Environmental implications of protectionist trade policies: mapping channels towards improved impact assessment

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As strategic trade interventions gain momentum[1,2] and climate commitments face mounting urgency, the intersection of trade and climate policy demands renewed scrutiny[3]. Recent shifts in economic governance suggest a departure from decades of liberalisation, with governments increasingly adopting measures to boost domestic competitiveness[4] or restrict imports[5]. While trade-restricting measures (tariff and non-tariff measures, import and export bans, etc.) directly limit market access, industrial policies aiming to strengthen domestic competitiveness and strategic autonomy (subsidies, local content requirements, etc.) indirectly affect trade too. The United States (US) has exemplified both trends in the past decade, through tariffs, trade agreement renegotiations, and policies promoting domestic clean-tech industries (e.g., the Inflation Reduction Act). The European Union (EU) has likewise linked industrial competitiveness to trade and climate policy. While retaining a climate rationale, the EU's carbon border adjustment mechanism (CBAM), industrial subsidies, tariffs targeting Chinese clean technologies, and responses to US trade measures reflect a broader shift in EU's trade and industrial strategy[6,7]. Emerging economies like China and India have also expanded domestic production mandates, particularly in key green sectors[8]. Although driven by different goals, these measures risk weakening international collaboration[9], distorting markets, and reprioritising domestic competitiveness over global cooperation, including on climate. Notably, the US withdrawal from the Paris Agreement illustrates how domestic priorities can override international climate commitments.

This paper advances understanding of the trade-climate nexus in a changing policy landscape by contributing to the literature on three fronts. First, while previous papers reviewed the main channels through which trade affects environmental outcomes[10–12], we integrate them into a unified framework that emphasises their interactions, enabling factors, and shifting relevance under protectionist and competitiveness-oriented trade policies. The proposed framework scopes and structures existing insights to convey the complexity of the trade-climate nexus and to clarify whether current trade regimes risk undermining or, under specific conditions, could support climate objectives. Second, we compare these mechanisms and channels with the capabilities of existing analytical capacities, highlighting data, modelling, and methodological gaps that must be addressed to enable a more accurate and comprehensive assessment of the environmental implications of evolving trade regimes. Third, we offer recommendations to close these gaps, setting clear methodological priorities to improve empirical and modelling assessments of trade's environmental outcomes in a rapidly changing world.

Understanding trade-climate linkages: channels, dynamics, and enabling conditions

Before scoping the analytical capacity to study and quantify the relationship between trade (policy) and climate (policy), and the gaps therein, we first discuss the channels in which this relationship may unfold and the factors influencing it, to underpin the complexity in trade-climate assessments.

Trade affects the environment through multiple interconnected mechanisms, some direct (e.g., transport emissions), while others indirect (changes in production structure and scale, consumption, firm behaviour, or innovation). These effects interact, amplifying or offsetting each other in context-dependent ways. This section provides a conceptual overview of the channels through which trade influences climate outcomes and their complex interactions across time. It also identifies critical dimensions—regulatory, institutional, and political—that shape the magnitude and direction of their effects (Supplementary Table 1 summarises these channels, their interactions, and relevant analytical approaches).

Key channels linking trade and emissions

One of the most immediate environmental effects of trade is the rise in transport-related emissions. Cross-border movement of goods relies on maritime shipping, aviation, and land transport, all major sources of greenhouse gas (GHG) emissions. In 2023, international aviation and shipping were responsible for roughly 3% of global fossil CO_2 emissions, with emissions continuing to rise in 2024[13,14]. Previous research has focused on emissions quantification[13,15–18], decarbonisation pathways across transport modes[19–21], and systemic feedbacks using integrated assessment models (IAMs) and computable general equilibrium (CGE) models[22,23] (see Supplementary Notes 1 and 2, and Supplementary Table 2, for data sources and models used to analyse international transport and other trade-climate channels). As trade openness increases, so do travel distances and freight activity, making *international transport* the most direct trade-climate channel. Protectionism may reduce emissions by lowering trade volumes and shortening travelled distances, though it could also induce inefficiencies or longer routes via trade diversion[25].

Beyond transport, trade influences emissions indirectly through structural changes in global production. It reallocates economic and industrial activity across countries according to comparative advantage and patterns of specialisation, driving efficiency gains that influence consumption, production, and supply chains, with environmental consequences. Decomposition analysis typically distinguishes three mechanisms through which trade influences emissions: the scale and income effect, composition effects (both inter- and intra-industry), and technique effects[26,27].

First, the *scale effect* arises when economic growth or trade liberalisation expands market size[28], thereby increasing energy and resource demand. Without strong environmental regulation, this increases emissions[29]. The Environmental Kuznets Curve (EKC) hypothesis suggests emissions rise with income until a turning point, after which environmental preferences and policies strengthen[30]. Yet, empirical evidence remains inconclusive[31]. Although the EKC reflects higher-order dynamics, where trade raises income and income shapes preferences (income effect, see figure 1), these effects are typically grouped under the scale category in decomposition studies. If protectionism leads to economic inefficiencies and dampens scale effects, it could also result in emissions reductions. The direction of consumer preference shifts due to income changes may also vary depending on the level of climate awareness and how this translates into changes in consumption choices..

Second, the *inter-industry composition effect* refers to how trade changes production allocation across sectors, shifting the geographical distribution of sectors and associated emissions. Depending on whether comparative advantage lies in emissions-intensive or low-emissions sectors, specialisation can either raise or lower emissions. Beyond inter-industry exchange of final goods, comparative advantages also drive trade fragmentation through global value chains, expanded by advances in logistics and digitalisation. Intermediate goods now represent roughly 50-60% of global trade[32]. Although inter-industry trade patterns manifest at the sector level, they often originate from firms' decisions. From the perspective of firm-level strategies, outsourcing and offshoring of production stages are often driven by cost minimisation. While cost efficient from a firm perspective, this process redistributes emissions across borders[33]. When environmental regulations are asymmetric across countries, internalising environmental costs in some regions but not others, this can create incentives for firms to relocate their pollution-intensive activities towards countries with laxer environmental regulations. These dynamics are captured by the Pollution Haven Hypothesis and Effect (PHH/PHE) and the Pollution Offshoring Hypothesis (POH), which suggest that laxer environmental regulation can attract emissions-intensive sectors or production stages (and are increasingly studied using firm-level data)[34–36]. Trade restrictions dampen inter-industry reallocation, but their net impact on emissions remains unclear. This ambiguity partly stems from the interaction between trade and environmental regulation: differences in regulatory stringency across countries can lead to offshoring, industrial relocation, and carbon leakage. The climate outcome of protectionist shifts thus depends on the relative emissions intensity of trading partners and on whether protectionism substitutes or complements environmental ambition. Trade policy itself may embed environmental distortions, as shown by Shapiro (2021)[37], who finds that tariffs and non-tariff barriers are systematically lower for CO_2-intensive industries, effectively subsidising emissions through trade regimes. More recent research emphasises the need to consider the full scope of GHG emissions and domestic fuel taxes, which may substantially reduce or even reverse the initially apparent bias of existent trade policies[38].

Third, the *intra-industry composition effect* captures productivity growth driven by firm selection and efficiency gains. Sector-level data and modelling often miss this channel, attributing emissions changes to technique effects (see below). As Cherniwchan et al. (2017) note[12], lower average emissions may reflect cleaner, more productive firms gaining market share. According to the Melitz model[39], trade liberalisation induces less productive firms to exit the market. The Pollution Reduction by Rationalisation (PRR) hypothesis suggests that surviving firms are both more efficient and cleaner[40], though empirical validation of this hypothesis is still limited. In parallel, trade-induced competition can boost efficiency within firms, spurring technology adoption[41], with productivity gains often, but not always, linked to cleaner processes[42]. Trade restrictions may weaken these channels, with uncertain implications for both productivity growth and decarbonisation.

Fourth, trade fosters innovation and technological change; this constitutes the *technique effect*. Building on Melitz and Redding (2021)[43], who identify competition, market expansion, specialisation, and diffusion as four trade-induced drivers of innovation, we distinguish two channels of technical change: (i) innovation, driven by the first three mechanisms, embedded in the scale and composition effects; and (ii) diffusion, through knowledge spillovers. Trade and foreign direct investment (FDI) support both channels by enabling the creation and diffusion of new technologies, thereby fostering long-term growth[44]. Knowledge spillovers occur through vertical linkages (interactions with foreign buyers and suppliers), labour mobility (staff moving from multinationals to domestic firms), and demonstration effects (local firms adopting foreign, often cleaner, practices and technologies). The effectiveness of these spillovers depends on domestic absorptive capacity, including skilled labour, the nature of FDI, and institutional quality[45]. While FDI can spur green innovation, its effects are often context-specific[45]. Indeed, technology uptake varies by region and financial systems[46]. Hence, the relationship between innovation and emissions and the extent to which protectionism affects it, depend on broader enabling conditions, as discussed below.

Interconnections across channels and time

Rather than acting in isolation, the channels discussed above—transportation, scale, inter- and intra-industry composition, and technical change—interact in complex and sometimes contradictory dynamics.

International transport enables or constrains other channels. For example, variations in transport costs influence trade volumes, outsourcing decisions, international competition, and thus domestic production structures and innovation incentives. Transport thus affects the climate directly through fossil fuel use and indirectly by shaping how other trade-emission mechanisms unfold. Scale effects are central: market expansion increases shipping and emissions but also amplifies composition and productivity effects. Scale incentivises R&D by raising returns and enhancing competitiveness in global markets[47–49]. Inter-industry specialisation, that could partly counterbalance the additional transport emissions caused by longer supply chains[24], reallocates resources toward sectors of varying innovation intensity[43] and may displace inefficient (and usually dirtier) firms, reinforcing innovation. Productivity growth can stimulate innovation by increasing returns to technology adoption, while also lowering production costs and consumer prices. This can drive higher consumption, amplifying scale effects[50]. Innovation and diffusion interact with all of the above, with innovation's net environmental effect depending on its direction and policy support[51]. Well-directed trade-induced innovation can help decarbonise transport through the uptake of cleaner fuels and improved logistics systems[52,53]. Yet even targeted clean innovation can carry trade-offs: by diverting R&D from other areas, it may slow down broader technological progress and dampen scale-driven growth[54], which may in turn have ambiguous effects on emissions. Diffusion spreads innovation gains across firms and regions, reinforcing both productivity and technological change. Trade shocks can disrupt these dynamics, by altering sectoral composition, innovation, and productivity. For instance, as Akcigit et al. (2018) show[55], tariffs may yield short-term benefits but ultimately discourage innovation and undermine long-term welfare, complicating their climate implications.

Temporal dynamics shape these feedbacks. Some effects are immediate; for instance, trade-driven growth in transport emissions. Others unfold more gradually and often face considerable delays (lead-in times), as it is the case for innovation, diffusion, and shifts in consumer preferences. These time asymmetries shape long-term emissions paths as well as structural or technological change, intersecting with path dependence and irreversibility. Innovation trajectories can lock economies into persistent technological pathways, while short-term trade shocks may trigger lasting shifts in production or trade patterns, as illustrated by the efficiency gains observed after the 1970s oil shocks[56]. Short-term channels like transport and scale typically raise emissions, while long-term ones like innovation and diffusion have more ambiguous or mitigating effects.

Enablers: regulations, institutions, politics

Besides temporal dynamics, three additional dimensions—regulatory frameworks, institutional quality, and stakeholder influence—act as enabling conditions shaping the magnitude and direction of trade's climate impact.

Regulation is a critical enabler, particularly the design and enforcement of environmental rules, shaping international dynamics in several ways. It steers innovation and diffusion toward low-carbon technologies, aligning trade-induced innovation with climate goals, though its effectiveness also depends on domestic technological capacity[51,57]. Regulatory asymmetries across countries can undermine climate goals, as differences in standards encourage relocation of polluting industries and carbon leakage (PHE). Standards harmonisation can mitigate this risk[58]. Several trade-related climate instruments—such as carbon border adjustments[59–61], output-based allocations, and cooperative approaches like climate clubs[62] or trade-and-climate treaties[63]—can help align competitiveness with decarbonisation, though they may also trigger fairness or coordination concerns[64].

Regulatory instability adds complexity, weakening credibility and investment signals. Instability from poor governance or arbitrary enforcement creates deeper uncertainty. This leads to a second enabler: institutional quality. Weak institutions undermine regulation, policy consistency, and investment credibility. Institutional quality shapes a country's ability to turn trade openness into environmental gains. It includes regulatory stability, absorptive capacity, innovation ecosystems, finance access, and human capital. Strong institutions support clean technology development and scale-up, as well as comparative advantages in clean industries[65], while limited capacity risks locking countries into carbon-intensive paths. Institutional quality thus affects both the depth and pace of emissions reductions achievable through trade.

A third critical dimension is stakeholder influence. Trade instruments are not merely economic tools; they are also political signals, and their climate impact depends on the strategic considerations that shape them. Sequencing is rarely neutral; it often reflects political calculations and stakeholder pressures. Protectionist measures on clean technologies, such as tariffs on electric vehicles or standards for battery production, often aim to foster domestic industries, retain strategic capacity, and build local supply chains, as seen for photovoltaics[66] and e-mobility. Such measures may raise short-term costs but can also build political support for transition. However, when driven by lobbying from carbon-intensive incumbents, they can entrench polluting industries and delay greener competitors, undermining policy credibility and investor confidence, as seen when lobbying secures protection for incumbents at the expense of cleaner alternatives[67]. Figure 1 illustrates key trade-emissions channels, their timing, and how enabling conditions shape their magnitude and direction.

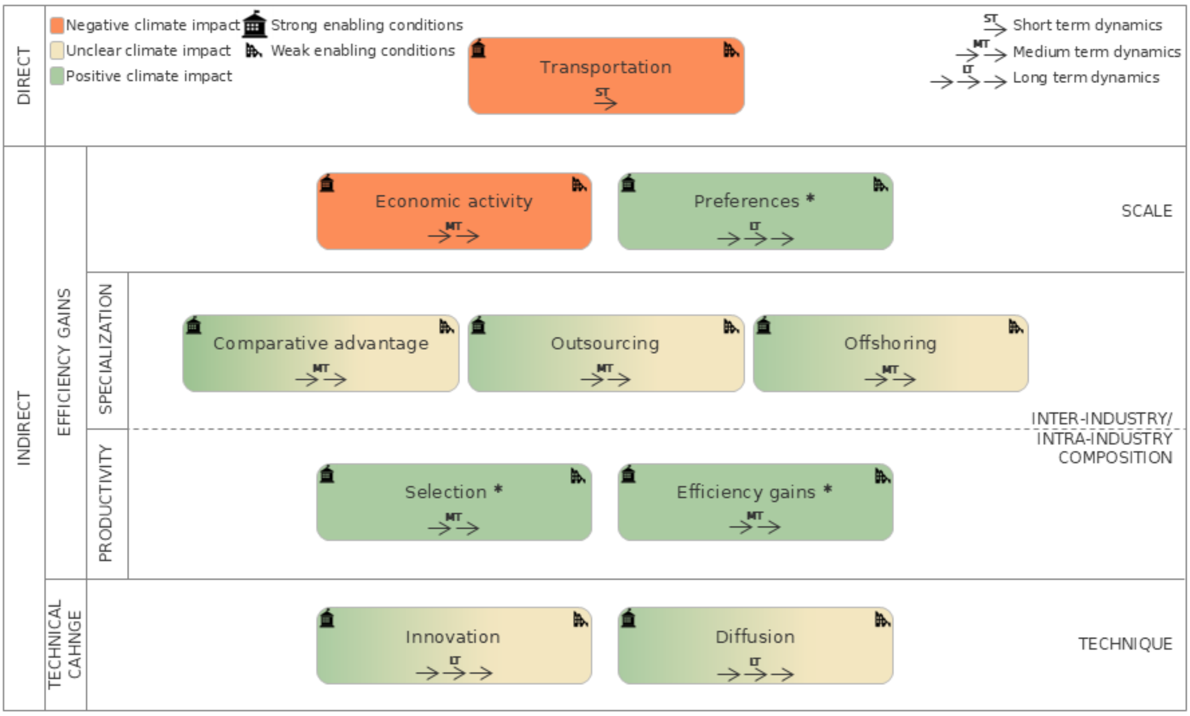

Figure 1: Key channels linking trade to emissions, their temporal dynamics and role of enabling conditions for trade's GHG emission impact. Source: own elaboration. **Climate benefits are theoretically expected, but empirical evidence supporting this channel is mixed or context dependent.*

Building analytical capacity and designing scenarios for future trade-climate projections

The previous sections outlined how trade influences emissions through multiple, interacting channels, and how their effects vary over time and across contexts. Building on that classification, this section turns to the analytical and modelling approaches needed to assess the climate implications of evolving trade patterns. What tools are needed? Which aspects of the trade-climate relationship should be prioritised to advance understanding and inform decision-making? And how can we identify risks and opportunities for the low-carbon transition?

Methods that trace competitiveness, industrial reallocation, and welfare under trade liberalisation do not automatically carry over to protectionist settings; whether effects are symmetric is uncertain. We argue that bridging this requires advances on three fronts: improved data detail, enhanced modelling, and an expanded scenario space. These advances should capture key trade-emission channels and enabling conditions to yield robust, policy-relevant insights.

The following subsections discuss how to strengthen each component within economy-wide assessments that consistently represent production, trade, and emissions to trace the channels linking trade and climate outcomes. While broadly relevant, several enhancements are especially important for analysing protectionist regimes, where shifting barriers reshape production and emissions dynamics.

Improving the granularity and type of available data

Numerous public datasets support empirical and modelling work to assess the climate implications of trade. Emission inventories like EDGAR[15], the Global Carbon Project[13], and those published by the IEA[16] and Eurostat[68] offer historical, sectoral GHG estimates. Newer initiatives like Carbon Monitor[17], GRACED[69], and Climate TRACE[70] provide high-frequency or spatial emissions data. Environmentally extended input-output (EEIO) databases—GTAP[71], EXIOBASE[72], FIGARO-E3[73], Eora[74], and GLORIA[75]—offer harmonised multi-regional input-output (MRIO) tables with environmental extensions. (see Supplementary Note 1 and Supplementary Table 2). Despite this richness, important data gaps remain for economy-wide assessments.

One issue is the limited integration between granular trade data and macroeconomic datasets, which hinders tracing emissions in global value chains[76]. There is an increasing need to monitor the trade in key technologies and the materials underpinning their deployment within global value chains, including critical raw materials, batteries, PV modules, wind-turbine parts, heat pumps, and electrolysers. Key trade databases—UN Comtrade[77] or the IMF's IMTS[78] and ITC's MACMAP[79], which reports market access conditions at the tariff-line level—offer detailed bilateral flows by product (up to several thousand product categories)) and partner (more than 200 economies). Other platforms, such as the World Integrated Trade Solution (WITS)[80], unify access, yet these data are seldom fully linked to macroeconomic or environmental accounts. Beyond these datasets, new big-data infrastructures, such as vessel-tracking, bill-of-lading, and satellite-based sources, further increase spatial and temporal resolution, providing high-frequency, spatially detailed evidence on supply-chain dynamics, transport-related emissions, and trade shocks[81–83]. This integration is critical under protectionism, where altered market access and trade diversion change embodied emissions.

Two aspects are often underrepresented in EEIO tables and national accounts. First, domestic and international trade-related costs, especially transport and logistics, are poorly captured. These shape trade's carbon intensity and supply-chain structure. Yet most databases use proportional linking, overlooking transport mode, distance, and logistics efficiency, limiting analysis of shifting trade patterns[22,84]. Complementary sources, such as the CEPII GeoDist dataset[85] and the World Bank Logistics Performance Index[86], could improve the representation of trade costs and transport emissions. International bunkers for shipping and aviation are not reported by trading partner, complicating allocation. Improved transport and logistics coverage is especially relevant for protectionist contexts, where rerouted supply chains and shifting modes may offset emission reductions from lower trade volumes.

Second, investment and financial data are often missing or insufficiently detailed from macroeconomic datasets. This limits assessments of feasibility and diffusion of technologies like electric vehicles, green hydrogen, or heat pumps and their financial implications. This typically renders most macro-economic and energy-system models unable to capture, in addition to high-level capital needs and costs, explicit investment matrices linking sources and destination sectors, thereby limiting insight into composition and sourcing, especially at higher sectoral resolution. Splitting these flows between domestic and foreign adds a further data challenge. Including detail in capital costs, risk, and support mechanisms would improve modelling of clean-tech manufacturing, trade, diffusion, and trade-climate implications[16]. Relevant data include the IEA World Energy Investment Datafile[87], OECD and Eurostat financial accounts by institutional sector[88,89], and UNCTAD or OECD FDI statistics[90,91], which together inform capital allocation, borrowing, and financing patterns across economies. Detailed investment and financial data are essential to trace the domestic reallocation of capital and reshoring of clean-tech industries that distinguish protectionist from liberalising dynamics.

Better alignment between firm-level data and sectoral aggregates also holds promise[92]. Firm-level data reveal heterogeneity in emissions intensities and energy use, often masked at aggregate levels[12,93]. Integration can improve estimates of abatement costs and policy responses[94], especially with standardised classifications linking micro and macro data. Datasets such as the World Bank Enterprise Surveys and S&P Global Corporate Emissions[95,96] offer comparable firm-level evidence across countries and sectors. However, firm-level data often remain proprietary or are not widely accessible. Linking firm- and sector-level data enables capturing heterogeneous firm responses as well as intra-sector dynamics to trade barriers, exit, restructuring, or localisation.

Detailed statistical information on innovation remains relatively modest. The IEA produces R&D expenditure data for energy technologies[97], but this only concerns public investment even if attempts are being made to establish data for private investment[98]. Tracking knowledge flows is also important for assessing spillovers, using patent data[99,100], PATSAT, or FDI data, the latter with limited industry detail[101]. Enhanced innovation data are key to assess whether trade restrictions hinder cross-border knowledge diffusion or instead stimulate domestic green innovation.

Another important dimension that is often underrepresented in most assessment frameworks due to the lack of corresponding data are heterogeneous households and related equity indicators. Evidence suggests that both trade and environmental policies can have heterogeneous effects across household types, requiring targeted policy solutions[102,103]. While data on income and consumption patterns across various household types are collected by statistical offices in many countries, harmonised accounts at the multi-regional or global levels are often of limited geographical coverage. Relevant sources include Luxembourg Income Study Database (LIS)[104], World Bank's Living Standards Measurement Study (LSLM)[105] and Eurostat's microdata collections[106]. Incorporating such microdata allows assessment of distributional consequences of protectionist measures, which may differ from liberalisation-driven adjustments. Household income categories differ in consumption patterns and substitution options, so trade measures can affect them unevenly, for instance, tariffs on basic goods (like energy and food) weigh more on low-income households, while those on items such as solar technologies mainly affect higher-income groups.

Finally, institutional indicators, such as governance quality indicators, help capture the pace and effectiveness of low-carbon transitions[107–109]. Although rarely included in trade-environment assessments, complementary datasets like Climate Watch[110], OECD PINE[111], and the Quality of Government Environmental Indicators[112] offer insights into policy, governance, and institutions. Institutional indicators are particularly informative in distinguishing strategic, climate-aligned protectionism from politically driven protection of carbon-intensive incumbents.

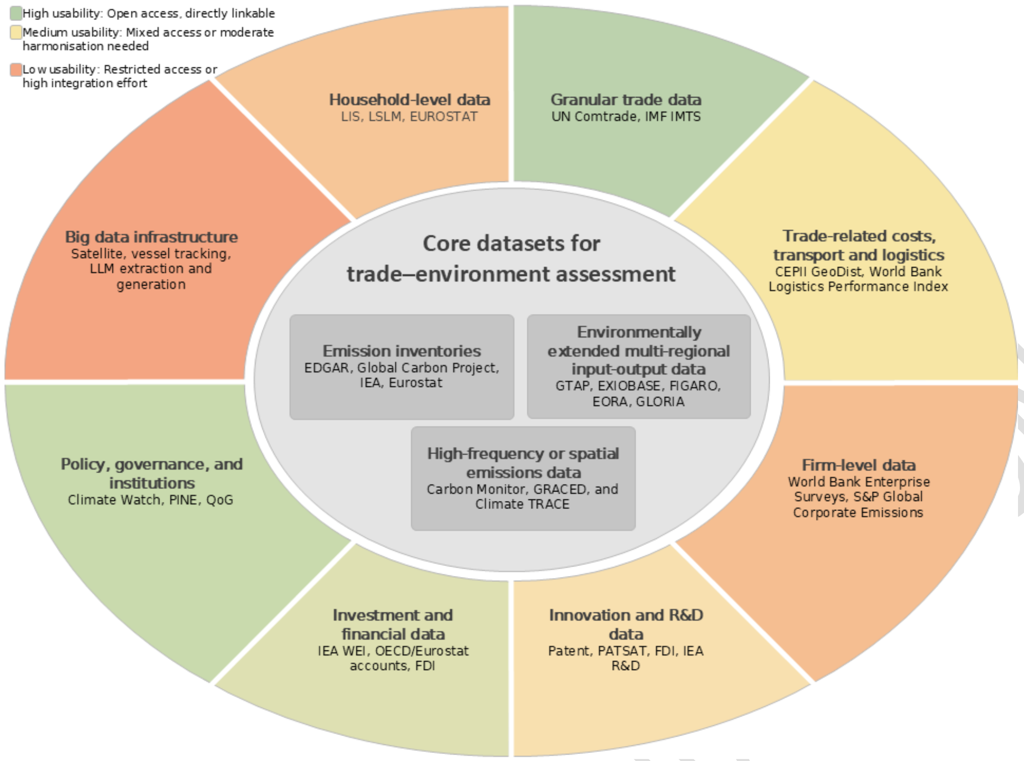

Figure 2: Core datasets currently used for assessing trade-environment linkages (centre) and complementary integrating data domains that could enhance macro-micro integration (outer ring). Outer colour intensity reflects the average expert score on data usability, mapped onto a continuous scale from 1 (low) to 3 (high). The rationale and scoring approach are presented in Supplementary Note 3.

Advancing economy-wide modelling frameworks

Numerous modelling approaches analyse trade-climate interactions, each suited to different dynamics. These include engineering and energy system models, which simulate technology-specific mitigation options, particularly in transport and industry[21,113]; microeconomic and firm-level models, like heterogeneous-firm trade models and econometric analyses of policy responses; and EEIO models, especially MRIO frameworks, widely used to trace embodied emissions, outsourcing effects, and carbon leakage[72,76]. Life Cycle Assessment (LCA) and consumption-based accounting offer complementary product- and demand-based perspectives on emissions[114–116]. Economy-wide models, including CGE and macro-econometric models and IAMs, assess systemic trade-climate effects like reallocation, innovation, socio-economic impacts, and carbon pricing[3,23,117]. Each approach has strengths and limitations; combining them can help quantify trade-climate impacts (see Supplementary Note 2).

Among these, economy-wide frameworks are best suited to analyse trade-climate links, as they capture direct responses and broader effects from income redistribution, production and trade shifts, inter-sectoral linkages, and competitiveness. The discussion below focuses on this family of models, outlining key priorities and limitations. Improvements concern both structural and dynamic features and the range of mechanisms captured.

A key development is integrating new trade theory into general-equilibrium frameworks. Traditional trade theories assume representative firms and comparative advantage driven by factor endowments; newer approaches emphasise firm heterogeneity in productivity and market access[39,118]. Building on earlier work on increasing returns, firm entry, and monopolistic competition[119], these theories explain how trade liberalisation drives intra-industry reallocation and productivity gains. Quantitative and spatial models extend this to show how trade costs and geography shape economies [120,121] and how climate change and trade interact[122,123]. These spatial IAMs often prioritise tractability over sectoral realism, abstracting from detailed industry heterogeneity, input-output linkages, and policy granularity. Yet, in practice, many CGE models still rely on simplified trade representations, such as Armington elasticities, which assume consumers differentiate goods by country of origin, or iceberg costs, which consider trade frictions as a loss of goods in transit. Incorporating firm heterogeneity would allow richer and more reliable analysis of trade dynamics, including differentiated effects of liberalisation or protectionism on firms by size, efficiency, and environmental performance. As Balistreri et al. (2024) show, model structure can influence outcomes more than parameter changes, underscoring the need for empirically validated assumptions. Comparative evaluation of alternative trade specifications (e.g., Armington vs Melitz) within comprehensive model validation and back-casting exercises remains limited. Incorporating firm heterogeneity and endogenous market structures is crucial for analysing protectionism, which distorts suppliers' market access and competitiveness, making supply-side trade modelling essential to capture resulting production and emission. Richer supply-side structures also capture trade-policy spillovers that Armington specifications overlook.

Temporal dynamics are central to trade-climate interactions, particularly for assessing protectionist measures, where trade-offs unfold over time. Tariffs might initially reduce transport emissions by promoting local production, but near-term capacity constraints or dirtier domestic activities could offset these gains. Over time, outcomes depend on whether domestic production becomes cleaner than displaced imports, and whether global supply chains for inputs are still needed, potentially shifting rather than reducing trade-related emissions. Capturing such dynamics requires models with temporal depth. Existing models range from static to recursively dynamic, with a few intertemporally optimising structures. While static or myopic models remain popular due to their computational simplicity, enhanced temporal treatments better capture investment responses, endogenous innovation, and learning-by-doing effects[124,125]. Many models used to support climate strategies tend to smooth over short-term impacts[126] and have thus been criticised over their ability to examine disruptions and crises[127]. Strengthening the temporal logic of models, especially for innovation and sectoral reallocation, can enable more accurate evaluation of such effects. This is especially relevant for protectionist settings, where short-term disruptions and delayed adjustment processes contrast with the smoother, long-run efficiency gains typical of liberalisation.

Enhancing model robustness and transparency via systematic model intercomparison and ensemble exercises helps identify how structural assumptions, closure rules, and parameter choices affect results[128]. Comprehensive sensitivity analysis across parameters, shocks, and behavioural elasticities helps map uncertainty and build policy confidence[129,130]. Recent developments in artificial intelligence and machine learning enables broader and faster exploration of uncertainty[131,132]. Such exercises are especially relevant for protectionist shocks, whose asymmetric and non-linear impacts across sectors and countries may be masked by structural or parametric assumptions.

Global value chains have long been studied via input-output and trade-in-value-added data[133,134], yet few embed these linkages in macro- or general-equilibrium settings[135,136]. Moreover, multinational corporations (MNCs) play a key role in transmitting trade policy shocks and diffusing innovation through FDI, technology transfer, and supply chain integration[137]. Their behaviour involves endogenous mark-ups and cost pass-through that vary with market structure. Facing trade barriers, MNCs may pursue “tariff-jumping” by reallocating production or investment across borders[138,139], shaped by both economic and political factors[140]. Explicit representation of these mechanisms—linking macroeconomic consistency with firm-level and innovation modules—improves assessment of emissions, competitiveness, and innovation under different trade regimes. Modelling global value chains and MNCs is therefore essential to capture tariff-jumping, supply-chain reconfiguration, and cross-border investment shifts central to the climate implications of protectionism.

Higher sectoral and technological resolution improves model realism and policy assessment. Several strategies integrate technological dynamics. A top-down structure may allow endogenous switching between technologies based on cost or policy signal[141]. Bottom-up modules can capture specific sectoral or technological constraint[142]. Hybrid approaches link CGE and techno-economic models to represent sector-specific constraints[143]. Coupling sectoral detail with macroeconomic dynamics yields hybrid frameworks that better capture trade-environment linkages. Integrating CGE models with agent-based models (ABMs), techno-economic models (TEMs), or operational transport models enhances behavioural, innovation, and spatial representations[125]. This detail is valuable for analysing protectionism, where targeted policies affect specific technologies or subsectors.

Broadening the socio-economic and environmental scope of models is equally important. Representing heterogeneous households and heterogeneous firms enables assessment of the distributional effects of trade and climate policies, critical for equity and political feasibility[103]. This can be achieved through explicit multi-household structures or linkage to microsimulation frameworks. In developing and emerging economies, including informal sectors can markedly change estimated impacts of carbon pricing or trade measures, yet most economy-wide models omit this key component[144]. Expanding frameworks to account for co-benefits, such as health gains from cleaner air or reduced degradation, would provide more comprehensive welfare assessments[145]. These additions strengthen models’ ability to capture the full range of social and environmental implications of trade-climate strategies.

Finally, enabling conditions—regulatory stringency, institutional capacity, and political-economy dynamics—critically shape how trade-climate measures perform. These factors influence both emissions outcomes and the pace and direction of technological change[146]. Several modelling strategies can capture these layers. Coupling general-equilibrium models with complementary frameworks captures sectoral regulation and institutional differences across countries. Enhancing treatment of capital flows, investment risk, and financial constraints reflects institutional conditions shaping technology uptake and trade responses. Econometric estimates, such as responsiveness to innovation incentives, can proxy institutional capacity. Above all, scenario-based approaches offer flexibility to explore regulatory and political-economy trajectories[147], as discussed in the following section. Incorporating such institutional and political-economy variables helps distinguish climate-aligned strategic protectionism from regressive forms driven by incumbent lobbying.

Figure 3 synthesises assessments of the utility and tractability of seven key enhancements from the viewpoints of analysts, international stakeholders, and domestic decision-makers. The rationale and scoring approach are presented in the Supplementary Note 3.

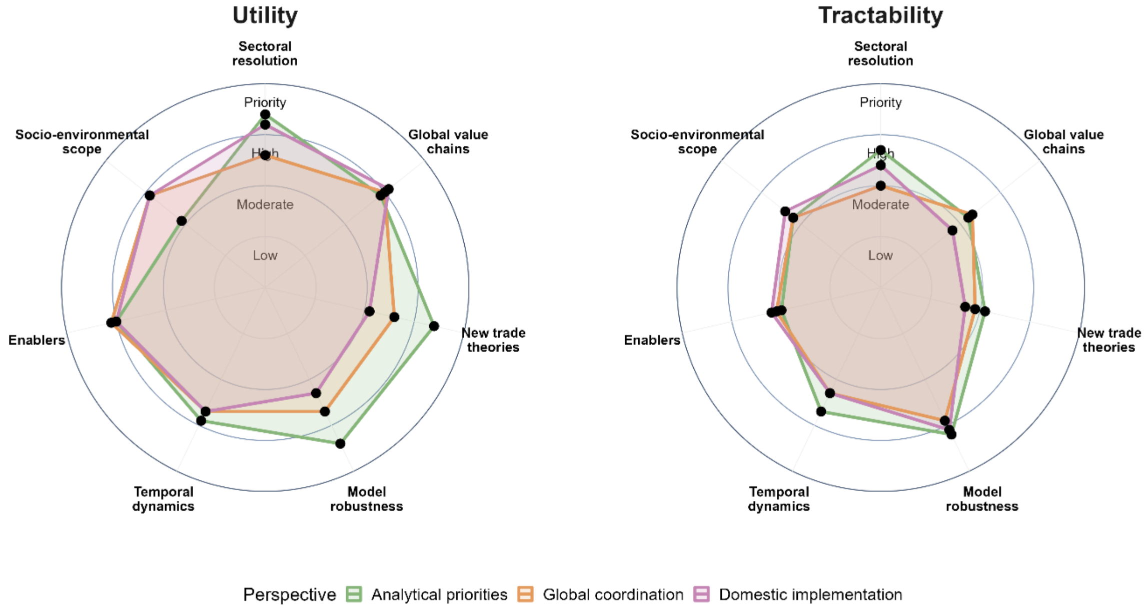

Figure 3: Utility and tractability of model enhancements across perspectives. Radar plots compare three perspectives (analytical priorities, global coordination, and domestic implementation) for the seven proposed model enhancements. Utility and tractability scores are shown on a four-level scale (low-moderate-high-priority). Filled polygons illustrate how each perspective prioritizes different modelling improvements across the utility and tractability dimensions.

Expanding the scenario space

Equally important as improving models is how they are used. Scenario design is key for assessing the climate and economic impacts of trade policy. While the scenario literature, including that reviewed by the IPCC, spans a wide range of futures, it still lacks explicit treatment of emerging geopolitical and trade dynamics. Other missing dimensions of relevance to trade include human capital/labour[148], circular economy[149–151], and different types of extremes[152].

Targeted trade-focused scenarios can illuminate how trade and climate policy interact. They can enable exploring first-order dimensions that may not be endogenous to models, as discussed above, by means of "what if" analysis of key drivers. Moreover, better-targeted scenarios can provide common assumptions that can be tested across different modelling tools, leveraging their respective strengths in the climate-trade domain. They can also offer a structured way to explore today's deep and qualitatively different trade uncertainty, shaped by geopolitical fragmentation, abrupt policy shifts, and potential shocks, through plural and conditional framing rather than single deterministic trajectories[153].

The critical dimensions previously discussed, including environmental ambition, institutional and financial capacity, and political economy, can serve as a foundation for more policy-relevant and trade-focused scenarios. Scenarios often span dimensions and trade-offs using quadrant (2x2 matrix) structures[154]. A well-known example is the Shared Socioeconomic Pathways (SSP) framework, which organises future worlds by challenges related to mitigation and adaptation[155]. While trade is implied in SSPs, and trade barriers are inherently considered in the SSP3 (regional rivalry) and SSP4 (inequality) narratives, the characterisation could better represent and quantify the recent paradigm shift on trade and industrial policy.

A similar structure could thus frame trade-climate scenarios along two axes: trade openness (from protectionism to globalisation) and climate ambition (from global inaction to stringent collective climate policy). This spectrum spans four extremes—defined here as green internationalism, low-carbon nationalism, fossil-fuelled protectionism, and grey globalisation—though arguably more plausible futures lie between these endpoints. Figure 4 exemplifies five such scenarios, including a green multilateralism reboot, where climate ambition is restored through cooperative trade, as well as fragmented trade and decarbonisation, where climate action persists despite rising protectionism.

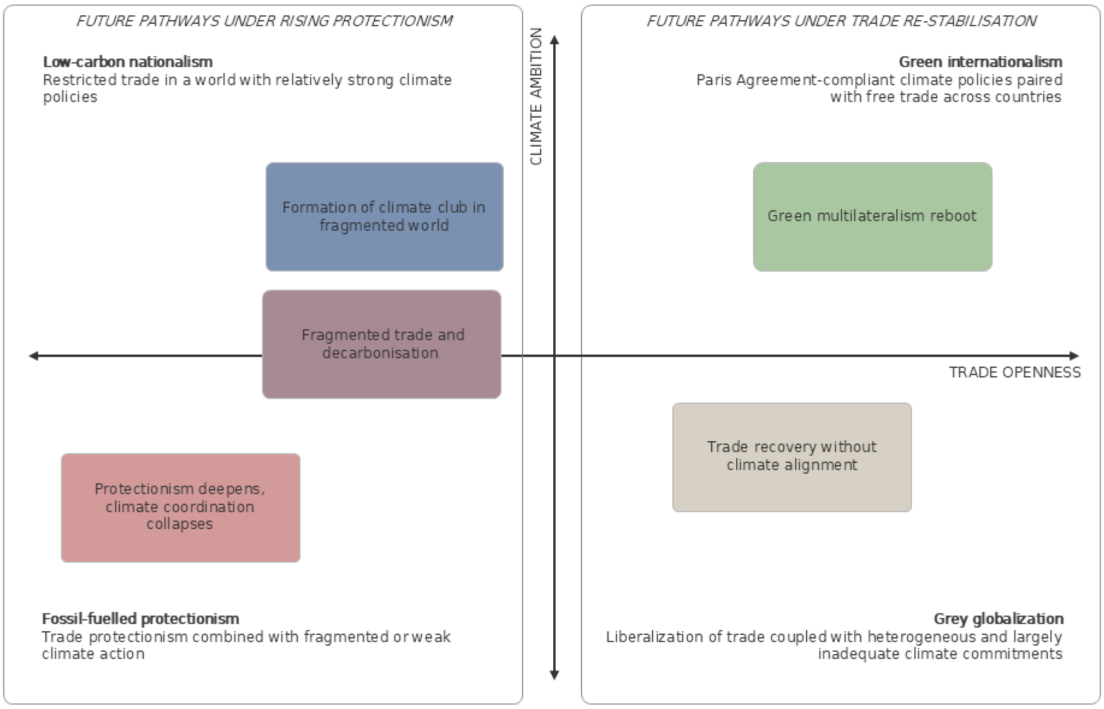

Figure 4: Illustrative scenario framework to examine climate action vis-à-vis trade openness and better capture the climate-trade interactions. Source: own elaboration.

Additional factors like institutional capacity and strategic political behaviour, already embedded in SSP narratives[156], could enrich these scenarios. A structured scenario space would support more robust ex-ante assessments of how protectionist measures shape long-term emissions and sustainability outcomes.

Conclusions and next steps

The relationship between trade and climate outcomes is complex and context-specific, operating through multiple economic channels that interact in non-linear ways. Protectionist measures may raise or lower emissions depending on the prevailing channel, context, and the time horizon considered. Above all, the final effect can be shaped by regulatory, institutional, and policy environments. By mapping the key trade-emissions channels and enablers, and highlighting the data, modelling, and scenario limitations that condition their analysis, this paper provides a foundation for assessing the climate consequences of evolving trade policies and for guiding targeted improvements in analytical frameworks. Building on these insights, we outline below a set of recommendations for future methodological enhancements and a forward-looking research agenda.

While existing modelling frameworks have made significant progress in capturing essential aspects of the trade-environment nexus, our analysis suggests that future advancements in this area can be achieved by pursuing developments along several key dimensions. *First,* progress lies in greater sectoral or commodity detail: although aggregation bias cannot be entirely avoided in economy-wide models, enhancing sectoral resolution in key areas—critical minerals, energy-transition technologies and fuels, emission-intensive agri-food activities, transport systems, and circular-economy practices—is essential. To achieve this, the research community should intensify efforts to collect and harmonise the fundamental data needed for such disaggregation. For instance, in critical-minerals supply chains, extraction-curve data across minerals and countries are not yet available globally. The same holds true for quantifying the downstream supply chains of energy-transition technologies, such as batteries and electric vehicles. For international transport, fossil-fuel use and emissions data at refined commodity levels remain missing, partly due to the bulk nature of these activities. While selected high-income countries have recently made progress, many developing economies still lag behind in data coverage and quality, though they are expected to experience the fastest growth ahead.

Second, a common limitation across many assessment frameworks is the lack of sufficient granularity beyond the firm level. This concerns two complementary dimensions. The first is distributional granularity, needed to capture how trade and environmental policies affect different household groups whose income levels, consumption baskets and exposure to price changes vary widely. The second is spatial granularity, reflecting sub-national differences in economic structure, environmental pressures and policy stringency that can shape the magnitude and distribution of impacts. Combining both dimensions would offer more policy-relevant insights by identifying *who* is affected and *where* impacts occur. Harmonised global datasets that integrate detailed household information with spatially resolved accounts remain largely undeveloped. *Third,* new model developments are needed to support richer institutional and spatial detail. These include parametrising production and consumption processes for newly introduced activities and consumer types, identifying substitution possibilities across inputs, consumption categories, and trade options. Supporting such parametrisation requires new research quantifying these relationships through econometric or optimisation techniques. This would also enable testing of alternative model specifications—e.g., using different trade mechanisms or demand systems—and validating them via historical or back-casting exercises. Beyond this, the complexity of trade-environment interlinkages often exceeds the scope of any single model, necessitating multi-model assessment frameworks. Developing standardised linking protocols and guidelines for such integrated frameworks would help ensure comparability and accelerate progress.

Fourth, while data and model developments provide essential foundation for comprehensive policy analysis, scenario design ultimately determines analytical validity and policy relevance. Two aspects warrant greater attention. On the one hand, standardised scenarios should reflect a more fragmented world, where groups of countries follow divergent priorities, some pursuing sustainability, others favouring self-sufficiency. Although there have been recent advances, mainstream scenario frameworks, such as the SSPs, still assume globally coherent development paths. On the other, future ad-hoc analyses should explore more radical transformations, such as degrowth or absolute resource-decoupling scenarios, to better understand alternative trajectories of the global economy and trade; while such exercises may have limited short-term policy relevance, they help map the decision space for long-term systemic transformations.

Looking ahead, recent advances in artificial intelligence are likely to reshape analytical frameworks, influencing not only data collection[157] and scenario generation[158] but also the design of modelling frameworks[159,160]. Machine learning and adaptive approaches could support models that update with new information, enhancing the analysis of complex, evolving trade-climate interactions.

Building on the methodological developments outlined above, future research should focus on understanding how institutional quality, regulatory capacity, and political-economy dynamics condition the trade-climate channels: under what conditions do these enabling factors cause protectionist measures to exacerbate environmental risks, and when can they instead support green industrial development? It will also be important to analyse how micro- to meso-level behavioural and structural responses, such as consumer preferences, sectoral composition effects, and innovation dynamics, interact with trade interventions amid rising geopolitical competition and uneven climate ambition, clarifying the conditions under which protectionist measures may yield climate-positive outcomes. At a broader systemic scale, further work is needed to understand how trade retaliation, strategic industrial policy, and supply-chain reconfiguration feed back into emissions, technology diffusion, investment patterns, and international cooperation. Advancing this agenda would strengthen the empirical basis needed to assess how different trade strategies interact with climate objectives. Ultimately, the question whether protectionism mirrors liberalisation cannot be answered with a simple symmetry argument. Although true for some isolated channels, the overall impact depends on complex interdependencies, temporal asymmetries, and enabling conditions that may generate path-dependent or irreversible outcomes. These factors make the climate consequences of protectionism potentially non-symmetric. Strengthening analytical capacity—via improved data, richer models, more diverse scenarios, and deeper conceptual and empirical grounding— will support systematic evaluation of when protectionism reinforces trade-offs or supports climate goals.

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P.R. coordinated the conception and writing of the paper with notable support from V.B. as well as feedback and contributions from all other authors. All authors collectively created the figures. All authors approved the final version of the manuscript.

Competing interests

The authors declare no competing interests.

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

During the preparation of this manuscript, the authors used ChatGPT (GPT-4-turbo, OpenAI) to improve the readability and language of the text. The authors reviewed and edited the content after using the tool and take full responsibility for the final version of the manuscript.

Materials & Correspondence

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Supplementary information

The online version contains supplementary material available at [XXX].

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