The Impact of Global Unequal exchange of Land on Food security and Biodiversity

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Abstract:

Global trade enables high-income economies to appropriate land resources from lower-income economies, exerting pressure on local agricultural production and ecosystems, yet these impacts have rarely been quantified. Here, based on Eora database we use an environmentally extended multi-regional input–output (EEMRIO) model to trace four types of land embodied in international trade (that is, land used for the production of imports and exports) from 1990 to 2021 and evaluate the unequal impacts of embodied land exchange on food security and biodiversity across income groups. We find that although high-income countries account for only one-quarter of the global population, they consistently act as net appropriators of resources and consume more than 60% of land embodied in trade. In contrast, lower-income countries serve as major net exporters of embodied land. Retaining this land for domestic production could contribute to alleviating already fragile food-insecurity conditions in these countries. The net outflow of embodied land imposes disproportionately severe biodiversity losses on lower-income countries. To safeguard agricultural production and ecosystem integrity in lower-income countries, a more sustainable and equitable framework for global land governance is urgently needed.

Introduction

Global trade link production and consumption across distant regions [1-3]. As these interconnections deepen, research has explored ecologically unequal exchange[4-6]. High-income regions tend to dominate geopolitics, international commerce, and value chains. In contrast, low-income regions typically lack advanced manufacturing and technological capabilities, positioning them at the lower end of global value chains and resulting in systematically lower wages, prices, and profits[7-9]. This structural asymmetry enables high-income regions to extract substantial quantities of embodied raw materials, energy, labor and land from lower-income regions [4, 10, 11]. This extraction can reduce production costs for affluent regions but imposes serious social and environmental burdens on exporting regions[12], including the displacement of potential domestic food production that could otherwise be realized if exported land were retained for local use[13], as well as associated mulnutrition[14, 15]. In addition, as resource extraction and production activities are moved to lower-income countries via global value chains, environmental impacts such as CO_2 emissions, biodiversity loss, and deforestation are also moved to lower-income countries. [16-19]. Meanwhile, high-income nations leverage their technological and supply-chain advantages to process these low-cost imported inputs into high-value-added products for export, thereby capturing substantial profits[20, 21]. This results in high-income countries achieving large value-added gains with minimal domestic resource use, while low-income countries expend significant labor and resources for relatively small monetary returns[9, 22].

Among all the resources high-income countries have extracted from low-income countries, land is particularly important because it is the fundamental physical basis for all anthropogenic activities, underpinning not only agricultural production but also ecosystem integrity and stability[18, 23-26]. Environmentally extended multi-regional input–output (EEMRIO) modeling has enabled researchers to track embodied land flows across global supply chains [27-29]. These studies demonstrate that consumption in one region can induce land-use changes elsewhere via complex supply chains[6, 10, 30, 31]. However, previous studies have largely focused on the exchange of cropland embodied in agricultural sectors or agricultural trade, overlooking the fact that many non-agricultural industries also drive substantial land use through their global supply chains[10, 27, 28]. Also, these researchers have typically examined the impacts of trade on food security and biodiversity separately, with little quantitative analysis of how land exchanges generate unequal agricultural and ecological losses across countries with different development levels [13, 32-34]. However, land simultaneously functions as a production space for food systems and as a habitat for biosystem. Therefore, these interdependent challenges must be analyzed jointly to better understand the trade-offs between ecological preservation and human well-being.

To fill these gaps, our study utilizes an EEMRIO model to track the spatial-temporal flows of land embodied in global trade. Our dataset comprises 184 countries and regions, with data spanning the years 1990 to 2021. To examine trade patterns across countries at different levels of economic development, we use the World Bank's country classification based on gross national income (GNI) per capita. Furthermore, to ensure that group-level patterns capture meaningful structural differences in global land trade, we treat China and India as separate categories rather than aggregating them within the World Bank income groups[4]. When China and India are included in the standard income classification, key temporal dynamics of land unequal exchange over 1990–2021 are obscured, especially China's transition from a major net exporter to a major net importer of embodied land. This classification also reflects the distinctive roles of China and India in global land-related value chains, which differ markedly from those of other countries within their respective income groups. By separating these two economies, we are better able to distinguish group-level structural changes from country-specific trajectories. Accordingly, countries are classified into six groups: high-income (HI), upper-middle-income (UMI), lower-middle-income (LMI), and low-income (LI) economies, with India (IND) and China treated as distinct groups. In addition, to analyze trade patterns across land types, we categorize land into four types: cropland, pasture, forest land, and other land. Subsequently, we use a food security index to estimate the impact of unequal land exchange on food security. In addition, we establish a new indicator called net Species Habitat Balance (netSHB) to quantify the net balance of the biodiversity loss associated with a country's import and export. This formulation allows us to distinguish countries that externalize biodiversity loss through import from those that bear biodiversity loss domestically in order to satisfy external demand. Additionally, by linking embodied land flows with value-added flows, we evaluate whether lower-income exporters face a "high land input–low value" pattern within global value chains[20, 21]. Finally, a Structural decomposition analysis (SDA) is carried out to identify the drivers behind the evolution of land inequality. Our study uncovers the potential production associated with unequal land exchange and establishes an integrated framework linking agricultural production impacts and ecological consequences. These insights provide valuable empirical evidence for policymakers and international institutions seeking to promote more sustainable, equitable, and resilient global land-use and trade systems.

Results

Unequal exchange of land embodied in global trade

Total land embodied in global trade nearly doubled from approximately 915 million hectares in 1990 to 1,780 million hectares in 2021, indicating a substantial expansion in the scale and global interconnectedness of land use through international trade.

The exchange of embodied land is characterized by persistent inequality. Throughout most of our study period, High-income countries (HI) acted as a net appropriator of all major land types—including cropland, forestland, pasture, and other land—from all other country groups, namely upper-middle-income (UMI), lower-middle-income (LMI), and low-income (LI) countries, as well as China and India (IND) (Supplementary Fig. 1-3). Among these groups, UMI countries consistently emerged as the dominant exporters, supplying nearly half of the total land embodied in global trade (Fig.1). These exporters are primarily located in Latin America and Southeast Asia, with countries Paraguay and Thailand ranking among the largest land exporters in 2021. Russia also stands out as a major exporter of embodied land, largely driven by its extensive exports of land-intensive agricultural products.

In contrast, HI countries consistently accounted for around two-thirds of global embodied land consumption (Supplementary Fig.4). This consumption is particularly concentrated in parts of Eastern Europe and the Middle East, such as the United Arab Emirates, Switzerland, Monaco, and Israel. These countries rely heavily on imports to compensate for their limited domestic land endowments. Notably, the United States, despite its vast land resources, has also become one of the world's largest net importers of embodied land, reflecting its high consumption levels and strong demand for land-intensive goods.

China's role changed dramatically, shifting from a major net exporter in 1990 (accounting for 17% of global exports) to the second-largest net importer in 2021 (17% of global imports). In contrast, India maintained a relatively balanced position, contributing less than 4% to both imports and exports (Fig. 1).

The reliance of HI countries on external land resources is further reflected in their domestic consumption structure. Over the entire study period, more than 20% of total land consumption in HI economies was sustained by net appropriation from other groups, with dependence on cropland and forestland reaching up to 30%, underscoring the extent to which land demand of these countries is externalized beyond national borders. However, there are notable exceptions, such as Canada and Australia, which exhibit large net exports. Conversely, most of the embodied land sustaining this consumption originated from UMI and LMI exporters (Supplementary Fig. 5). For example, the European Union sources much of its imported embodied land from Sub-Saharan Africa, Russia and Ukraine, reflecting reliance on external cropland and forest products, while the United States draws a substantial share from Latin America, where exports are dominated by land-intensive commodities such as wheat, beef, cocoa, and coffee, as well as tropical plantation crops (Supplementary Fig. 6).

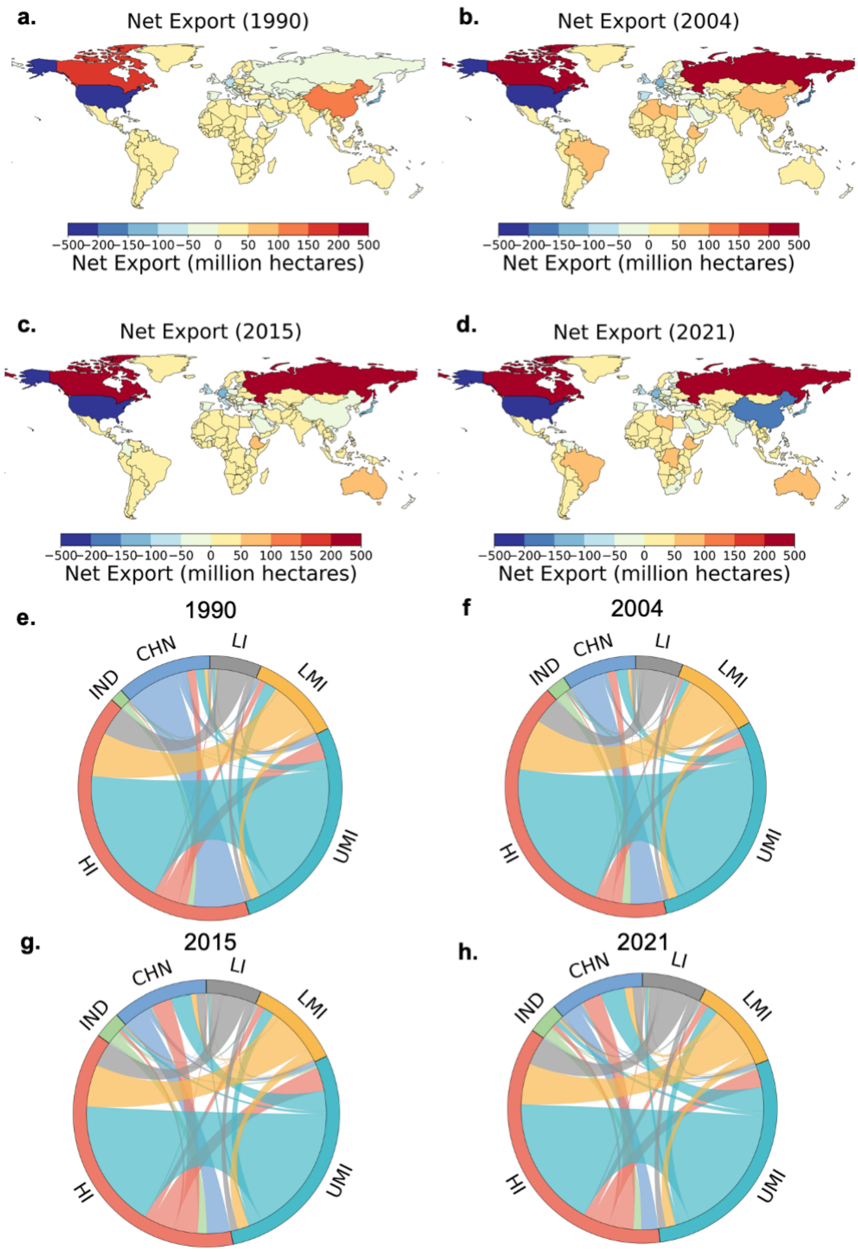

Fig.1| Flow of Embodied Land in Global Trade in 1990, 2004, 2015 and 2021. Panels **a–d** present the spatial distribution of net exports at the country level, where net exporters are shaded in red and net importers in blue. Panels e-h depict the flows of land embodied in trade between six country groups classified by income level (HI, UMI, LMI, LI, CHN, IND).

The implications of land unequal exchange on food security

After examining the commodity composition of embodied land exports, we find that embodied land exports of LI countries are dominated by a narrow range of land-intensive commodities, mainly cereals, oil crops, and fiber crops (see Supplementary Fig.7 for details). For instance, among the top three low-income exporters, Tajikistan's export structure is centered on cotton, onions, and shallots, and a small variety of fruits;

Pakistan's export land is largely devoted to rice and other cereals; while Benin's exports are overwhelmingly concentrated in cotton and oil crops.

However, the land that sustains these exports could otherwise be allocated to domestic food production or more diversified agricultural systems aimed at improving food security. However, current trade patterns divert fertile land toward systems designed for foreign markets. By 2021, the cropland appropriated by high-income countries from low-income exporters could have produced approximately 37 million tons of maize, 290 million tons of potatoes, 48 million tons of rice, and 39 million tons of wheat (see Supplementary Fig. 8). To put this in perspective, 37 million tons of maize alone contains sufficient calories to feed roughly 123 million people for an entire year[35]. Such land appropriation, therefore, represents a direct displacement of potential domestic food supply, reinforcing food dependency and external vulnerability.

The concept of food security is widely recognized as being founded on four key pillars: availability, access, utilization, and stability[36]. Building on this framework, the Food and Agriculture Organization (FAO) has established a comprehensive set of indicators to assess food security across these four dimensions at the national and regional levels (see Methods)[37]. For each pillar, we select a representative set of indicators and standardize them to a 0–1 scale, where 0 denotes the poorest food security performance, and 1 indicates optimal performance. From the correlation between food security performance and net export of embodied land, we find that an unequal land exchange pattern is strongly reflected in food security indicators (Fig. 2).

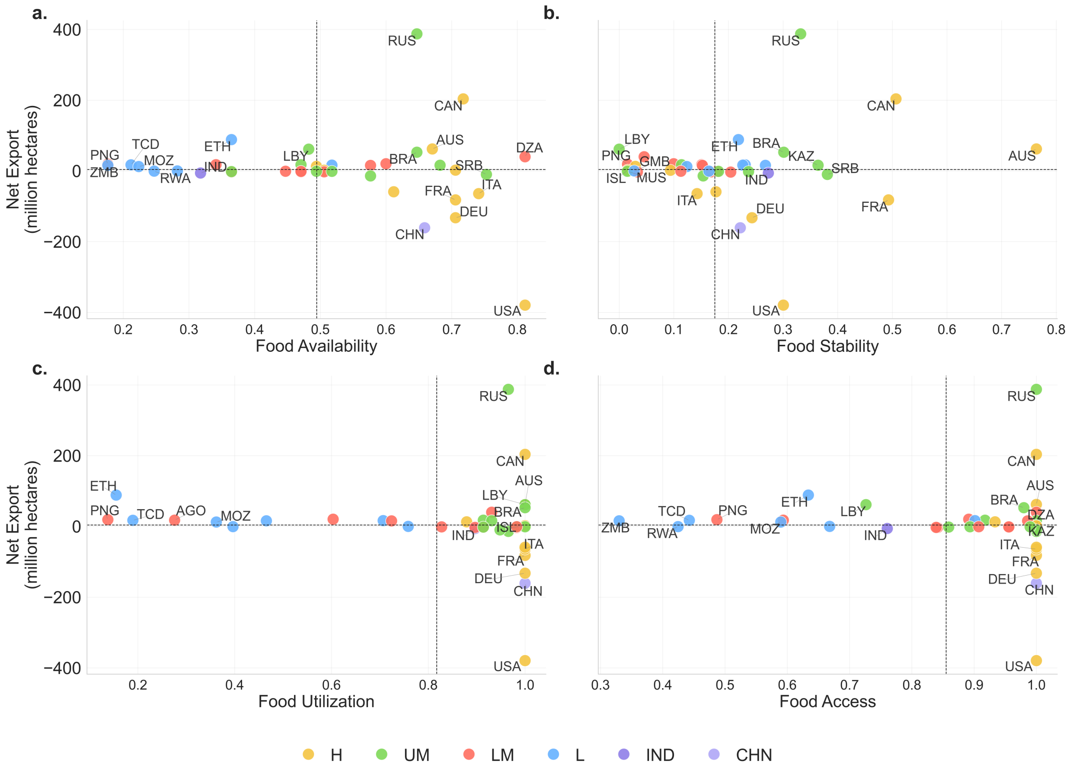

Fig.2 | Relationships between net land trade position and food security performance across four dimensions, 2021. Panels **a–d** show the association between net export of embodied land (y-axis) and the four pillars of food security—food availability (a), food stability (b), food utilization (c), and food access (d)—for 10 selected countries in each group. For each pillar, the indicator is standardized to a 0–1 scale, where 0 denotes the poorest food security performance, and 1 indicates optimal performance. Vertical dashed lines indicate the global average value of each indicator, while the horizontal dashed line represents a net-trade balance of zero (import = export). Each dot represents a country, color-coded by income group.

Many major low- and lower-middle-income exporters perform well below the global average in food availability, access, and utilization, while maintaining net-exporter positions. In contrast, most high-income countries, which are net importers of embodied land, exhibit superior food security performance. Only a few land-abundant or sparsely populated nations—such as Australia, Canada, and Russia—stand out as net exporters within the high-income group; yet even these countries remain among the best performers in food security in their income category, particularly in food stability.

Overall, the results reveal that lower-income exporters bear the opportunity costs of supplying global markets while struggling with food insecurity at home[38], whereas wealthier importers externalize their land requirements to maintain stable and diversified food supply.

The implications of unequal exchange of land on biodiversity

Crucially, the expansion of export-oriented agriculture in lower-income countries often occurs at the expense of natural ecosystems, leading to extensive biodiversity loss and ecological degradation. Forests, wetlands, and other biodiverse habitats are frequently cleared or fragmented to make way for croplands and pastures that supply international markets, accelerating the destruction of habitats[39].

In this study, we assess the biodiversity dimension of unequal exchange using the net Species Habitat Balance (netSHB), defined as the difference between the biodiversity loss embodied in a country's land-related imports and the biodiversity loss embodied in its exports. A positive netSHB indicates that a country's imports embody more biodiversity loss than is generated by its exports, implying a net outsourcing of biodiversity impacts to other regions. Conversely, a negative netSHB indicates that a country's exports embody more biodiversity loss than is embodied in its imports, meaning that biodiversity loss is borne domestically to support external demand.

As shown in Fig. 3, HI countries exhibit consistently positive netSHB values for both cropland- and forest-related land use. This pattern indicates that biodiversity loss associated with their land-based consumption is, on balance, outsourced to other countries through trade. Many Western and Northern European economies, together with several oil-rich Middle Eastern countries, display particularly high positive netSHB values, reflecting a strong net reliance on biodiversity loss occurring outside their own broader.

In contrast, many lower-income countries across South America and central Africa display persistently negative netSHB values, indicating that biodiversity losses are borne domestically to support the production of goods for international markets, thereby placing these regions in the position of net absorbers of global biodiversity costs. Notably, a small number of high-income countries, especially Australia, also exhibit negative netSHB. The negative balance is primarily driven by their large net exports of embodied land, rather than by domestic consumption pressures.

Overall, these results reveal a pronounced ecological asymmetry embedded in global trade. Biodiversity losses are systematically shifted from high-income importing economies to lower-income and resource-rich exporting regions. By highlighting the net redistribution of biodiversity impacts through trade, the netSHB framework provides a clearer picture of how global consumption patterns contribute to uneven ecological burdens across countries.

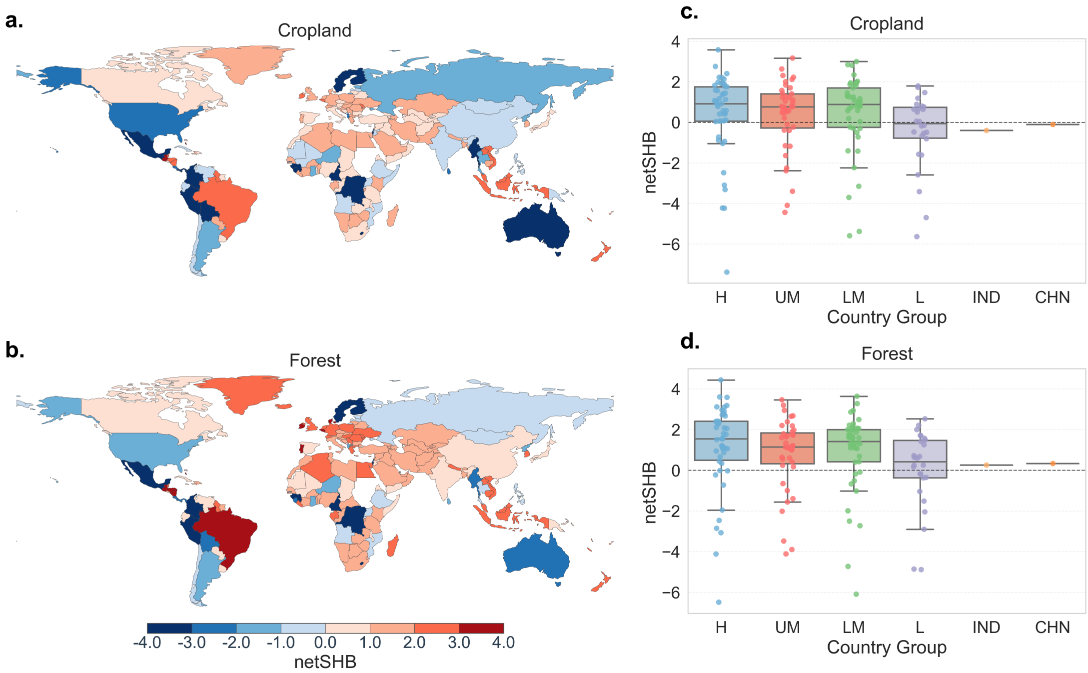

Fig. 3 | Net biodiversity loss embodied in cropland and forest trade, 2021. Panels **a** and **b** map the net Species Habitat Balance (netSHB) associated with cropland and forest, respectively. Countries with positive values are reflected in red, negative values are shaded in blue. Panels **c** and **d** present the distribution of netSHB across income groups. In each box plot, the central horizontal line represents the group median; the lower and upper bounds of the box show the 25th and 75th percentiles; and the whiskers denote the most extreme values within 1.5 times the interquartile range. Individual dots represent country-level observations.

Value-added disparities of embodied land

Across all land types, HI countries consistently generated the highest value-added per hectare of land embodied in export over the study period. Their per-hectare value rose steadily from 1990 to 2008, declined during the global financial crisis, and partially recovered thereafter, remaining far above that of other groups. On average, one hectare of embodied cropland exported by HI countries generated 27 times more value-added than a hectare exported by LI countries, 13 times more than India, 8 times more than LMI countries, 5 times more than UMI, and 3 times more than China. A similarly large differential is observed for pasture land, whereas the value-added differentials per unit of cropland and forest land is less pronounced (Supplementary Fig.10). This disparity reflects systemic differences in countries' positions within global value chains: HI countries export land-based products with far higher processing intensity, technological content, and market prices, enabling them to extract far more value from each hectare of land.

China exhibits a markedly different trajectory. The value-added per hectare of embodied land in exports increased strongly across all land types—especially pasture and other land, which grew roughly fourteen-fold and ten-fold, respectively. By 2021, China's value-added per hectare surpassed that of HI countries for most land categories other than cropland (Supplementary Fig. 8). This rise reflects a combination of China's movement up land-related global value chains through higher levels of processing in agricultural and agro-industrial exports, and shifts toward higher value-added land-based products and crops. These allows China to obtain more monetary return from each unit of land embodied in its exports. Lower-income countries, by contrast, experienced little or no growth in value-added per hectare. Their land-embodied exports continued to yield low and stagnant monetary returns, consistent with patterns reported in previous research[4, 40].

From a flow perspective (Fig. 4), high-income (HI) countries account for a large share of the value-added embodied in global land trade between 1991 and 2004, while the associated environmental costs are ultimately borne by Lower-income countries. Meanwhile, LI and LMI countries import land-embodied value-added at levels that far exceed the value they capture from their own exports, reflecting their structurally disadvantaged position in global value chains. After 2004, the value-added per hectare of land embodied in export of HI countries kept decreasing and was finally exceeded by China.

These findings demonstrate that global trade structures enable high-income countries to appropriate substantial monetary value from land-embodied exports. while lower-income countries exporting larger quantities of embodied land, they only capture a relatively small fraction of the associated monetary gains. This constitutes a clear form of monetary asymmetry, compounding the ecological inequalities documented earlier.

These results reveal a decoupling between the physical flows of land and the monetary returns derived from them. While lower- and middle-income countries export large quantities of land embodied in primary and land-intensive products, they capture only a relatively small share of the associated value-added. In contrast, high-income economies export relatively smaller amounts of embodied land yet extract disproportionately high value-added returns per hectare. This systematic mismatch between who supplies land resources and who captures value-added constitutes a core mechanism of unequal exchange, whereby biophysical resources flow from lower-income to higher-income economies, while value-added benefits flow in the opposite direction.

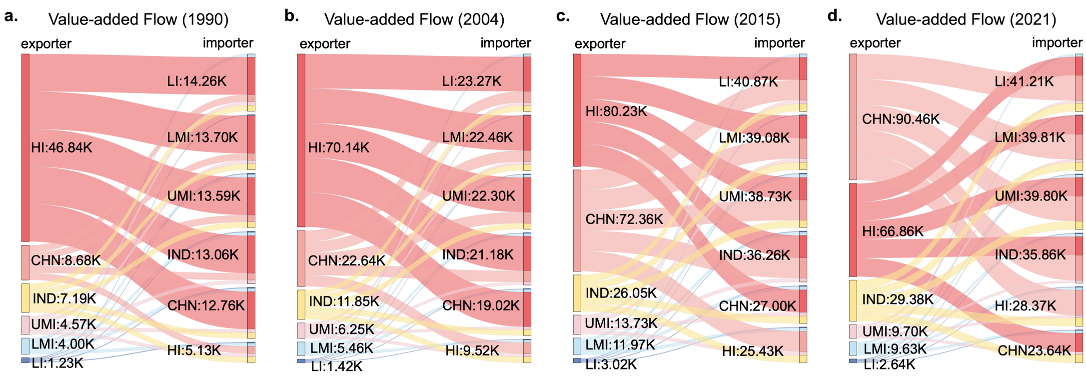

Fig.4 | The flow of value-added per unit of land embodied in exports and imports (million/ha) by country group, 1990, 2004, 2015, 2021. These diagrams represent the flow of value-added per unit of land embodied in global trade among six country groups.

The drivers of changes in embodied land inequality

Based on the previous analysis, we observe that the net appropriation of embodied land by high-income (HI) countries exhibits a long-term fluctuation pattern: an overall increase from 1990 to a peak around 2004, followed by a decline through the 2010s, reaching its lowest point around 2015, and then rising again until 2021 (supplementary Fig.1-3). To investigate the drivers behind these shifts, we conduct a structural decomposition analysis (SDA) of the land embodied in exports and imports, using three periods—1990–2004, 2004–2015, and 2015–2021—to capture the key phases of the trend. SDA enables us to attribute changes in land footprints to their underlying domestic and international determinants.

During the time period 1990–2004, land embodied in exports increased sharply across most country groups, with growth rates of around 100%, reflecting a pronounced global expansion of land-based production in international markets. In contrast, HI countries experienced only a modest increase in LEE (approximately 18%) over the same period. The patterns in land embodied in imports (LEI) show a markedly different trend. HI countries experienced a substantial increase in LEI (+93%), driven predominantly by rising domestic final demand for land-intensive goods. Meanwhile, several lower-income groups saw declines in LEI, particularly LI and UMI countries (Fig.5). This period's widening inequality was fueled primarily by higher final demand, consistent with global analyses showing that growing consumption is the major driver of increased resource use.

Between 2004 and 2015, the pace of net land appropriation by high-income (HI) countries slowed and, in some cases, temporarily reversed. During this period, HI countries recorded the largest increase in LEE (+84%), reflecting continued growth in foreign demand for their exports. By contrast, most other country groups saw minimal changes or declines in LEE, driven largely by reductions in their domestic direct land-use intensity. HI countries' LEI fell by 30%, while other country groups experienced increases of 30–70%. China exhibited the sharpest growth in LEI, driven primarily by rapid expansion in domestic final demand. These findings align with the idea that efficiency gains can partially counteract consumption-driven increases in resource use[41], leading to a temporary narrowing of global land inequality.

From 2015 to 2021, changes in land embodied in exports and imports were driven by a combination of factors, with land intensity, trade structure, and domestic final demand contributing to varying degrees. A notable feature during this period was the marked reduction in LEE for China, driven by a 17% decrease of domestic land intensity. Meanwhile, UMI and LMI countries saw a considerable increase in LEE during this period, mainly driven by increased land intensity and demand structure, respectively. This period highlights the growing complexity of land appropriation, where various factors such as technological advancements, and global trade structures have more differentiated impacts on different country groups.

Fig. 5 | Contributions of each driver to changes in land embodied in export and import for 1990–2004, 2004–2015, and 2015–2021. Panels **a–f** illustrate changes in **LEE** across different country groups for the three periods, while panels **g–l** depict changes in **LEI**. The decomposition includes five key drivers: **l**, representing the direct land intensity vector. **T**, indicating the trade structure of intermediate inputs. **H**, capturing production technology. **D**, representing the trade structure of final products. **y**, indicating final demand level. Each driver consists of two components: changes occurring **domestically** (r) and those occurring **abroad** (−r), respectively.

Discussion

Global trade has enabled high-income countries to appropriate vast land resources from lower-income countries[30]. Our analysis shows that this unequal exchange has persisted over the past three decades, for which data was available. Net land appropriation by high-income countries grew rapidly during the 1990s and into the early 2000s, peaking at roughly one billion hectares per year by the early 2000s. This surge coincided with the era of neoliberal globalization and structural adjustment policies, which compelled many developing economies to expand land-intensive commodity exports[5, 42, 43]. Trade liberalization during this period opened access for foreign agribusiness to tropical cropland and forests, contributing to a sharp rise in land appropriation by wealthy nations. After 2000, however, this net land flow moderated due to two major factors. First, some emerging economies began retaining more land for domestic use rather than exporting it and importing embodied land from other countries. Second, the global financial crisis of 2008 caused a downturn in international trade that temporarily reduced demand for land-intensive commodities[44]. Yet by the late 2010s, high-income nations' net land imports had resurged to around 0.8 billion hectares, indicating that the structural imbalance in global land trade endures despite these transient disruptions. The persistent nature of these flows underscores a deeply entrenched global pattern of unequal land appropriation. Our results are consistent with previous studies suggesting that economic growth and technological advancement in the "core" regions of the world are often achieved at the expense of resources in peripheral regions[45]. In our analysis, high-income countries function as the core of the global economy, appropriating substantial amounts of land embodied in trade from lower-income country groups that occupy peripheral positions. This pattern is consistent with findings reported by Dorninger et al.[4] and Hickel et al.[46] Moreover, we find that net land appropriation by HI countries peaked in the early 2000s, a temporal pattern that closely aligns with the results documented by Hickel et al.[5]

While unequal land exchange has bolstered consumption in high-income countries, it has also made them heavily dependent on foreign land. Our analysis reveals that a substantial fraction of the land used in high-income economies – often about 20–30% of the land supporting their total consumption – is effectively outsourced through net imports (Supplementary Fig. 5). Such reliance creates long-term vulnerabilities. As developing countries industrialize and urbanize, their domestic demand for land resources is growing. For example, China transitioned from a net exporter to a net importer of land around 2015. This change signals a restructuring of global resource flows that could challenge high-income countries' longstanding land advantages[47]. Moreover, climate change and environmental degradation further threaten the productivity of agricultural and forest land worldwide[39, 48]. Countries that currently export land-intensive goods may not be able to sustain past supply levels as their ecosystems become increasingly strained. Thus, high-income nations that have benefited from imported land face growing risks to their supply chains and resource security. The dependence of high-income economies on lower-income economies is consistent with the findings of Hickel et al.[5], who show that more than 50% of labor consumed in the Global North is net appropriated from the Global South. In addition to North–South trade patterns, the growing importance of South–South trade has also reshaped global land flows over the past two decades. Emerging and upper-middle-income economies—especially China—have increasingly joined in global land-related tarde, reflecting deeper economic integration within the Global South. Such exchanges have been associated with changes in production networks and market connections among developing regions [49].

Conversely, the continuous outflow of land resources from lower-income countries has imposed severe burdens on their development prospects and environments. This transfer effectively shifts productive capacity away from local needs to meet external demand. In other words, land that could be used for domestic food production, biofuel feedstock, sustainable agriculture, or conservation is instead allocated to producing low-value-added export commodities, limiting the ability of exporting countries to achieve their own food security and development goals. For example, our analysis indicates that the cropland exported from lower-income countries in 2021 could have produced enough staple crops to feed hundreds of millions of people had it been retained for domestic use. This loss of potential food production contributes to price volatility and undermines food sovereignty in these regions[35]. Furthermore, the pressure to maintain agricultural exports often leads to intensive land use and environmental degradation, creating a self-reinforcing cycle of ecological strain. While export-oriented agriculture can generate local employment and income, these benefits are often outweighed by broader structural disadvantages. Many lower-income countries remain locked into primary commodity exports, which yield limited value-added and expose them to price volatility and environmental degradation. These constraints reinforce economic dependencies and hinder diversification into higher-value sectors[48]. In essence, unequal land trade not only diverts critical resources from pressing domestic needs but also entrenches lower-income nations in unsustainable land-use practices and development trajectories, raising important questions about who ultimately benefits from this exchange.

The ecological consequences of this imbalance are also profound. High-income countries effectively externalize many environmental costs of their consumption by displacing land use and its associated impacts to other countries. One stark example is biodiversity loss. To satisfy foreign demand, lower-income regions have accelerated the conversion of biodiverse forests and other natural habitats into croplands and pastures[39, 50]. Our species-habitat loss analysis indicates that many wealthy nations cause more habitat destruction abroad through consumption than within their own borders. In contrast, lower-income countries bear the bulk of biodiversity decline within their territories, as their natural ecosystems are exploited to produce export commodities. This pattern is consistent with the findings of Schwarzmueller and Kastner[34], who find that countries in Western Europe, North America, and the Middle

East generate a substantial share of their biodiversity footprint outside their national boundaries. The erosion of natural habitats and species in lower-income nations – driven by external demand – constrains their capacity for conservation, degrading not only their environment but also their natural heritage and resilience[51, 52].

Beyond these ecological impacts, there is a striking disparity in the monetary gains derived from land trade. High-income countries capture far greater value from each hectare of land embodied in trade than do the lower-income countries. This outcome reflects the structurally disadvantageous positions of lower-income nations within global value chains[7-9]. These countries primarily export raw or minimally processed goods with limited value-added, whereas high-income nations capture most of the value through manufacturing, branding, and distribution. As a result, lower-income countries effectively exchange valuable land resources and associated environmental costs for disproportionately low monetary returns[53].

Together, these dynamics amplify global inequalities. By appropriating land without providing equivalent returns, high-income countries essentially underpin their own prosperity at the expense of the ecosystems and livelihoods of poorer regions. International trade, in this case, redistributes effective land ownership in a way that widens pre-existing disparities. Before trade, some middle-income countries had higher per capita land endowments than richer countries. After accounting for trade flows, however, we find that high-income nations substantially expand their effective land availability, while lower-income countries see their per capita land resources shrink. This shift grants wealthy nations access to more land (and thus more production and carbon-sink capacity) than their own territories provide, effectively bolstering their ecological advantage. At the same time, it intensifies resource scarcity in less affluent regions. Additionally, the diversion of food production capacity toward exports exacerbates nutritional and developmental divides. Land that could improve diets and reduce hunger in food-insecure nations is instead used to support consumption patterns in wealthy societies – often for the production of resource-intensive goods such as livestock feed for the meat and dairy industries[54, 55]. The persistence of these patterns over three decades, despite global economic and political changes, indicates that they are deeply embedded in the current world system.

Addressing such entrenched disparities is challenging because they are maintained by the ordinary functioning of markets and supply chains rather than by overt coercion[40]. Nonetheless, confronting this inequity is essential for any transition towards sustainability.

Achieving a more equitable exchange of land resources will require coordinated action on several fronts. First, international trade policies should be reformed to account for the full social and ecological costs of land-intensive commodities. Internalizing environmental externalities – through measures such as sustainability standards or import tariffs proportional to the land and habitat footprint of imports – would help ensure that prices reflect true costs and that exporting countries are compensated for the depletion of their natural capital[56]. Aligning trade with environmental accountability could discourage excessive land exploitation and generate funds for conservation in regions that supply global markets. Second, lower-income countries need support to move up global value chains and capture more value from their own land. Investing in local processing, manufacturing, and agricultural technology can enable these countries to export higher-value goods instead of raw materials and low value-added goods[57]. This kind of development would allow producers to retain a greater share of the economic benefits from their land and reduce their dependency on trade in primary commodities. Third, strengthening land governance and community rights in exporting countries is crucial. Empowering smallholder farmers, indigenous communities, and other local stakeholders with secure land tenure can help ensure that land-use decisions prioritize local food security and environmental well-being[58]. Rigorous social and environmental safeguards on large-scale land acquisitions – such as transparency requirements and impact assessments – would further protect against unsustainable land grabbing, helping to conserve critical ecosystems while supporting local livelihoods[59]. Fourth, demand-side transformations in high-income nations must complement these supply-side interventions. Reducing overconsumption and shifting diets toward less land-intensive foods (for example, more plant-based diets) would reduce the land footprint of wealthy populations[60]. Cutting food waste and improving resource efficiency through circular economy practices can likewise lower the pressure placed on global land resources. Finally, global governance mechanisms should explicitly address ecological unequal exchange as a barrier to sustainable development. This could involve incorporating land-footprint and habitat-loss indicators into international sustainability targets, setting commitments to reduce net land appropriation by wealthy nations, and exploring compensation or benefit-sharing schemes for countries that have historically provided land and biodiversity services to the global economy[40]. Such measures would acknowledge the debt owed to regions that have sacrificed environmental assets for international trade. We recognize that these interventions face political and economic obstacles, especially from vested interests that profit from the status quo. However, the escalating climate and biodiversity crises, coupled with enduring food insecurity in many parts of the world, underscore the urgency of reform. Our findings highlight that rebalancing land flows is not only a moral imperative but also a practical necessity for a sustainable and food-secure future.

Methods

The aggregations of country group

Countries are initially classified according to the World Bank's income categories based on gross national income (GNI) per capita. Following Dorninger et al.[4] ,we make a slight adjustment to this classification by treating China and India as separate groups.

This adjustment is motivated by both analytical and demographic considerations. Analytically, when China and India are aggregated into the four standard income groups (LI, LMI, UMI, and HI), the temporal evolution of land exchange across income groups becomes much less pronounced over 1990–2021. Separating China and India allows key dynamics to be captured more clearly, particularly China's transition from a major net exporter to a major net importer of embodied land, and India's growing influence associated with rapid population growth. Moreover, China and India individually account for a large share of population and land-related trade within the UMI and LMI groups, respectively. Treating them separately avoids group-level results being dominated by single large economies and improves interpretability. In addition, this adjustment ensures broadly comparable population sizes across the remaining income groups. As a result, based on the World Bank thresholds, low-income (LI) countries have GNI per capita of USD 1,640 or less; lower-middle-income (LMI) USD 1,640–4,130; upper-middle-income (UMI) USD 4,130–12,630; and high-income (HI) above USD 12,630. In 2021, HI, UMI, LMI, and LI groups each accounted for approximately 15–16% of the global population, while China and India accounted for 18.7% and 17.8%, respectively.

Environmental Input-output Analysis (EEMRIO)

Environmentally Extended Multi-Regional Input-Output (EEMRIO) analysis represents a powerful framework for quantifying the complex environmental and socioeconomic impacts embodied in global supply chains. This methodology builds upon the foundational work of Leontief [61], who developed input-output analysis to capture economic interdependencies. The core of EEMRIO analysis lies in multi-regional input-output (MRIO) tables that integrate national input-output tables with bilateral trade accounts. These tables record the exchange of goods and services between various sectors across multiple economies through three key components: Intermediate demand (Z): Transactions between industries; Final demand (y): Goods and services consumed by end users; Value-added (v): Contributions to production from primary factors.

The fundamental accounting principle maintains that for each industry, total output must equal total input. Mathematically, total output (x) equals all sales for intermediate production plus final demand: $x = Zi + y$, total input (x) equals all interindustry purchases plus value-added: $x' = \mathrm{i}'Z + v$, here i' is a column-vector with all elements equal to 1 for summation. In a balanced MRIO table, $Zi + y = i'Z + v$.

The demand-driven input-output model can be expressed as:

$$x = (I - A)^{-1}y = Ly \tag{1}$$

Where I is the identity matrix, $A = Z\hat{x}^{-1}$ is the technology coefficient matrix, with elements $a_{ij}^{sr} = z_{ij}^{sr}/x_j^r$ representing inputs of sector i in economy s is required to produce per unit output of sector j in economy r [62].

$L = (I - A)^{-1}$ is the Leontief inverse matrix, The Leontief inverse is particularly significant as its elements l_{ij}^{sr} quantify the total (direct and indirect) inputs from sector i in economy s required to satisfy one unit of final demand from sector j in economy r. This captures the potentially infinite chain of production relationships. For example, a consumer electronics device sold in one country might be assembled in another using components manufactured across multiple countries, with raw materials extracted and processed in yet others[7, 22]. Final demand matrix is represented as Y, with elements y_i^{sr} indicates the final demand for products of sector i in economy s by economy r.

What distinguishes EEMRIO from conventional input-output analysis is the integration of extension tables (e) that record non-monetary flows associated with economic activities, such as raw materials, energy use, labor and GHG emissions[4, 10, 11]. These environmental and socioeconomic coefficients are represented in an intensity vector $q = e\hat{x}^{-1}$, showing the direct use of non-monetary flows per unit of industry output. We focus on embodied land in our study, thus q_i^s indicates the direct land intensity of sector i in economy s.

As our study focuses on flows between country groups with different income, we aggregate 184 countries into six country groups (see Supplementary table.1). Then, we aggregate Eora MRIO table into one sector and one final demand department. Thus, the total land use (including both direct and indirect) embodied in global trade can be shown as:

$$F = \hat{q}LY$$
$$= \begin{bmatrix} q^1 & 0 & \dots & 0 \\ 0 & q^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & q^6 \end{bmatrix} \times \begin{bmatrix} l^{11} & l^{12} & \dots & l^{16} \\ l^{21} & l^{22} & \dots & l^{26} \\ \vdots & \vdots & \ddots & \vdots \\ l^{61} & l^{62} & \dots & l^{66} \end{bmatrix} \times \begin{bmatrix} y^{11}\ y^{12} & \dots & y^{16} \\ y^{21}\ y^{22} & \dots & y^{26} \\ & \vdots & \\ y^{61}\ y^{62} & \dots & y^{66} \end{bmatrix} \tag{2}$$

Where diagonalization of land intensity q (indicated by hats "^") allows for regional attribution of impacts. Element f_{ij}^{sr} quantifies the amount of non-monetary flows embodied land in the total upstream inputs from sector i in economy s required to satisfy final demand for sector j in economy r.

Modern EEMRIO databases like Eora provide high-resolution data covering 189 countries and 26 sectors with time series extending from 1990-2021, allowing for comprehensive analysis of global trade patterns and their associated environmental and social impacts[63]. Considering the data availability, we only put 184 countries into calculation and merge 26 sectors into one. This powerful analytical framework can reveal hidden connections between consumption in one region and resource used in another, facilitating more holistic approaches to sustainable development and policy formulation.

Food Security Indicators

The concept of food security is commonly understood as being based on four fundamental pillars: availability, access, utilization, and stability[13]. Food availability refers to having enough food of appropriate quality. Food access means individuals have the resources to obtain sufficient food for a nutritious diet. Utilization involves consuming food in combination with clean water, sanitation, and healthcare to meet nutritional needs. Finally, stability ensures that food remains consistently available and accessible, without risk of loss due to crises or seasonal changes[37]. FAO developed a comprehensive suite of food security indicators to assess food security at the national level, based on these four pillars[37]. For Food Availability, we use the Average Dietary Energy Supply Adequacy (percent), which expresses the Dietary Energy Supply as a percentage of the Average Dietary Energy Requirement, providing an index of the calorie adequacy of the food supply. Food Stability is measured by the Cereal Import Dependency Ratio (percent), which is calculated as (imports - exports) / (production + imports - exports) to show the percentage of the available domestic cereal supply that must be imported. For Food Utilization is represented by the Percentage of Population Using at Least Basic Drinking Water Services (percent), it measures the share of the population that uses basic or safely managed drinking water services. Finally, Food Access is tracked using the Prevalence of Undernourishment (percent), which estimates the probability that a randomly selected person in the population consumes insufficient calories to maintain an active and healthy life.

As some indicators are positive, some are negative, we standardize the indicators using the method as below:

For positive indicators：

$$X_{ij} = \frac{\mathrm{X_{ij}} - \mathrm{X_{min\,j}}}{\mathrm{X_{max\,j}} - \mathrm{X_{min\,j}}} \tag{3}$$

For negative indicators：

$$X_{ij} = \frac{X_{\max j} - X_{ij}}{X_{\max j} - X_{\min j}} \tag{4}$$

The Calculation of net Species Habitat Balance (netSHB)

In early studies, Wilting et al.[64] were among the first to systematically quantify national biodiversity footprints from a consumption-based perspective, revealing that approximately half of biodiversity loss in developed countries was attributable to overseas consumption. Building on this approach, Marquardt et al.[65] developed an environmentally extended multi-regional input-output (EEMRIO) model covering 140 regions, which was used to estimate consumption-based biodiversity loss using four different indicators: Mean Species Abundance (MSA) loss, Relative Abundance (RA) loss, Relative Within-Sample Species Richness (RWSR) loss, and Vulnerability-Weighted Global Relative Species (VGSR) loss. Although these studies did not explicitly incorporate the Species Habitat Index (SHI), their analytical frameworks are methodologically similar.

More recent research has directly integrated SHI into trade-based biodiversity assessments. For instance, Schwarzmueller and Kastner[34] utilized FAO bilateral trade data to link national SHI scores with international trade flows, constructing a consumption-based indicator of species habitat loss. Additionally, Rabeschini et al.[66] compared the SHI with two other biodiversity indicators—cSAR and STAR—and concluded that SHI is particularly suitable for assessing historical land-use change and its impacts on biodiversity.

The Species Habitat Index (SHI) is a composite metric that captures changes in suitable habitat across a country's species assemblage. Specifically, it measures the proportion of suitable habitat remaining relative to a baseline year, typically 2001. SHI is derived by estimating changes in both the extent and quality of species' habitats over time, based on land-use transformations. The Map of Life (MOL)[67] project aggregates species-level habitat integrity scores into a national-level index, weighting each species according to the share of its global distribution that falls within a given country. As a result, nations with endemics or highly threatened species contribute more significantly to the national SHI score. An SHI value of 100 indicates no loss in suitable habitat since 2001, whereas 0 represents maximum habitat degradation.

To quantify the biodiversity loss embodied in a country's net land use flows, we develop an indicator termed net Species Habitat Balance (netSHB). The indicator captures the balance between the biodiversity loss embodied in a country's land-related import and the biodiversity loss embodied in its land exports.

We begin by calculating the import-weighted average SHI loss of an importing country r. For each partner country s, we compute the difference between its Species Habitat Index (SHI) in the target year and its baseline value in 2001, which reflects the species habitat loss $(100 - SHI_s)$. This SHI loss is weighted by the amount of land that country r imports from s (im_{sr}). Dividing the weighted sum by the total land embodied in import of country r, yields the average species habitat loss embodied in its land import.

$$iwaSHI_r = \frac{\sum_{s \neq r}^{N} im_{sr} * (100 - SHI_s)}{\sum_{s \neq r}^{N} im_{sr}} \tag{5}$$

Next, to account for the biodiversity loss embodied in a country's land exports, we calculate an analogous export-weighted measure from the perspective of the exporting country r. Here, r is the source country, and s indexes all destination countries that import land from r. The SHI loss of the exporting country $(100 - SHI_r)$ is weighted by the land volumes exported to each destination (ex_{rs}).

$$ewaSHI_r = \frac{\sum_{s \neq r}^{N} ex_{rs} * (100 - SHI_r)}{\sum_{s \neq r}^{N} ex_{rs}} \quad (6)$$

Finally, netSHB is defined as the difference between the biodiversity loss embodied in a country's import and that embodied in its exports:

$$ceSHB_r = iwaSHI_r - ewaSHI_r \quad (7)$$

Value-added per hectare of land embodied in export

Conventional monetary trade databases based on gross bilateral trade flows are unable to accurately capture the distribution of value-added across countries, as they do not identify the original country where value is generated. intermediate goods account for approximately two-thirds of total international trade[53]. In the context of highly integrated global supply chains, imported intermediate inputs are frequently used in the production of export goods. As a result, a country's gross exports to a trading partner often embody value-added originating from third countries rather than from the exporter itself. Therefore, to accurately assess how monetary value-added is distributed through land-related trade, we follow Dorninger et al.[4] and calculate the value-added per hectare of land embodied in exports, expressed in constant 2015 international US dollars (USD). Specifically, we compute group-level average value-added per unit of land by dividing the total value-added embodied in exports by the total land area embodied in those exports.

Just like the calculation of land footprint mentioned before, value-added embodied in global trade can be calculated by

$$B = \hat{p}LY \quad (8)$$

where vector $p = v\hat{x}^{-1}$ is the amount of value-added (v) per unit of industry output. Element b_{ij}^{sr} quantifies the amount of value-added from sector i in economy s embodied in the final demand of economy r for sector j.

Finally, we divide value-added b_{ij}^{sr} by corresponding embodied land flow f_{ij}^{sr} and derive the value-added per hectare of land embodied in export from country s to r.

$$value - addedperhectare = \frac{b_{ij}^{sr}}{f_{ij}^{sr}} \quad (9)$$

Where each element represents the amount of value-added per hectare of land embodied in trade from sector i in economy s to economy r for sector j.

Structural Decomposition Analysis (SDA)

To further investigate the driving factors behind the temporal changes in land embodied in trade, we employ structural decomposition analysis (SDA). SDA is widely used to explore the driving forces behind changes in resource use or emissions embodied in trade, such as materials resources, carbon emissions, and other environmental impacts[22]. Compared to index decomposition analysis (IDA), SDA based on input-output models can capture both direct and indirect effects along the supply chain and distinguish between the effects of production processes and final consumption patterns.

Following the EEMRIO framework we mentioned before, land embodied in exports [68] and land embodied in imports (LEI) for country group r can be expressed as:

$$LEE^r = \sum_{s \neq r}^{N} \hat{q}^r L^{rr} \mathrm{Y}^{rs} + \sum_{s,k \neq r}^{N} \hat{q}^r L^{rs} \mathrm{Y}^{sk} \quad (10)$$

Here, land embodied in exports is divided into two parts, the first part is direct effects, representing the land embodied in economy r's final goods and service that are consumed in economy s directly. The second part is indirect effects, representing the land embodied in economy r's intermediate goods and service that are exported to economy s but consumed in all other economies.

$$LEI^r = \sum_{s,k \neq r}^{N} \hat{q}^k L^{ks} \mathrm{Y}^{sr} + \sum_{s \neq r}^{N} \hat{q}^s L^{sr} \mathrm{Y}^{rr} \quad (11)$$

Here, land embodied in imports (LEI) can also be divided into two parts, the first part is direct effects, representing the land embodied in economy r's consumption of final goods and service that are produced in all other economies. The second part is indirect effects, representing the land embodied in economy r's imports of intermediate goods and service that are produced in economy s but consumed in economy r.

To facilitate the presentation of the SDA process, we simplify equation (10) and (11) as follows:

$$LEE^{r} = \hat{q}LY \tag{12}$$

$$LEI^{r} = \hat{q}LY \tag{13}$$

Where, q is land intensity vector, which represents land requirement per unit of output. $L = (I - A)^{-1}$ is the Leontief inverse matrix, reflecting the production structure. Y is the final demand matrix.

The changes of LEE and LEI can be denoted by two polars. The first polar is forward, we first change the variables in sequence.

$$\Delta LEE_{t-1,t}^{r} = f^{LEE} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_t Y_t} \times \frac{\hat{q}_{t-1} L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_t} \times \frac{\hat{q}_{t-1} L_{t-1} Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} \tag{14}$$

$$\Delta LEI_{t-1,t}^{r} = f^{LEI} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_t Y_t} \times \frac{\hat{q}_{t-1} L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_t} \times \frac{\hat{q}_{t-1} L_{t-1} Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} \tag{15}$$

The second polar is backward, we change the variables in an opposite order.

$$\Delta LEE_{t-1,t}^{r} = k^{LEE} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_t L_t Y_{t-1}} \times \frac{\hat{q}_t L_t Y_{t-1}}{\hat{q}_t L_{t-1} Y_{t-1}} \times \frac{\hat{q}_t L_{t-1} Y_{t-1}}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} \tag{16}$$

$$\Delta LEI_{t-1,t}^{r} = k^{LEI} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_t L_t Y_{t-1}} \times \frac{\hat{q}_t L_t Y_{t-1}}{\hat{q}_t L_{t-1} Y_{t-1}} \times \frac{\hat{q}_t L_{t-1} Y_{t-1}}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} \tag{17}$$

By calculating the geometric average of (14) and (16), (15) and (17) respectively, we can decompose the changes of LEE and LEI between year t-1 and t as follows.

$$\Delta LEE_{t-1,t}^{r} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} = \sqrt{f^{LEE} \times K^{LEE}} = \underbrace{\sqrt{\frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_t Y_t} \times \frac{\hat{q}_t L_{t-1} Y_{t-1}}{\hat{q}_{t-1} L_{t-1} Y_{t-1}}}}_{1} \times \underbrace{\sqrt{\frac{\hat{q}_{t-1} L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_t} \times \frac{\hat{q}_t L_t Y_{t-1}}{\hat{q}_t L_{t-1} Y_{t-1}}}}_{2} \times \underbrace{\sqrt{\frac{\hat{q}_{t-1} L_{t-1} Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} \times \frac{\hat{q}_t L_t Y_t}{\hat{q}_t L_t Y_{t-1}}}}_{3} \tag{18}$$

$$\Delta LEI_{t-1,t}^{r} = \frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} = \sqrt{f^{LEI} \times K^{LEI}} = \underbrace{\sqrt{\frac{\hat{q}_t L_t Y_t}{\hat{q}_{t-1} L_t Y_t} \times \frac{\hat{q}_t L_{t-1} Y_{t-1}}{\hat{q}_{t-1} L_{t-1} Y_{t-1}}}}_{1} \times \underbrace{\sqrt{\frac{\hat{q}_{t-1} L_t Y_t}{\hat{q}_{t-1} L_{t-1} Y_t} \times \frac{\hat{q}_t L_t Y_{t-1}}{\hat{q}_t L_{t-1} Y_{t-1}}}}_{2} \times \underbrace{\sqrt{\frac{\hat{q}_{t-1} L_{t-1} Y_t}{\hat{q}_{t-1} L_{t-1} Y_{t-1}} \times \frac{\hat{q}_t L_t Y_t}{\hat{q}_t L_t Y_{t-1}}}}_{3} \tag{19}$$

Then, the changes of LEE and LEI between year t-1 and t can be decomposed intp three-part effects. where part 1 represents the effect of changes in land intensity, part 2 reflects the effect of changes in the production structure, and part 3 illustrates effect of changes in final demand.

Based on the decomposition method of Dietzenbacher et al.[69] and Fu et al.[22], we can further decompose the Leontief inverse matrix into $L = (I - H \circ T)^{-1}$, where H represents production technology and T indicates intermediate product input trade structure (T). Also, the final demand Y can be further decomposed into $Y = y \circ D$, where y reflects the levels of demand and D illustrates the final product trade structure. "$\circ$" denotes Hadamard product (element-by-element multiplication of matrices). Moreover, given the rapid increase in global fragmentation, changes in foreign countries can affect a region's LEE and LEI. To study whether the drivers of LEE and LEI originates from domestic or foreign. We further decomposed the drivers into domestic and foreign components to trace their respective impacts, we use "r" and "-r" to represent domestic and foreign factors respectively. Further details about the calculation of each driver can be found in Supplementary information.

Therefore, the final decomposition of changes in LEE and LEI can be written as:

$$\Delta LEE_{t-1,t}^{r} = \sqrt{f^{LEE}(q^{(r)}, q^{(-r)}, H^{(r)}, H^{(-r)}, T^{(r)}, T^{(-r)}, D^{(r)}, D^{(-r)}, y^{(r)}, y^{(-r)}) \times K^{LEE}(q^{(r)}, q^{(-r)}, H^{(r)}, H^{(-r)}, T^{(r)}, T^{(-r)}, D^{(r)}, D^{(-r)}, y^{(r)}, y^{(-r)})} \tag{20}$$

$$\Delta LEI_{t-1,t}^{r} = \sqrt{f^{LEE}(q^{(r)}, q^{(-r)}, H^{(r)}, H^{(-r)}, T^{(r)}, T^{(-r)}, D^{(r)}, D^{(-r)}, y^{(r)}, y^{(-r)}) \times K^{LEE}(q^{(r)}, q^{(-r)}, H^{(r)}, H^{(-r)}, T^{(r)}, T^{(-r)}, D^{(r)}, D^{(-r)}, y^{(r)}, y^{(-r)})} \tag{21}$$

The changes of LEE and LEI are decomposed into five effects, and each driver is divided into domestic (r) and foreign effects (-r).

q: effect of changes in land intensity.

H: effect of changes in production technology.

T: effect of changes in intermediate product input trade structure.

y: effect of changes in the level of final demand.

D: effect of changes in the final product trade structure.

For multi-year periods, we calculate the cumulative effect by chaining annual decompositions:

$$\Delta LEE_{0-t}^{r} = \frac{LEE_t^r}{LEE_0^r} = \frac{LEE_1^r}{LEE_0^r} \times \frac{LEE_2^r}{LEE_1^r} \times \cdots \times \frac{LEE_t^r}{LEE_{t-1}^r} = \Delta LEE_{0,1}^r \times \Delta LEE_{1,2}^r \times \cdots \times \Delta LEE_{t-1,t}^r \quad (22)$$

$$\Delta LEI_{0-t}^{r} = \frac{LEI_t^r}{LEI_0^r} = \frac{LEI_1^r}{LEI_0^r} \times \frac{LEI_2^r}{LEI_1^r} \times \cdots \times \frac{LEI_t^r}{LEI_{t-1}^r} = \Delta LEI_{0,1}^r \times \Delta LEI_{1,2}^r \times \cdots \times \Delta LEI_{t-1,t}^r \quad (23)$$

This comprehensive SDA framework enables us to quantify the relative contributions of technological change, structural transformation, and demand growth to the observed patterns of unequal land exchange.

Limitations

Our study has several potential limitations related to methods and data. We employ a global environmentally extended multi-regional input–output (EEMRIO) framework to trace land flows embodied in international trade. While this approach is well-suited for capturing cross-country patterns of land appropriation, it does not account for within-country unequal exchange. Land appropriation may also occur within a country, where economically dominant “core” regions appropriate land resources from more peripheral regions[27, 70]. Such subnational inequalities in land use and resource appropriation cannot be captured in a country-level EEMRIO analysis and therefore remain beyond the scope of this study.

We use the FAOSTAT food insecurity index to represent countries’ food security performance across four pillars[37]. This dataset provides broad country coverage and captures multiple indicators corresponding to each pillar of food security. However, relying on a set of disaggregated indicators may not fully reflect the multidimensional nature of food security. In this respect, a single comprehensive composite index could offer a more integrated and holistic representation of the four pillars of food security.

In addition, uncertainties inherent to EEMRIO modeling may affect the magnitude of estimated footprints. As documented in previous studies, environmental footprint results can vary due to differences in geographical resolution, sectoral aggregation, and technology assumptions used in different EEMRIO databases[71]. However, after harmonizing the environmental extensions between different EEMRIOs, footprint estimates for major economies typically converge, with discrepancies below 10% for carbon footprints[72] and 15% for material footprints[73]. These findings indicate that, despite remaining uncertainties, the overall patterns identified in this study are robust to known limitations of EEMRIO-based analyses.

Data availability

All the data used in this study is from open access sources. Specifically, the global MRIO tables are from Eora (https://worldmrio.com). The Gross National Income (GNI) and total population data are obtained from the World Bank (https://data.worldbank.org). The food production yield data, food export data and food insecurity index for each country all come from the FAOSTAT database (https://www.fao.org/faostat/). The original data on loss in SHI is provided by the Map of Life project (https://mol.org/indicators/). FAOSTAT food and agricultural trade data are used to identify the dominant export product categories of main embodied land exporters (https://www.fao.org/faostat/en/#data/TCL).

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Supplementary Information

Content

A. Supplementary results

HI countries' net land appropriation

Here we have a more detailed examination of HI countries' net land appropriation across specific country groups and land types reveals distinct spatial and temporal patterns (Supplementary Fig.1-3). Among all sources, UMI countries contributed the largest share of net-appropriated land throughout the study period. The appropriation from UMI countries showed a marked increase from 1990, peaking around 2005 at over 600 million hectares, before declining slightly and stabilizing around 500–550 million hectares after 2015. Forest land and other land remained the dominant land types appropriated from UMI countries, although cropland also accounted for a notable share.

LMI countries were the second-largest source of net-appropriated land, with total appropriation rising steadily until around 2005, reaching nearly 200 million hectares, before experiencing a moderate decline in the subsequent years. Similar to the UMI group, forest land and other land were the main land types appropriated, while cropland remained stable and significant across the entire period.

Net appropriation from LI countries also increased over time, growing from below 60 million hectares in 1990 to over 120 million hectares by 2021. The composition of land types in LI appropriation was relatively balanced, with consistent contributions from cropland, forest land, and other land throughout the period.

In contrast, HI countries' net appropriation from India was relatively modest in magnitude, peaking around 2005 at 35 million hectares. After that, it declined steadily and remained below 25 million hectares in the later years. Cropland was the most heavily appropriated land type from India, followed by pasture and other land.

China presented a unique trend. HI countries' net appropriation from China increased sharply from 1990, peaking around 2005 at over 100 million hectares. However, this was followed by a dramatic reversal. By 2015, the net appropriation had not only declined significantly but had turned negative, indicating that China had become a net land appropriator from HI countries. This reversal was most pronounced in other land and pasture categories, underscoring China's strategic transformation in its global trade and land-use position.

Together, these results illustrate the shifting geography of HI countries' land dependencies, with growing reliance on UMI and LMI countries, declining dependence on China, and relatively stable patterns in appropriation from LI countries. These changes reflect broader transformations in global trade relationships, land-use dynamics, and geopolitical strategies surrounding land-intensive production.

The impact of land unequal exchange on effective land area per capita

Without considering trade, many lower-income countries appear to have substantial land endowments on a per capita basis. For example, UMI countries have the highest native land endowments across all land types, with approximately 372,290 hectares of cropland per million people, 1.64 million hectares of forest per million people, 271,355 hectares of pasture per million, and 1.07 million hectares of other land per million (Supplementary Fig. 9a, left bars). HI countries initially had less favorable per capita land endowments compared to UMI—averaging about 339,138 hectares of cropland and 926,141 hectares of forest per million people. LMI and LI countries had moderate land endowments, while China and India had the lowest per capita land availability in all categories, primarily due to their large populations.

However, unequal exchange through trade fundamentally alters this distribution. After accounting for land embodied in trade (Supplementary Fig. 9a, right bars), HI countries emerge as the primary beneficiaries in all land categories. Their effective per capita land availability increases across the board. For instance, HI countries' effective forest area rises to 1.24 million hectares per million people, a 33% increase over their pre-trade level. Effective cropland for HI increases to 450,163 hectares per million (a 32% rise), and effective pasture to 396,969 hectares per million (an 18% rise). In contrast, most other groups see declines in per capita land available once trade is considered.

The changes in land per capita due to trade (Supplementary Fig. 9b–e) show that only HI countries consistently gained disposable land area through global trade over 1990–2021. Every other country group experienced a decline in per capita land availability as a result of land embodied in net exports. UMI countries, in particular, saw the greatest reduction in disposable land per million people across all land types. Their per capita forest area fell by about 14%, pasture by 12%, and cropland by 11%.

After high-income countries had appropriated additional land resources from all other groups, HI countries became the group with the highest effective per capita land availability in every category except forestland. Before accounting for net imports, HI countries had on average 719,433 fewer hectares of forest per million people than UMI countries; after net imports, this gap shrank to 178,016 hectares. By appropriating land resources from lower-income nations, HI countries not only increased their own land endowments but also exacerbated global disparities. The reduction in "disposable" land for UMI and other lower-income countries likely impedes their ability to sustain economic growth, food production, and environmental conservation. Moreover, this land appropriation can lead to greater ecological and social stress in countries already struggling with land scarcity.

China's position experienced a structural shift over the study period. Before the 2010s, like other lower-income groups, China experienced a reduction in its disposable land area due to trade. However, after around 2010, China began to benefit modestly from trade, similar to HI countries, as it became a net land importer. Although China's net gain in land area per capita has been small compared to HI countries, it has grown consistently, reflecting China's changing role in international land trade.

B. Supplementary methods

In the Structural Decomposition Analysis (SDA) method, the definition and calculation method of each driver affecting the changes in LEE and LEI are as follows.

The direct land intensity (q)：$q = e\hat{x}^{-1}$ with elements q^s indicates the direct land intensity of in economy s.

Production technology (H): $h^r = \sum_{s=1}^{N} A^{sr}$ with elements h^r shows aggregate intermediate inputs per unit of gross output by economy r.

Trade structure of intermediate inputs (T): $t^{sr} = a^{sr}/h^r$ with elements t^{sr} reflects the input shares of each economy in aggregated inputs per unit of gross output by economy r.

Final demand level (y): $y^r = \sum_{s=1}^{N} y^{sr}$ with elements y^r represents gross final demand of economy r.

Final demand trade structure (D): $d^{sr} = y^{sr}/y^r$ with elements d^{sr} demonstrates the shares of each economy to satisfy the gross final demand of economy r.

To further distinguish the domestic and foreign contributions to the change of LEE and LEI, we divide each driver into two parts, with "r" illustrates domestic effects and "-r" indicates foreign effects.

Taking economy r and the direct land intensity q as an example:

$$q^r = q^{(r)} + q^{(-r)} = \left[0 \ldots q^{(r)} \ldots 0\right]' + \left[q^{(1)} \ldots q^{(r-1)}\ 0\ q^{(r+1)} \ldots q^{(N)}\right]'$$

$q^{(r)}$ only contains the domestic direct land intensity and other elements are zero. In contrast, $q^{(-r)}$ contains the direct land intensity of all economies except economy r.

By the same way other drivers can also be divided into domestic and foreign effects.

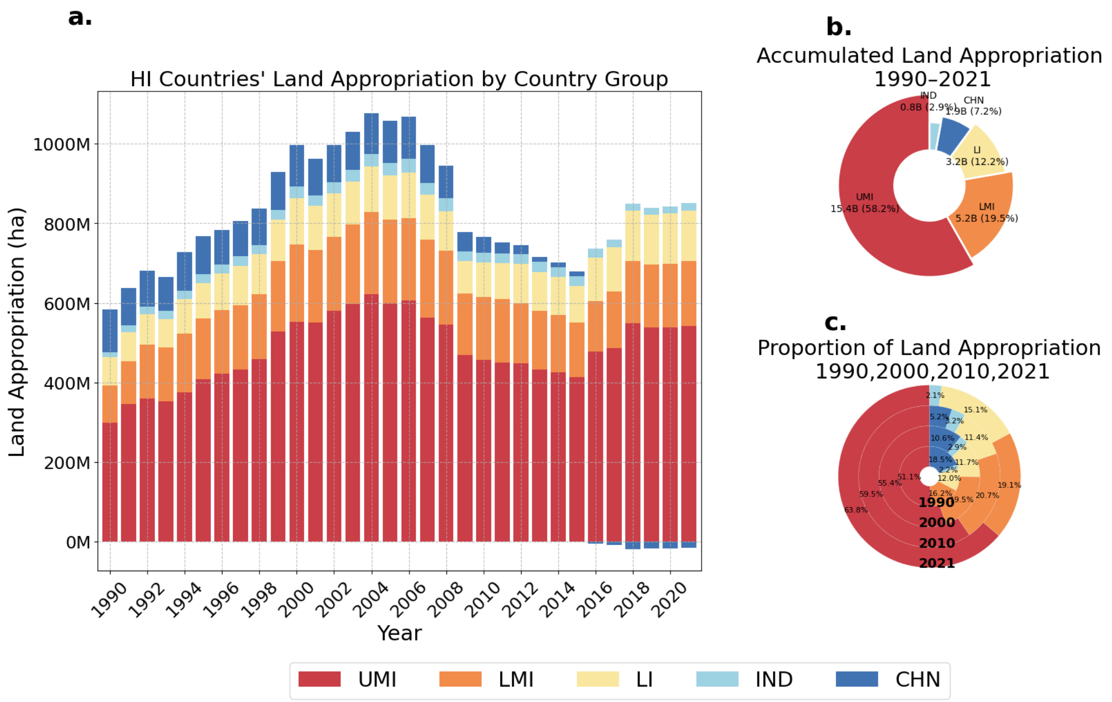
$$H^r = H^{(r)} + H^{(-r)}$$

$$T^r = T^{(r)} + T^{(-r)}$$

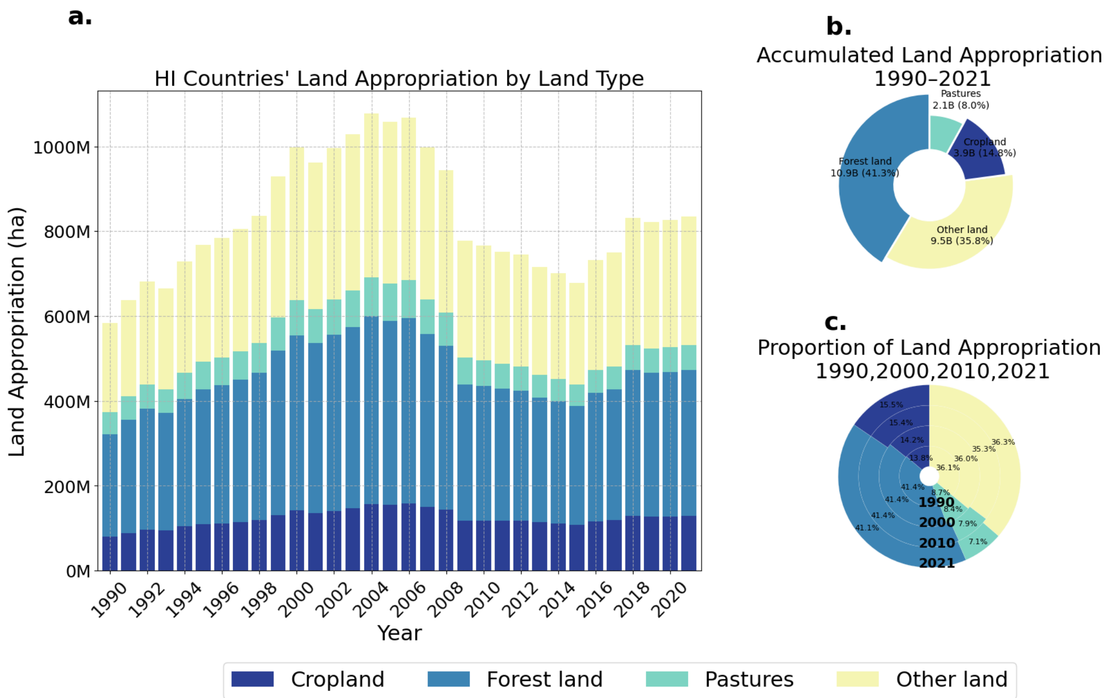
$$y^r = y^{(r)} + y^{(-r)}$$

$$D^r = D^{(r)} + D^{(-r)}$$

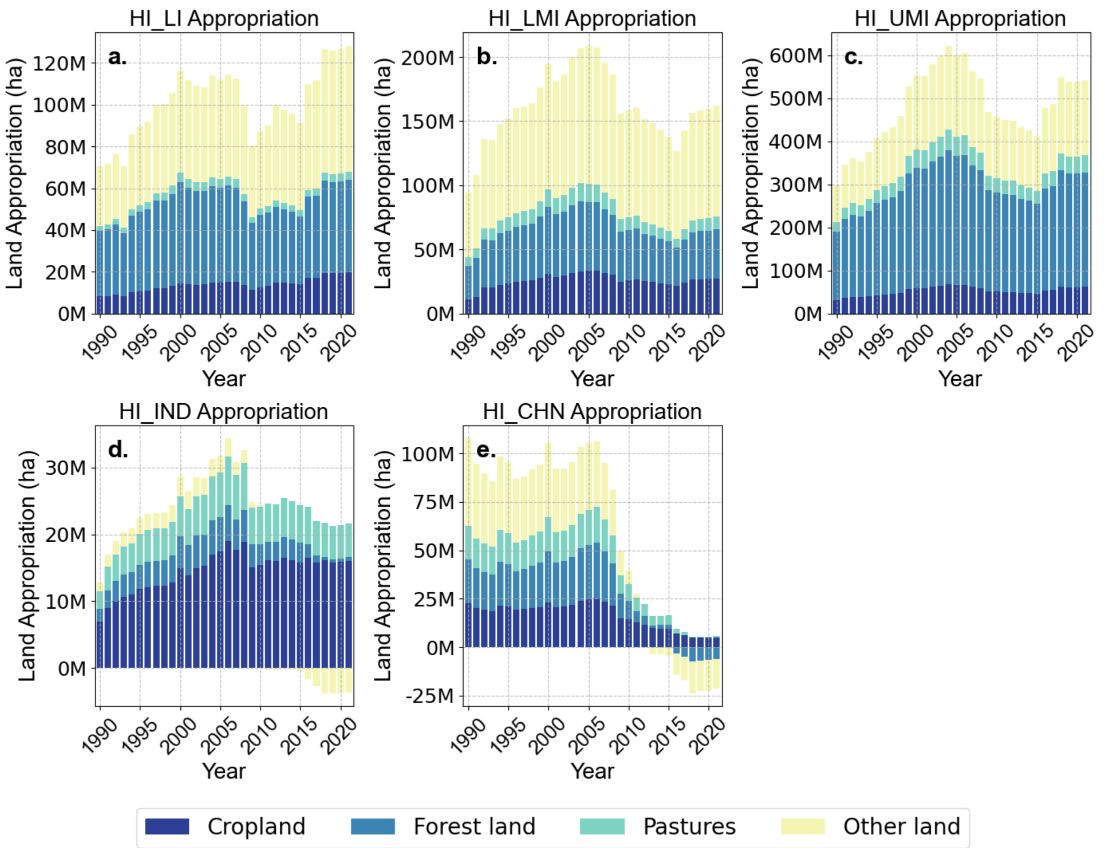
C. Supplementary figures and tables



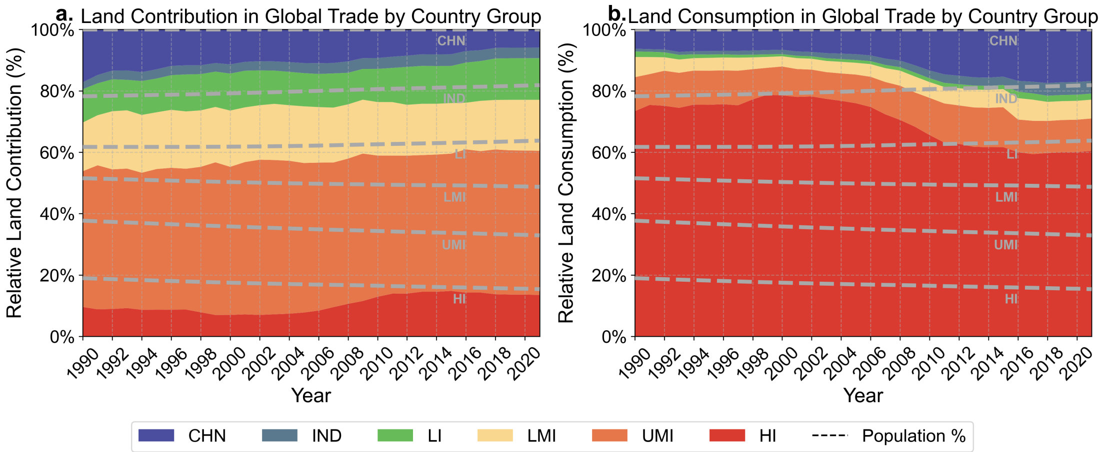
Supplementary Fig. 1 | HI country' net appropriation of land (ha) from other country groups, by country group, 1990–2021. Panel **a** represents the value of HI countries' net land appropriation on other country groups (UMI, LMI, LI, IND, CHN) from 1990-2021. Panel **b** illustrates the accumulated value of HI countries' net land appropriation on other country groups during 1990-2021. Panel **c** shows the proportion of HI countries' net land appropriation attributed to each country group.



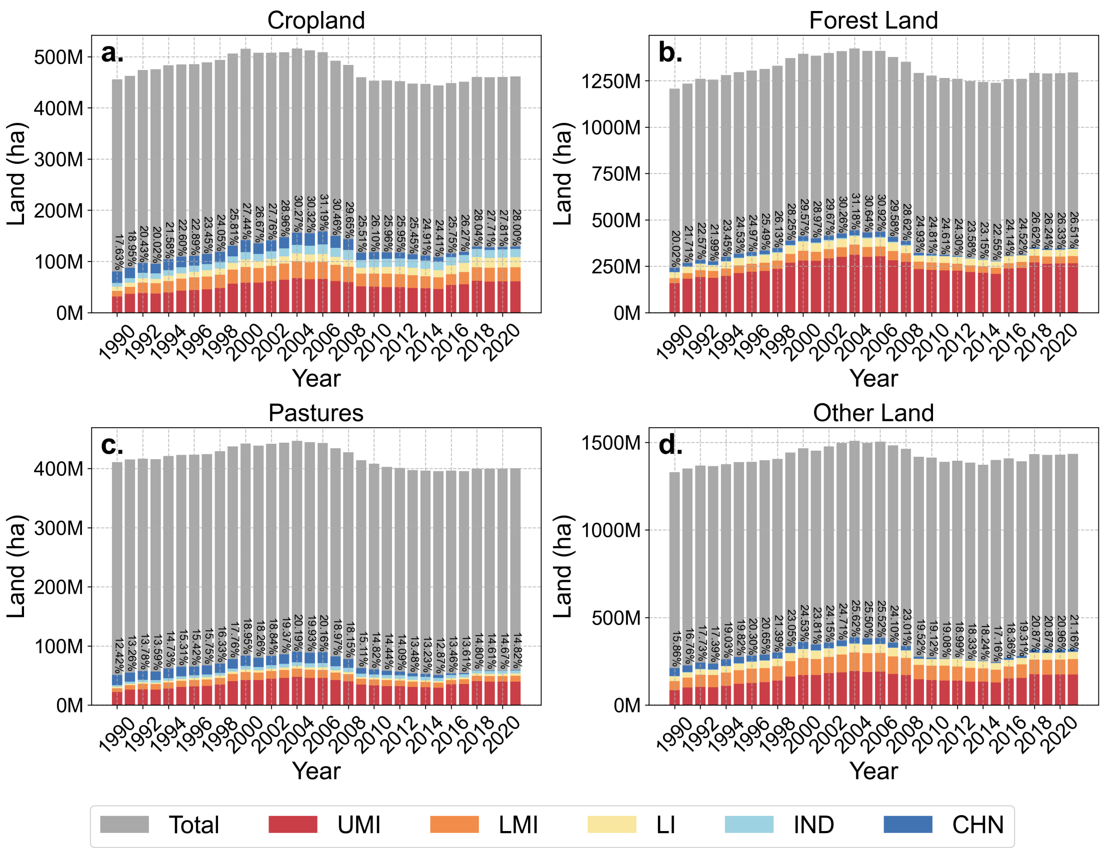
Supplementary Fig. 2 | HI country' net appropriation of land (ha) from other country groups, by land type, 1990–2021. Plot **a** represents the value of HI countries' net land appropriation on four land types (cropland, forestland, pasture, other land) from 1990 to 2021. Panel **b** illustrates the accumulated value of HI countries' net land appropriation on four land types during 1990-2021. Panel **c** shows the proportion of HI countries' net land appropriation attributed to each land types.



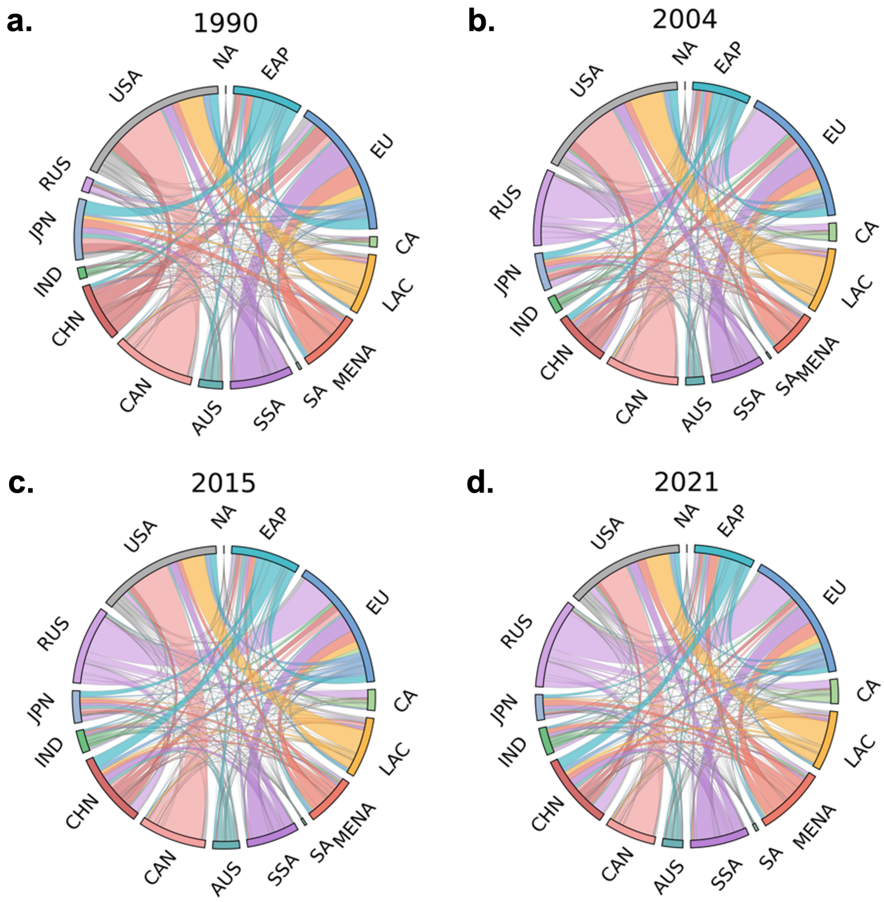
Supplementary Fig.3 | HI countries' net land appropriation from each country group, decomposed by land types.



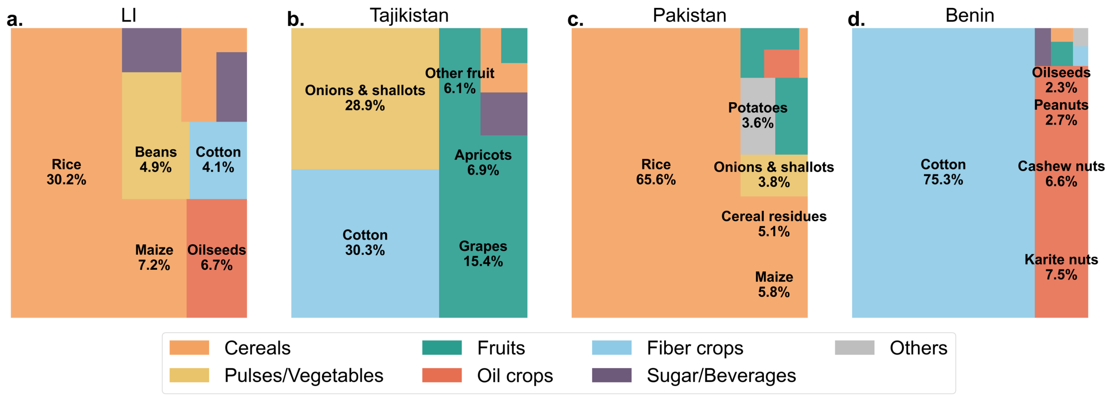
Supplementary Fig.4 | Proportional Land Contribution and Consumption in Global Trade by Country Group (1990-2021) Panel **a** illustrates the proportional land contribution to global trade. Panel **b** indicates the proportional land consumption in global trade. Different country groups (high-income countries abbreviate to HI, upper-middle income countries to UMI, lower-middle income countries to LMI, low-income countries to LI, China to CHN and India to IND) are represented in different colors, HI in red, UMI in blue, LMI in purple, LI in gray, IND in orange, and CHN in green. The gray broken line represents the population proportion of each country group.



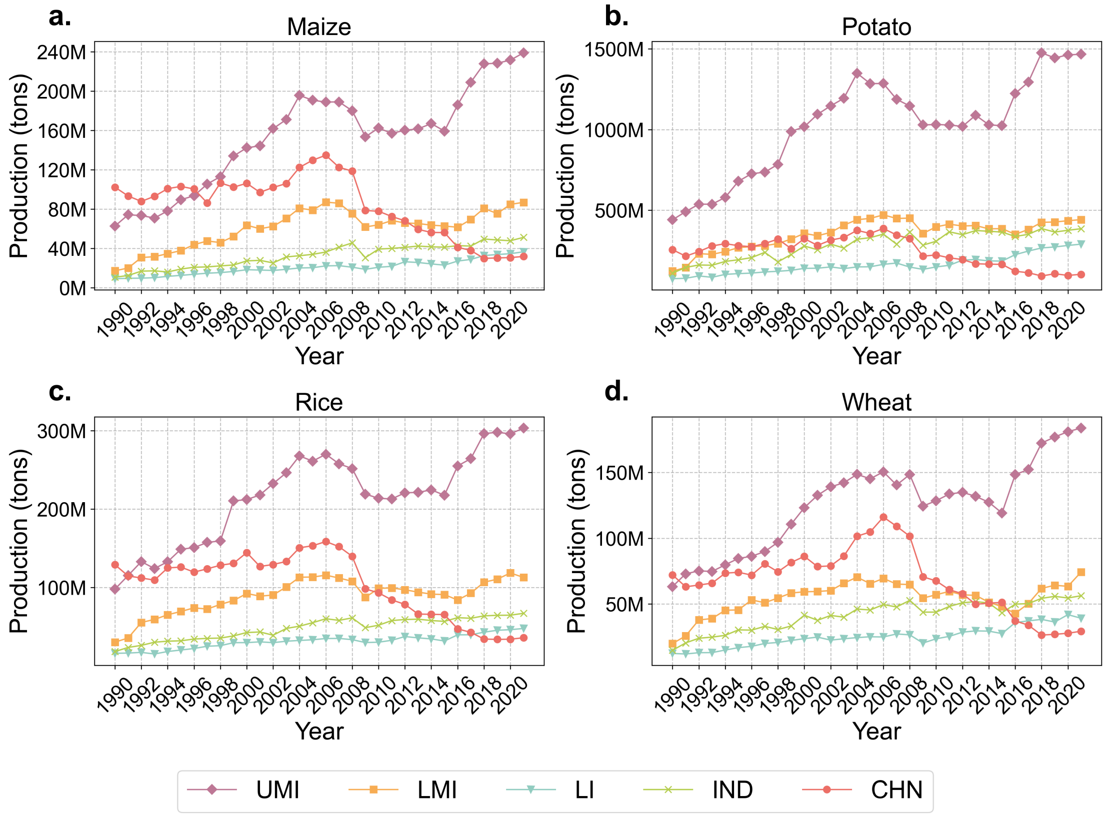
Supplementary Fig.5 | HI country's net appropriation of land (ha) from other country groups as a share of HI country's consumption of land (ha), 1990-2021. The light gray bar represents total land consumed in HI country including domestic land, land embodied in HI-HI trade, land embodied in import from other country groups and minus land embodied in export to other country groups. The red bar represents HI country's net appropriation of land from UMI country, the blue bar represents net appropriation from LMI country, the purple bar represents net appropriation from LI country, the dark gray bar represents net appropriation from India, the yellow bar represents net appropriation from China. Panel **a** shows HI country's net appropriation and HI country's consumption of cropland, Panel **b** shows HI country's net appropriation and HI country's consumption of forest, Panel **c** shows HI country's net appropriation and HI country's consumption of pasture, Panel **d** shows HI country's net appropriation and HI country's consumption of other land.



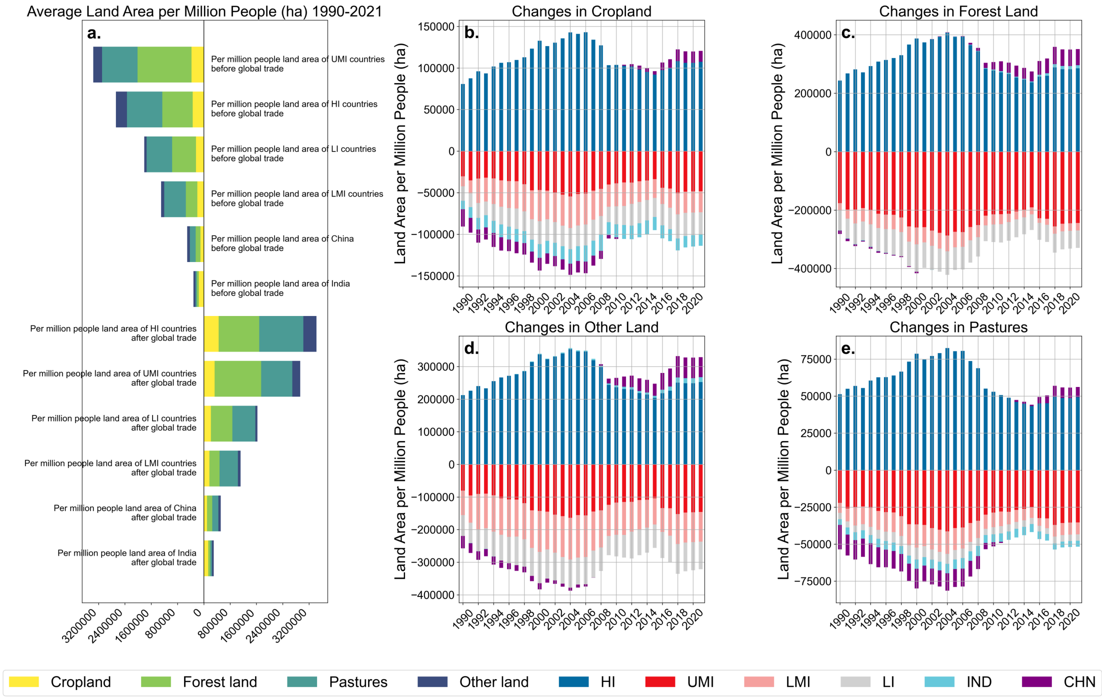
Supplementary Fig.6| Land Flow Embodied in Global Trade in year 1990, 2004, 2015 and 2021 among 15 regions. NA: Other North America; EAP: Other East Asia & Pacific; EU: European Union; CA: Central Asia, Latin America & Caribbean; MENA: Middle East & North Africa; SA: Other South Asia; SSA: Sub-Saharan Africa; AUS: Australia; CAN: Canada; CHN: China; IND: India; JPN: Japan; RUS: Russia; USA: the United States).



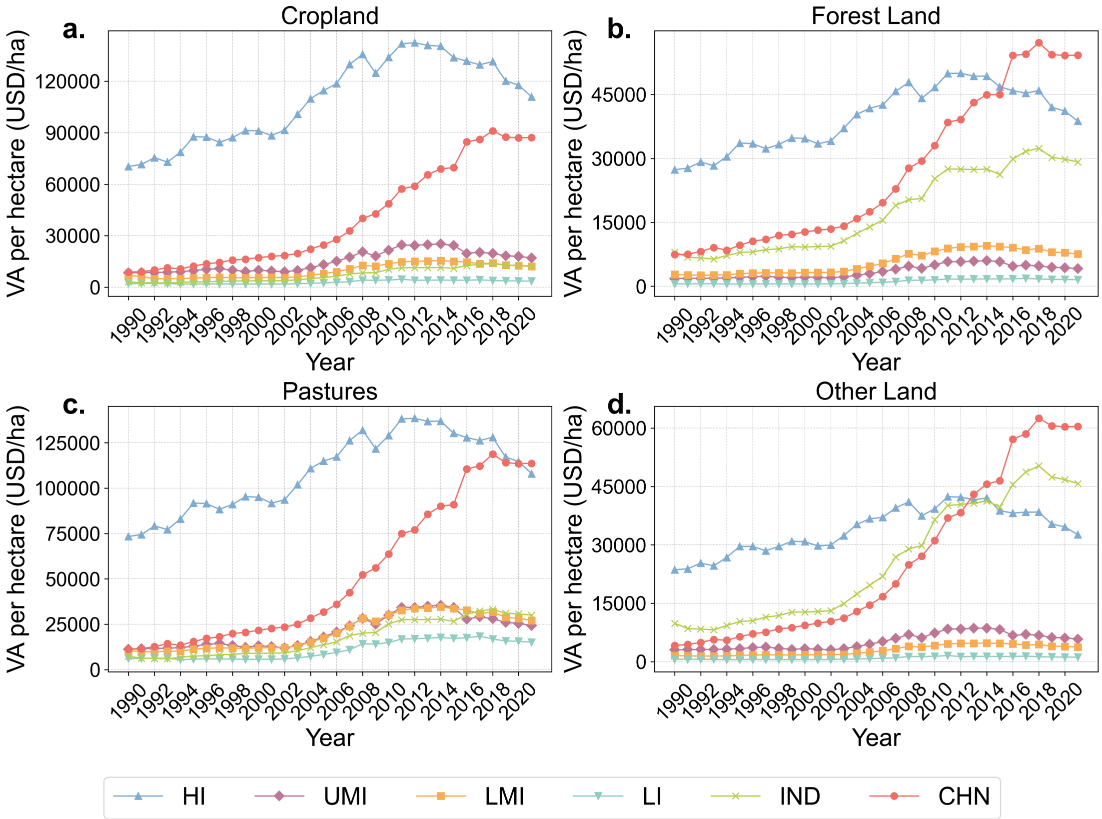
Supplementary Fig.7 | Composition of food exports in low-income economies. Panel **a** displays the aggregate structure of food exports from all low-income (LI) countries, whereas panels **b–d** depict the export composition of the three largest LI exporters. The area of each box represents the share of each food category in total exports, and color shading distinguishes major product classes of agricultural commodities.



Supplementary Fig.8 | Potential food production loss on appropriated land, 1990-2021. Food yield data from the FAO (https://www.fao.org/faostat/) was used to estimate the food production potential of land appropriated by HI country across different country groups. The red line represents food production in UMI country, the blue line represents LMI country, the purple line represents LI country, the dark gray line represents India, and the yellow line represents China. Panel **a** shows maize production, Panel **b** shows potato production, Panel **c** shows rice production, and Panel **d** shows wheat production.



Supplementary Fig. 9 | Land area per million people, 1990-2021. Panel **a** illustrates the average land area per million people across different country groups from 1990 to 2021. For each group, the left bars represent land area per million people prior to global trade, while the right bars represent the corresponding figures after global trade. Panels **b** through e depict the changes in land area per million people after global trade for each country group, with land categorized into four types: cropland, forest land, pasture, and other land.



Supplementary Fig. 10 | Value added per unit of land embodied in exports in constant international 2015 USD, 1990–2015. The red line represents TiVA of HI country, the blue line represents UMI country, the purple line represents LMI country, the dark gray line represents LI country, the yellow line represents India, the green line represents China. Panel **a** shows TiVA of cropland in each country group, Panel **b** shows forest, Panel **c** shows pasture, Panel **d** shows other land

Supplementary Table. 1 | country classification by income level.

H	UM	LM	L	India	China
GNI>$12,630	$4,130<GNI<$12,630	$1,640<GNI<$4,130	GNI<$1,640		
Population: 1.20Billion	Population: 1.37Billion	Population: 1.24Billion	Population: 1.18Billion	Population: 1.41Billion	Population: 1.42Billion
N=65	N=44	N=34	N=39	N=1	N=1
Andorra	Albania	Algeria	Afghanistan	India	China (Hong Kong, Macao, Taiwan)
Antigua	Argentina	Bangladesh	Angola		
Aruba	Armenia	Bhutan	Benin		
Australia	Azerbaijan	Bolivia	Burkina Faso		
Austria	Belarus	Cambodia	Burundi		
Bahamas	Belize	Cape Verde	Cameroon		
Bahrain	Bosnia Herzegovina	Congo	Central African Republic		
Barbados	Botswana	Cote dIvoire	Chad		
Belgium	Brazil	Djibouti	DR Congo		
Bermuda	Bulgaria	Egypt	Eritrea		
British Virgin Islands	Colombia	Gaza Strip	Ethiopia		
Brunei	Cuba	Ghana	Gambia		
Canada	Dominican Republic	Honduras	Guinea		
Cayman Islands	Ecuador	Iran	Haiti		
Chile	El Salvador	Kenya	Kyrgyzstan		
Costa Rica	Fiji	Laos	Lesotho		
Croatia	Gabon	Mauritania	Liberia		
Cyprus	Georgia	Mongolia	Madagascar		
Czech Republic	Guatemala	Morocco	Malawi		
Denmark	Guyana	Nicaragua	Mali		
Estonia	Indonesia	Nigeria	Mozambique		
Finland	Iraq	Papua New Guinea	Myanmar		
France	Jamaica	Philippines	Nepal		
French Polynesia	Jordan	Samoa	Niger		
Germany	Kazakhstan	Sao Tome and Principe	North Korea		
Greece	Lebanon	Sri Lanka	Pakistan		
Greenland	Libya	Swaziland	Rwanda		
Hungary	Malaysia	Tunisia	Senegal		

Iceland	Maldives	Ukraine	Sierra Leone
Ireland	Mauritius	Uzbekistan	Somalia
Israel	Mexico	Vanuatu	South Sudan
Italy	Moldova	Venezuela	Sudan
Japan	Montenegro	Viet Nam	Syria
Kuwait	Namibia	Zimbabwe	Tajikistan
Latvia	Paraguay		Tanzania
Liechtenstein	Peru		Togo
Lithuania	Russia		Uganda
Luxembourg	Serbia		Yemen
Malta	South Africa		Zambia
Monaco	Suriname		
Netherlands	TFYR Macedonia		
New Caledonia	Thailand		
New Zealand	Turkey		
Norway	Turkmenistan		
Oman			
Panama			
Poland			
Portugal			
Qatar			
Romania			
San Marino			
Saudi Arabia			
Seychelles			
Singapore			
Slovakia			
Slovenia			
South Korea			
Spain			
Sweden			
Switzerland			
Trinidad and Tobago			
UAE			
UK			
USA			
Uruguay			