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Livestock antimicrobial use embodied in global supply chains

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The excessive use of antimicrobials has led to increasing levels of antimicrobial resistance that can spread between livestock, humans and the environment, with important One Health implications. Antimicrobial use in the livestock sector represents 73% of global antimicrobial consumption, yet how such antimicrobial use is embedded within international trade and global production networks remains unclear. Here we quantify global antimicrobial footprints and trace them through global supply chains from 2010 to 2020. Global livestock antimicrobial footprints peaked at 118.6 kilotons (kt) in 2013, then fell to 84.0 kt by 2020. China and the USA contributed nearly 60% of the global antimicrobial footprint. Most use remained in domestically produced goods, yet the trade-embodied share rose from 16% to 20%, signalling growing cross-border spillovers. Developed economies showed higher per capita use via trade, whereas developing economies' use was concentrated in local production. Brazil surpassed China as the largest exporter of antimicrobials used in livestock production by 2020. Intriguingly, non-food products, particularly the clothing, services and manufacturing sectors, account for half of the trade-embodied antimicrobial footprint. Thus, global spillover of the effects of antimicrobial use extends well beyond the food system thus requiring policymakers to broaden their focus to better address antimicrobial resistance threats.

Livestock production has a crucial role in food security and sustainable development[1–3]. The global surge in livestock production has been driven by a combination of rising consumer demand and supply-side expansion. Over the past decades, global demand for animal protein has increased fivefold, rising from 70 million tons to 350 million tons. This surge is projected to continue, with an additional 12% growth anticipated between 2019 and 2029, particularly in developing countries[4–7]. However, this rapid growth has heavily relied on the extensive antimicrobial use (AMU) in livestock farming, primarily for growth promotion and mass prophylaxis[8]. Livestock production accounts for approximately 73% of global antimicrobial consumption, exerting selective pressure that drives emergence and spread of antimicrobial resistance (AMR) from herds to humans and the environment via manure, food, contact and water—amplifying risks across the animal–human–environment interface central to One Health and challenging global health and sustainability[9–11]. The UN General Assembly has identified AMR as a pressing global threat, linked to 700,000 deaths each year, with warnings that unabated trends could drive annual mortality to 10 million by 2050[12]. A recent projection estimates that AMR may directly cause 1.91 million deaths and be linked to 8.22 million fatalities worldwide by 2050[13]. Besides, AMR can make many previously easily treatable infections difficult to manage, increasing the risk of disease spread and treatment costs[12,14,15].

Whereas, to effectively regulate the AMU, it is necessary to accurately account for the usage in different regions/countries, which not only helps to understand the trends but also provides a scientific

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basis for formulating reasonable regulatory policies. This challenge is particularly acute in developing countries, where the lack of regulation in antimicrobial supply chains and non-compliance in usage contribute to rampant misuse[16–18]. However, the absence of consistent monitoring systems makes it difficult to accurately assess the actual levels of AMU in livestock production[6,19]. To address the challenges, 196 countries have committed to developing national action plans to combat AMR, under the World Health Organization (WHO) framework[20,21]. Despite these efforts, the primary responsibility for reducing AMU has been placed on individual countries, especially China and the USA, with a strong emphasis on local policy interventions to curb misuse and residues[6,9,17].

However, the on-site policies may be locally successful, but increase pressures elsewhere, driven by international trade. Livestock product demand is not solely local but also notably international, with livestock products trade accounting for approximately 10% of global merchandise trade[22]. This trade is largely fuelled by growing demand from Asia, particularly China and Japan. Moreover, livestock by-products are integral to multiple industries such as apparel and chemicals, embedding AMU into global supply chains[23,24]. AMU permeates global supply chains through both direct and indirect applications across all production stages, driven by demand for final goods. A concrete example is leather production, which involves a multi-stage supply chain, from livestock farming and slaughtering to industrial processing (for example, tanning and dyeing). Intermediate inputs such as animal-based fats and enzymes, often derived as livestock by-products, create linkages between primary products (for example, meat) and secondary products (for example, leather) within the agri-industrial system. Consequently, the antimicrobial footprint of leather includes antimicrobials used not only in animals raised for hides but also in livestock whose by-products contribute to leather processing. This indicates that AMU is closely linked to the production of both food and manufactured goods, resulting in important spillover effects along global supply chains. These effects challenge the traditional perspective of on-site responsibility, suggesting a need for a new perspective that allocates responsibility between producers and consumers across borders.

In this study, we link antimicrobial estimates in livestock production with a global multi-regional input–output (MRIO) model, enabling us to quantify the antimicrobial footprint via global supply chains from 2010 to 2020. The footprints encompass both direct and indirect AMU throughout the production stages of food and non-food products. We first estimate global AMU in chicken, cattle and pigs across 16 antimicrobial types for each country/region using Bayesian regression[6], based on official data from 43 countries and product-level data from the UN Food and Agriculture Organization (FAO). We then utilize the EXIOBASE model to quantify AMU embodied in global supply chains. We further examine the socio-economic drivers behind trends in AMU for each country/region using structural decomposition analysis. By shifting the focus from on-site to off-site responsibility, we aim to reshape the understanding of how responsibility for AMR should be shared between producers and consumers globally. This supply chain perspective aligns with the One Health framework by integrating animal, human and environmental factors, revealing how trade-driven AMU spillovers transcend borders and need interdisciplinary and multi-sectoral strategies to mitigate AMR risks.

Results

Reduced livestock-related antimicrobial footprints

A substantial reduction in global livestock-related antimicrobial footprints was observed from 2010 to 2020 (Fig. 1a). Antimicrobial footprints peaked at 118.6 kilotons (kt) in 2013, then consistently declined to 84.0 kt by 2020. The decline was particularly pronounced after 2016 UN High-level Meeting on AMR[21], where the global footprint plummeted by 20% from 106.8 kt in 2016 to 85.8 kt in 2017. This trend aligns with reports from the World Organisation for Animal Health (WOAH) on AMU in food-producing animals[25]. The decline was particularly contributed by China and the USA, which together accounted for approximately 60% of global antimicrobial footprints throughout the study period. China's antimicrobial footprint decreased from 57.7 kt in 2010 to 41.0 kt in 2020, whereas the USA saw a reduction from 9.7 kt to 7.0 kt over the same period.

Developed countries experienced more substantial declines in antimicrobial footprints than developing countries (Fig. 1d). Western Europe and developed economies in the Asia–Pacific (for example, Australia), saw average reductions of 31% and 11%, respectively. It is worth noting that developing countries with a sizeable livestock sector also saw a massive decline in antimicrobial footprint, such as Russia (34%) and Brazil (31%). In contrast, developing countries in South America and the Asia–Pacific observed smaller declines of 11% and 7%, respectively. However, some developing countries including India, Indonesia, Africa and the Middle East countries, even saw increases in antimicrobial footprints. For example, Indian antimicrobial footprint grew from 3.1 kt to 3.6 kt, representing a 16% increase. The disparity between developed and developing countries indicates greater efforts in reducing AMU in the developed countries, particularly in European countries. Though it is worth noting that livestock production activities have shifted to developing countries. The European Union's Farm to Fork strategy and zero-pollution action plan aims to halve AMU in farmed animals by 2030 compared to 2018[26].

To track the spillover effect, we further divide antimicrobial footprints into those from local products and those embodied in imports. Local AMU accounted for about 82% of the total antimicrobial footprint (Fig. 1b). AMU embodied in imports started at 17.9 kt in 2010, peaked at 21.7 kt in 2015 but declined to 16.1 kt by 2020. Despite the overall reduction, the share of trade-related antimicrobials in the total footprint increased from about 16% in 2010 to 20% in 2020, highlighting the growing spillover effect through global supply chains (Fig. 1c). In 2010, Western Europe and the USA were the largest contributors to trade-related AMU, accounting for 21% and 16% of total trade-related AMU, respectively. However, their trade-related AMU declined by 33% and 29%, respectively, by 2020 (Fig. 1e), which leads their shares to decline to 16% and 12% of the global total trade-related AMU, respectively. In contrast, China's trade-related AMU rose by more than triple from 0.4 kt to 2.0 kt, with the share of the global trade-related AMU increasing from 2% to 13%. This reflects China's massively growing imports of livestock products, especially beef. China's beef imports surged from 0.02 to more than 2 million tons during the study period[27].

There is heterogeneity in antimicrobial types in terms of their changes over the period. Among the 16 antimicrobial categories studied, tetracycline, widely used as a growth promoter in animal husbandry[28], made up the largest portion of the global antimicrobial footprint, accounting for 55% in 2010 (Supplementary Fig. 1). However, the use of tetracycline dropped by more than half, from 61.2 kt to 25.2 kt, over the study period, reducing its share to 29% by 2020. Conversely, penicillin usage increased notably, from 3.8 kt to 14.7 kt, making it the second-largest antimicrobial used in animal production by 2020[25], with its share rising from 3% to 18%. In terms of AMU embodied in trade, tetracycline followed a similar pattern, with its share dropping from 52% to 22%, whereas penicillin's share surged from 4% to 19% (Supplementary Fig. 1). The decline in tetracycline use is associated with stricter global policies, for instance, the prohibition of tetracyclines as growth promoters—a policy implemented in 108 countries. This includes major users such as the USA, which instituted its ban in 2017[25]. The increase in penicillin usage could be linked to the decreased use of tetracyclines, which may have led to higher disease risks in livestock, necessitating more penicillin for treatment[29].

Outsourced antimicrobial footprints in developed economies

High per capita antimicrobial footprints are found in developed economies (Fig. 2). The global per capita antimicrobial footprint shows a

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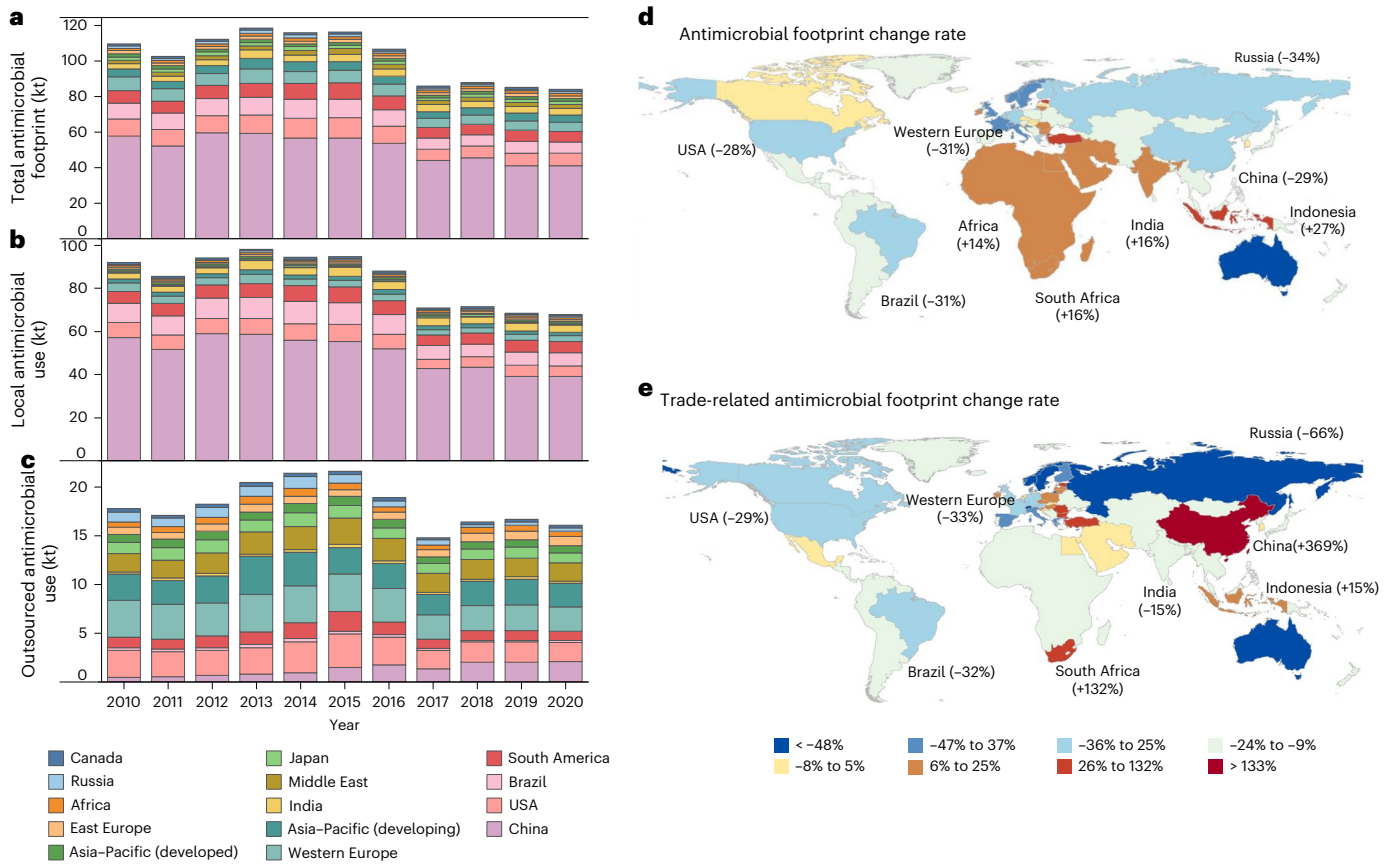


Fig. 1 | Global and regional dynamics of livestock antimicrobial footprints (2010–2020). a, Livestock antimicrobial footprints across regions during 2010–2020. **b**, Local antimicrobial use driven by demands across regions during 2010–2020. **c**, Imported antimicrobial use driven by demands across regions during 2010–2020. **d**, The change rate of total antimicrobial footprints during 2010–2020. **e**, The change rate of trade-related antimicrobial footprints during 2010–2020. Basemap data in **d** and **e** from the World Bank Official Boundaries under a Creative Commons license CC BY 4.0.

decline from 15.6 g per capita in 2010 to 10.6 g per capita in 2020. Brazil, China, Spain, Luxembourg and Canada were the top five countries with the highest per capita antimicrobial footprints in 2020. The high per capita footprints in Brazil and China were primarily due to extensive AMU in their livestock industries. As major livestock producers, these countries have a remarkable impact on global AMU. China accounts for half of the world's pig population, whereas Brazil contributes 20% of global beef production[30]. Both countries also exhibit notably higher AMU intensities. In Brazil, the antimicrobial intensity was 139 mg per PCU (population correction unit) kg for cattle and 440 mg per PCU kg for pigs in 2010—three times the global average (41 mg per PCU kg for cattle and 136 mg per PCU kg). China's figures were even more pronounced, with 1,014 mg per PCU kg for chickens in 2010, 20 times than the global average (54 mg per PCU kg), although the intensities later were almost halved in 2020. However, both countries have seen considerable declines in their per capita antimicrobial footprints, with Brazil dropping from 47 g per capita to 30 g per capita and China from 43 g per capita to 29 g per capita by 2020, largely due to stricter policies implemented since 2015 (refs. 31–33). By contrast, the high per capita antimicrobial footprints in developed countries were driven by high household consumption. For instance, per capita household consumption in Canada and the USA was 5% and 50% higher than the OECD (Organisation for Economic Cooperation and Development) average, respectively[34]. However, Canada's slower pace in regulating farmyard AMU[35] compared to other developed countries resulted in a smaller decline (−12%) in its per capita antimicrobial footprint, compared to the USA (−33%).

In developing countries, most of the per capita antimicrobial footprint came from local source rather than imports, with 8.8 g per capita from local products and 2.0 g per capita from imports (Fig. 2). Conversely, in many developed economies, the per capita antimicrobial footprint from imports exceeded that from local products, indicating a notable spillover effect due to reliance on global supply chains. This pattern was particularly evident in European countries with strict AMU regulations, where domestic policies reduced local AMU (with 6.2 g per capita) and import contributes more than half of the per capita footprint (9.9 g per capita). However, there was considerable variation across countries. For example, both Portugal and Spain had high per capita antimicrobial footprints driven by strong demand for pig meat. In Spain, this footprint was primarily due to the country's large-scale pig farming, which produces 20% of the EU's pigs (EUROSTAT, https://ec.europa.eu/eurostat). In contrast, Portugal's antimicrobial footprint was more heavily influenced by imports, with pig meat accounting for half of the country's imported antimicrobial footprint[36].

Half of trade-related antimicrobial use is non-food

The global supply chain facilitated pronounced flows of antimicrobial footprints, shaped by regional differences in livestock antibiotic use intensity over the period. The data reveal that the antimicrobial flows predominantly originate from regions with high AMU intensity and move towards regions with lower intensity (Fig. 3), highlighting that major global exporters are typically associated with higher AMU intensity.

We found that Brazil overtook China as leading exporter by 2020. In 2010, China, as the world's manufacturing hub, was the largest exporter of trade-related antimicrobials, accounting for 46% of the global trade-related antimicrobial footprint (Fig. 3a). The primary importers

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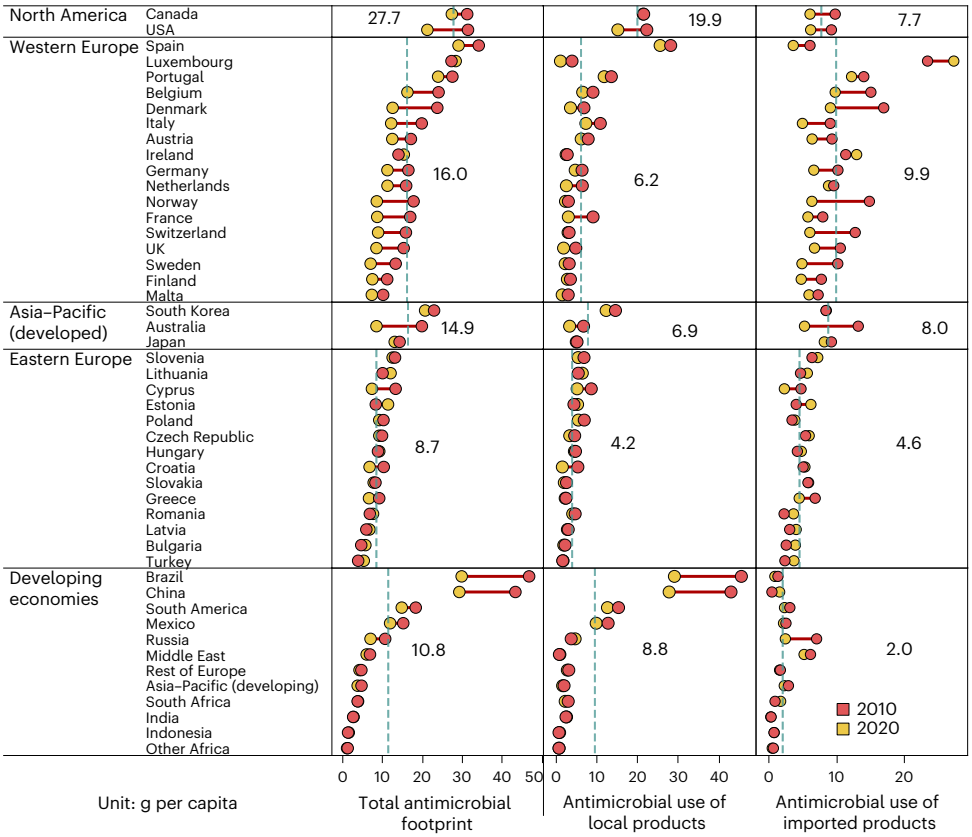


Fig. 2 | Per capita antimicrobial footprint across economies in 2010 and 2020. The dashed line represents the average level of the per capita antimicrobial use.

of these antimicrobials were the USA, Asia–Pacific developing countries and Japan, with the USA leading imports at 1,737 kg net imports from China, followed by Asia–Pacific countries (1,592 kg) and Japan (593 kg). Brazil ranked as the second-largest exporter, with the Middle East being a key importer, receiving 798 kg of antimicrobials embodied in net imports. However, by 2020, Brazil had overtaken China as the largest exporter of AMU embodied in trade (Fig. 3b). Brazil's AMU embodied in exports increased by 60% from 2,430 to 3,895 kg, whereas China's export more than halved from 8,148 to 3,884 kg. In 2010, China was a net exporter of trade-related AMU to Brazil (51 kg), but by 2020, this pattern had reversed, with Brazil becoming a net exporter to China (860 kg). This shift is associated with China's increasing demand for meat, especially beef. Brazil supplied 43% of China's meat imports in 2020, with other South America countries such as Argentina and Uruguay contributing approximately 30% of China beef imports[37]. This made the same reverse between China and other South America countries, where China switched from the net exporter (248 kg) to the net importer (272 kg) to other South America countries in terms of the trade-related AMU.

From 2010 to 2020, the composition of AMU footprints embodied in global trade shifted remarkably, with food-related products playing an increasingly dominant role (Fig. 3c). In 2010, food-related AMU was responsible for 44% of the total AMU embodied in trade, with processed food products (11%), beef (11%), pigs (10%) and chicken (8%) being the major contributors. By 2020, their combined share rose to 51%, driven largely by the increased AMU footprint in the global trade of beef (16%) and chicken (10%). This increase is closely tied to the rising meat demand in developing countries, particularly China. The share of AMU embodied in China's beef imports increased from 4% to 27% of the country's total imported AMU footprint. Similarly, Africa and the Middle East saw an increase in the share of AMU embodied in their chicken imports, from 11% to 25% for Africa and from 28% to 39% for the Middle East.

AMU embodied in global trade was not solely driven by food trade; non-food products and services accounted for more than half of trade-related AMU, despite a slight decline from 56% in 2010 to 49% in 2020 (Fig. 3c). Manufactured products were the largest contributor, accounting for 19% of total trade-related antimicrobial footprints, followed by service (14%), food-related service (9%) and clothes (7%) in 2020. All countries, regardless of affluence, heavily relied on the imports of manufactured products, particularly from China. A large portion of these imports were linked to the chemical industry and electronics manufacturing, where animal-derived products are essential. For example, chemicals accounted for 33% of AMU embodied in imported manufactured products, and animal-derived products such as cholesterol used in television screens made up 11% of these imports. It is interesting to see the high AMU embodied in the apparel sector, as raw materials used in clothes production are often animal-based, such as fur and leather. Western European countries and the USA have particularly high AMU embodied in the clothes imports, accounting for more than 50% of the total AMU embodied in the clothes trade. It indicates the global apparel trade pattern where the developed countries outsourced the apparel products from developing countries, such as China. Figure 3c also shows the decline in the AMU embodied in clothes trade from 2,088 kg to 1,170 kg over the period, with the proportion decreasing from 11% in 2010 to 7% in 2020. This could be attributed to the better antimicrobial management in developing countries, particularly in China.

Developed countries in Asia–Pacific and China, showed substantial AMU in the service sector, with more than 30% of their trade-related antimicrobial footprints. The high share of services driven by AMU reflected the intractable and indirect links between service sectors and animal products along supply chains. Construction services and public services are crucial in terms of the trade-related AMU, requiring more manufactured products, which are indirectly linked to animal products

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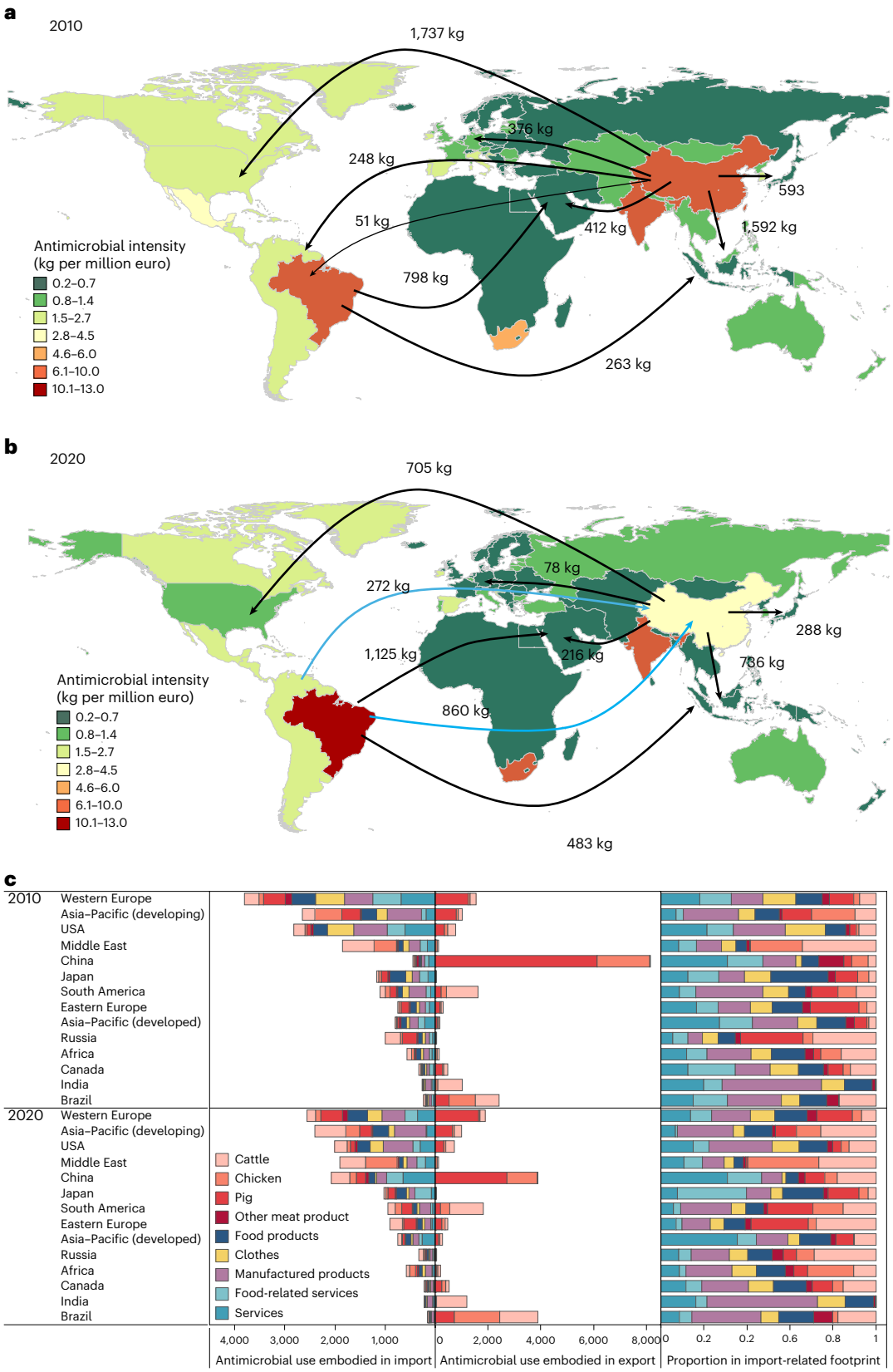


Fig. 3 | Livestock antimicrobial use embodied in international trade. **a**, Antimicrobial use embodied in imports in 2010, with highlighting key antimicrobial flows embodied in trade. **b**, Antimicrobial use embodied in imports in 2020, with highlighting key antimicrobial flows embodied in trade. Blue arrows reflect the trend reversed in comparison with 2010 trend. **c**, Antimicrobial use embodied in imports and exports between 2010 and 2020, along with the share of antimicrobial use embodied in imports by product category. Basemap data in **a** and **b** from the World Bank Official Boundaries under a Creative Commons license CC BY 4.0.

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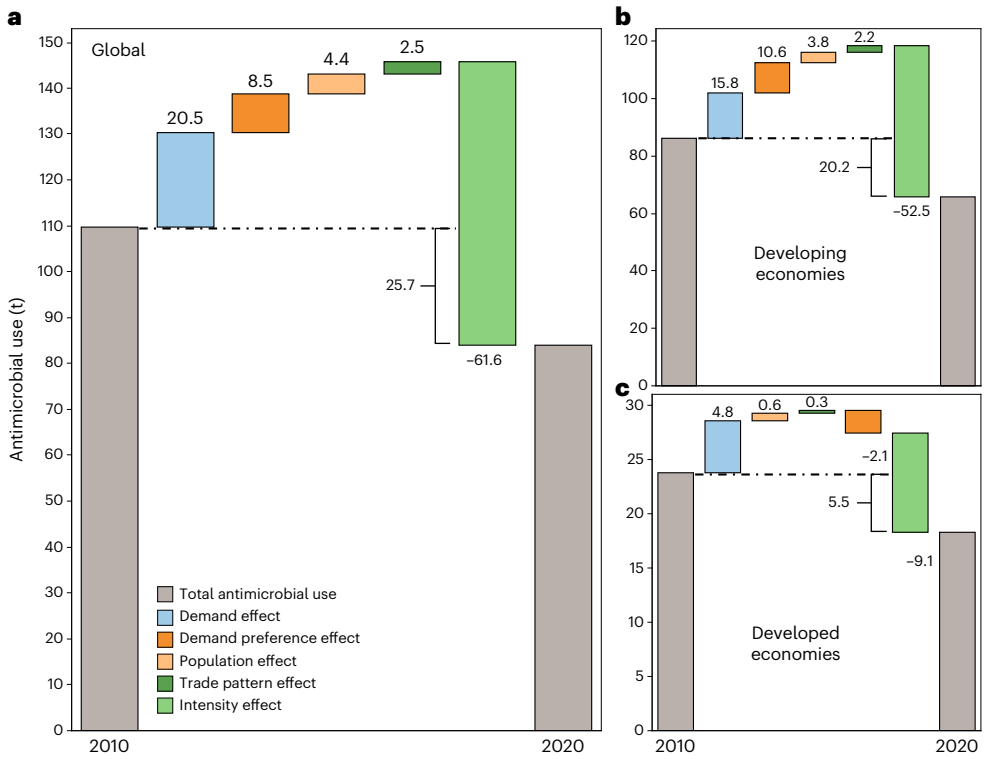


Fig. 4 | Drivers of trade-related antimicrobial footprint shifts. a–c, Socio-economic driving factors contributing to changes in total antimicrobial footprints from 2010 to 2020 at the global level (**a**) and separately for developing (**b**) and developed (**c**) countries.

via the supply chains. Food-related services (the hospitality sector and healthcare) are more directly linked to animal products, particularly due to the high consumption of food and medicine. These sectors are particularly high in countries with higher food imports. For example, Japan and China had 32% and 15%, respectively, of their trade-related antimicrobial footprints driven by demand for food-related services in 2020.

Drivers of trade-related antimicrobial footprint shifts

We further explore the driving factors of changes in antimicrobial footprints embodied in global supply chains. The decline in total antimicrobial footprints (25.7 kt) between 2010 and 2020 can be attributed to several socio-economic factors (Fig. 4a). Population growth and increased affluence drove up AMU by 4.4 kt and 20.5 kt, respectively. However, these increases were more than offset by reductions due to intensity effects, which were the primary driver of the overall decline, reducing antimicrobial footprints by 61.6 kt. This was largely due to stricter policies and better AMU management, particularly in developing countries, where China led with a 60% reduction in AMU intensity, from 7 kg per million euros to 2 kg per million euros of livestock output. This is largely attributable to China's national action plan to contain AMR since 2016[38], where tetracycline use decreased from 36.2 to 15.9 t from 2010 to 2020 (Supplementary Fig. 2). Rising intensive animal husbandry practices in China, where the intensive farming rate increased from 45% to 65% from 2010 to 2020, led to higher antimicrobials for medical use, such as penicillin and macrolides. The former increased more than tenfold from 0.54 to 6.8 t, whereas the latter increased by four times from 1.9 to 5.2 t. However, the increase of the medicine-related antimicrobials was still relatively small in comparison with the decrease of the growth promoter (tetracyclines).

Globally, changes in demand preferences contributed to the rise in AMU, although their impact varied by region. In developing countries, changes in demand preferences were the major effect in driving up AMU by 10.6 kt (Fig. 4b), whereas in developed countries, changes in demand preferences reduced the antimicrobial use by 2.1 kt (Fig. 4c). In developed countries, this reduction was linked to the decreased share of meat products and chemical products in total demand. The former saw a slower demand growth with 12%, where the share of the total demand decreased from 1% to 0.9%. The latter saw the demand decline by 22%, making the share of demands decrease from 0.8% to 0.5%. These sectors are intensive users of antimicrobials along their supply chains. The trend could be more associated with increasing vegetarian in the western countries[39]. Drivers of antimicrobial footprint change varied (Supplementary Fig. 3). Most regions saw net reductions in AMU, but China and Eastern Europe rose. In China, demand-preference shifts dominantly rise the embodied antimicrobials (+0.93 kt), probably from surging service demand. For example, healthcare doubled, lifting its share from 4% to 6% of the total demands. Eastern Europe's increase reflected higher expenditure and preference for livestock: pig and beef demand grew 30% and 24%, outpacing total demand growth (14%). Other developing Asia–Pacific countries had the largest positive preference effect (+ 0.57 kt), partly via more imported manufactures, yet AMU intensity declines produced a net drop in AMU for these countries. The USA, Western Europe and developed Asia–Pacific similarly fell in the embodied antimicrobial footprints, driven by AMU intensity reductions in trading partners, particularly China.

Discussion

Our study uncovers a critical link between global trade and AMU in livestock production: between 16% and 20% of livestock AMU is tied to international trade, with noteworthy contributions from non-food items such as clothing, services and manufactured goods. This finding calls for an urgent reassessment of AMR strategies, advocating for a comprehensive global governance framework that extends beyond local policies and addresses the complexities of AMR in a globalized economy.

Our analysis reveals global antimicrobial footprints declined sharply over the past decade, falling from a 2013 peak of 118.6 kt to 84.0 kt in 2020 (−29%). The drop, especially after 2016, coincides with

national action plans in major livestock producers (China, USA, Brazil, and India) following the UN's 2015 AMR call to action[40]. China's use fell from 57.7 kt (2014) to 41.0 kt (2020), illustrating the effect of coordinated policy. Our trend aligns with WOAH reporting from up to 157 countries since 2016, which shows a 27% reduction in livestock AMU from 2016 to 2018[25]. COVID-19's 2020 impact was nuanced (details in Supplementary Fig. 4).

The integration of local policies with global governance is imperative to effectively combat AMR on a global scale. Recent years have seen noticeable progress in antimicrobial management, especially in developed countries. For instance, the EU's zero-pollution action plan would halve AMU in farmed animals by 2030[26]. However, the counterfactual scenario suggests that cutting the AMU for local products by 50% in EU countries only plays a limited effect for global AMU mitigation (Supplementary Fig. 5). EU countries only represent around 5% of global AMU in 2020, which may reduce to 3% in 2030. We showed that even a sharp reduction in EU, AMU may not lower global levels, given the complex embeddedness of countries in international supply chains and the rising antimicrobial consumption in developing countries, a cocktail leading to outsourcing of AMU along global supply chains. Whereas the local policies are foundational, they must be bolstered by global governance to mitigate spillover effects and prevent the emergence of pollution havens, akin to challenges observed in carbon emissions management[41,42]. This underscores the need for more comprehensive and ambitious efforts from major antimicrobial users, such as China, Brazil and the USA, to ensure that local successes do not inadvertently shift the burden to other regions, undermining global AMR control efforts.

Strengthening international cooperation is essential given the interconnected nature of global supply chains. Whereas 196 countries have committed to developing national action plans against AMR since 2015, with 178 countries issuing such plans by December 2023, only 27% of them effectively monitor and implement these plans, with a mere 11% of them allocating national budgets for their execution[43]. The lack of multi-sectoral coordination and implementation capacities, and inadequate technical and financial support have hindered progress. Establishing a global monitoring network is essential for swiftly tracking and assessing the impact of antimicrobials. Developing countries, as key suppliers of raw materials for livestock products, are particularly affected by AMR linked to local livestock AMU. It is crucial to also consider the consumption of livestock-derived goods in developed countries in efforts to combat AMR. Engaging the Quadripartite organizations (FAO, WHO, WOAH and UN Environment Programme) at national, regional and global levels through a One Health approach is a promising step[44]. Furthermore, integrating global governance of AMU within international trade can enhance the fight against AMR.

Our findings resonate deeply with the One Health framework, which recognizes the inseparable linkages between animals, humans and the environment in addressing AMR. AMR risk is not confined to farms or national borders but is systemically embedded in global consumption patterns. This trade-mediated spillover underscores the need for transboundary accountability, where consumer nations share responsibility for AMU occurring in supplier countries. Within One Health, this shifts the paradigm from isolated sectoral interventions to integrated governance across agriculture, trade, public health and environmental policy. To advance AMR mitigation in a One Health context, we think future research should prioritize: (1) integrated modelling combining MRIO with AMR transmission models; (2) policy experiments testing trade-linked incentives (for example, AMR tariffs, sustainable certification) to reduce embodied AMU; (3) cross-sectoral data platforms harmonizing AMU, AMR and trade statistics under the Quadripartite and (4) more funding dedicated for tackling AMR in developing countries. Such efforts will enable evidence-based and cooperative strategies to mitigate global AMR risk.

Shifting patterns of AMU in livestock are reshaping global governance priorities. The past decade has seen a global reduction in AMU in livestock, driven by AMR control efforts, which has in turn decreased antimicrobial footprints embodied in international trade. Notably, the dynamics have shifted between 2010 and 2020, with China, initially the largest contributor, being overtaken by Brazil as the primary source of antimicrobials in the global supply chain. Brazil's rise is closely associated with its dominant position as the world's largest exporter of ruminant meat[37]. China, in turn, found AMU intensity decreased, while increasingly relying more on imported food. For example, China's reliance on imports for ruminant meat has increased from 7% to 14% between 2010 and 2020[41]. As a new major exporter, Brazil could benefit from adopting China's policies that have successfully reduced antimicrobial intensity[12,31], including stringent regulations on sales, prescription and usage of antimicrobials, particularly growth promoters, and the promotion of alternatives such as traditional Chinese medicine, where traditional Chinese medicine offers promising avenues for reducing AMU in livestock production through its application as both therapeutic agents and feed additives[45]. Meanwhile, some auxiliary practices in China have also contributed to the decline in China's AMU intensity, such as the training of veterinarians and farmers in disease prevention and the rational use of antimicrobials[46].

Global demand patterns are also shifting, with developing regions increasingly driving the demand for antimicrobial-intensive products. As developed countries become more self-sufficient in livestock production, regions such as Asia–Pacific and the Middle East are increasingly reliant on international trade to meet their growing needs. This dependence presents challenges for livestock systems due to geographical and climatic constraints[1], particularly as populations in these regions continue to rise. Leveraging advanced technologies, such as artificial intelligence for sustainable agriculture and innovative farming practices, can help these regions monitor disease occurrence in real-time[47], reduce AMU and build climate-resilient livestock systems.

Important role of non-food products in driving the antimicrobial footprint in international trade should be emphasized. Our study reveals that half of the total antimicrobial footprint embodied in international trade is linked to the demand for clothing, services and manufactured goods. This finding highlights that the global spillover effects of AMU extend well beyond the food system, requiring policymakers to broaden their focus. Specifically, attention should be directed towards countries with large manufacturing industries, where stringent antimicrobial control policies must be implemented. For instance, the clothing industry in developing countries dominates the market, exporting large quantities of textiles and clothing to developed regions[48]. These market dynamics are well aligned with the antimicrobial footprints in international trade. China, for example, has long dominated the global textile and apparel market. However, its share of global clothing exports has declined in recent years as the rising competitiveness of emerging producers such as Bangladesh, Cambodia, Vietnam and Indonesia[49]. However, following production, apparel is typically transported in bulk to major distribution hubs, then distributed to retail outlets, predominantly in the UK, EU and US markets[48]. In addition, responsibility must be shared between manufacturing and consumer countries, as antimicrobial control policies without compensation could harm the economies of developing countries and discourage implementation efforts. Notably, the IO framework considers 'fifth quarter' components of livestock (by-products such as skins or fur) as a part of food processing sector, which means that impacts from the non-food sector (apparel) can be attributed first to food processing and ultimately be traced to the livestock sector.

To build consolidated livestock AMU at a global scale, reliance on the governmental or intergovernmental organization reports used in this study could be a challenge, unless more countries can publicly report their livestock-related AMU. However, it may take a long time with more international efforts to push forward the reporting.

Given that the AMR dataset at regional scale is more comprehensive[7], building machine learning model to yield the AMU based on AMR dataset could be an approach. Meanwhile, the commercial data of the sale of livestock antimicrobials could be another supplement to official reports and as a key data to train the machine learning model. Besides, the lack of global data on antimicrobial manufacturing restricts our ability to validate these estimates against production volumes. Moreover, our footprint reflects AMU volume rather than post-metabolism residues or environmental persistence, and integrating biotransformation, excretion and fate models remains a critical gap for tracing true AMR-relevant exposure along supply chains. A source-to-sink analysis, tracing antimicrobials from manufacturing to their use in livestock production, could provide a more comprehensive understanding of supply-side dynamics and enhance estimate accuracy. Nonetheless, export-oriented farming may employ distinct AMU practices compared to local production, potentially affecting trade-embodied footprint estimates. Data distinguishing these systems are scarce, introducing uncertainty that future research should address through enhanced reporting or integration of commercial sales data.

Methods

Building livestock antimicrobials use inventory

Livestock antimicrobial use (AMU) data for countries are very limited and usually not publicly accessed. World Organisation for Animal Health (WOAH) is the management authority for global livestock AMU, where governments submit the official data. It is known that WOAH collects data on livestock AMU annually from 157 countries. However, these data are only publicly available in aggregate form for five regions: Europe, Africa, the Americas, the Middle East, and Asia/Far East/Oceania[25]. We therefore collected and compiled livestock antimicrobial data from various sources, including the government reports on veterinary antimicrobials and academic reports or literatures reporting the estimated use of veterinary antimicrobials, as listed in Supplementary Table 1. Despite of various sources, the data on antimicrobial sales, usage, consumption or imports were all considered as AMU, which is in accordance with the WOAH criteria[25]. However, there are inconsistencies among data from different sources. To harmonize the data from different sources, we used official data from government reports as benchmarks to scale the data. Specifically, we collected the livestock AMU of 43 countries with publicly available data, where the data of 31 European Economic Area countries (including the UK at that time) were collected from the European Surveillance of Veterinary Antimicrobial Consumption for the period from 2010–2020. The data of China, Japan, South Korea, Thailand, Australia, New Zealand, Chile, Canada, the USA and Serbia were collected from their government reports. The data of Timor–Leste (2014–2019) and Cameroon (2014–2019) were collected from the academic literatures[50,51].

To build the livestock antimicrobial inventory, the data of livestock AMU collected for 43 countries across countries include three types: (1) total livestock AMU; (2) livestock AMU by three livestock species (cattle, chicken or poultry and pig), which together represent over 80% of global livestock biomass[6]; (3) livestock AMU categorized by 16 antimicrobial types (Supplementary Table 2). Total livestock AMU can be found in all 43 countries. However, livestock AMU by livestock species and antimicrobial types varied largely by countries. Some countries (for example, Australia) only disclosed the overall livestock AMU over a period, whereas some published the livestock AMU by antimicrobial types in certain years (for example, China). At least one year data of livestock AMU by livestock species and antimicrobial type can be found in 39 countries, respectively, while the antimicrobial type is not always in accordance.

Because livestock species are different in the production cycle and characteristics, the PCU is used to standardize livestock species, which accounts for differences in livestock weight and number of production cycles per year between countries. Thus, PCUs were calculated with parameters collected from FAOSTAT (Food and Agriculture Organization Statistics) and referred to previous study as follows[6]:

$$\mathrm{PCU}_k = \mathrm{An}_k\,(1+n_k)\left(\frac{Y_k}{R_{\frac{\mathrm{CW}}{\mathrm{LW}},k}}\right) \tag{1}$$

where An_k is the number of livestock species, k in each country. n_k is the number of production cycles for each livestock species[52–54]. Y_k is the quantity of meat in each country for each livestock species. $R_{\frac{\mathrm{CW}}{\mathrm{LW}},k}$ is the carcass weight (CW) to live weight (LW) ratio for each livestock species.

However, collected data for 43 countries are normally not consistent. Step 1 is to fill in the missing value for 43 countries. For countries with known data of overall AMU and AMU by species, we use overall AMU to adjust the aggregate of AMU by species to make an alignment. Then we calculated AMU intensity (AMU per unit of PCU) by species of known countries. For 43 countries, the calculated AMU intensity is not yearly consistent. Specifically, we first use AMU intensity by species of similar country as a proxy to fill in the missing value. For example, if AMU intensity of pig in Finland in unknown, we use the Denmark value as a proxy, because of similar regulation and management of Nordic countries. For countries with known data at different years, we interpolate the AMU intensity by species for each country, by linear interpolation:

$$t = t_0 + (y - y_0)\,\frac{(t_1 - t_0)}{(y_1 - y_0)} \tag{2}$$

where t_1 and t_0 are total AMU for year 1 and year 0. y_1 and y_0 are year 1 and year 0. Once we know the intensity, we can calculate AMU by species by multiplying intensity and PCU by species, which is then benchmarked by overall AMU for the countries if data are available.

If the countries have a few missing values with consistent known data, we will use linear extrapolation to estimate the missing value. For example, the AMU intensity by species of Luxembourg is from 2012 to 2020, we use linear extrapolate to extend the trend and estimate missing value for 2010 and 2011. Given the AMU intensity is defined as the AMU dividing PCU, we can calculate the AMU by using the AMU intensity multiplying the PCU for each species. To obtain AMU by three species and by 16 antimicrobial types, we use bi-proportional balancing technique estimate AMU by antimicrobial types[55]. We create a matrix with total AMU by three species as row and total AMU by 16 antimicrobial types as column. We preliminarily assume that the country with missing data have similar structure of antimicrobial types as the proxy country. The bi-proportional balancing technique would adjust the proxy structure to fit known total AMU by three species and total AMU by 16 antimicrobial types, which could generate a unique structure AMU by species and by types for each country. We select two countries (representing developing countries and developed countries, respectively) with available data from 43 countries according to their location, as proxy for each continent (Supplementary Table 3). Despite the assumption of using rough proxy, the bi-proportional balancing technique can partially eliminate the uncertainty as the solution of the bi-proportional balancing technique largely depends on the known aggregated values (total AMU by three species and AMU by 16 antimicrobial types). All mapping relationships and classifications are listed in Supplementary Tables 4–7.

Global antimicrobial consumption estimates

Next step is to estimate the AMU by species and types of other 147 countries based on the data for 43 countries as a sample. We choose Bayesian linear regression to estimate the AMU by livestock species for other countries. Bayesian linear regression is a widely used statistical model approach in many areas[6,9,56], and it can integrate our prior knowledge using a prior distribution. A Bayesian regression model treats the regression coefficients and model residual variances as random variables, resulting in a more flexible model. In this work, a four-step

procedure is used to build the model and estimate the coefficients in the linear model.

First, specify a Bayesian linear model. For a linear model with following form:

$$Y = X\beta + \varepsilon \tag{3}$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2) \tag{4}$$

where Y is the dependent variable (log-transformed AMU (kg)), X is the design matrix containing independent variables (log-transformed PCU) containing with the first column of ones capturing the intercept term in the model, β contains the regression coefficients, and an error term ε is used to capture the model residual, following a Gaussian distribution with mean zero and variance σ_ε^2.

Second, specify a prior distribution for our regression coefficients. In our research, the prior distributions used for the regression coefficients were assumed to be Gaussian, with mean and variance corresponding to the animal-specific AMU per PCU that could be obtained from the sample countries in the dataset (Supplementary Table 1), $\beta \sim N(\mu, \sigma_\beta^2)$. With the above prior distribution, the likelihood function can be written as

$$\pi(y|\beta, \sigma_\varepsilon^2) \sim N(X\beta, \sigma_\varepsilon^2) \tag{5}$$

Third, choose the model type. We choose a conjugate model because the posterior distribution is analytically tractable. Three models were created separately for cattle, chickens and pigs because the amounts of AMU for them were different, and it is also reasonable to assume that these consumptions are independent and the posterior distribution is

$$\pi(\beta, \sigma_\varepsilon^2|y, x) = \prod f(y_i; X\beta, \sigma_\varepsilon^2) \tag{6}$$

The product ($\prod f(y_i; X\beta, \sigma_\varepsilon^2)$) is over the countries providing data. $f(y_i; X\beta, \sigma_\varepsilon^2)$ is a Gaussian probability density function with mean $X\beta$ and variance σ_ε^2 evaluated at y_i.

Fourth, estimate the coefficients. We can estimate the regression coefficients from the posterior distribution using the mean values for each animal from the Bayesian linear regression model in equation (5). It is notable that the sample for the Bayesian linear models is based on data for 43 countries. Given the importance of Brazil and India in terms of AMU, the Bayesian linear models for Brazil and India were built using the data of the USA and China, respectively, considering the variant antimicrobials usage in different regions and their shared production profiles (for example, USA/Brazil as top cattle exporters; China/India as poultry leaders. The inventory we build is for 192 countries, three species and 16 antimicrobial types. The data-generation process is visualized in Supplementary Fig. 6, which outlines the full workflow from data compilation to prediction.

To quantify uncertainty in AMU estimates, we conducted a Monte Carlo simulation (50 iterations) using a triangular distribution for each species–country combination where empirical data were unavailable (Supplementary Figs. 7 and 8). The distribution has the peak located at the predicted mean from the Bayesian linear regression model, with lower and upper bounds set at 50% and 150% of the mean, respectively. The resulting standard deviation was divided by the mean to calculate relative uncertainty, expressed as a percentage. Lower and upper bounds for AMU were derived as mean ± standard deviation.

Environmentally extended MRIO modelling

The study applied an environmentally extended MRIO model to estimate antimicrobial footprints in 49 countries or regions from 2010 to 2020. The MRIO model traces spillover effects across regionally dispersed supply chains, providing a comprehensive estimate of the upstream environmental impacts[57–62]. We used EXIOBASE 3.8 as the MRIO database[63], covering 44 economies and five rest-of-the-world regions for 1995 to 2022. Given the AMU inventory is for 192 countries, we then aggregate them into 49 regions to fit the resolution of EXIOBASE (Supplementary Table 8). EXIOBASE offers the most detailed sectoral breakdown, covering 200 product categories from 1995 to 2022, and includes extensive environmental and social satellite accounts[64]. The model has been adjusted by GDP deflators sourced from World Bank to phase out the impact of price. Population data for each country were sourced from the World Bank (https://databank.worldbank.org/).

To calculate the antimicrobial footprints, we adopted the Leontief demand model[65]:

$$x = Ax + y \tag{7}$$

$$f = \hat{\mathbf{e}}(I - A)^{-1}y \tag{8}$$

where A is the technical coefficient matrix and y is the final demand vector, including household consumption, government consumption and capital formation in each country. Total output x can be expressed as $x = (I - A)^{-1}y$, where I is an identity matrix. Multiplying this by the diagonalized environmental extension vector $\hat{\mathbf{e}}$, which represents AMU (in kg) per million euros of sectoral output, yields the antimicrobial footprint of each country. However, it is noted that the study assumes that all food animals/livestock production used antimicrobials due to the framework of IO model, but it might be not true for all food animals. Therefore, it could affect the pattern of trade-related antimicrobials use.

Structural decomposition analysis

Structural decomposition analysis was used to identify socio-economic drivers of change in antimicrobial footprints from 2010 to 2020 in all 49 countries or regions[66,67]. We decompose the changes in consumption-based AMU into five factors: antimicrobial intensity (E), production structure (L), consumption structure (Ys), consumption per capita (Yc) and population (P). The five factors decomposition originated from the IPAT equation (Impact, Population, Affluence, and Technology)[68], reflecting that environmental impact is determined by population size, affluence and technology ($I = P \times A \times T$). There are many previous studies adopting the five factors decomposition, such as carbon footprint[69], air pollution[70] and water footprint[71].

The change in AMU ΔAnti was expressed as:

$$\begin{aligned}
\Delta\mathrm{Anti} &= \mathrm{Anti}_t - \mathrm{Anti}_{t-1} \\
&= E_t \times L_t \times \mathrm{Ys}_t \times \mathrm{Yc}_t \times P_t - E_{t-1} \times L_{t-1} \times \mathrm{Ys}_{t-1} \times \mathrm{Yc}_{t-1} \times P_{t-1} \\
&= \Delta E \times L_t \times \mathrm{Ys}_t \times \mathrm{Yc}_t \times P_t + E_{t-1} \times \Delta L \times \mathrm{Ys}_t \times \mathrm{Yc}_t \times P_t + E_{t-1} \\
&\quad \times L_{t-1} \times \Delta\mathrm{Ys} \times \mathrm{Yc}_t \times P_t + E_{t-1} \times L_{t-1} \times \mathrm{Ys}_{t-1} \times \Delta\mathrm{Yc} \times P_t \\
&\quad + E_{t-1} \times L_{t-1} \times \mathrm{Ys}_{t-1} \times \mathrm{Yc}_{t-1} \times \Delta P
\end{aligned} \tag{9}$$

where Δ denotes the change in a factor between two timesteps. Owing to the complexity of a structural decomposition analysis with five factors, resulting in 120 equivalent decomposition forms, we simplified the analysis by using the decompositions methods, as described by Dietzenbacher and Los[72].

Data visualization

Data visualization was performed using Tableau (version 2024.1) and ArcGIS (version 10.8). Bar charts, created with Tableau, were used to depict quantitative comparisons of AMU by country, species and type, facilitating the identification of trends and patterns. Geospatial maps, generated with ArcGIS, illustrate the spatial distribution of AMU across regions, highlighting geographical variations and potential hotspots.

Reporting summary

Further information on research design is available in theNature Portfolio Reporting Summary linked to this article.

Data availability

The EXIOBASE 3.8 data are available via Zenodo athttps://zenodo.org/record/3583071#.YPA5e0kzabg (ref. 63). The antimicrobial data sources are collected from either administration report or literatures, namely China (http://www.moa.gov.cn/gk/sygb/); Japan (https://www.maff.go.jp/nval/english/AMR/Monitoring/index.html); Thailand (https://amrthailand.net/Report); South Korea (https://www.qia.go.kr/english/html/Animal_livestock/02AnimalLivestock_003-5.jsp); Australia (https://apvma.gov.au/); New Zealand (https://www.mpi.govt.nz/animals/); Chile (https://www.sag.gob.cl/ambitos-de-accion/declaracion-de-venta-de-antimicrobianos); Canada (https://www.canada.ca/en/public-health/services/surveillance/canadian-integrated-program-antimicrobial-resistance-surveillance-cipars/cipars-reports.html); USA (https://www.fda.gov/animal-veterinary/cvm-updates/fda-releases-annual-summary-report-antimicrobials-sold-or-distributed-2020-use-food-producing); Europe-31 (https://www.ema.europa.eu/en/veterinary-regulatory/overview/antimicrobial-resistance/european-surveillance-veterinary-antimicrobial-consumption-esvac#annual-report-on-sales-of-veterinary-antimicrobials-section); Serbia (https://www.alims.gov.rs/ciril/veterinarski-lekovi/promet-i-potrosnja-veterinarskih-lekova/); Timor–Leste (ref. 50); Cameroon (ref. 51). The details can be found in Supplementary Table 1.

Code availability

Code is available via Github at https://github.com/HeranZheng/Antibiotic-footprint. MATLAB R2024a is used in this work.

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Author contributions

H.Z., J.Z. and B.M. proposed original conceptualization and led the writing and revisions. H.Z. conducted the supply chain modelling; H.Z., Q.W., J.Z. and B.M. drafted the manuscript. B.M., S.Q. and H.Z. supervised the manuscript. Q.W., X.H., K.T., J.M., P.P., M.B., C.H. and Y.W. contributed to the writing and revisions. All authors have discussed, read and approved the content of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed
☐	☒ The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☒	☐ A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐ The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☒	☐ A description of all covariates tested
☒	☐ A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☒	☐ A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☒	☐ For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☐	☒ For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐ For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐ Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software used
Data analysis	Matlab R2024a

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

The EXIOBASE 3.8 data are available at: https://zenodo.org/record/3583071#.YPA5e0kzabg. The antimicrobial data sources are collected from either administration report or liturature, namely China (http://www.moa.gov.cn/gk/sygb/) ;Japan(https://www.maff.go.jp/nval/english/AMR/Monitoring/index.html);Thailand(https://amrthailand.net/Report);South Korea(https://www.qia.go.kr/english/html/Animal_livestock/02AnimalLivestock_003-5.jsp);Australia(https://apvma.gov.au/);New Zealand(https://www.mpi.govt.nz/animals/);Chile(https://www.sag.gob.cl/ambitos-de-accion/declaracion-de-venta-de-antimicrobianos);Canada(https://

www.canada.ca/en/public-health/services/surveillance/canadian-integrated-program-antimicrobial-resistance-surveillance-cipars/cipars-reports.html);USA(https://www.fda.gov/animal-veterinary/cvm-updates/fda-releases-annual-summary-report-antimicrobials-sold-or-distributed-2020-use-food-producing);Europe-31(https://www.ema.europa.eu/en/veterinary-regulatory/overview/antimicrobial-resistance/european-surveillance-veterinary-antimicrobial-consumption-esvac#annual-report-on-sales-of-veterinary-antimicrobials-section); Serbia(https://www.alims.gov.rs/ciril/veterinarski-lekovi/promet-i-potrosnja-veterinarskih-lekova/); Timor Leste(Ting, S. et al. Antimicrobial use in animals in timor-leste based on veterinary antimicrobial imports between 2016 and 2019. Antibiotics, 2021 (10): 426.);Cameroon(Mouiche, M.M.M. et al. Challenges of antimicrobial consumption surveillance in food-producing animals in sub-Saharan African countries: Patterns of antimicrobials imported in Cameroon from 2014 to 2019. J. Glob. Antimicrob. Resist. 2020 (22): 771–778.). The details can be found in Supplementary TableS1.

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	N/A
Population characteristics	N/A
Recruitment	N/A
Ethics oversight	N/A

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We link antimicrobial estimates in livestock production with a global multi-regional input–output (MRIO) model, enabling us to quantify the antimicrobial footprint via global supply chains from 2010 to 2020. The footprints encompass both direct and indirect antimicrobial use throughout the production stages of food and non-food products. For example, the antimicrobial footprint of beef includes direct use in feeding cattle and indirect use in services supporting husbandry. We estimate global antimicrobial use in chicken, cattle, and pigs across 16 antimicrobial types for each country/region using Bayesian regression, based on official data from 43 countries and product-level data from the UN Food and Agriculture Organization (FAO).
Research sample	We sourced data from 43 countries and product-level data which are only publicly available data
Sampling strategy	N/A
Data collection	N/A
Timing	N/A
Data exclusions	N/A
Non-participation	N/A
Randomization	N/A

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging