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Systemic risks from climate-related disruptions at ports

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Supplementary Information

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Supplementary Methods

Port downtime risk estimation

To estimate port downtime risk (*DR*), we use the results as set out in previous work[1]. This work currently present the only source of detailed (port-level) downtime estimates, on a global scale, associated with (i) extreme weather events exceedance operational thresholds and (ii) the impact of climate-related hazard damaging port infrastructure.

We estimate the DR per hazard considered, which include operational thresholds and four climatic hazards (i.e. coastal, fluvial, pluvial flooding and cyclone wind), with the data to do this summarised in Supplementary Table 4. A more detailed description is included in Ref[1]. In brief, we can summarise the steps as follows:

- For the operational thresholds (*OT*) considered, we evaluate the yearly exceedance probability over the historical period (1979-2018) and use this to estimate the annual expected downtime (*DT*) associated with extreme weather events.
- For the four climate-related hazards (*h*), we first quantify the hazard impact to port infrastructure (e.g. port terminals, road, rail, transmission lines) and the reconstruction time associated with them. This is performed per return period (e.g. inverse of the exceedance probability, $p = 1/RP$) available for the hazards considered. This reconstruction time is the estimated *DT* of different port infrastructure assets which together contribute to the port's overall operational status.
- To derive a port-level downtime per hazard, we use a fault three analysis (FTA), which captures how disruptions to the different components of the port lead to loss in functionality to the port as a whole. A FTA is performed per hazard and return period, such that we end up with a representative *DT* per return period.

We then estimate the *DR* for the port by adding up the *DT* associated with the *OT* and the *DT* per climate-related hazard:

$$DR = DT_{OT} + \sum_{1}^{h} \int_{0}^{1} QDT(p)dp$$

with *QDT* the inverse cumulative probability function of the *DT* per failure probability *p*. The integral is performed using the trapezoidal rule, which is commonly applied to estimate the risk integral using discrete *RP* estimates.

Data coverage

The data coverage for the analysis is a global subset of 1320 ports for which we have both port-level downtime risk estimates and information on maritime connections, maritime trade flows and supply-chain dependencies (see below). We believe that these 1320 ports capture almost all global maritime transport in absolute terms given the large concentration of trade flows in only a small subset of ports, as found in previous work (e.g. less than 60 ports globally capture 50% of maritime trade and less than 400 ports capture 90% of maritime trade)[2].

Relationship trading partners and port-to-port downtime risk

We test whether the number of port trading partners (that is the number of ports that are the last port of call of the incoming vessels at the port of interest, see 'Port-to-port downtime risk' below) has effect on the indirect downtime risk. To do this, we count the number of port partners (*NP*) of incoming vessels, and account for the direct downtime risk at ports. The latter is to account for the fact that ports (p) with a high direct downtime risk (DR) have a high likelihood of downtime risk at their geographically near trading partners.

In short, we formulate the regression:

$$PtPDR_p = \beta_0 + \beta_1 DR_p + \beta_2 LN(NP_p) + \epsilon$$

Both coefficients are statistically significant ($p < 0.01$) with a model fit with R^2 of 0.21. A high direct downtime risk is associated with a higher port-to-port downtime risk ($\beta_1 = 0.24$), while a higher number of trading partners is associated with a lower port-to-port downtime risk ($\beta_2 = -0.07$).

Port-to-port downtime risk

To derive the port-to-port network, we construct a database of vessel movements (based on Automatic Identification System or AIS data) between 1320 ports in our subsample, covering around 98,000 trade-carrying vessels in total. Based on the order of visits between 2019 and 2020, we can construct the connections between ports (which we call routes). Details of this dataset are included in previous work[2,3]. On every route, a vessel carries an amount of goods (the loaded capacity), which we approximate by multiplying the payload (or utilisation rate) on the route with the carrying capacity of the vessel (its DWT). When then aggregate across all vessels and divide by two to get the average loaded capacity on every transport route for the year 2019-2020. This results in a dataset of 150,000 routes between the 1320 ports.

For every port of interest, we look at the loaded capacity across all routes from the origin ports to the port of interest in our sample. We then combine this with the downtime risk at these ports (Extended Figure 1) to derive the loaded capacity at-risk. Supplementary Figure 4 shows examples of the loaded capacity at-risk for six ports; Rotterdam (Netherlands), Los Angeles-Long Beach (United States), Jeddah (Saudi Arabia), Durban (South Africa), Suva (Fiji) and Santos (Brazil). To estimate the port-to-port downtime risk, we take a weighted mean of the loaded capacity at-risk across all the origin ports.

Maritime trade at-risk

To estimate the maritime trade at-risk, we utilize the output of the Oxford Maritime Transport (OxMarTrans) model, a global maritime transport model that can simulate the route allocation of bilateral maritime trade flows. A detailed overview of the OxMarTrans model is provided in ref[2]. The base year for the trade flows is 2015, as this dataset is linked to a global multi-regional input-output table (see below), for which 2015 was the latest available year at the time of performing the analysis.

Adopting 2015 as a base year does present an inconsistency with the maritime transport network, which has 2019-2020 as base year. However, given the relatively slow evolution of the maritime transport network and the concentration of transport flows between major ports, we expect this inconsistency to be relatively small.

For every country's maritime trade exports, we look which ports are being used to export goods (often at a domestic port of the exporting country if a country is not a landlocked country), tranship goods (often a foreign port), and import goods (often at a trading partner's domestic port if the trading partner is not a landlocked country). We can do a similar exercise for a country's maritime imports, looking at the ports used to export goods (often a trading partner's domestic port if the trading partner is not a landlocked country), tranship goods, and import goods (often at a domestic port of the importing country if a country is not a landlocked country). This results in a network of >2.1 million unique port-country pair combinations across >25,000 unique country pairs and 11 economic sectors. For the results reported, we only look at the aggregate flows across the 11 sectors.

By combining the amount of trade flowing through each port (either in volume or value terms) with the annually expected downtime at this port, we can construct an overview of a country's trade-dependent ports and the trade at-risk at these ports, allowing us to rank port in terms of their criticality for maritime trade of any country of interest. Supplementary Figure 5 shows the top 200 ports with the highest trade at-risk for six example countries (Netherlands, Brazil, United States, Fiji, South Africa and Brazil). We can construct a country downtime risk metric by taking a weighted mean (weighted with the amount of a country's trade flows going through a port) across all ports in a country's "port portfolio", and multiply this with the total trade flow to estimate the total trade at-risk. We can do this for both a country's imports as well as exports, the total of which is similar on a global scale, but different on a country scale.

Economic activity at-risk

The economic activity at-risk metric builds upon the maritime trade network described in 'Maritime trade at-risk', but goes one step further. This metric does not only capture how a supply-chain is exposed to downtime because you trade through a certain port, but also how you are exposed as a firm because you rely on firms upstream in your supply-chain that trade through a port prone to downtime (the firms you depend on, 1st order suppliers, or firms that the firms that you depend on depend on, 2nd order suppliers, etc). In other words, as a supply-chain, you may be indirectly exposed to port disruptions without your direct input or consumption goods flowing through a at-risk port (e.g. you are exposed to closure of a raw materials exporting port without you directly using raw materials in your production process).

To estimate this, we expand the methodology described in Verschuur et al.[2], who evaluated the criticality of ports for global and domestic supply-chains by hypothetically extracting the trade through this port from a global multiregional input-output table (MRIO). In short, this is done by removing the sector-specific trade flows through a port (which connect industries across countries) and re-evaluating the industry output and consumption in the MRIO tables.

The methodology adopted is a variation of the Hypothetical Extraction Method (HEM)[4–6] used in I-O analysis, in which a sector is hypothetically set to zero (the i-th row and j-th column of matrix $\boldsymbol{A}$) in order to evaluate the interindustry dependencies and importance for the economy through changes in the industry output. Here, we quantify the output changes to the economy by removing the trade flows going through a port from the I-O table. To do this, we use both supply-driven (Ghosh) and demand-driven (Leontief) versions of the I-O table to find the forward (supply-driven, *f*) and backward (demand-driven, *b*) linkages. The use of a Ghoshian model is justified here as we look at reductions in industry output during short-term shocks instead of a long-term supply-driven economy (see Rose and Wei for a discussion on this assumption[7]).

In a MRIO table, the input coefficients matrix ($\boldsymbol{A}$) for country is derived from its interindustry trade ($\boldsymbol{Z}$) and industry output ($\boldsymbol{x}$). For a country k = 1, this consists of $\boldsymbol{A}^{11} = \boldsymbol{Z}^{11}(\hat{x})^{-1}$ for domestically produced inputs and $\boldsymbol{A}^{k1} = \boldsymbol{Z}^{k1}(\hat{x})^{-1}$ for inputs imported from country k $(k \neq 1)$. We perform the HEM per port in our dataset, and re-evaluate the impacts of the extracted port-level trade flows on global industry output and consumption within the MRIO tables. We do this by both modifying the interindustry trade matrix ($\boldsymbol{Z}$) and the final demand matrix ($\boldsymbol{y}$) to account for the trade flows going through a port. First, we remove the port-level trade flows (both import, export and transhipment) from $\boldsymbol{Z}$ and re-evaluate the new $\boldsymbol{A}_{p,1}$ using the demand-driven model and the new $\boldsymbol{B}_{p,1}$ using the supply-driven model ($\boldsymbol{B}_{p,1} = \widehat{\boldsymbol{x}^{-1}}\,\boldsymbol{Z}$). We find the backward losses in industry output ($\Delta\boldsymbol{x}_{p,1,ind,b}$) by re-calculating industry output ($\boldsymbol{x}_{p,1,ind}$) with the modified direct requirement matrix:

$$\Delta\boldsymbol{x}_{p,1,ind,b} = \boldsymbol{x} - \left(\boldsymbol{I} - \boldsymbol{A}_{p,1}\right)^{-1}\boldsymbol{y} \quad (\mathbf{1})$$

And the new industry output for the forward linkages ($\Delta\boldsymbol{x}_{p,1,ind,f}$):

$$\Delta\boldsymbol{x}_{p,1,ind,f} = \boldsymbol{x} - \boldsymbol{v}\left(\boldsymbol{I} - \boldsymbol{B}_{p,1}\right)^{-1} \quad (2)$$

with $\boldsymbol{v}$ the vector of value-added. The changes in industry output is the summation of the changes in domestic output ($\Delta\boldsymbol{x}_{dom,ind,b}$; $\Delta\boldsymbol{x}_{dom,ind,f}$) and change in output for the rest of the global economy ($\Delta\boldsymbol{x}_{row,ind,b}$; $\Delta\boldsymbol{x}_{row,ind,f}$). Moreover, we evaluate the change in industry output due to the port-level trade embedded in direct consumption. This is done by modifying the demand matrix ($\boldsymbol{y}$) with the equivalent reduction in domestic final consumption (imports) and the reduction in final consumption in other countries (exports). (Backward) Output losses associated with changes in final consumption in a port in country 1 ($\boldsymbol{y}_{p,1}$) can be found by solving:

$$\Delta\boldsymbol{x}_{p,1,con,b} = \boldsymbol{x} - (\boldsymbol{I} - \boldsymbol{A})^{-1}\left(\mathbf{y} - \mathbf{y}_{\mathbf{p},\mathbf{1}}\right) \quad (\mathbf{3})$$

From $\Delta\boldsymbol{x}_{p,1,con,b}$ we can find changes in domestic output ($\Delta\boldsymbol{x}_{dom,con,b}$) and changes in output for the rest of the economy ($\Delta\boldsymbol{x}_{row,con,b}$) in a similar fashion as described above. The forward losses associated with trade in final consumption are simply the trade flows of final consumption, with imports leading to a reduction of domestic consumption ($\Delta\boldsymbol{c}_{dom,con,f}$) and exports leading to a reduction in foreign consumption ($\Delta\boldsymbol{c}_{row,con,f}$).

The total output and consumption losses are the summation of the different components, which can be further subdivided in domestic or foreign economic activity exposed (foreign here meaning not the country the port is located in) and the forward and backward economic activity exposed:

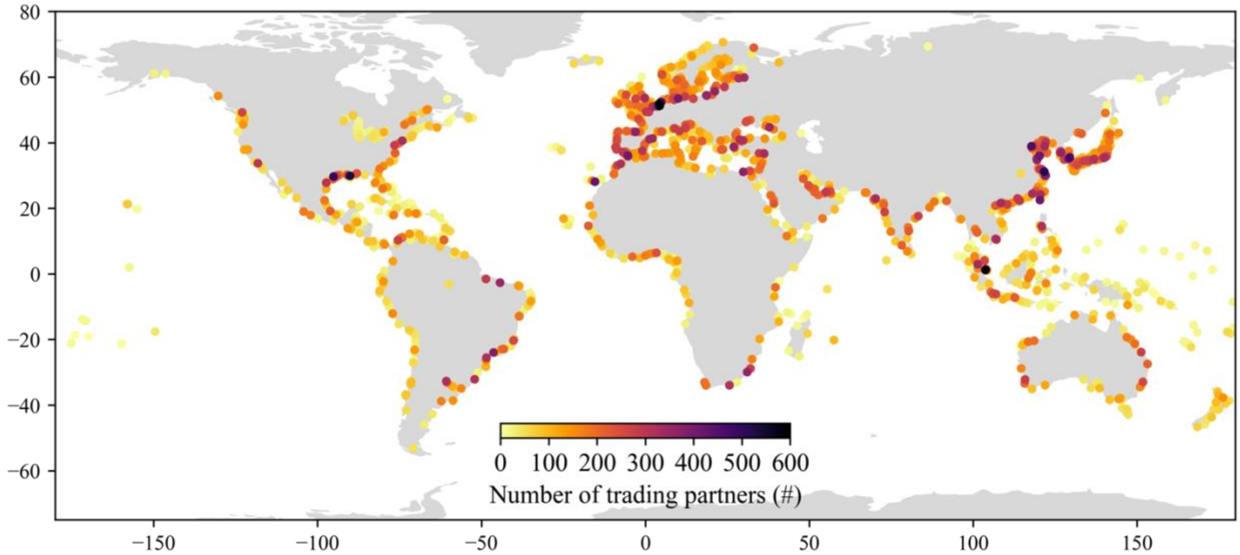
$$\begin{aligned} EA\ exposed = {} & (\Delta\boldsymbol{x}_{dom,ind,b} + \Delta\boldsymbol{x}_{dom,con,b}) + (\Delta\boldsymbol{x}_{dom,con,f} + \Delta\boldsymbol{x}_{dom,ind,f}) + (\Delta\boldsymbol{x}_{row,ind,b} \\ & + \Delta\boldsymbol{x}_{row,con,b}) + (\Delta\boldsymbol{c}_{row,con,f} + \Delta\boldsymbol{c}_{row,ind,f}) \quad (4) \end{aligned}$$

In the main text, we only consider forward dependencies, which are more relevant for short-term port-disruptions (which in most cases will not directly cause backward propagation of the shock, only in extreme circumstances). However, in Supplementary Figure 3 and the data provided with this paper, we also include the backward dependencies.

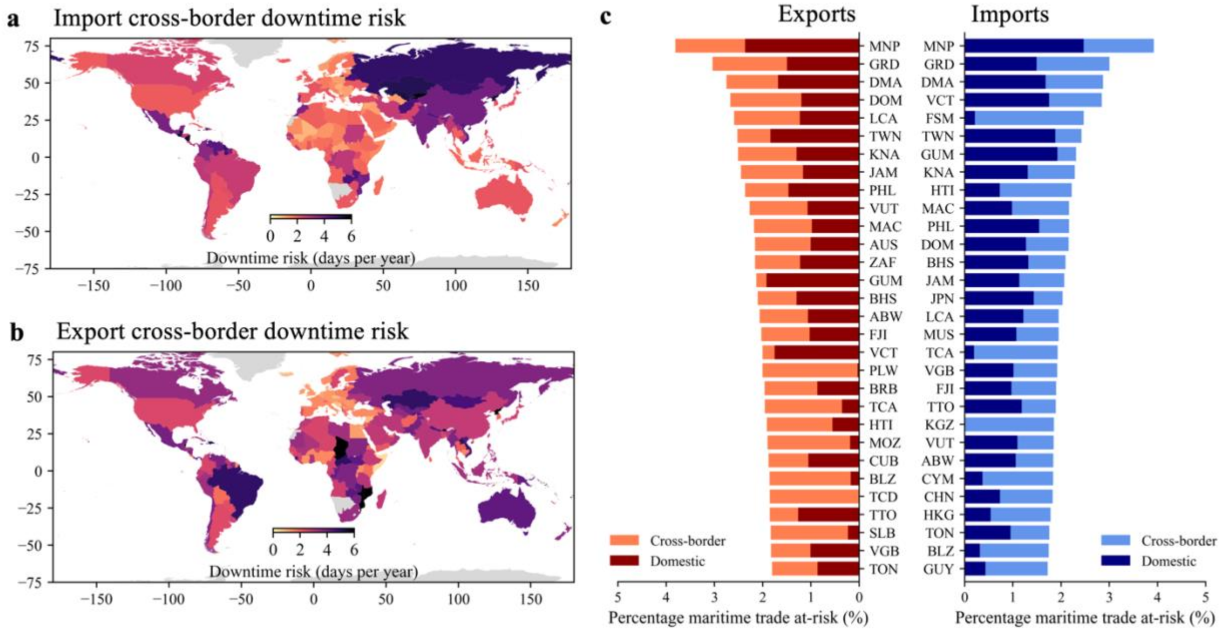
This analysis is done for all 1320 ports in our dataset. Using this formulation, we evaluate, per country and per sector, which percentage of its consumption or industry output is directly (because of a firm's input coming through a port) or indirectly (because of a firm's 1st, 2nd or higher order suppliers input or output coming through a port) influenced by the trade flowing through the port of interest. To illustrate this, Supplementary Figure 6 shows the percentage of a country’s total industry output influenced by six example ports, namely Rotterdam, Los Angeles-Long Beach, Jeddah, Santos, Port Hedland and Durban.

To find the industry output and consumption at-risk of a given supply-chain in a given country, we reverse the perspective and look at what fraction of the industry output and consumption is at-risk every year because of expected annual downtime at all the ports that this supply-chain depends upon (see the formulation of Economic activity at-risk in the main methods). Similar as with the maritime trade at-risk, one can evaluate the top ports in terms of industry output or consumption at-risk for any country of interest, as for instance shown for six countries in Supplementary Figure 7 (top 200 ports). This can be done at both the sector-country level as well as the aggregate country-level.

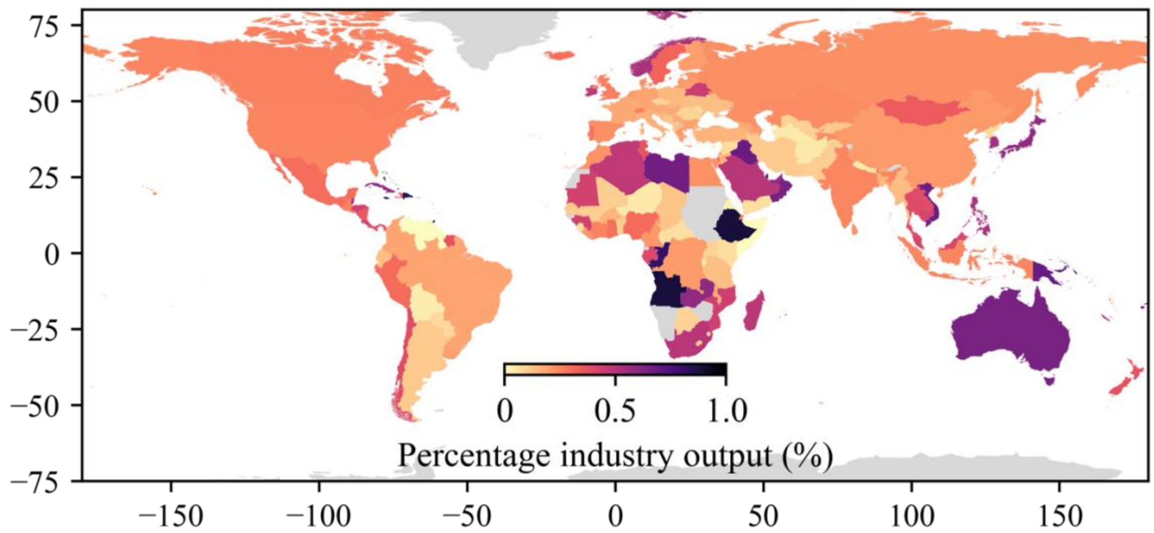
Supplementary Figures



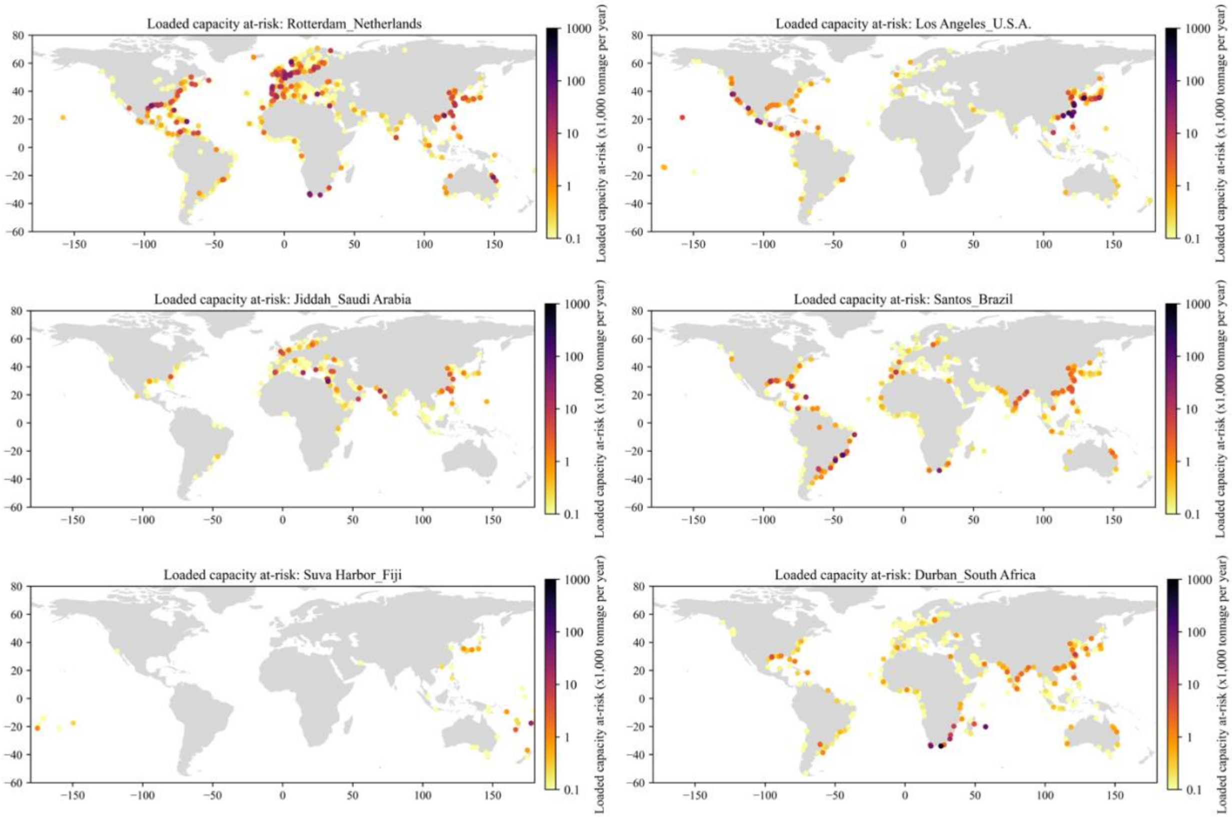
Supplementary Figure 1. Number of port trading partners. The number of ports that a port directly depends upon in the maritime transport network. These trading ports are ports that vessels have last visited before calling at the port of interest. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).



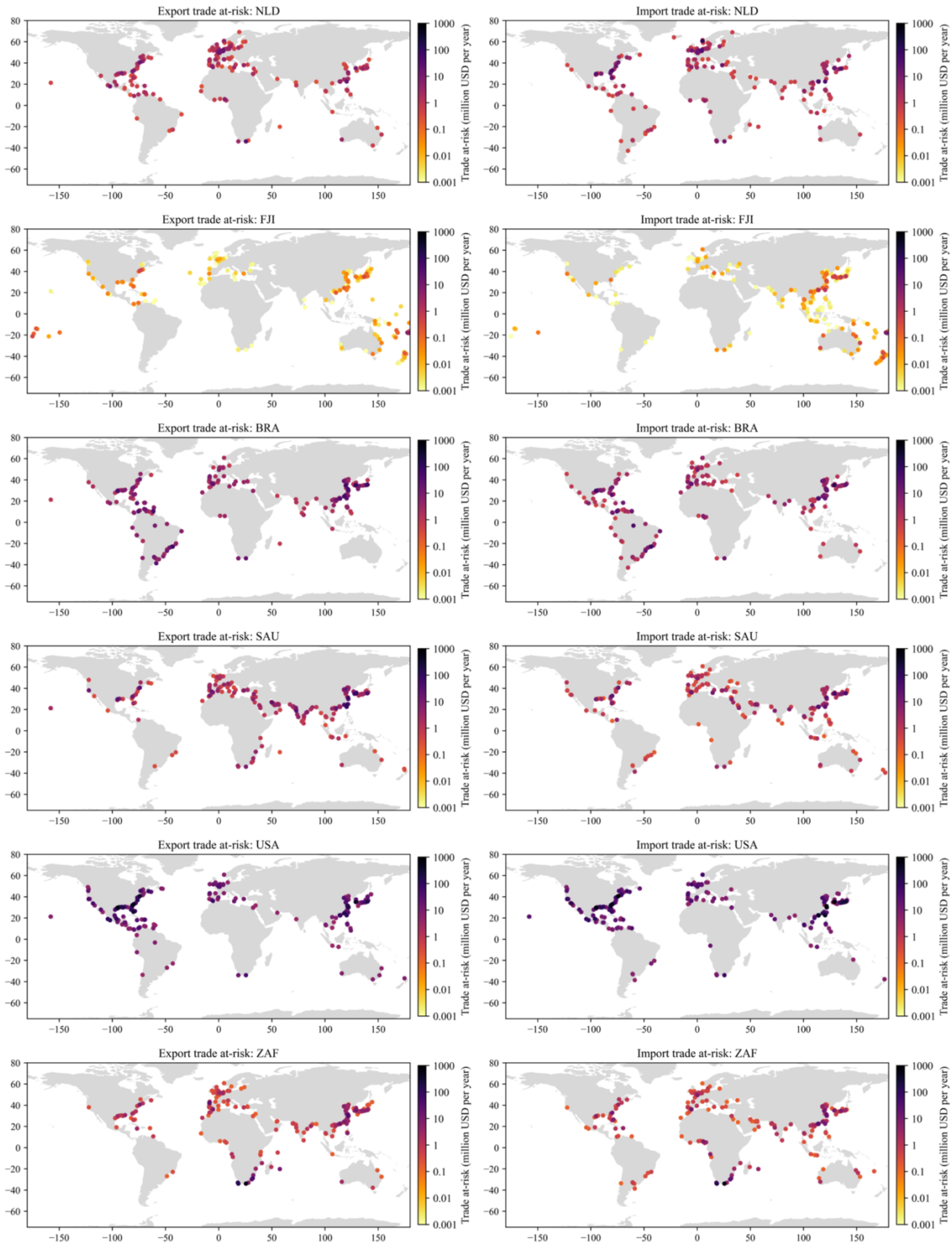
Supplementary Figure 2. Maritime trade volume at-risk. (a) Cross-border downtime risk for country's import flows, (b) same as (a) but for exports. (c) Top-30 countries in terms of maritime trade at-risk (in volume terms), including a breakdown between domestic and cross-border downtime risk. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).



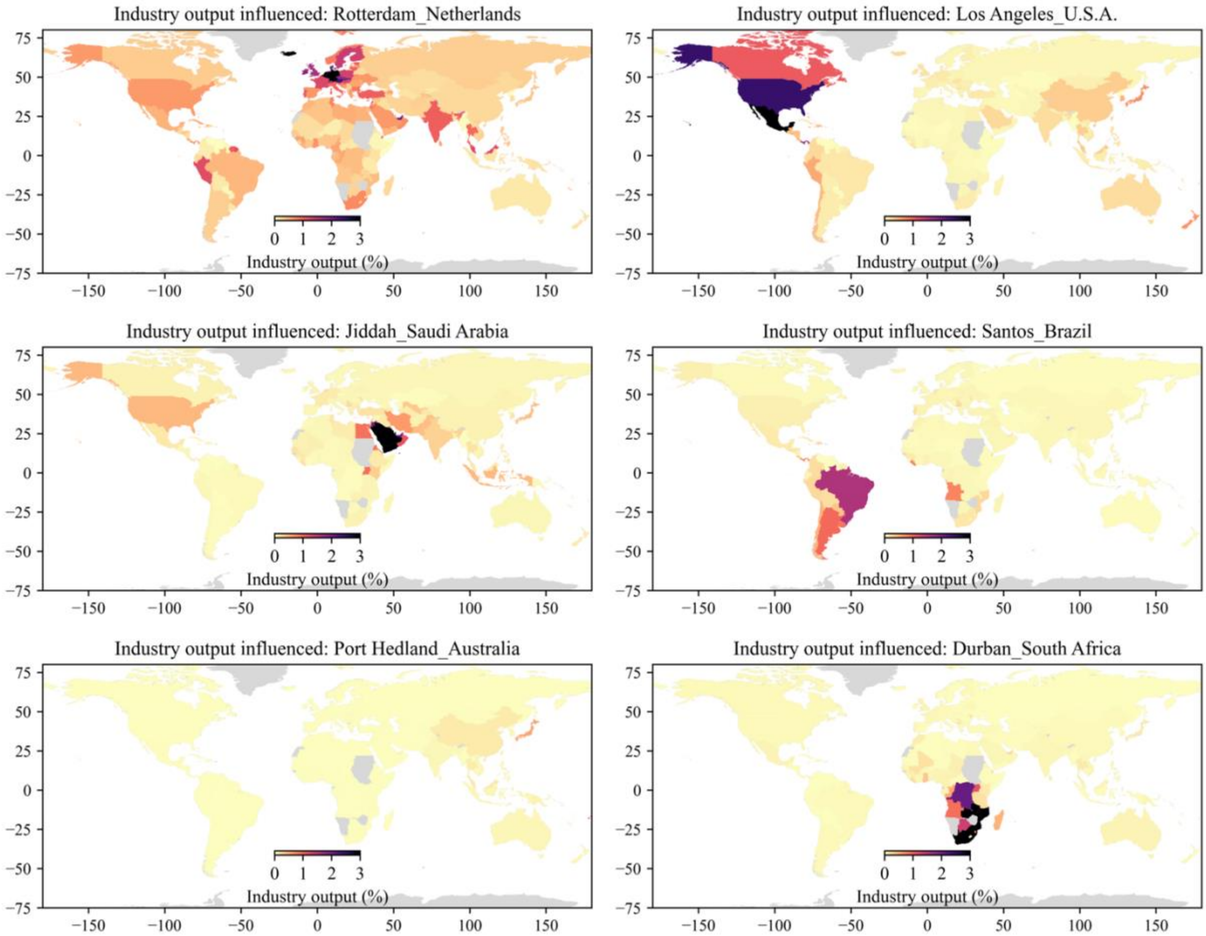
Supplementary Figure 3. Backward industry output at-risk. Percentage of industry output at-risk (% per year) given backward (demand driven) ripple effects through supply-chains due to climate-related port disruptions. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).



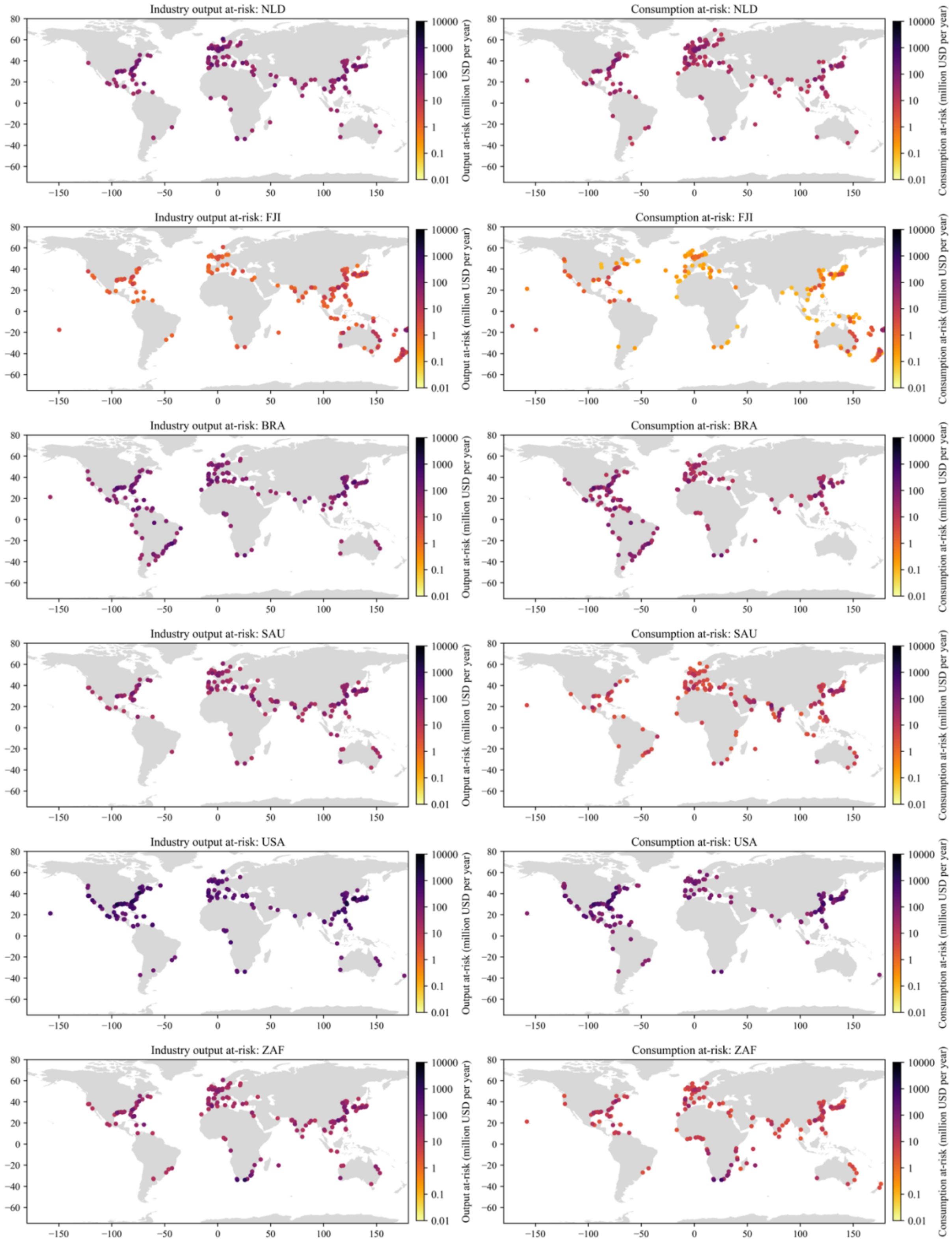
Supplementary Figure 4. Loaded capacity at risk for six example ports. The loaded capacity at-risk in transport-dependent ports in maritime transport network (i.e. trading ports). The loaded capacity quantifies the expected annual amount of loaded capacity (volume of goods carried) on a route service the port of interest times the expected annual downtime at the trading port. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).



Supplementary Figure 5. Top 200 most critical ports for maritime trade. The top-200 most critical ports for maritime trade (in value terms) for six example countries. The import or export trade at-risk is estimated by combining the country's absolute amount of import of exports flowing through a port with the expected annual downtime at this port. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).



Supplementary Figure 6. Industry output influenced by trade through ports. The aggregate industry output of country's supply-chains influenced by trade through a port of interest. The industry output influenced is derived by hypothetically removing the port's trade flows from a multiregional input-output table and re-evaluating the industry output of supply-chains globally. This therefore captures all forward dependencies of a country's industry output on trade through a given port. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).



Supplementary Figure 7. Top 200 most critical ports for supply-chains. The top-200 most critical ports for country's supply-chains (in terms of industry output and consumption) for six example countries. The industry output and consumption at-risk is estimated by combining the country's absolute amount of industry output or consumption influenced by trade through a port with the expected annual downtime at this port. The base map is derived from Global Administrative Areas (GADM) dataset (available at gadm.org).

Supplementary Tables

Supplementary Table 1. Sector specific trade at-risk in volume terms, including the fraction of cross-border risk.

Sector	Trade at-risk (million tonnes)	Fraction import cross-border (%)	Fraction export cross-border (%)
Agriculture	2.8	61.4	75.6
Electrical and Machinery	22.4	69.2	48.7
Fishing	0.3	60.1	74.4
Food & Beverages	4.3	59.1	74.0
Metal Products	7.2	66.5	57.1
Mining and Quarrying	8.1	50.0	77.2
Other Manufacturing	8.3	69.2	48.8
Petroleum, Chemical and Non-Metallic Mineral Products	19.7	58.5	60.4
Textiles and Wearing Apparel	4.1	70.1	55.9
Transport Equipment	2.0	69.4	53.1
Wood and Paper	1.7	58.8	66.1

Supplementary Table 2. Sector specific trade at-risk in value terms, including the fraction of cross-border risk.

Sector	Trade at-risk (million tonnes)	Fraction import cross-border (%)	Fraction export cross-border (%)
Agriculture	7.5	58.0	78.8
Electrical and Machinery	1.6	67.1	51.2
Fishing	0.1	62.8	67.7
Food & Beverages	5.7	59.4	67.9
Metal Products	5.1	71.5	55.3
Mining and Quarrying	48.4	58.5	69.4
Other Manufacturing	0.9	72.7	45.5
Petroleum, Chemical and Non-Metallic Mineral Products	45.5	58.9	64.5
Textiles and Wearing Apparel	0.4	70.2	55.6
Transport Equipment	0.4	66.6	55.2
Wood and Paper	2.0	57.4	72.7

Supplementary Table 3. Sector specific industry output and consumption at-risk, including the fraction of cross-border risk.

Sector	Industry output at-risk (USD billion)	Fraction cross-border (%)	Consumption at-risk (USD billion)	Fraction cross-border (%)
Agriculture	2.71	67.59	0.58	74.11
Electrical and Machinery	25.39	66.90	9.72	56.81
Fishing	0.32	63.30	0.05	71.25
Food & Beverages	6.95	65.90	2.28	74.43
Metal Products	11.43	62.37	0.39	58.62
Mining and Quarrying	1.99	59.59	0.06	63.22
Other Manufacturing	2.67	67.28	1.69	59.16
Petroleum, Chemical and Non-Metallic Mineral Products	23.58	58.34	2.85	65.38
Textiles and Wearing Apparel	5.02	65.59	3.73	58.71
Transport Equipment	9.55	68.50	4.25	51.10
Wood and Paper	3.74	63.27	0.42	61.14

Supplementary Table 4. Overview of the hazards used for the downtime risk estimates.

Hazard type	**Description**	**Time dimension/return period**
Operational thresholds	Exceedance of threshold set for non-cyclonic wind, temperature, waves and overtopping. This is based on ERA5 reanalysis data[8].	1979-2018
Cyclone wind	Extreme wind associated with cyclones, typhoons and hurricanes. Based on synthetic cyclone wind dataset covering 10,000 years[9].	We extracted 13 return periods based on this (1, 2, 5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000, 10000) to perform the risk integral.
Pluvial and fluvial flooding	Flood maps for pluvial (extreme rainfall) and fluvial flooding (riverbank overflow) per port. Based on flood hazard model of JBA Consulting (https://www.jbaconsulting.com/), which covers flood depth and extent per port.	The JBA flood model has flood hazard maps for six return periods (20, 50, 100, 200, 500, 1500), which are used to perform the risk integral.
Coastal flooding	Extreme water levels are derived based on global datasets of tides, storm surges and waves, see Ref[1]. These extreme water levels are overlaid with a digital elevation model per port, predicting the inundation extent and depth.	Coastal flood maps are derived for 10 return periods (2, 5, 10, 20, 50, 100, 200, 500, 1000, 5000), which are used to perform the risk integral.

Supplementary References

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