a cell with the smallest marginal loss is removed first, leading to the most critical areas remaining last. As such, a cell with a CP index nearly zero has been deleted in an early stage of the process, whereas the highest value cells (CP $\approx$ 1) are removed last. An additive benefit function was selected as a cell removal rule, which is appropriate if the feature samples from a larger regional feature pool (36). Only species threatened by agriculture were selected for mapping conservation priority using IUCN Threats Classification Scheme and binomial generalized linear models. As a result, this screening revealed that agricultural activities likely increase the extinction risk of 7,143 out of the initial 8,427 species. We used projected maps of these species in five taxonomic groups (1,436 vascular plants, 449 amphibians, 327 reptiles, 4,022 birds, and 909 mammals) as biodiversity feature maps. These maps are projected by ENM using maximum entropy modelling (MaxENT) algorithm and species occurrence data from the Global Biodiversity Information Facility (GBIF) (95) at 0.5° × 0.5° grid (ca. 60 × 60 km at the equator) resolution (see the details in *SI Appendix*, *Appendices 3 and 4* and Ohashi et al. 96). These five taxonomic groups have contributed to the most significant decline in biomass on land due to historical human impacts (97). For each taxon, we selected the species with the most reliable occurrence records from the entire GBIF dataset. In contrast to various ecological niche modeling methods developed for presence–absence data (e.g., generalized linear models) which cover only a limited number of species at a global scale (98), we applied the MaxENT algorithm due to its ability to accommodate species data of small or incomplete sample size and presence-only species records (99). Following the approach of Phillips et al. (100), the effect of sample selection bias is reduced by equal treatment of both occurrence and pseudo-absence datasets.

SI Appendix, Fig. S13*A* shows the relationship between the importance ranking and the absolute conservation value under each scenario. Because the Zonation algorithm gives rank for each cell one by one, CP map pixels have equal frequency distribution for each CP index interval (histogram bins, *SI Appendix*, Fig. S13*B*). CP index scale is equivalent to percentile scale, which can be identified from boxplots. For example, if a pixel has a CP index = 0.751, its value will be bigger than that of 75% of the map pixels. Therefore, we classify absolute CP values into relative rank using a percentile scale. Accordingly, medium-high CP is more than the median, high CP more than the third quartile, and very high CP more than the 90th percentile.

We used current protected area (World Database on Protected Area, https://www.protectedplanet.net accessed in August, 2019) as removal mask layer. We treated the grid with more than 50% covered by protected area types I, II, and III as already be earmarked for conservation: These cells will be removed only after there are no more cells with lower mask level values left, and thus will be included in the top fraction of the solution. We weighted each species using a combination of IUCN Red List Categories and regional occurrence proportion, then normalized the weight based on the number of species in each taxon (see the details in *SI Appendix*, *Appendix 3*). Weight of regional occurrence proportion was calculated by iterative proportional fitting to adjust the proportion of taxonomic groups and native regions of the modeled species to the whole species assessed in the IUCN Red List. Although the IUCN Red List assessment does not cover all species in the world, we expect these weighted scores to reflect the species richness of the region.

Global crop and livestock distribution maps were combined to estimate land use of 42 agricultural commodities and six livestock systems (cattle, sheep, goat, pigs, duck, and chickens) in 2010. The global crop distribution maps (or the Spatial Production Allocation Model maps, hereafter MapSPAM maps) and livestock maps analyzed at 5 min of arc (approximately 10 × 10 km at the equator) (101) and 1 km (102) resolutions, respectively, were sourced from https://www.mapspam.info/ and https://livestock.geo-wiki.org/home-2/, respectively. For MapSPAM maps, land use refers to the actual area where a crop is grown circa 2010, but does not capture crop production intensity which can influence, positively and negatively, species threats (103). Since the original livestock maps only represent livestock density (heads/km^2) in 2006, we estimated physical land use for livestock in 2010 by converting the density into the physical area used for housing, exercise, and grazing of animals (see details in *SI Appendix*, *Appendix 2*). To estimate conflicts between conservation and agriculture, global crop and livestock land-use maps were then resampled to fit the spatial resolution of 0.5 decimal degrees of the CP map. In calculating the total area of each pixel, we excluded the pixel's permanent water surface area using Global Surface Water data (104).

Linking Biodiversity Risks to Final Consumers. Conservation risk hotspots link countries, sectors, and consumers in globalized agricultural supply chains. We use a physical trade model to assess the drivers of conservation risk hotspots from a consumption perspective, for 197 countries and one unspecified area. The model is calculated from production and bilateral trade data for 2010 obtained in the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) (105). Here, we assume that agricultural products are consumed in the country of import, or domestically in the country of production, and attribute conservation risk hotspots accordingly. We aggregate 160 crop commodities and ~270 primary/processed crop products in FAOSTAT's production and trade data, respectively, into 42 MapSPAM's crop commodities. Similarly, 54 primary and processed livestock products are grouped into six livestock commodities. These aggregations may expand the footprint of a consumer to map pixels where a FAOSTAT's commodity is not produced. The processed agricultural products are converted into their primary commodity equivalents using protein conversion factors. We utilize calories instead for products containing no protein, such as sugar and vegetable oils (olive, coconut, soybean, oil palm, etc.) (106). This approach can avoid double counting from technical conversion factors based on commodity mass (107). To build the physical trade model, we adopted the method proposed by Kastner et al. (108, 109) that accounts for reexports of processed food or agricultural products and their use as inputs in the feed sector. Details on calculating the physical trade model and crop and livestock land-use footprints are given in *SI Appendix*, *Appendix 2*. To our knowledge, the disaggregation of feed cropland for each livestock commodity has never been done at the level of detail as this study. While FAOSTAT has limitations due to its reliance on estimated data, it is superior in terms of detailed commodity classification, global coverage for domains of production, trade, and food/commodity balances and compatible with the spatial data used. Both MapSPAM and livestock distribution maps were constructed to align with FAOSTAT national statistics. Livestock feed is also estimated mainly based on food and commodity balance sheets of FAOSTAT.

The cropland in the MapSPAM maps is classified into four production systems for each crop: irrigated high-input production, rainfed high-input production, rainfed low-input production, and rainfed subsistence production. While most of the products from irrigated and rainfed high-input systems are produced for large-scale domestic markets and export, agricultural output from rainfed low-subsistence systems is produced primarily for local consumption. We assign the production source of global agricultural supply chains to these production systems by comparing MapSPAM's production volumes and FAOSTAT export volumes for a crop. If the total export volume of a crop is smaller than the production volume from irrigated and rainfed high-input systems, all nondomestic consumer impacts are assigned to these production systems, and the remaining land use is attributed to domestic consumption. Conversely, if the export volume of a crop is greater than the production volume from such systems, the difference is allocated to rainfed low-input subsistence productions. Such an allocation approach ensures a more accurate assessment of the embodied ecological impacts in trade at the sub-national level. We also note that the assumption that high-yield goods go to export markets may not always be accurate; there could be cases where export markets prefer low-yield goods due to either quality or price considerations. However, using physical production accounts enables analysis of biodiversity impacts according to a highly detailed agriculture commodity classification.

Data, Materials, and Software Availability. The results, calculated as described in the Methods, are based on the data from FAOSTAT (https://www.fao.org/faostat/en/#data) (105), MapSPAM (https://doi.org/10.7910/DVN/PRFF8V) (110), Livestock

Geo-Wiki (https://livestock.geo-wiki.org/home-2/) (111), GBIF (https://www.gbif.org/) (95), WorldClim (https://www.worldclim.org/data/index.html) (112), and MCD12C1v006 (https://lpdaac.usgs.gov/products/mcd12c1v006/) (113) databases, all of which are publicly available. The footprint maps are available online at https://agriculture.spatialfootprint.com/biodiversity/ (114) and provided in *SI Appendix*. Codes are available at https://github.com/nguyenthoang/SACCf (115)

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