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Analysis of world trade data with machine learning to enhance policies of mineral supply chain transparency

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A B S T R A C T

The increasing integration of supply chains worldwide and the establishment of resilient material flows emphasize the significance of transparency. As regulations and policies around mineral supply become more stringent, organizations are actively seeking effective tools to assess the transparency of their supply chains. Ensuring supply chain transparency plays a vital role in international trade data since it addresses the issue of inconsistent reporting by two parties involved in a transaction, sometimes referred to as bilateral asymmetries. Nevertheless, bilateral asymmetries might be utilized as a proxy to examine discrepancies in the transparency of supply chains.

This paper presents a methodology to evaluate supply chain transparency using bilateral asymmetries as a proxy and provide insights into policy changes. We used a machine learning-based methodology on UN Comtrade data to study asymmetry trends in 116 million trade transactions over 30 years. The analysis demonstrates different levels of asymmetry among commodities and countries, suggesting differences in the transparency of supply chains. We exemplified the implementation of the methodology by analyzing 14 commodities associated with lithium batteries and their primary resources. The findings identify seven commodities that exhibit good (reliable) reporting practices, while two commodities (Cobalt and Lithium Primary Batteries) demonstrate bad (unreliable) reporting patterns. This indicates specific areas that should be examined and improved through policy changes. The paper presents a succinct and practical approach to measuring and strengthening supply chain transparency, giving actionable insights for policymakers and stakeholders for future actions.

1. Introduction

Material flows are crucial in the modern global economy. Hence, building sustainable, resilient, and transparent supply chains of materials is critically important and has implications for markets, security, and governance. Organizations strive to comply with regulations, streamline operations, ensure output quality, and promote process sustainability (Montecchi et al., 2021). The globalization of supply chains and the presence of conflict-affected and high-risk areas (CAHRAs) characterized by armed conflicts, violence, and institutional weaknesses further underscore the importance of transparency. To address these issues, the OECD recommends that companies identify circumstances related to the trade of products containing minerals sourced from CAHRAs; adopt and implement a risk management plan, establish a system of controls and traceability, and ensure compliance (OECD, 2016).

The White House recognizes transparency as a fundamental pillar of resilience along with other world leaders by underscoring its significance in raising awareness of risks throughout the supply chain(The White House, 2021). Similarly, the UN Security Council urges states to identify supply chain risks and regularly publish comprehensive import and export statistics for natural resources. These efforts contribute to the investigation and prevention of illegal exploitation (UNSC Resolution 1952; 2010). International Energy Agency, 2022 recommends that companies explore measures to enhance market transparency, including market assessments. Strengthening international collaboration between producers and consumers by providing reliable and transparent data is crucial. Additionally, collecting reliable data to assess risk levels and incorporating it into decision-making processes is essential.

To offer solutions that can overcome the struggles in supply chains, several tools have been generated. For instance, the Responsible Minerals Initiative, 2023 (RMI) supports companies in making informed sourcing decisions for tin, tantalum, tungsten, and gold. By identifying high-risk areas in mineral supply chains, the RMI assists in mitigating transparency-related challenges. Business for Social Responsibility & UN Global Compact, 2014 examines and surveys various traceability practices, mostly focusing on single commodities. It advises companies to particularly identify and concentrate on commodities that are most relevant to their business based on associated risks and potential adverse impacts.

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While Schrijvers et al. (2020) primarily review methods for determining raw material criticality in a different domain, their findings indicate that transparency can benefit these methods. Machine learning and big data can be utilized to create proxy indicators, which serve as initial screening tools for further investigation (Schrijvers et al., 2020). However, A comprehensive analysis containing all countries and commodities involved in trade activities, targeted to analyze countries' performances in commodity trade reporting to assist in evaluating supply chain transparency, is missing. On the other hand, international trade databases provide data by compiling reports from statistical authorities of countries. One of the largest databases, The United Nations Commodity Trade Statistics Database (UN Comtrade, https://comtrade.un.org/), provides open access trade data to the public. The supply chain's transparency can be effectively evaluated by examining the inconsistent reporting between the two parties participating in a trade transaction, known as bilateral asymmetries (BA), in the international trade data. This approach could serve as a reliable instrument for assessing supply chain transparency.

Chen et al. (2022) discuss the necessity for accessibility, completeness, and reliability of trade databases and focus specifically on UN Comtrade and advancing the use of it in physical trade flow analysis. They underline three data quality issues in UN Comtrade: Outliers, which cause significant deviation in data, missing values (MV), and BA. By its nature, each trade transaction is expected to be collected at least by two parties, the origin (exporter) and the destination (importer). Therefore, two different reports recording the same trade are provided, which often do not coincide with each other. This inconsistency is referred to as BA and is frequently investigated in the literature. Tsigas et al. (1992) mention the earlier studies on the inconsistency, referring to Morgenstern (1974); Parniczky (1980), where they trace the issue back to 1885.

Six reasons of BA that is significant on transparency are mentioned. These are, (i)**Mis-invoicing**, which is reporting trade values different than the actual values (Carrere and Grigoriou, 2015; Ferrantino and Wang, 2008; McDonald, 1985; Parniczky, 1980; Tsigas et al., 1992; Yeats, 1990) that can also be used to hide the trade to/from countries in embargoes (Javorsek & UN.ESCAP, 2016); (ii)**Role of re-exports and re-imports** (transshipment or entrepot trade) when the commodity pass through a third country or area but not reported appropriately (Carrere and Grigoriou, 2015; Feenstra et al., 1999; Ferrantino and Wang, 2008; Fisman et al., 2008; Fung and Lau, 2001; Javorsek & UN.ESCAP, 2016; Morgenstern, 1974; Parniczky, 1980; Tsigas et al., 1992; Yeats, 1990); (iii)**Reporting quality differences between developed and developing countries** (Tsigas et al., 1992), (iv)**Reporting quality differences between exports and imports** where corresponding authorities focus on reporting imports more precise than exports due to tariffs and import restrictions (Carrere and Grigoriou, 2015; Parniczky, 1980; Tsigas et al., 1992), (v)**Misclassification of the commodities**, which occurs when one or both of the parties report the commodity under a false class (Carrere and Grigoriou, 2015; Ferrantino and Wang, 2008; Javorsek & UN.ESCAP, 2016; Morgenstern, 1974; Parniczky, 1980; Tsigas et al., 1992; Yeats, 1990), and last, (vi)**Trade valuation differences** which is the difference in reporting format of exports and imports (Carrere and Grigoriou, 2015; Ferrantino and Wang, 2008; Fung and Lau, 2001; Javorsek & UN.ESCAP, 2016; Morgenstern, 1974; Parniczky, 1980; Tsigas et al., 1992). These formats are Cost, Insurance, Freight (CIF), and Free on Board (FOB), where CIF values contain the cost of insurance and freight on top of FOB, thus expected to be higher.

To investigate BA in the trade data, Tsigas et al. (1992) adopt statistical methods for quantifying the systematic component of unreliability in trade data between 1962 and 1987 and reveal that some countries consistently over or under-report their trade data; Chen et al. (2022) review data statistics criteria and discusses main data issues in Comtrade stated in Zhang et al. (2022) which introduces an estimation methodology to the missing values and Jiang et al. (2022) introduces a framework to detect and handle the outliers. Feenstra et al. (1999); Feenstra and Hanson (2004); Ferrantino and Wang (2008); Fisman et al. (2008); Fung and Lau (2001) focus on Hong Kong, where the effect of re-exports is significant; The quality of intra-African countries reports using statistical methods to compare with other countries is given by Yeats (1990); McDonald (1985) by explaining the variations in the trade data asymmetries with statistical evidence.

We notice that most of the reasons of BA stated are directly caused by the misinformation on the trade reports, which are either sourced by the companies reporting them or the statistical agencies neglecting this misinformation. This causality can also be explained by deliberate actions (Carrere and Grigoriou, 2015). Accordingly, we propose that BA analysis on trade data can be employed as a useful proxy for assessing supply chain transparency, whose outcomes can help organizations identify patterns and anomalies that may indicate a lack of transparency, which is also shown to vary significantly between countries and commodities.

This paper presents a methodology to evaluate supply chain transparency using bilateral asymmetries as a proxy and provide insights into policy changes. We use a machine learning-based methodology on UN Comtrade data to study asymmetry trends in 116 million trade transactions containing almost all commodities reported between 200 countries from 1992 to 2020. We investigate countries' trade reporting performances and classify the commodities as good (reliable) or bad (unreliable) by analyzing the BA.

To address these, we propose an approach that follows a machine learning (ML) based spatiotemporal pattern analysis of BA using two different clustering algorithms: K-Means and Self-Organizing Maps (SOM), followed by a cluster analysis to detect different patterns in BA to evaluate supply chain transparency of commodities and countries; and defining good and bad reporting. Furthermore, a case study is presented to show the proposed approach's implementation explicitly. Considering its emerging importance in mineral supply chains and its transparency, a group of 14 battery materials is selected. Batteries are one of the fundamental driving forces of the transition to clean energy, the decline of fossil fuels, and the increase in their relation to battery demand (Koyamparambath et al., 2022). The supply risk of battery materials is much higher than fossil fuels; the International Energy Agency, 2022 calculates a growth of nearly 40 times for battery demand from Electric Vehicles while 25 times for utility-scale battery storage in a scenario that meets the Paris Agreement Goals. Criticality of the materials, especially minerals, used in clean technology requirements, including battery materials, are apparent in the critical material studies in literature (Jin et al., 2016). By applying the proposed approach, we evaluate and differentiate these 14 commodities based on their transparency. The case study and its findings aim to demonstrate how our methodology enables decision-makers to identify the supply chain of their commodities of interest in terms of exhibiting good or bad performance.

The structure of the paper is as follows. Section Two explains the proposed methodology, including data collection, preprocessing, implementing the machine learning models, and interpreting the results. A case study on battery materials is given in Section Three, followed by Results and Discussion including conclusion in Section Four.

2. Methodology

The methodology (Fig. 1) unfolds in five distinct stages: Stage 1 commences the process with the data collection. It's followed by data preprocessing at Stage 2, which prepares the dataset to the application of Unsupervised Machine Learning Models in Stage 3, ultimately producing clusters. In Stage 4, a comprehensive analysis of these clusters takes place, with the findings interpreted in Stage 5. Each of these stages are explained and elaborated through the implementation of the proposed approach, in the following sections, providing clarity and coherence to the overall methodology.

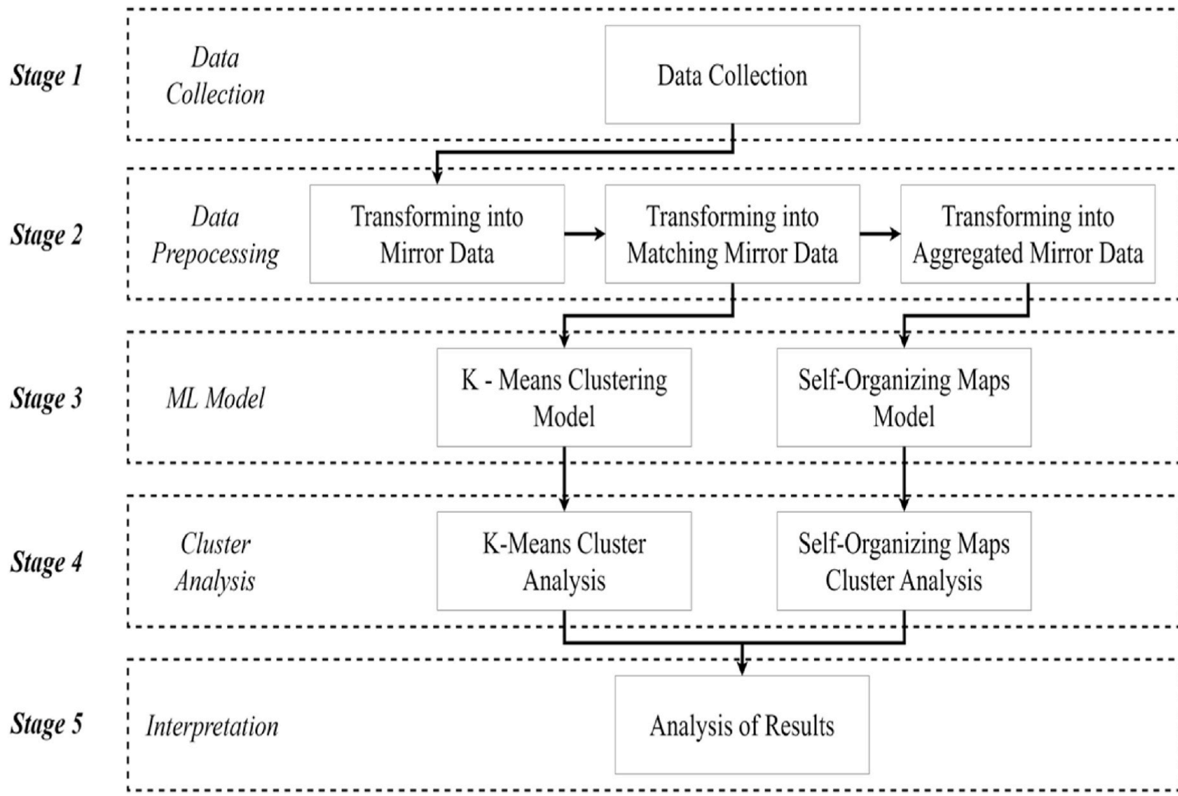

Fig. 1. Overview of the methodology.

2.1. Data collection (Stage 1)

The UN Comtrade dataset contains monthly and yearly import and export statistics of approximately 200 countries and areas (UN Comtrade, 2016). Details of dataset are given in Appendix (A1). Commodities are classified under Harmonized System (HS) Codes. HS is an international product classification system, administrated by World Customs Organization. First two number of the code denotes the Chapter, a broad category of the commodities, while the latter two pairs of numbers denote heading and subheading, respectively, and provide more detail about them (International Trade Administration, 2023). For instance, Chapter 87 (HS87) represents "Vehicles other than railway or tramway rolling stock, and parts and accessories thereof"; HS 8703 represents "Motor cars and other motor vehicles principally designed for the transport of persons" and HS 870321 represents "Of a cylinder capacity not exceeding 1000 cc" as a subgroup of 8703 (US International Trade Commission, 2023).

We use yearly data between 1992 and 2021 to overcome the asymmetries arising from the time of shipments and avoid seasonal impact; and we consider all reported HS Codes (Over 7000). Our dataset consists of 625,207,423 entities (as rows) and 22 variables (as columns) reported for country or area basis. For example (E1), one row of the dataset is: Germany reported an export of 186,774 Motor Vehicles (HS 8703) to Spain in 2019 weighing 301,745,736 KG and valued at 5,046,980,051 USD.

2.2. Data preprocessing (Stage 2)

Initially, the required columns from the dataset, using the indices at A1; C2, C8, C10, C13, C16, C18, C19 and C20; are filtered. Then, the dataset is transformed into Mirror Data (MD) to investigate further asymmetries. MD is a representation of bilateral data where each quantity is reported twice for a given data point (Cate, 2014). For instance, in E1, a point in mirror data would be in the year 2019, Motor Vehicles (HS 8703) are traded from Germany to Spain. The exporter (Germany) reports that 186,774 vehicles weighing 301,745,736 kg are sold with a value of 5,046,980,051 USD, and the importer (Spain) reports that 367,206,372 KG of vehicles is bought at the cost of 6,063,434,246 USD.

Resulting MD consists of 458,657,481 data points; however, a significant portion of the trade records is reported only by one country, causing numerous empty cells. Thus, we define a new dataset called Matching Mirror Data (MMD), where we remove the rows that contain missing cells in MD. MMD has a size of 116,847,330, and all its cells contain, Quantity, KG, and USD values reported by both partners. Note that MMD has a considerably smaller size than MD (25.5%). This can be foreseen as the UN states, "the trade statistics may not be reported for each and every year, and UN Comtrade does not estimate missing data" (UN Comtrade, 2016). Therefore, whether these empty cells are not reported, or the country is intentionally unreported is unclear. Even though existing studies have been conducted on estimating the missing values (Zhang et al., 2022), the possible bias due to estimation is a substantial risk, considering the amount. Consequently, we utilize MMD in our work as it has over 100 million of data points.

We define the measure for BA with the discrepancy values between two MMD reported trade amounts. Let, EX_{ft}^{yc} and IM_{ft}^{yc} represent the trade value of commodity c, from country f (exporter) to importer country t (importer), in year y; reported by the exporter and importer, respectively. Discrepancy (D_{ft}^{yc}) and Absolute Discrepancy (AD_{ft}^{yc}) between these reported values are:

$$D_{ft}^{yc} = EX_{ft}^{yc} - IM_{ft}^{yc} \tag{1}$$

$$AD_{ft}^{yc} = \left| EX_{ft}^{yc} - IM_{ft}^{yc} \right| \tag{2}$$

The size of discrepancies varies between commodities. Therefore, comparing them using the values results in dominating larger amounts over smaller ones. To avoid this effect, we scale the discrepancies, similar to (Ferrantino and Wang, 2008), by dividing these discrepancies given in equations (1) and (2) to the average value of both countries' reports which yields Scaled Discrepancy (*SD*) and Absolute Scaled Discrepancy (*ASD*) values, respectively as follows.

$$\mathrm{SD}_{\mathrm{ft}}^{\mathrm{yc}} = \frac{\mathrm{EX}_{\mathrm{ft}}^{\mathrm{yc}} - \mathrm{IM}_{\mathrm{ft}}^{\mathrm{yc}}}{\left(\mathrm{EX}_{\mathrm{ft}}^{\mathrm{yc}} + \mathrm{IM}_{\mathrm{ft}}^{\mathrm{yc}}\right) * 0.5} \tag{3}$$

$$\mathrm{ASD}_{\mathrm{ft}}^{\mathrm{yc}} = \frac{\left|\mathrm{EX}_{\mathrm{ft}}^{\mathrm{yc}} - \mathrm{IM}_{\mathrm{ft}}^{\mathrm{yc}}\right|}{\left(\mathrm{EX}_{\mathrm{ft}}^{\mathrm{yc}} + \mathrm{IM}_{\mathrm{ft}}^{\mathrm{yc}}\right) * 0.5} \tag{4}$$

Here, SD_{ft}^{yc} ranges between -2 and 2 and ASD_{ft}^{yc} ranges between 0 and 2. which does not focus on the direction of the discrepancies. The value of 0 means both partners reported the same value hence there exists no discrepancy. For SD_{ft}^{yc}; Value 2 refers to exporter reports a trade amount while the importer reports 0 for the same transaction and for value -2 vice versa. For ASD_{ft}^{yc} value 2 refers to one country reporting a trade amount of 0 while the other partner reported a positive value.

As a final step of data preprocessing, we create aggregated datasets of the MMD to apply to Self-Organizing Maps (SOM) Model. Initially, we create a sub-dataset by taking columns "Year," "Exporter," "Importer," "HS," "ASD of Quantity," "ASD of Weight," and "ASD of Value (USD)". Afterwards, we divide the dataset into three parts, each showing a different magnitude of trade, ASD of Quantity, Weight (KG), and Value (USD). To perform spatiotemporal pattern analysis better, we expand each dataset by changing the "Year" values into columns. In this way, each data line represents the temporal pattern of a trade connection between countries over the years. However, there are no trade records for each year for every exporter, importer, and commodity combination resulting in 80.2% of the cells become empty. Due to the high percentage of missing cells, and accuracy difficulties in their predictions, we aggregate the data on three focus attributes, Exporter, To, and Commodity. Considering narrow distribution of the discrepancy values for each year (*t*) and country (*c*), the average function (*AVG*) is used to aggregate the dataset.

$$ASD_f^y = AVG\left(ASD_{ft}^{yc}\right) \tag{5}$$

$$ASD_t^y = AVG\left(ASD_{ft}^{yc}\right) \tag{6}$$

$$ASD_c^y = AVG\left(ASD_{ft}^{yc}\right) \tag{7}$$

Here, ASD_f^y is indexed by exporter countries and aggregated over all importers and commodities, ASD_t^y is indexed by importer countries and aggregated over all exporters and commodities and ASD_c^y is indexed by commodities and aggregated over all exporter and importer countries.

Aggregation also does not yield complete datasets. We notice 29%, 28%, and 18% of Exporter, Importer, and Commodity datasets are empty cells, respectively. which are accumulated in the years 2021 and 1992 to 1999. Removing these years, we notice that 102 of 207 Exporter (From) countries, 107 of 208 Importer (To) countries, and 5445 of 7843 Commodities are fully reported in the 21-year period of 2000–2020. We filtrate the remaining data from the aggregated datasets out. These processed datasets are referred to as Aggregated Exporter, Importer, and Commodity datasets, respectively.

The fundamental statistical analyses are performed to determine the distribution of the scaled discrepancy, $\mathrm{SD}_{\mathrm{ft}}^{\mathrm{yc}}$, in terms of Quantity, Weight, and Value which are illustrated in (Fig. 2). The data partially shows a Gaussian pattern in the middle, having the spikes at the values -2 and 2. Normality tests using Anderson-Darling are rejected at 1% significance ($p < 0.01$) (SciPy, 2023).

Furthermore, histograms of the absolute scaled discrepancy, $\mathrm{ASD}_{\mathrm{ft}}^{\mathrm{yc}}$ (Fig. 2) show that the data is accumulated into the extremes (0 and 2) and exhibit a bathtub curve shape.

As the discrepancies do not follow a normal distribution, implementing a multivariate statistical analysis will be inadequate for comparing the discrepancies in commodities and the reporting qualities of countries. Pairwise tests can be considered, however, are merely impractical considering data of more than 7000 commodities and 200 countries. Thus, ML is preferred to investigate the spatiotemporal pattern of the discrepancies.

2.3. Machine learning models (Stage 3)

Among many other unsupervised ML methods, K-Means and SOM are selected and implemented due to their effectiveness in clustering with respect to their spatiotemporal influences. K-means algorithm aims to partition a dataset into a given number of clusters. Starting from an initial clustering, K-Means iteratively enhances the grouping of data

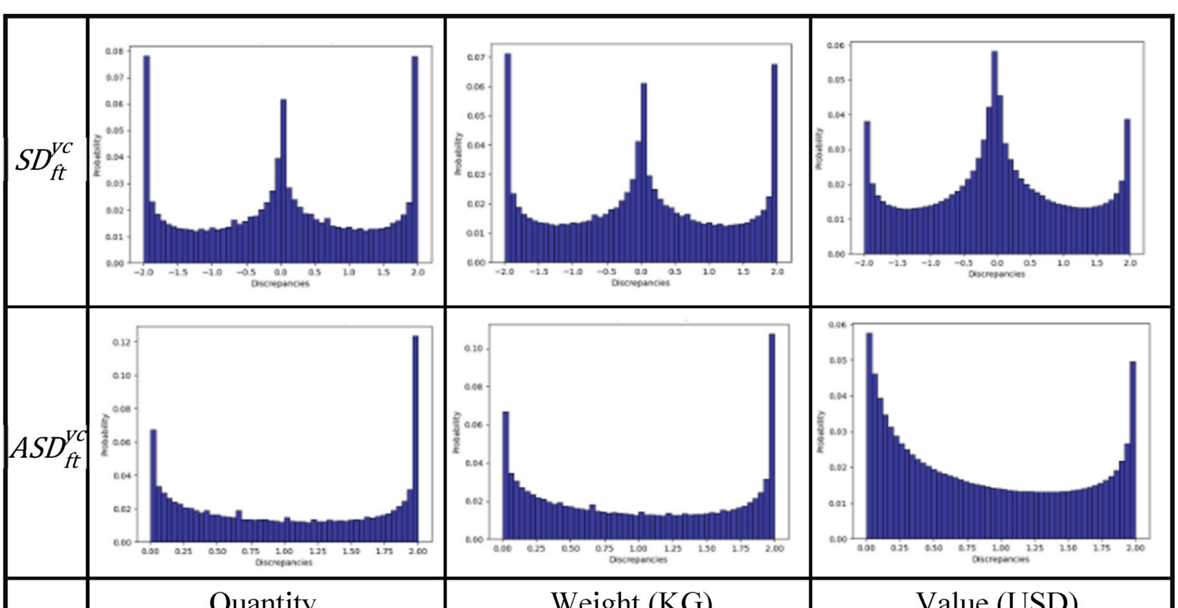

Fig. 2. Distribution of Quantity, Weight, Value $\mathrm{SD}_{\mathrm{ft}}^{\mathrm{yc}}$ and $\mathrm{ASD}_{\mathrm{ft}}^{\mathrm{yc}}$, respectively.

points until convergence criteria are satisfies. In each iteration, the algorithm relocates each point to its nearest cluster center and updates these centers by computing the mean of the member points (Mannor et al., 2011). In the end, each data point will be assigned to one of the K clusters. Moreover, SOM (Kohonen, 1982, 1990), is a neural network model used for unsupervised learning and dimensionality reduction. SOM organizes high-dimensional data onto a lower-dimensional grid, where each cell represents a grouping of the data based on its patterns. The algorithm iteratively adjusts the weights of cells based on the similarity between the data points and its surrounding points called neighbors. This adaptability allows each cell to specialize in recognizing specific patterns within the dataset. (Xuegong Zhang and Yanda Li, 1993).

We depict that K-Means is powerful to separate the dataset where we can efficiently analyze the difference of magnitude in discrepancies within exporters, importers, and commodities, while SOM allows us to investigate these discrepancies better as it is strong in detecting spatiotemporal patterns and clustering (Miljkovic, 2017) and performs well in high-dimensional datasets.

2.3.1. K-means clustering model

We consider three datasets to train our K-Means model and choose the one explaining the patterns more explicitly. These are the MMD with discrepancy values calculated for each transaction in Quantity, Weight, and Value units. Quantity amounts are given in 42 different unit types, therefore, does not provide a homogenous dataset, unlike the other two. (Fig. 2) implies that the discrepancies in the Value dataset are smoother than the ones in Weight discrepancies. This could prevent us from determining the cutoff points between good and bad reporting practices, and it also includes additional discrepancies due to CIF/FOB valuation. Therefore, solely Weight discrepancies dataset is used to train the algorithm. Using elbow method (Trupti M. Kodinariya & Dr. Prashant R. Makwana, 2013), we determine the appropriate number of clusters (K) as three and executed the algorithm using Scikit-Learn package from Python (Pedregosa et al., 2011).

2.3.2. Self-Organizing Maps model

We choose the weight dataset to train the SOM model to comply with the K-Means model. We use Aggregated Exporter, Importer, and Commodity datasets to identify spatiotemporal patterns and compare commodity reporting practices. We start by initializing the SOM, which requires several parameters to fit the model. These are: shape (rectangular or hexagonal); size (3x3, 4x4, etc.), and learning rate (alpha coefficients). Shape parameter adjusts the organization of the grid, thus the neighborhood of the cell (in rectangular, each cell has 4 neighbors, in hexagonal its 6) and size parameter adjusts the number of cells, which can be treated as number of clusters. The alpha coefficients, determines the magnitude of adjustments in each iteration. Alpha is given as two values $\propto_i$ and $\propto_j$ where it starts with the learning rate $\propto_i$ and linearly decrease down to $\propto_j$ during convergence. To determine these parameters, trials of several combinations for each dataset are made, and the results are investigated to observe the separation of patterns and granularity (Wehrens and Buydens, 2007).

As the first SOM model, we use the aggregated data for KG discrepancies of exporters as our input. In the data, export reporting discrepancy patterns of 101 countries exist. After performing our trial, we choose SOM with a 3x3 rectangular model with an alpha coefficient (0.05, 0.01), resulting in nine clusters. As the second model, we use the aggregated data for importers' KG discrepancies and choose a 3x3 hexagonal model with an alpha coefficient (0.06, 0.01) which separates the data better in the trials, resulting in nine clusters containing 106 countries. Finally, we use the aggregated data for KG discrepancies of commodities, including discrepancy patterns of 5445 commodities. A 3x3 hexagonal model with an alpha coefficient (0.07, 0.01) is chosen with similar trials, resulting in nine clusters. We execute the algorithm using the Kohonen package in R (Wehrens and Buydens, 2007; Wehrens & Kruisselbrink, 2018).

2.4. Cluster analysis (Stage 4)

We perform cluster analysis to observe the implemented ML models' outcomes. The analyses are performed separately, considering their different structure in K-Means and SOM clusters.

2.4.1. K-means cluster analysis

After execution of the K-Means model, three clusters, CL1, CL2 and CL3 each centered at 0.23566, 0.98051, and 1.79786, respectively are generated. The summary statistics of these clusters are given in Appendix (A2). As we discuss in Section 2.2, an absolute scaled discrepancy value of 0 denotes no difference between trade reports while a discrepancy value of 2 denotes maximum possible asymmetry between them (one party reports a positive trade amount while the other party reports 0). Thus, smaller values of discrepancies are favorable while larger values might point out asymmetry issues in trade reporting. Consequently, CL1, CL2 and CL3 are labeled as Small (SDC), Medium (MDC), and Large (LDC) Discrepancy Clusters, respectively which eases our interpretation in following sections. The SDC is found to be right-skewed, and LDC is left-skewed, whose behavior can be recognized better in (Fig. 3(a)). MDC covers the largest interval width of 0.8; however, it is the smallest in terms of the number of observations. SDC and LDC are close to each other in both size (~40 million, Fig. 3(b)) and their coverage interval width of 0.6.

During the spatial and commodity-based analysis, the selected data group is observed to be separated with different percentages into the SDC and LDC. The data is classified as "**Good Reported**" or "**Bad Reported**," based on whether it is significantly more skewed towards the SDC or LDC, respectively.

There are 205 countries and areas that reported exports. Exporters with low trade transactions may confuse the results, thus we choose top 153 countries (Top 75% in terms of number of records) and provide the distribution of the records under them. List of exporter countries can be found in Appendix (A3). SDC Percentage has a mean, $\mu = 40\%$ and standard deviation $\sigma = 11\%$, while LDC Percentage has a mean, $\mu = 35\%$ and standard deviation $\sigma = 10\%$ according to A3.

On the import side, there are 208 countries and areas that reported imports. Similarly, top 156 importers are selected, and results are provided at Appendix (A4). For importers, SDC Percentage has a mean, $\mu = 36\%$ and standard deviation $\sigma = 7\%$, while LDC Percentage has a mean, $\mu = 37\%$ and standard deviation $\sigma = 5.7\%$ according to A4.

In terms of commodities, our dataset has 7843 different commodities (HS codes), for which we can evaluate reporting performances. To simplify and observe the bigger picture, we group similar commodities under the clustered dataset based on HS Chapters (US International Trade Commission, 2023). We remove Chapter-99 since it is not specific to a commodity, rather called "Temporary Legislation" and only used for import reporting and provide the results of 96 actively used HS Chapters in Appendix (A5). For these 96 HS Chapters, SDC Percentage has a mean, $\mu = 40\%$ and standard deviation $\sigma = 7.5\%$, while LDC Percentage has a mean, $\mu = 34\%$ and standard deviation $\sigma = 5.8\%$ according to A5.

2.4.2. Self-organizing map cluster analysis

The data points in the SOM clusters are time series of discrepancies for each country or commodity. As a result, SOM can also distinguish temporal patterns and group them into clusters, which can be observed in (Fig. 4) for each model. For example, Cluster-1 in the exporter model shows an increasing trend, while Cluster-7 in the importer has an inconsistent pattern. Both Cluster-3 and Cluster-7 in commodity show a stable pattern, however, discrepancies in Cluster-3 are obviously higher.

To interpret the results generated by SOM, we employ an advanced cluster analysis method for each dataset. First, we determine the magnitude of discrepancies by calculating the mean of all data points in each cluster. We use it to evaluate the reporting quality as **good** or **bad**,

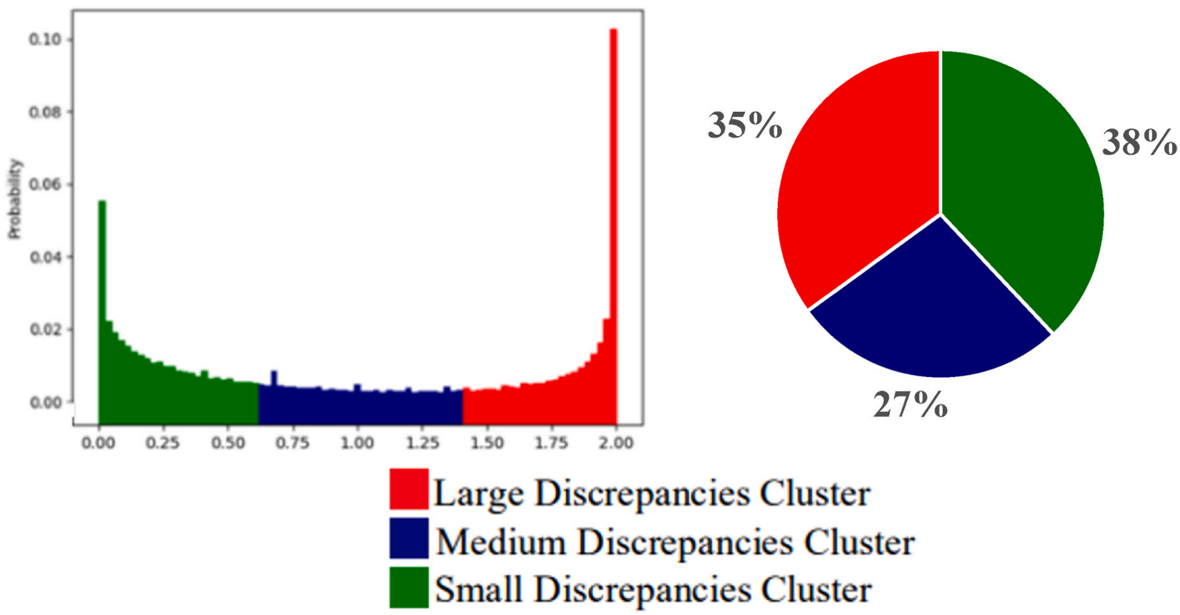

Fig. 3. (a)Data distribution in the clusters obtained from K means clustering on the left, (b)Percentages of the data fall under the corresponding cluster on the right.

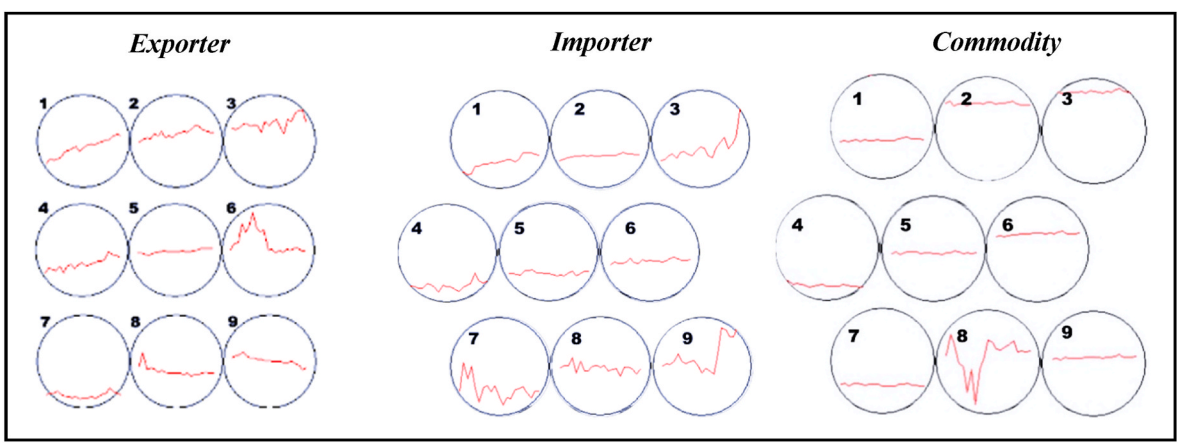

Fig. 4. Visualization of temporal patterns of SOM Cluster.

where good corresponds to a lower mean and vice versa, if the metric differs notably. Second, we analyze the cluster trends to observe temporal patterns, by calculating the mean for every year, and fit a linear model to the means to find its slope for each cluster. If the linear model shows a significant upward or downward trend with a high R^2, we conclude that the corresponding cluster represents decreasing or increasing reporting quality, respectively. In the final step, we perform consistency analysis to classify temporal patterns of discrepancies as consistent or not. This is done by computing the difference between the mean values for consecutive years for detrending and calculate the standard deviation of these differences which results in standard deviation of differences (DSD) that measures the relative consistency of the data over the years. We conclude that the cluster with highest DSD represent inconsistent reporting quality. Similar to K-Means, we perform cluster analyses separately for Exporter, Importer and Commodity whose results can be observed in Table 1.

Consequently, all of 101 exporters and 106 importers are clustered under nine different clusters, which can be observed in Appendix, (A6) and (A7), respectively. For the commodities, the clusters are well separated, where eight of them show consistent patterns with different means, and the remaining contains inconsistently reported commodities. To simplify our interpretation process, we merge Cluster-1 and Cluster-7; and Cluster-2 and Cluster-6 as one cluster, Good and Bad, reported commodities. As a result, among 5445 commodities, 239, 1311, 1803, 1703, 320, and 67 commodities are clustered in the Best, Good, Medium, Bad, Worst, and Inconsistent reported commodities clusters, respectively. Considering the numbers, 88.5% of the commodities fall under Good, Medium, and Best Clusters. Similar to K-Means Results, commodities are investigated using HS chapters for simplicity. The number of commodities in each cluster is counted for each chapter. Furthermore, each chapter is evaluated by the distribution of commodities under these clusters, which can be observed in Appendix (A8).

We notice several chapters show significant differences compared to the expected. For example, 56% and 44% of commodities listed under Chapter-91 (Clocks and watches and parts thereof) fall to the Worst, and Bad reported Commodity Clusters, respectively, making Chapter-91 the **worst-reported chapter**. On the other hand, Chapter-1 (Live Animals) is found to be the **best-reported chapter** as 60% and 33% of the commodities under that chapter clustered into the Best and Good reported commodity chapters, respectively.

2.5. Interpretation (Stage 5)

Interpreting the results of SOM is straightforward, as it separates the

Table 1
SOM cluster analysis for exporter, importer and commodity.

Cluster Number	Count	Mean	Slope	R^2	DSD	Description:
SOM RESULTS FOR EXPORTER COUNTRIES						
1	13	0.94	0.013	0.95	0.02	Exporters with Decreasing Reporting Quality
2	11	1.1	0.006	0.57	0.03	Exporters with Bad Reporting Quality
3	8	1.21	0.01	0.43	0.08	Exporters with Worst Reporting Quality
4	9	0.85	0.007	0.67	0.045	Exporters with Good Reporting Quality
5	19	0.99	0.003	0.81	0.008	Exporters with Medium Reporting Quality
6	3	1.12	−0.02	0.22	0.16	Exporters with Inconsistent Reporting Quality
7	18	0.67	0.001	0.06	0.03	Exporters with Best Reporting Quality
8	7	0.91	−0.006	0.45	0.06	Exporters with Medium Reporting Quality
9	13	1.03	−0.006	0.76	0.02	Exporters with Medium Reporting Quality
SOM RESULTS FOR IMPORTER COUNTRIES						
1	6	0.91	0.009	0.9	0.02	Importers with Decreasing Reporting Quality
2	19	0.97	0.003	0.8	0.008	Importers with Medium Reporting Quality
3	4	1.03	0.014	0.48	0.09	Importers with Decreasing Reporting Quality
4	13	0.83	0.003	0.26	0.03	Importers with Best Reporting Quality
5	17	0.92	0	0	0.02	Importers with Good Reporting Quality
6	26	1.03	0.001	0.25	0.014	Importers with Medium Reporting Quality
7	3	0.91	−0.009	0.17	0.17	Importers with Inconsistent Reporting Quality
8	15	1.09	−0.002	0.2	0.05	Importers with Bad Reporting Quality
9	3	1.26	0.02	0.42	0.13	Importers with Worst Reporting Quality
SOM RESULTS FOR COMMODITIES						
1	694	0.82	0	0.6	0.009	Commodities with Good Reporting
2	776	1.15	0	0.05	0.001	Commodities with Bad Reporting
3	320	1.27	0	0.003	0.01	Commodities with Worst Reporting
4	239	0.62	0	0.02	0.01	Commodities with Best Reporting
5	814	0.9	0	0.1	0.008	Commodities with Medium Reporting
6	929	1.07	0	0.66	0.008	Commodities with Bad Reporting
7	617	0.73	0	0.12	0.01	Commodities with Good Reporting
8	67	0.98	0	0.07	0.14	Commodities with Inconsistent Reporting
9	989	0.98	0	0.37	0.008	Commodities with Medium Reporting

countries and commodities directly into clusters where each can be distinguished if there is an issue with their reports. However, K-Means clusters the transactions itself. For that reason, we can only compare the countries and commodities, when we aggregate these transactions and observe the distribution of these transactions under these clusters which are provided in A3, A4 and A5. We can distinguish the countries and commodities by noticing the anomality in their percentages under SDC and LDC, where we define anomality as a percentage larger than sum of mean μ and standard deviation σ of the corresponding cluster distribution. For instance, Paraguay is defined as a good export reporting country as 66% ($>50.36 = \mu + \sigma$) of its transactions fall under SDC.

Accordingly, both of our models suggest:

i. In terms of exports, Cambodia, Hong Kong, Canada, Mozambique, Namibia, Qatar, Israel, Singapore, UAE, Malta, New Zealand, and Chile are reporting significantly worse; while Azerbaijan, Brazil, Argentina, Armenia, Bolivia, Belarus, Colombia, Peru, Ecuador, El Salvador, Kyrgyzstan, Moldova, Nicaragua, Paraguay, Russia, Ukraine, North Macedonia, and Uruguay are reporting significantly better than others.
ii. Regarding imports, Mexico, Mozambique, Cambodia, Canada, China, Egypt, Ethiopia, Malaysia report significantly worse; while Romania, Albania, Argentina, Croatia, Georgia, Italy, Kyrgyzstan, Latvia, Lithuania, Paraguay, Switzerland, and Uruguay report significantly better than others.
iii. Regarding commodities, HS Chapters 42, 61, 62, 64, 67, 71, 85, 90, 91, and 97 are reported worse; while Chapters 2, 4, 8, 10, 11, 17, 18, 21, 23, 24, 26, 28, 31, 36, 47 are reported better than others.

3. Case study: battery materials

Critical battery materials (both cathode and anode inputs) that are frequently studied and emphasized in the literature, **Natural Graphite** (Jin et al., 2016; Koyamparambath et al., 2022), **Magnesium** (Jin et al., 2016; Koyamparambath et al., 2022), **Cobalt** (Jin et al., 2016; Sun et al., 2019), **Lithium** (Jin et al., 2016), and **Nickel** (Jin et al., 2016) are chosen, which are also in critical raw materials list by the European Commission (European Commission, 2020). Additionally, two major battery products, Lithium-ion batteries and Primary Cells and Batteries with lithium, are included in the analyses. For each commodity, the SOM Cluster and Percentage of transactions that fall into SDC, MDC, and LDC from the K-means are listed in Table 2.

The results of SOM model indicate that Natural Graphite, Cobalt Oxides and Hydroxides, Hydroxide, and peroxide of Magnesium, Lithium Carbonate, Lithium oxide and hydroxide, Nickel oxides and hydroxides, Nickel powders, and flakes fall into good cluster. Further, the portion of their trade records falling into SDC outperformed overall data in more than 10%, hence, a significant difference is observed in positive direction. We can conclude that these 7 commodities are good in reporting.

Nickel Ores and Concentrates and Magnesium and articles, including waste and scrap, contain more of their data in SDC and show better performance compared to the overall data; however, they are classified as Medium in SOM. In contrast, even though Natural magnesium carbonate (magnesite) contains more data in LDC, SOM classifies it as Medium again. The good reported commodities show that there is always room for improvement, especially for the commodities classified as medium in reporting. It shows the importance of targeting these commodities in future policies to enhance their supply transparency.

On the other hand, the portion of Cobalt Ores and Concentrates' trade records falling into LDC has notably higher than overall data which might point out to bad transparency practices for Cobalt Ores. Moreover, the SOM model supports this finding as this commodity is placed under the Bad cluster. DR Congo, the major mining source of Cobalt (van den Brink et al., 2020) is not even in our lists in Appendix as

Table 2
Case study results for battery materials.

HS CODE	Commodity Name	SOM Cluster	K-Means SDC	K-Means MDC	K-Means LDC
2504	Natural Graphite	Good	49%	22%	28%
2605	Cobalt Ores and Concentrates	Bad	33%	27%	40%
2822	Cobalt Oxides and Hydroxides	Good	48%	22%	30%
8104	Magnesium and articles thereof, including waste and scrap:	Medium	42%	23%	35%
281610	Hydroxide and peroxide of magnesium	Good	51%	22%	27%
251910	Natural magnesium carbonate (magnesite)	Medium	37%	21%	42%
283691	Lithium Carbonate	Good	51%	22%	27%
282520	Lithium oxide and hydroxide	Good	53%	21%	26%
2604	Nickel Ores and Concentrates	Medium	46%	17%	37%
750210	Nickel oxides and hydroxides	Good	49%	24%	27%
7504	Nickel powders and flakes	Good	51%	24%	25%
850650	Primary cells and batteries with lithium	Bad	25%	29%	46%
8507	Electric storage batteries	Inconsistent	41%	21%	38%
850760	Lithium-ion batteries	N/A	26%	30%	44%
OVERALL DATA			38%	27%	35%

it has too few trade records thus, we filter it out in section 2.4.1. This is not a surprise as the challenges in the supply of Cobalt is discussed in literature and it is known that Cobalt supply chain is opaque (Mugurusi and Ahishakiye, 2022; van den Brink et al., 2020). However, it is a great example to show how our model can detect a commodity that shows significant transparency issues from the inconsistency in its trade reports, and its applicability to commodities where this insight is not available. Further, our results show the high contrast in the performance of the reports of Cobalt Ores and Concentrates versus Cobalt Oxides and Hydroxides. In the supply chain of Cobalt, ores are the products of mines, while oxides and hydroxides are products of refineries (Crundwell et al., 2020). The weak governance of mining and refining facilities is known (van den Brink et al., 2020) but our results add up a further granularity to the topic by pointing out that the pitfall of Cobalt supply chain transparency might be sourced in the mining stage. However, we would like to underline that proposing a causality to this disparity is beyond this paper's scope but would offer significant potential for a future work.

Furthermore, Primary cells and batteries with lithium (HS 850650) are classified as bad in reporting by both ML methods and Lithium-ion batteries (HS 850760) seem to be bad in reporting according to K-Means, with a more significant portion of its transactions under LDC. However, SOM input does not contain this cluster due to its missing data. For this reason, we also check its parent category, Electric Storage Batteries (HS 8507), which falls into the inconsistent cluster of SOM. The distribution of discrepancies of HS 850650 and 850760 (Fig. 5) significantly differs from the overall data (Fig. 2, Weight ASD_{ft}^{yc}).

According to Comtrade 45% of exports and 20% of imports of these two commodities are done by China and Hong Kong. Moreover, our models found that Hong Kong is a bad export reporter while China is a bad import reporter, which might point out that the transparency problems of Lithium batteries is caused by these two countries. It will be

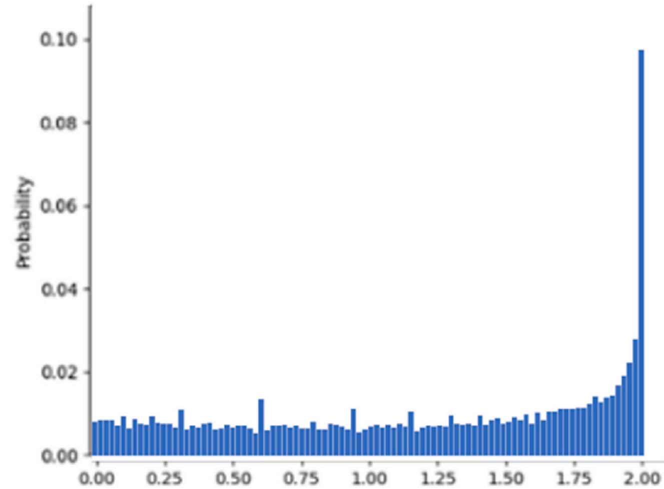

Fig. 5. Discrepancy distribution of HS 850650 and HS 850760.

bold to conclude the study with this outcome as again it is beyond this paper's scope however, we suggest further investigation that must be focused on the impact of China on the battery supply chain which is also previously stated in related work (Marcos et al., 2021).

4. Results and Discussion

We utilize a dataset containing 116 million trade transactions, encompassing all MMD data. The K-Means approach allows us to examine all countries and commodities within the dataset. However, due to the limited clarity of temporal patterns offered by K-Means, we employ the Self-Organizing Maps (SOM) that enables us to analyze commodities and countries separately and evaluate their performance by assessing trends and consistency over the years. Combining these two methods is highly valuable in analyzing spatiotemporal data, providing complementary results.

Our methodology provides a scale of good and bad reporting categories for most exporter and importer countries and offers valuable insights into supply chain transparency for over 7000 commodities on a global scale. Our findings reveal certain instances of inadequate reporting practices. Notably, countries such as Burkina Faso, Burundi, Ethiopia, Mozambique, Myanmar, Niger, Nigeria, Philippines, and Sudan, listed by the EU as CAHRAs (European Union, 2023), are also identified as having poor reporting. Furthermore, Cobalt, a critical mineral predominantly sourced from the Democratic Republic of Congo, another CAHRA country, exhibits deficient reporting practices.

Our results can help identify and pinpoint key countries and minerals that would most benefit from control systems and traceability as recommended by the OECD guidelines. Additionally, we observe that several developed countries, including Canada, New Zealand, Qatar, and the UAE, demonstrated subpar reporting practices. Notably, numerous global leaders emphasize the importance of transparency and promote it. The United Nations Security Council (UNSC) has urged countries to regularly publish comprehensive import and export statistics for natural resources (UNSC Resolution 1952; 2010). Our methodology can help aid in the identification of key countries for improved transparency.

The growing demand for tools and methods to evaluate and assess supply chain issues is evident, particularly for companies heavily reliant on critical commodities to comply with due diligence. Our methodology can serve as a base for an initial screening tool for further investigation, as it is relatively easy to reproduce and maintain using an openly accessible data source.

As further work, the trade flow of a specific commodity or a group can be investigated using the methodology presented here, drilling down to yearly patterns and selected countries. This can then be further augmented by using qualitative data to point out significant issues in its supply chain transparency and use the results to evaluate the methodology's performance. Policy and regulations will thus be better informed and more effective in creating wider, transparent, and well-governed markets and trade.

4.1. Conclusion

The methodology outlined in this study for examining spatiotemporal patterns of BA in the trade data provides an unbiased instrument for evaluating transparency in global supply chains. Moreover, it functions as an impartial evaluation tool to measure the efficacy and influence of implemented policies. With the case study, we demonstrate that the presented tool in this paper shows satisfactory performance to detect transparency insights for a large number of commodities. The specific conclusions are four-fold:

i. Most trade reports worldwide exhibit trade data asymmetry, irrespective of the item or country. Nevertheless, there are notable variations in the magnitude and time frame of disparities across countries and commodities. the presented work and its findings provide the most effective methods for identifying priority countries and commodities and implementing suitable monitoring and regulation most efficiently.
ii. The BA in global trade data can serve as a proxy for assessing transparency in supply chains. By prioritizing the important areas of opacity, policy, and resources may be allocated in a targeted and efficient manner.
iii. The proposed machine learning models are mutually beneficial since they offer distinct perspectives on similar matters. K-Means allows for the classification of all transactions and the evaluation of each commodity and country in the dataset. On the other hand, SOM can reveal the consistency and temporal patterns and straightforwardly classify most instances.
iv. The case study on the commodity analysis related to batteries reveals that primary cells and lithium-ion batteries, as well as cobalt ores and concentrates, are reported to be substantially worse than other end products; this underscores the necessity of concentrating on particular trade aspects rather than attempting to address the vast, broader context.

Authorship contribution statement

Umut Mete Saka: Data Curation, Methodology, Investigation, Formal analysis, Writing - original draft.

H. Sebnem Duzgun: Project administration, Investigation, Funding acquisition, Conceptualization, Methodology, Supervision, Writing – review & editing.

Morgan D. Bazilian: Writing – review & editing.

CRediT authorship contribution statement

Umut Mete Saka: Formal analysis, Investigation, Methodology, Writing – original draft. **Sebnem Duzgun:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Writing – review & editing. **Morgan D. Bazilian:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A.1
The raw data descriptions in Comtrade dataset

Index	Variable	Description
C1	Classification	Indicates the product classification used and which version (HS, SITC)
C2	Year	Year of observation
C3	Period	Combination of year and month (for monthly), year for (annual)
C4	Period Desc.	The period of time to which the measured observation is intended to refer
C5	Aggregate Level	Hierarchical level of commodity/service category
C6	Is Leaf Code	Identification whether a product code has the most basic level (i.e., sub-heading for HS)
C7	Trade Flow Code	Trade flow or sub-flow (exports, re-exports, imports, re-imports, etc.)
C8	Trade Flow	Description of trade flows
C9	Reporter Code	The country or geographic area to which the measured statistical phenomenon relates
C10	Reporter	Description of reporter
C11	Reporter ISO	ISO 3 code of reporter
C12	Partner Code	The primary partner country or geographic area for the respective trade flow
C13	Partner	Description of partner
C14	Partner ISO	ISO 3 Code of partner
C15	Commodity Code	Product code in conjunction with classification code
C16	Commodity	Description of commodity/service category
C17	Qty Unit Code	Unit of primary quantity
C18	Qty Unit	Abbreviation of primary quantity unit
C19	Quantity	Value of primary quantity
C20	Net weight (KG)	Net weight
C21	Trade Val. (US$)	Primary trade values
C22	Flag	Combination of year and month (for monthly), year for (annual)

Table A.2
Summary Statistics of K-Means Clusters

Cluster	Count	Percentage	Median	Mean	Min	Max
CL1 (SDC)	44,163,691	37.8 %	0.207283	0.236824	0	0.608082
CL2 (MDC)	31,230,265	26.7 %	0.978234	0.983712	0.608082	1.389185
CL3 (LDC)	41,453,374	35.5 %	1.853796	1.799027	1.389186	2
ALL DATA	116,847,330	100 %	0.942619	0.990663	0	2

Table A3: K-Means Results for Exporter Countries

Exporter Country	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
Albania	27,454	50%	27%
Algeria	22,373	55%	23%
Andorra	17,759	47%	30%
Angola	15,322	23%	53%
Argentina	710,690	59%	21%
Armenia	52,735	61%	20%
Australia	1,350,979	30%	43%
Austria	2,922,387	37%	35%
Azerbaijan	37,606	58%	23%
Bahamas	4117	24%	50%
Bahrain	45,176	36%	39%
Bangladesh	95,454	26%	44%
Barbados	38,982	42%	30%
Belarus	351,941	65%	17%
Belgium	3,406,135	36%	37%
Belgium-Luxembourg	295,707	40%	34%
Belize	5054	30%	30%
Benin	5337	42%	32%
Bolivia	68,822	57%	21%
Bosnia Herzegovina	226,047	53%	25%
Botswana	31,183	32%	41%
Brazil	1,785,184	51%	26%
Brunei Darussalam	15,322	23%	53%
Bulgaria	765,470	43%	33%
Burkina Faso	9942	38%	36%
Cambodia	77,962	28%	46%
Cameroon	15,974	43%	32%
Canada	1,640,954	29%	46%
Chile	484,720	38%	46%
China	6,079,868	35%	37%
Colombia	528,259	53%	24%
Congo	5156	29%	45%
Costa Rica	242,467	46%	31%
Côte d'Ivoire	81,073	47%	28%
Croatia	578,663	45%	31%
Cuba	9492	48%	27%
Cyprus	113,957	34%	42%
Czechia	2,237,742	42%	32%
Denmark	2,379,200	35%	37%
Dominica	5115	50%	24%
Dominican Rep.	68,943	34%	40%
Ecuador	164,327	52%	25%
Egypt	241,010	33%	39%
El Salvador	174,913	53%	24%
Estonia	526,894	38%	38%
Eswatini	30,791	42%	36%
Ethiopia	27,544	34%	39%
Faeroe Isds	4281	50%	26%
Fiji	39,408	29%	41%
Finland	1,533,612	38%	36%
France	4,998,420	39%	32%
French Polynesia	8722	39%	35%
Georgia	61,090	48%	32%
Germany	7,029,924	44%	28%
Ghana	46,762	29%	43%
Greece	1,000,552	39%	35%
Greenland	8729	85%	9%
Grenada	5250	51%	21%
Guatemala	273,368	46%	30%
Guyana	19,287	36%	34%
Honduras	76,030	44%	32%
Hong Kong	1,526,303	18%	58%
Hungary	1,405,750	39%	37%

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Exporter Country	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
Iceland	96,281	39%	35%
India	2,984,921	33%	39%
Indonesia	1,116,477	38%	37%
Iran	126,916	41%	31%
Ireland	778,624	29%	44%
Israel	506,487	27%	46%
Italy	5,705,225	42%	29%
Jamaica	43,045	42%	29%
Japan	2,665,883	36%	37%
Jordan	81,172	37%	37%
Kazakhstan	106,533	50%	28%
Kenya	162,779	41%	33%
Kuwait	51,616	31%	43%
Kyrgyzstan	26,649	50%	28%
Lao People's Dem. Rep.	12,978	31%	38%
Latvia	508,031	39%	36%
Lebanon	231,263	36%	35%
Lesotho	4897	28%	51%
Lithuania	767,902	37%	38%
Luxembourg	472,903	29%	44%
Macao	50,543	33%	41%
Madagascar	64,953	42%	30%
Malawi	20,742	40%	33%
Malaysia	1,230,746	35%	39%
Mali	6151	32%	41%
Malta	71,514	30%	45%
Mauritius	108,202	34%	39%
Mexico	872,213	37%	38%
Mongolia	17,657	41%	34%
Montenegro	31,457	52%	27%
Morocco	246,648	40%	34%
Mozambique	11,302	26%	48%
Myanmar	47,581	23%	49%
Namibia	67,499	24%	53%
Nepal	23,108	26%	47%
Netherlands	4,298,370	34%	37%
New Caledonia	6565	37%	38%
New Zealand	643,161	31%	46%
Nicaragua	77,903	53%	25%
Nigeria	12,477	24%	51%
North Macedonia	195,166	59%	22%
Norway	1,029,215	36%	36%
Oman	51,035	36%	39%
Pakistan	364,643	27%	44%
Panama	181,049	21%	53%
Paraguay	60,456	66%	16%
Peru	410,873	51%	25%
Philippines	238,718	30%	43%
Poland	2,318,756	42%	32%
Portugal	1,415,955	36%	37%
Qatar	13,722	22%	61%
Rep. of Korea	2,286,612	39%	36%
Rep. of Moldova	80,544	60%	23%
Romania	965,082	39%	38%
Russian Federation	1,175,428	53%	26%
Rwanda	7769	36%	38%
Saint Lucia	11,521	46%	26%
Saint Vincent and the Grenadines	9145	51%	23%
Saudi Arabia	159,098	37%	36%
Senegal	39,491	38%	35%
Serbia	500,440	56%	23%
Serbia and Montenegro	31,444	53%	24%
Singapore	1,407,966	24%	50%
Slovakia	985,829	41%	35%
Slovenia	1,129,378	45%	31%
So. African Customs Union	100,071	9%	86%
South Africa	1,352,817	38%	35%
Spain	4,295,344	40%	33%
Sri Lanka	316,553	34%	39%
Sweden	2,648,369	35%	36%
Switzerland	3,045,536	36%	38%
Syria	36,759	31%	39%
Tanzania	58,833	35%	38%
Thailand	1,965,109	34%	41%
Togo	15,912	35%	38%
Trinidad and Tobago	104,435	40%	33%

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Exporter Country	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
Tunisia	171,732	41%	35%
Turkey	2,811,909	44%	29%
Uganda	42,788	39%	35%
Ukraine	592,315	60%	22%
United Arab Emirates	869,624	24%	50%
United Kingdom	4,898,701	34%	37%
Uruguay	139,558	64%	18%
USA	4,950,830	31%	40%
Uzbekistan	23,979	55%	21%
Venezuela	52,865	45%	30%
Viet Nam	591,128	31%	36%
Yemen	5808	40%	33%
Zambia	38,646	36%	39%
Zimbabwe	55,148	40%	34%

Table A. 4
K-Means Results for Importer Countries

Importer Country	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
Albania	262,379	46%	29%
Algeria	481,870	36%	37%
Andorra	140,233	63%	18%
Angola	326,189	28%	42%
Argentina	940,573	46%	31%
Armenia	312,048	42%	34%
Australia	1,791,559	33%	41%
Austria	1,919,108	38%	34%
Azerbaijan	397,208	40%	34%
Bahamas	69,835	21%	49%
Bahrain	465,543	35%	37%
Bangladesh	296,125	35%	38%
Barbados	81,904	33%	37%
Belarus	639,815	42%	33%
Belgium	1,858,699	37%	35%
Belgium-Luxembourg	207,182	43%	32%
Belize	80,151	25%	42%
Benin	55,143	32%	40%
Bolivia	486,564	42%	35%
Bosnia Herzegovina	631,137	46%	29%
Botswana	76,362	36%	36%
Brazil	1,336,441	43%	32%
Brunei Darussalam	192,005	26%	46%
Bulgaria	1,128,993	46%	28%
Burkina Faso	124,446	28%	43%
Cabo Verde	88,113	36%	34%
Cambodia	205,148	27%	44%
Cameroon	106,806	33%	39%
Canada	1,655,886	30%	46%
Chile	1,143,431	41%	31%
China	2,040,646	31%	43%
Colombia	967,361	42%	33%
Congo	106,904	28%	43%
Costa Rica	612,131	38%	35%
Côte d'Ivoire	273,348	35%	37%
Croatia	1,151,152	45%	29%
Cuba	84,453	32%	40%
Cyprus	779,517	37%	35%
Czechia	1,745,545	39%	34%
Denmark	1,726,693	39%	34%
Dominican Rep.	374,361	29%	41%
Ecuador	647,185	43%	32%
Egypt	562,368	28%	43%
El Salvador	478,545	40%	34%
Estonia	1,056,853	35%	38%
Eswatini	79,235	49%	29%
Ethiopia	265,175	26%	46%
Faeroe Isds	57,488	34%	36%
Fiji	212,280	28%	42%
Finland	1,549,014	36%	37%
Fmr Sudan	77,732	24%	49%
France	2,722,207	40%	33%
French Polynesia	177,013	33%	38%

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Table A. 4 (*continued*)

Importer Country	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
Georgia	513,592	52%	25%
Germany	3,444,797	39%	33%
Ghana	370,045	28%	44%
Greece	1,464,853	42%	30%
Greenland	85,575	64%	19%
Guatemala	624,666	40%	32%
Guinea	55,284	31%	40%
Guyana	90,305	32%	39%
Honduras	336,962	37%	37%
Hong Kong	1,385,598	31%	42%
Hungary	1,507,316	41%	33%
Iceland	606,743	33%	37%
India	1,473,518	32%	39%
Indonesia	1,095,852	36%	37%
Iran	283,149	35%	36%
Ireland	1,066,375	31%	40%
Israel	938,561	31%	39%
Italy	2,712,123	47%	28%
Jamaica	201,289	32%	39%
Japan	1,768,863	41%	34%
Jordan	468,944	35%	36%
Kazakhstan	667,911	42%	33%
Kenya	426,878	33%	38%
Kuwait	539,172	35%	37%
Kyrgyzstan	204,098	44%	31%
Lao People’s Dem. Rep.	60,961	21%	51%
Latvia	1,099,085	46%	28%
Lebanon	691,586	39%	33%
Lithuania	1,211,854	45%	29%
Luxembourg	683,003	33%	37%
Macao	173,795	24%	49%
Madagascar	281,131	34%	38%
Malawi	129,783	33%	38%
Malaysia	1,320,791	30%	43%
Maldives	242,670	25%	45%
Mali	87,192	30%	42%
Malta	539,627	36%	35%
Mauritius	502,278	35%	36%
Mexico	895,711	33%	43%
Mongolia	207,057	39%	34%
Montenegro	327,400	42%	32%
Morocco	648,168	39%	34%
Mozambique	122,117	26%	45%
Myanmar	173,778	25%	48%
Namibia	156,927	35%	37%
Nepal	87,931	27%	45%
Netherlands	2,474,396	34%	38%
New Caledonia	128,695	32%	38%
New Zealand	1,163,162	33%	39%
Nicaragua	360,089	35%	39%
Niger	70,529	30%	42%
Nigeria	241,721	23%	49%
North Macedonia	622,756	45%	30%
Norway	1,641,269	40%	33%
Oman	351,548	35%	37%
Pakistan	570,025	29%	42%
Panama	346,491	31%	41%
Paraguay	426,538	47%	28%
Peru	834,670	43%	32%
Philippines	497,310	33%	38%
Poland	1,703,768	40%	34%
Portugal	1,416,563	43%	30%
Qatar	282,870	32%	41%
Rep. of Korea	1,529,973	39%	35%
Rep. of Moldova	377,387	46%	30%
Romania	1,574,556	44%	31%
Russian Federation	1,808,151	39%	35%
Rwanda	115,290	31%	42%
Saudi Arabia	772,781	31%	41%
Senegal	222,840	34%	37%
Serbia	776,465	39%	35%
Serbia and Montenegro	62,129	38%	34%
Seychelles	79,613	27%	44%
Singapore	1,625,886	30%	44%
Slovakia	1,213,018	35%	37%
Slovenia	1,260,930	40%	33%

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Table A. 4 (*continued*)

Importer Country	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
So. African Customs Union	197,650	29%	52%
South Africa	1,333,494	37%	37%
Spain	2,411,499	40%	34%
Sri Lanka	571,591	34%	38%
Sudan	74,915	25%	47%
Sweden	1,931,042	40%	32%
Switzerland	2,229,489	46%	29%
Syria	61,022	39%	31%
Tanzania	380,470	30%	42%
Thailand	1,439,659	35%	38%
Togo	83,622	31%	39%
Trinidad and Tobago	183,940	33%	38%
Tunisia	548,267	38%	34%
Turkey	1,606,046	43%	32%
Uganda	305,583	29%	42%
Ukraine	935,515	42%	34%
United Arab Emirates	1,134,154	34%	38%
United Kingdom	2,733,855	38%	35%
Uruguay	579,001	48%	28%
USA	2,846,343	37%	38%
Uzbekistan	109,803	40%	33%
Venezuela	187,570	42%	32%
Viet Nam	638,133	31%	38%
Yemen	92,512	30%	42%
Zambia	296,575	33%	40%
Zimbabwe	206,657	34%	38%

Table A. 5
K-Means Results for Commodities, aggregated under HS Chapters

HS Chapter	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
1	138,405	45%	31%
2	551,585	51%	24%
3	898,054	43%	30%
4	600,561	56%	22%
5	167,151	44%	33%
6	217,805	41%	34%
7	883,679	48%	27%
8	938,026	51%	26%
9	695,314	43%	30%
10	301,365	53%	25%
11	420,302	50%	27%
12	616,344	46%	29%
13	188,109	46%	29%
14	77,249	37%	37%
15	722,072	49%	28%
16	489,667	48%	27%
17	424,259	51%	26%
18	357,195	52%	24%
19	724,355	50%	24%
20	1,186,306	47%	27%
21	753,695	49%	26%
22	863,201	49%	26%
23	313,120	56%	23%
24	179,164	50%	27%
25	1,006,130	48%	30%
26	158,826	49%	30%
27	570,870	46%	32%
28	2,101,693	49%	30%
29	3,545,029	45%	32%
30	964,096	37%	36%
31	310,947	48%	29%
32	1,654,511	44%	30%
33	1,387,307	41%	31%
34	1,175,288	42%	31%
35	560,860	46%	30%
36	134,165	49%	29%
37	303,058	33%	42%
38	1,946,467	45%	30%
39	5,347,308	44%	30%
40	2,541,744	36%	37%
41	447,500	39%	35%

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Table A. 5 (*continued*)

HS Chapter	Total Number of Records	Small Disc. Cluster Percentage	Large Disc. Cluster Percentage
42	908,002	29%	42%
43	157,911	34%	38%
44	1,766,561	40%	34%
45	114,213	35%	38%
46	168,472	32%	39%
47	165,836	51%	27%
48	3,253,063	41%	34%
49	1,172,029	34%	37%
50	107,847	36%	35%
51	415,374	45%	29%
52	1,468,016	39%	33%
53	260,931	42%	30%
54	1,109,491	39%	34%
55	1,239,388	41%	32%
56	967,932	39%	34%
57	468,363	33%	39%
58	864,174	33%	37%
59	761,314	38%	34%
60	600,460	37%	35%
61	3,531,668	28%	43%
62	3,913,567	28%	43%
63	1,640,498	32%	39%
64	1,064,981	31%	41%
65	394,351	30%	39%
66	166,597	31%	39%
67	185,838	29%	43%
68	1,395,410	39%	35%
69	1,135,884	37%	37%
70	1,860,224	38%	36%
71	625,057	27%	47%
72	2,699,967	48%	29%
73	4,749,778	36%	37%
74	1,229,168	39%	35%
75	233,099	39%	35%
76	1,528,813	42%	32%
78	114,059	45%	32%
79	182,605	41%	34%
80	104,936	34%	39%
81	340,303	39%	37%
82	2,596,816	32%	39%
83	1,831,177	35%	37%
84	12,242,889	33%	38%
85	8,298,923	30%	43%
86	192,141	36%	38%
87	2,355,682	36%	34%
88	196,953	29%	43%
89	120,209	34%	38%
90	3,648,841	29%	42%
91	354,755	24%	49%
92	345,280	33%	38%
93	178,185	38%	35%
94	1,823,222	36%	35%
95	1,001,141	32%	40%
96	1,631,952	34%	38%
97	88,683	28%	46%

Table A.6
SOM Clusters of Exporter Countries

Exporter Countries Reporting Quality							
Worst	Bad	Decreasing	Inconsistent	Medium		Good	Best
(Cluster 3)	(Cluster 2)	(Cluster 1)	(Cluster 6)	(Clusters 5, 8, 9)		(Cluster 4)	(Cluster 7)
Cambodia	Australia	Barbados	Botswana	Austria	Guatemala	Albania	Azerbaijan
Hong Kong	Canada	Belize	Chile	Belgium	Italy	Brazil	Argentina
Mozambique	Ethiopia	Czechia	Egypt	Cyprus	Madagascar	C. Rica	Armenia
Namibia	Fiji	Estonia		Denmark	Malawi	Croatia	Bolivia
Niger	Ireland	Finland		Greece	Zimbabwe	Benin	Belarus
Qatar	Israel	France		Guyana	Turkey	Germany	Colombia
Singapore	Luxembourg	Hungary		Iceland	China	Peru	Ecuador
UAE	Malta	Jamaica		Japan	Indonesia	Poland	El Salvador
	Mexico	Latvia		Jordan	Malaysia	Slovenia	Georgia

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Table A.6 (*continued*)

Exporter Countries Reporting Quality							
Worst	Bad	Decreasing	Inconsistent	Medium		Good	Best
(Cluster 3)	(Cluster 2)	(Cluster 1)	(Cluster 6)	(Clusters 5, 8, 9)		(Cluster 4)	(Cluster 7)
	N. Zealand	Lithuania		S. Korea	Mauritius		Kazakhstan
	Philippines	Morocco		Lebanon	S. Arabia		Kyrgyzstan
		Romania		Netherlands	India		Moldova
		Slovakia		Norway	Viet Nam		Nicaragua
				Portugal	S. Africa		Paraguay
				Senegal	Thailand		Russia
				Spain	Uganda		Ukraine
				Sweden	Tanzania		N. Macedonia
				Switzerland	USA		Uruguay
				U.K.	Zambia		
				Bulgaria			

Table A. 7
SOM Clusters for Importer Countries

Importer Countries Reporting Quality							
Worst	Bad	Inconsistent	Increasing	Medium		Good	Best
(Cluster 9)	(Cluster 8)	(Cluster 7)	(Cluster 1, 3)	(Clusters 2, 6)		(Cluster 5)	(Cluster 4)
Aruba	Botswana	Bulgaria	Armenia	Australia	Madagascar	Azerbaijan	Albania
Mexico	Cambodia	Burundi	Belarus	Austria	Malawi	Barbados	Argentina
Mozambique	Canada	Ecuador	Belize	Belgium	Malta	Bolivia	Croatia
	China		Finland	Benin	Mauritius	Brazil	Georgia
	Egypt		Grenada	Cabo Verde	Morocco	Chile	Italy
	Ethiopia		Hungary	Costa Rica	Netherlands	Colombia	Kyrgyzstan
	Fiji		Kazakhstan	Cyprus	New Zealand	Greece	Latvia
	India		Niger	Czechia	Nicaragua	Guatemala	Lithuania
	Ireland		Poland	Denmark	Philippines	Japan	Moldova
	Malaysia		Slovenia	El Salvador	Russia	Norway	N. Macedonia
	Mauritania			Estonia	S. Africa	Peru	Paraguay
	Namibia			France	S. Arabia	Portugal	Switzerland
	Tanzania			French Polynesia	S. Korea	Romania	Uruguay
	Uganda			Germany	Singapore	Senegal	
	Viet Nam			Guyana	Slovakia	Sweden	
				Hong Kong	Spain	Turkey	
				Iceland	Thailand	Ukraine	
				Indonesia	UAE		
				Israel	UK		
				Jamaica	USA		
				Jordan	Zambia		
				Lebanon	Zimbabwe		
				Luxembourg			

Table A. 8
SOM Clusters for commodities, aggregated under HS chapters

Commodities Reporting Quality							
HS Chapter	Total Number of Commodities	Best	Good	Medium	Bad	Worst	Inconsistent
		Cluster 4	Clusters 1, 7	Clusters 5, 9	Clusters 2, 6	Cluster 3	Cluster 8
1	15	9	5	1	0	0	0
2	55	10	28	14	3	0	0
3	55	0	13	29	11	2	0
4	35	12	15	5	2	1	0
5	23	1	6	6	7	2	1
6	11	0	4	4	3	0	0
7	64	6	29	17	11	1	0
8	60	5	33	16	5	1	0
9	27	0	11	10	4	2	0
10	17	4	10	2	1	0	0
11	35	5	16	9	5	0	0
12	41	7	16	11	7	0	0
13	12	0	7	4	1	0	0
14	7	1	0	4	2	0	0
15	59	3	29	23	4	0	0

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Table A. 8 (*continued*)

Commodities Reporting Quality							
HS Chapter	Total Number of Commodities	Best	Good	Medium	Bad	Worst	Inconsistent
		Cluster 4	Clusters 1, 7	Clusters 5, 9	Clusters 2, 6	Cluster 3	Cluster 8
16	28	1	13	10	4	0	0
17	19	0	11	6	1	1	0
18	17	6	8	2	1	0	0
19	21	2	9	10	0	0	0
20	43	1	29	9	4	0	0
21	22	2	12	7	1	0	0
22	31	2	14	12	3	0	0
23	29	10	13	3	3	0	0
24	11	1	7	2	0	1	0
25	91	8	42	29	12	0	0
26	49	5	25	12	6	1	0
27	52	10	19	13	6	4	0
28	206	19	104	61	19	3	0
29	289	27	122	114	24	2	0
30	31	0	2	13	8	8	0
31	27	2	14	9	2	0	0
32	59	2	24	25	8	0	0
33	36	0	8	21	7	0	0
34	29	0	7	19	3	0	0
35	22	3	12	4	2	1	0
36	14	4	5	5	0	0	0
37	31	0	1	13	8	7	2
38	78	1	39	28	9	1	0
39	148	9	51	66	22	0	0
40	76	0	18	33	18	6	1
41	12	2	3	5	2	0	0
42	24	0	0	3	18	3	0
43	16	0	2	10	4	0	0
44	56	2	17	17	17	3	0
45	11	0	2	3	6	0	0
46	4	0	0	1	3	0	0
47	27	5	14	7	1	0	0
48	93	2	25	32	25	9	0
49	30	0	0	13	12	5	0
50	15	0	7	4	4	0	0
51	46	5	16	22	3	0	0
52	135	3	38	64	29	1	0
53	32	1	8	15	7	0	1
54	66	1	7	35	23	0	0
55	118	8	25	59	24	2	0
56	39	0	2	23	14	0	0
57	25	0	0	12	12	1	0
58	46	0	0	13	31	2	0
59	34	1	3	24	6	0	0
60	9	0	0	5	4	0	0
61	111	0	0	7	80	24	0
62	129	0	0	10	102	16	1
63	58	0	0	16	35	6	1
64	30	0	2	6	19	3	0
65	13	0	0	3	10	0	0
66	9	0	0	3	6	0	0
67	12	0	0	0	12	0	0
68	52	2	10	20	18	2	0
69	38	1	6	7	18	5	1
70	75	0	15	26	28	5	1
71	64	0	0	7	21	36	0
72	196	17	93	48	33	5	0
73	136	0	10	61	56	8	1
74	63	1	23	15	23	1	0
75	25	0	4	15	6	0	0
76	50	3	16	17	14	0	0
78	12	3	3	3	3	0	0
79	15	0	7	6	2	0	0
80	9	0	0	7	2	0	0
81	32	1	6	12	13	0	0
82	79	0	0	28	46	3	2
83	47	0	8	13	25	1	0
84	551	2	61	197	236	31	24
85	261	0	6	38	165	40	12
86	31	1	13	10	7	0	0
87	84	0	11	45	23	5	0
88	16	0	5	4	4	3	0
89	20	0	1	10	7	2	0

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Table A. 8 (*continued*)

Commodities Reporting Quality							
HS Chapter	Total Number of Commodities	Best	Good	Medium	Bad	Worst	Inconsistent
		Cluster 4	Clusters 1, 7	Clusters 5, 9	Clusters 2, 6	Cluster 3	Cluster 8
90	165	0	1	28	114	12	10
91	57	0	0	0	25	32	0
92	24	0	2	11	10	1	0
93	19	0	7	7	3	2	0
94	40	0	0	29	9	0	2
95	33	0	0	14	15	1	3
96	63	0	1	32	27	1	2
97	13	0	0	0	6	5	2
TOTAL	**5445**	**239**	**1311**	**1803**	**1705**	**320**	**67**
	100%	4%	24%	33%	31%	6%	1%

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