OPEN ACCESS

ISSN: 2835-7868

Thimm H and Schmidt V (2025): 411
J Earth Envi Sci, 2025; 4(1):100136
DOI: 10.71010/JEES.2025-e136

Research Article

Journal of Earth & Environment Science

# A Straight Forward Method to Analyze the Variation Dynamics of Corporate Top Polluter Rankings Exemplified Through the German PRTR Register

**Heiko Thimm*** **and Vanessa Schmidt**

Pforzheim University, School of Engineering Tiefenbronner Str. 65, D-75175 Pforzheim

***Corresponding author:** Heiko Thimm, Email: heiko.thimm@hs-pforzheim.de

**Citation:** Thimm H and Schmidt V (2025) A Straight Forward Method to Analyze the Variation Dynamics of Corporate Top Polluter Rankings Exemplified Through the German PRTR Register. J Earth Envi Sci: JEES-136.

**Received Date:** April 06, 2025; **Accepted Date:** April 14, 2025; **Published Date:** April 21, 2025

***Abstract***

*Public pollution registers such as the European Pollutant Release and Transfer Register (E-PRTR) play a vital role in promoting environmental transparency and accountability. While pollution rankings at various levels-regions, countries, industry sectors, and cities-are widely used, limited research has focused on analyzing the temporal dynamics of these rankings. This study introduces a straightforward data analysis and visualization method to explore the variation dynamics of top polluter rankings over time. The method involves determining pollution ranks based on reported amounts and quantifying rank changes between periods using a simple numeric scheme. This approach facilitates the effective visualization of dynamic shifts and measures variation strength using a dedicated formula. The proposed method is demonstrated using data from the German PRTR register, a subset of the E-PRTR containing approximately 80,000 pollution reports from German businesses. The analysis focuses on the dynamic changes in the top 10 polluters from 2007 to 2022 for two pollution categories: Release of Heavy Metals into Water and Release of GHGs into the Air across several industry sectors. The study provides valuable insights into ranking stability, shifts in pollution hotspots, and sector-specific performance, offering a practical tool for stakeholders seeking data-driven insights into environmental performance over time.*

**Keywords:** corporate pollution reporting, German PRTR register, data science, machine learning, pollution prediction

## 1. Introduction

Across the globe, companies in industrialized countries are required to report the environmental impact of their facilities. Environmental authorities typically make these reports publicly accessible through online registers. For instance, within the European Union (EU), where approximately 50,000 industrial facilities operate, companies must report emissions of air pollutants, water pollutants, wastewater discharges, and waste amounts when specified thresholds are exceeded. These reports are published in the European Pollutant Release and Transfer Register (E-PRTR) [1], a central pollution register.

Pollution registers like the E-PRTR establish transparent reporting and data management rules for pollutant releases and transfers. Public access to these registers is believed to support pollution reduction by encouraging industries to monitor and minimize their environmental impact and facilitating public participation in environmental decision-making. Additional benefits include improved public health, industrial innovation, technological advancement, and cleaner production processes [2], which, over time, can result in cost savings for both industries and governments [3]. The E-PRTR website not only provides access to pollution data but also offers analytical and visualization tools for stakeholders. Recommendations for using PRTR data and tools have been outlined by the OECD [4].

Polluter rankings at different levels of aggregation—such as regions, countries, industry sectors, and cities-are widely used and often shared with the public. However, limited research has focused on the dynamics of these rankings over time. Existing studies primarily explore variations in air quality [5,6]. Yet, understanding the temporal dynamics of industrial pollution rankings can support data-driven decision-making and benefit stakeholders from government agencies, businesses, investors, and the general public. For instance, the E-PRTR allows users to analyze ranking dynamics related to air and water pollutants, wastewater discharges, and waste transfers for 91 key substances. Such analyses can reveal insights into overall ranking stability, regional pollution shifts, and best practices for pollution reduction. Industry associations, for example, can assess whether top polluters within a specific sector remain consistent over time or if rankings shift dynamically.

Despite these potential benefits, there is currently a lack of suitable methods and tools to effectively reveal and visualize the temporal dynamics of polluter rankings. Addressing this gap, this research introduces a straightforward data analysis and visualization method designed to explore pollution datasets like the E-PRTR. The method identifies dynamic variations in top polluter rankings over time, with filtering options based on industry sector, location, pollution type, or specific substances, providing stakeholders with a practical tool for assessing long-term environmental performance. Notably, the proposed approach offers these insights without directly disclosing the identities of the business entities, ensuring privacy while maintaining transparency.

The proposed method involves two primary steps applied to a given time period with two or more top polluter rankings (e.g., annual sector-specific rankings). First, pollution ranks are determined based on reported pollution amounts. Second, rank changes between pairs of ranking lists are quantified using a simple numeric scheme that enables effective visualization and measures the variation strength between ranking lists. This approach ensures that stakeholders can monitor pollution trends and assess performance dynamics without compromising the confidentiality of individual businesses.

To demonstrate the method, data from the German PRTR register [7]-a subset of the E-PRTR containing approximately 80,000 pollution reports from German businesses-are analyzed. The dynamic changes in the top 10 polluters for the years 2007–2022 are visualized for two categories: Release of Heavy Metals into Water and Release of Greenhouse Gases (GHGs) into the Air across multiple industry sectors.

The following sections are structured as follows: Section 2 provides an overview of related work, Section 3 describes the proposed method, Section 4 demonstrates its application using the German PRTR dataset, and Section 5 presents conclusions and suggestions for future research.

## 2. Related Work

Using environmental data to generate rankings has gained increasing attention in the research community and by practitioners. The research results often serve as basis for today's popular pollution rankings, which are mostly focused on air pollution at various different levels of granularities including world regions, countries, municipalities, and cities.

A particular active area seems to be the air quality research area. Various studies of researchers of this area have introduced innovative approaches to understand and depict the variation dynamics of air quality data effectively. One notable study by Kuo et al. [5] presents a machine-learning-aided visual analysis workflow designed to investigate air pollution data. This methodology employs multiple machine learning techniques to explore various aspects of air pollution, including feature extraction, spatial distribution, and temporal evolution. The developed visual analytics system offers a flexible workflow, enabling domain experts to examine different facets of air pollution data according to their specific analytical requirements. Another significant contribution is the work by Melnikov et al. [6] who applied Dynamic Principal Component Analysis (DPCA) to identify relationships among multiple air pollutants in the Houston metropolitan area. Their approach captures the time-dependent correlation structure of pollutants, revealing diurnal and seasonal patterns and providing insights into the dynamic nature of air quality. Plocoste et al. [8] utilized the Visibility Graph (VG) method to analyze particulate matter (PM10) time series in the Caribbean basin. Their study highlights the fractal nature of PM10 time series and offers a comprehensive description of PM10 dynamics over an 11-year period, demonstrating the robustness of VG in characterizing time series properties. Varapongpisan et al. [9] proposed the use of drift-diffusion analysis, a method originally developed for studying turbulent flows, to identify underlying dynamical models of particulate matter smog, ozone, and nitrogen dioxide concentrations. Their analysis provides evidence of explicit time-dependent dynamics in pollutant behavior, offering a novel perspective on air pollution studies.

However, the analysis of variation dynamics within environmental data considering the large spectrum of different pollutant emissions, waste production and transfer from industrial facilities, has only gained little attention in the research literature so far.

Erhart and Erhart (2023) [10] conducted a study on the environmental ranking of European industrial facilities by toxicity and global warming potentials, employing advanced ranking methods to evaluate environmental performance. Their research emphasizes the importance of clear visual representation to facilitate the interpretation of complex data sets. Similarly, the study by Shaw [11] introduced a pollution ranking method to assess the environmental impact of emerging technologies, highlighting the necessity of comparing technological advancements against sustainability criteria. To enhance air quality assessment, Payus et al. [12] developed an extended air pollution index (API) capable of capturing the effects of climate change and El Niño events. Their approach demonstrates how integrated indices can offer a more comprehensive understanding of air pollution trends. From a visual analytics perspective, Deng et al. [13] introduced AirVis, a tool designed to explore air pollution propagation patterns through interactive visualization techniques. By combining geospatial data with temporal patterns, AirVis supports domain experts in identifying key pollution sources and tracking their dispersion.

Compared to these approaches, the method described in this study offers a straightforward technique for examining variations in corporate pollution rankings. By applying a simple scheme to measure and visualize the variation dynamics of pollution rankings, the proposed method allows stakeholders to intuitively grasp shifts in top polluter lists across different periods. This approach bridges the gap between numerical analysis and visual interpretation, enhancing both the clarity and accessibility of environmental data analysis.

## 3. Proposed Method to Explore Top Polluter Variation Dynamics

A generic method is proposed that can be applied to any sequence of discrete-time data where the data points specify empirical pollution data attributed to a certain group of business entities. The pollution data refer to reported or measured amounts of environmental pollution such as annual release of lead into water or release of CO2 into the air. The group of business entities that caused these pollution amounts could be companies belonging to a specific industry sector, geographic region, or any other grouping of interest to stakeholders. A dataset might contain annual lead releases from German production facilities over the years 2007 to 2022 as used later in this article to exemplify the proposed method.

Importantly, the method ensures confidentiality by providing insights into pollution ranking dynamics without directly revealing the identities of the business entities. This feature safeguards sensitive information while still enabling stakeholders to assess variations in pollution rankings, promoting transparency without risking reputational harm due to misinterpretation or incomplete data.

The core principle of the proposed method is that, for each of the sequence's data points the business entities are ranked based on their pollution amounts. The entity with the highest pollution amount receives the first rank ($r_1$), the second-highest receives the second rank ($r_2$), and so forth until the ranking list of length t is completed. The ranking step results a sequence of ranking lists $L_q$ ($q = 1, 2, \ldots, m$) of the top-t polluters. The method aims to measure and reveal variations between the ranking lists at adjacent time points using a straightforward measurement approach.

Table 1 contains the assignment scheme of the proposed method to numerically quantify the deviation strength and to visualize the deviation strength through color codes. The color codes are used in column diagrams with the time dimension represented on the x-axis and the colored top-t lists on the y-axis. The earliest ranking list within the time interval is assigned grey color for all occupied ranks because it has no previous ranking list to compare. Unoccupied ranks of the earliest ranking list are assigned a light grey color. The assignment is performed based on the result of the comparison between a rank $r_i$ (i= 1, 2, …, t) on the list $L_q$ and a rank $r_j$ (j=1,2, …, t) on the List $L_{q+1}$ with k=i=j. In order to quantify the comparison result, a *deviation number* $d_{q+1,k} \in \{0, 1, 2, 3, 4, 5\}$ is employed. For each of the k comparisons of the respective ranks in list $L_q$ and list $L_{q+1}$ with k = 1, 2, …, t a deviation number $d_{q+1,k}$ is obtained to quantify the difference between each pair of subsequent ranking lists $L_q$ and $L_{q+1}$. The deviation between corresponding ranks in a pair of lists is determined by comparing the business entities occupying those ranks. If the same entity holds identical ranks in both lists, it indicates no rank change. In this case, the respective deviation number is assigned a value of 0 and a dark green color code is considered for visualization. If a different entity appears at the compared rank, the method checks whether that entity was present on the previous top-t list. If that entity did not appear on the previous list $L_q$ the entity on list $L_{q+1}$ is viewed as a \`newcomer´ and the comparison is assigned a deviation number of 2. In case the entity held another rank on list $L_q$ the comparison yields a deviation number of 1. The scheme also accounts for instances where ranks are unoccupied at certain time points—for example, if the number of pollution measurements or reports is lower than the desired list length t.

**Table 1:** Scheme for measurement and visualization of variation dynamics.

| **Result of comparison between rank $r_i$ and rank $r_j$** | **Value assigned to deviation number $d_k$** | **Color code assigned to rank segment in list $L_J$** | **Comment** |
|---|---|---|---|
| neither $r_i$ nor $r_j$ is occupied by a rank holder | 0 | light green | Empty rank in both lists; no change |
| rank holders of $r_i$ and $r_j$ are the same entity | 0 | dark green | no change |
| rank holders of $r_i$ and $r_j$ are different entities, but the rank holder at $r_j$ appeared on the list $L_q$ | 1 | light yellow | Rank change |
| rank holders of $r_i$ and $r_j$ are different entities and the rank holder at $r_j$ did not appear on the list $L_q$ | 2 | light red | Rank change by newcomer |
| rank $r_i$ is occupied but rank $r_j$ is unoccupied | 3 | violet | Change to unoccupied rank |
| rank $r_i$ is unoccupied, but the rank holder at $r_j$ appeared on the list $L_q$ | 4 | dark yellow (orange) | Gap in list $L_q$ filled in list $L_{q+1}$ |
| rank $r_i$ is unoccupied and rank holder $r_j$ did not appear on the list $L_q$ | 5 | dark red in list | Gap in list $L_q$ filled in list $L_{q+1}$ with a newcomer |
| no comparison operation performed for first top-t list $L_1$ | - | light grey (white) | Empty rank in list $L_1$ |
| no comparison operation performed for first top-t list $L_1$ | - | grey | Occupied rank in list $L_1$ |

To quantify the overall variation between two subsequent ranking lists $L_q$ and $L_{q+1}$, an indicator referred to as *variation strength* is defined. The indicator is denoted by $V_{q,q+1}$ with $V_{q,q+1} \in \mathbb{N}$ and computed according to the following formula:

$$V_{q,q+1} = \sum_{k=1}^{t} d_{q+1,k}$$

The variation strength reveals interesting insights about just two adjacent ranking lists. However, it can be assumed that in most practical cases the subject of investigation is a sequence of m ranking lists at q = 1, 2, …, m data points. Therefore, a further indicator is required in order to measure the variation strength of sequences of ranking lists (i.e. to measure the consistency of the sequence). Hence, a further indicator is defined which is referred by *relative variation strength.* This indicator which measures the average variation strength for the sequence of ranking lists is denoted by $rV_{1,m}$ with $rV_{1,m} \in \mathbb{R}$ and computed through the following formula:

$$rV_{1,m} = \frac{(V_{1,2} + V_{2,3} + \cdots + V_{m-1,m})}{m-1}$$

When there is little variation among the sequence of ranking lists the formula results a relatively small value for this indicator. Conversely, for cases with a high variation dynamic the formula computes relatively high values. The color codes described in Table 1 were selected such that the diagrams of these cases contain a relatively large number of yellow colored ranks and red colored ranks. Logically, cases with a low variation dynamic (i.e. relatively constant ranking lists) result relatively small values for these indicators and diagrams with relatively large numbers of green colored ranks.

## 4. Method Exemplification Based on the German PRTR Dataset and Further Use Cases

The proposed method was developed in the context of our other ongoing research that targets to explore possibilities to predict top polluters through the use of Machine Learning (ML) techniques.

The German PRTR dataset serves for this other research area as data foundation. The application of the method in this context is briefly described in the subsequent sections to exemplify the method based on real world data. This is followed by a discussion of other potential use cases that benefit from the method's insights.

### 4.1. The German PRTR Dataset—General Background and Technical Aspects

The German Federal Environmental Protection Agency publishes on its official website a public version of the German PRTR dataset [7]. In the first two months of each calendar year the website is usually updated with the latest version of the dataset. In October 2024 the dataset used for this research was downloaded containing around 80.000 reports for the years 2007 to 2022. Every report concerns one of the following PRTR pollution types: dangerous waste, nondangerous waste, wastewater shipment of specific substances, controlled release and inadvertent release of specific substances into the air, controlled release and inadvertent release of specific substances into water. Reports of these pollution types specify pollution amounts for one specific substance which are grouped into substance groups such as heavy metals, pesticides, greenhouse gases (GHG), and dioxins. In the current version of the German PRTR a set of 91 key pollutants are defined as substances that the reports may refer to.

The reports have been collected from approximately 5.000 companies, which include small companies, small and medium-sized enterprises, and large enterprises with complex structures and locations all over the globe. For the classification of company activities, the PRTR distinguishes 65 different activities. A total of 105.163 classified activities are registered for the 16-year time period, 83.484 of which are registered as so-called `main activities´.

The companies are classified on a yearly basis according to their general business activities via the Nace Code standard version 2.1 [14]. For each year, every business activity performed by a company is also classified through a PRTR-specific code. Furthermore, business activities are also annually assigned to one of the following nine predefined business branches: waste and wastewater management, chemical industry, energy sector, intensive livestock farming and aquaculture, food industry, metal industry, mineral processing industry, paper and wood industry, and other industrial sectors.

Reports that concern wastewater shipments, releases into the air, and releases into water, respectively, specify annual amounts (e.g., total amounts of the calendar year) of a particular substance. Reports that concern waste do not specify aggregated annual total amounts of waste, i.e., several notifications of the same company for the same year may be contained in the dataset.

### 4.2. Variation Dynamics of Top 10 PRTR Polluters for the Time Period 2007-2022

The method was applied in order to obtain insights about the variation dynamics of top ten PRTR polluters for the time period 2007 to 2022. These are branch-specific companies that contributed for a specific pollution type the ten largest annual amounts of pollution. That is in this example a series of m=16 ranking lists with a list length of t=10 is analyzed.

Through the method it was found out that the annual branch-specific top 10 polluters do not remain constant over time periods of several years. Branches with even substantial variations of the annual top 10 polluters were obtained in the analysis. For example, these findings substantiated the assumption that it can be difficult even for specialist to make reliable forecasts of top polluters.

Some of the analyses results of the investigations for the pollution type `release of heavy metals into water´ and `release of GHG into the air´ are described and discussed in the following.

Obviously, the method could not be applied right away on the raw PRTR data and required various data preparation steps. First, the reports of the time period together with relevant company data were extracted from the PRTR database and stored in a spreadsheet table. Then, the reported annual total pollution amounts for the focused pollution types were computed. In the subsequent step the annual branch-specific ranks of the companies were obtained through a straightforward comparison of the pollution amounts.

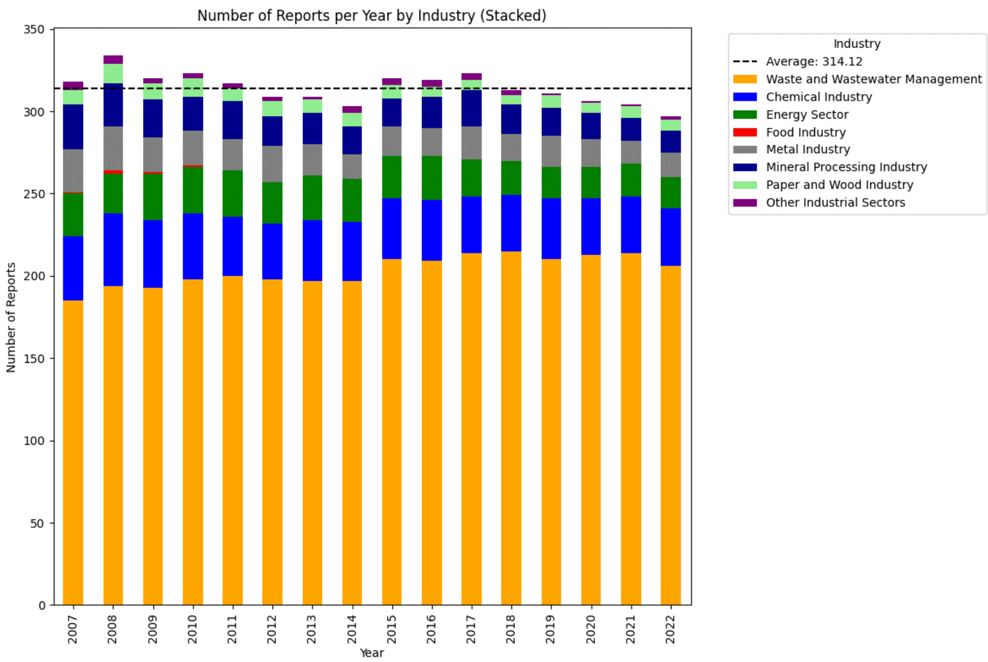


**Figure 1:** Number of reports regarding release of heavy metals into water for the time period 2007-2022 divided by branches.

The stacked column diagram of Figure 1 displays the total number of annual pollution reports for the time period 2007-2022 for different branches that report `release of heavy metals into water´. For every year an average number of about 314 reports was reported by all branches together.

As it can be obtained from the diagram companies from the paper and wood industry and companies from other industrial sectors have issued very few pollution reports regarding release of heavy metals into water for this time period in comparison to the other branches. The variation dynamics of the top 10 polluters of these two branches is visualized in the diagrams of Figure 2 and Figure 3. The low number of reports of both industries results into unoccupied ranks in the starting column for the year 2007 signified by segments in light grey color.

As described in Table 1 segments in violet indicate that a particular rank is unoccupied for the first time. When the same rank remains unoccupied at the next time point the color changes to light green. Since the two industries both have relatively low numbers of reports the diagrams in Figure 2 and Figure 3 contain considerable numbers of violet and light green segments. For example, the diagram visualizing the variation dynamics of the paper and wood industry (Figure 2) in the year 2019 contains a dark red segment. This indicates that the unoccupied rank $r_7$ in the list of the year 2018 (light green segment) changes in the list of the year 2019 to a rank $r_7$ that is occupied by a newcomer company. The change of rank $r_8$ between the same lists is signified by an orange segment on the list of the year 2019 because the corresponding rank holder of list 2019 was already contained on the list of 2018 (i.e. no newcomer).

The red top segments at 2014 add further indication that noticeable list changes occurred from 2013 to 2014. However, the dominating dark green segments at the top ranks for most years of both branches indicate that, in general, holders of the top three ranks remained mostly the same for most years of the time period 2007 to 2022.

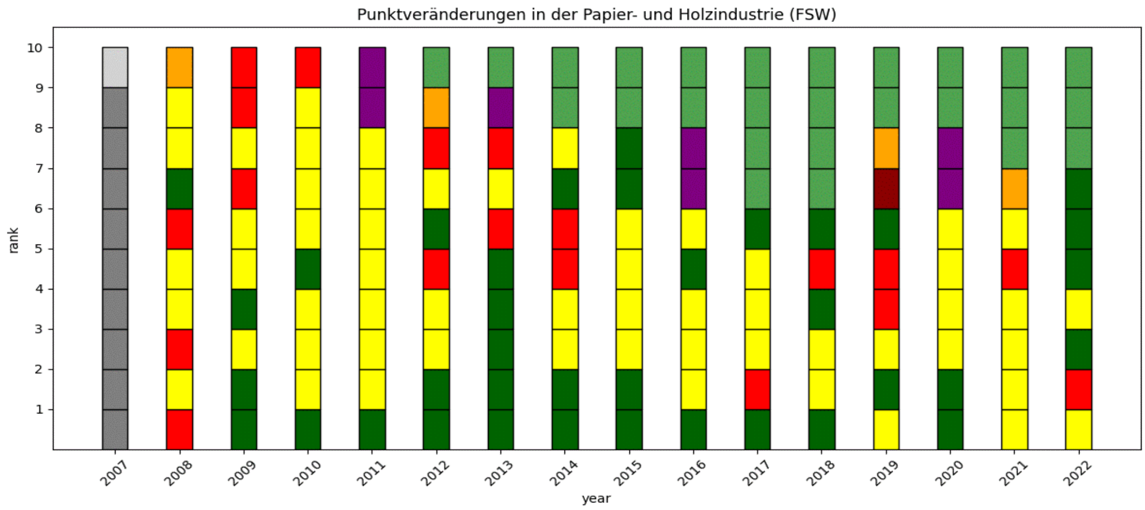


**Figure 2:** Variation analysis of branch paper and wood industry regarding releases of heavy metals into the water.

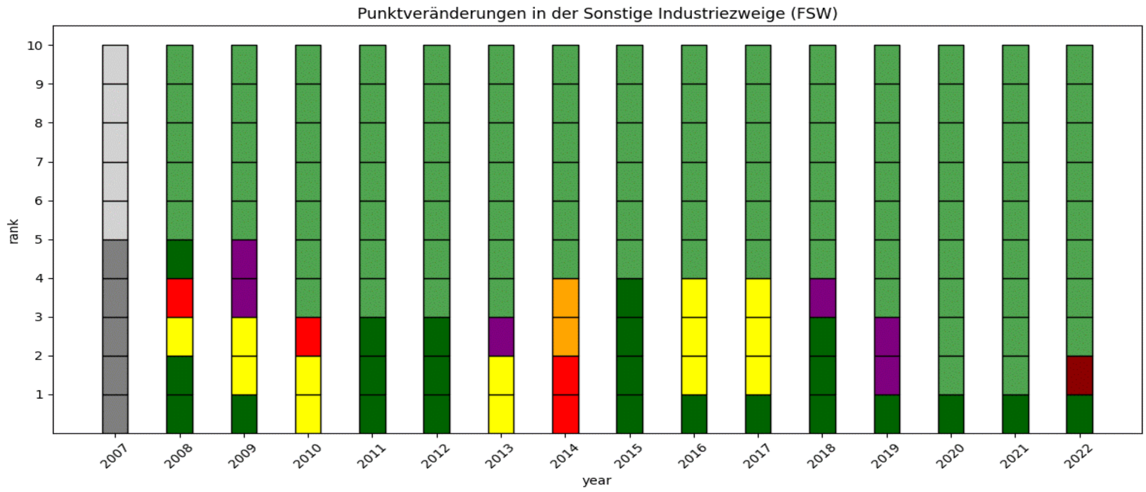


**Figure 3:** Variation analysis of branch other industrial sectors regarding releases of heavy metals into the water.

The following further exemplification of the method is performed with the branches waste- and wastewater management and chemical industry. The companies from these branches have issues substantially larger numbers of pollution reports than the previously discussed branches.

The top 10 polluter variation dynamics for the branch waste- and wastewater management for this time frame is displayed in the diagram of Figure 4. The relatively high number of red and yellow segments indicate that there has been a lot of change among the annual branch-specific top 10 polluter lists in most of the years. Fewer changes occurred in the same time period in the annual top 10 polluter lists of the chemical industries which is displayed through the diagram of Figure 5.

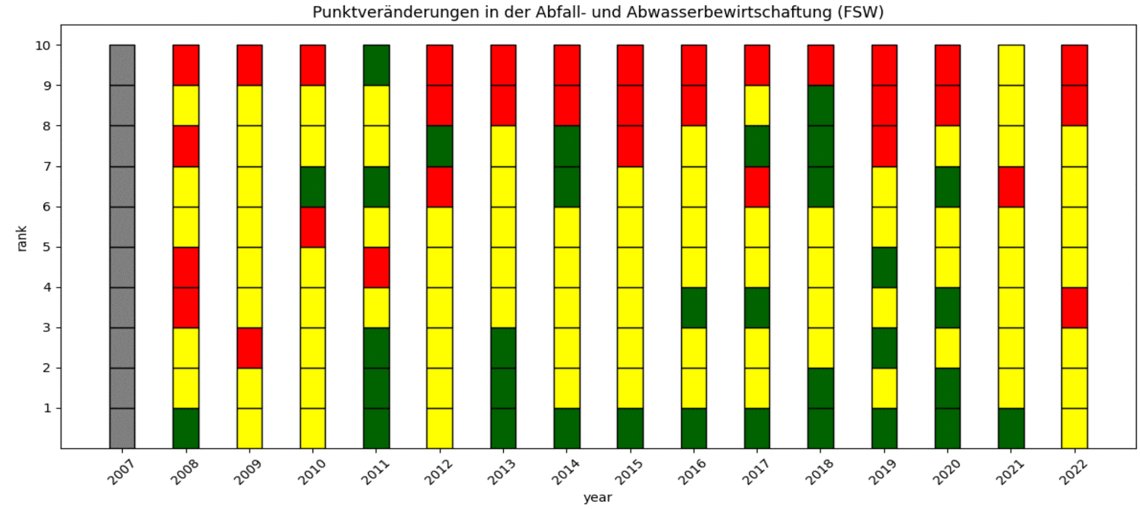


**Figure 4:** Variation analysis of branch waste and wastewater management regarding releases of heavy metals into the water for the time period 2007-2022.

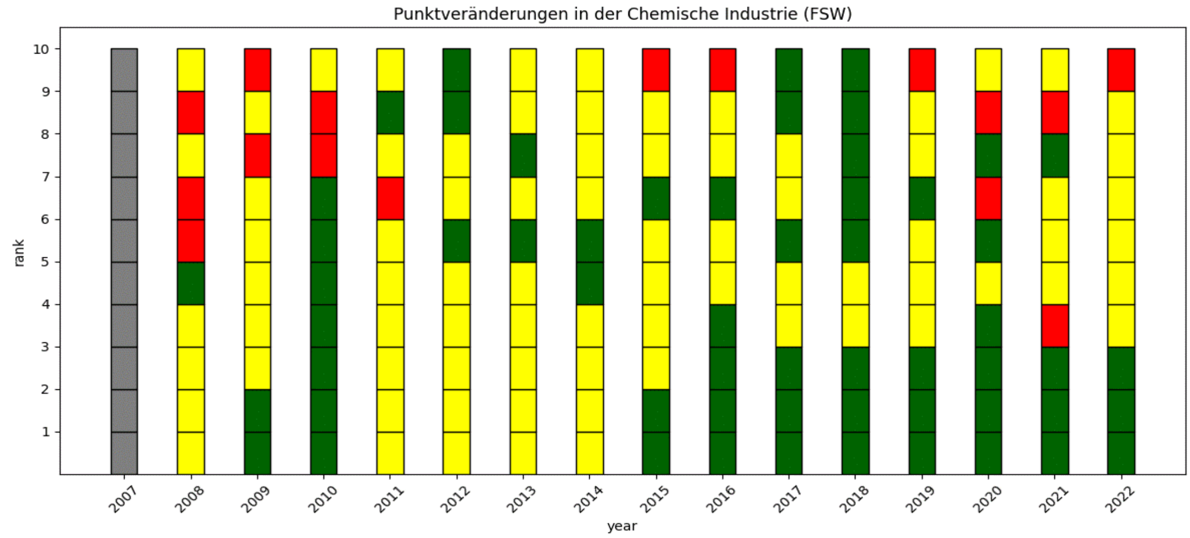


**Figure 5:** Variation analysis of branch chemical industries regarding releases of heavy metals into the water for the time period 2007-2022.

Confirmation of the visually obtained observation that there has been a higher variation dynamic in the branch waste and wastewater management than in the chemical branch is provided by Table 2 which contains the relative variation strengths. For heavy metal releases into water, the waste and wastewater management sector exhibited a relative variation strength of $rV_{1,16}$= 0.2686. In comparison, the chemical industry showed a lower relative variation strength of $rV_{1,16} = 0.2257$, indicating more consistent emissions over the same period.

| **Branch** | **$rV_{1,16}$ for release of heavy metals into the Water** | **$rV_{1,16}$ for release of GHG Into the Air** |
|---|---|---|
| chemical industry | 0.2257 | 0.1486 |
| energy sector | 0.3614 | 0.1914 |
| food industry | 1.0000 | 0.4096 |
| Intensive livestock farming and aquaculture | - | 0.7264 |
| metal industry | 0.3029 | 0.1043 |
| mineral processing industry | 0.2729 | 0.2271 |
| other industrial sectors | 0.5640 | 0.8798 |
| paper and wood industry | 0.4356 | 0.2843 |
| waste and wastewater management | 0.2686 | 0.4057 |

**Table 2:** Variation Strengths of Top 10 Polluters for time period 2007 to 2022 for two pollution types.

The diagrams in the Figures 6, 7, and 8 concern the pollution type `release of GHG into the air´. With an annual average of about 604 reports about twice as much pollution reports for this pollution type are contained in the PRTR data collection as for the above discussed two branches. The investigation of the variation dynamic for this pollution type also reveals a higher variation dynamic for the branch waste and wastewater management than for the branch chemical industries. The more constant branch chemical industries can be visually obtained from the larger number of green ranks when comparing the two diagrams. This difference is also evident in the relative Variation Strengths of the two compared branched contained in Table 2. For the chemical branch a Variation Strength of $rV_{1,16} = 0.1486$ was obtained which is by far lower than the value of $rV_{1,16} = 0.4057$ obtained for the branch waste and wastewater management.

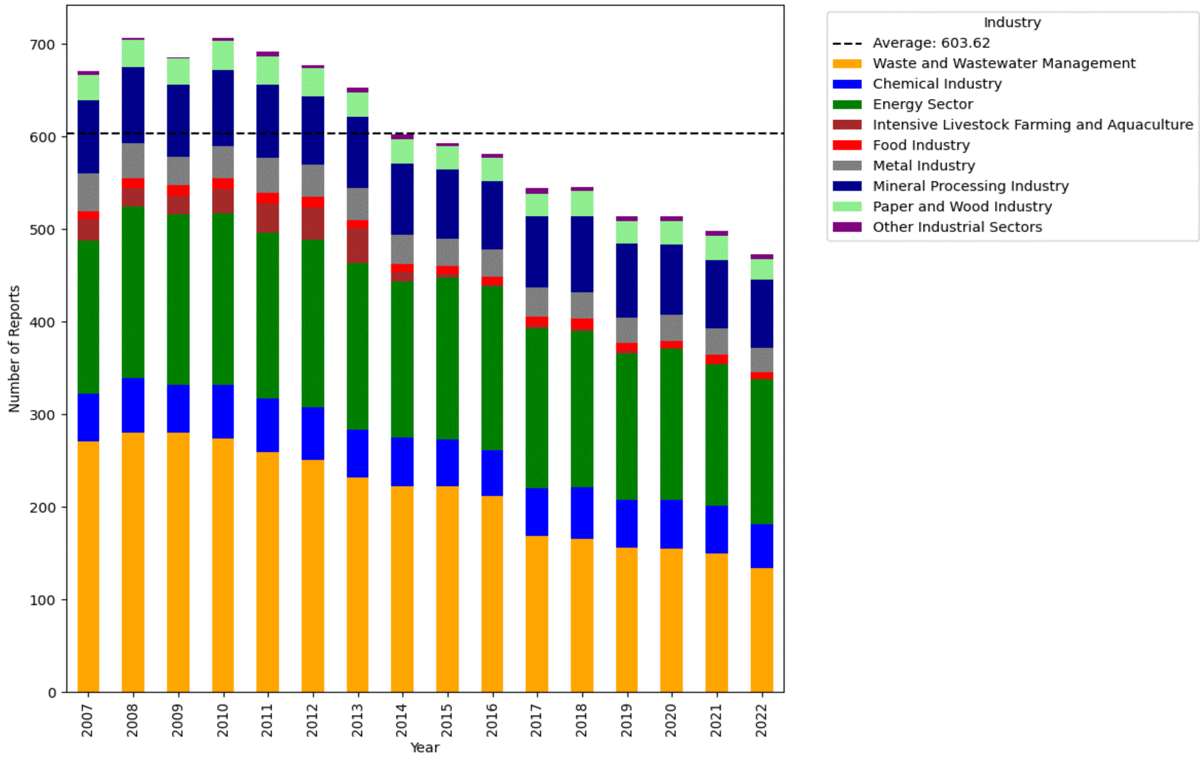


**Figure 6:** Number of reports regarding release of GHG into the air for the time period 2007-2022 divided by branches.

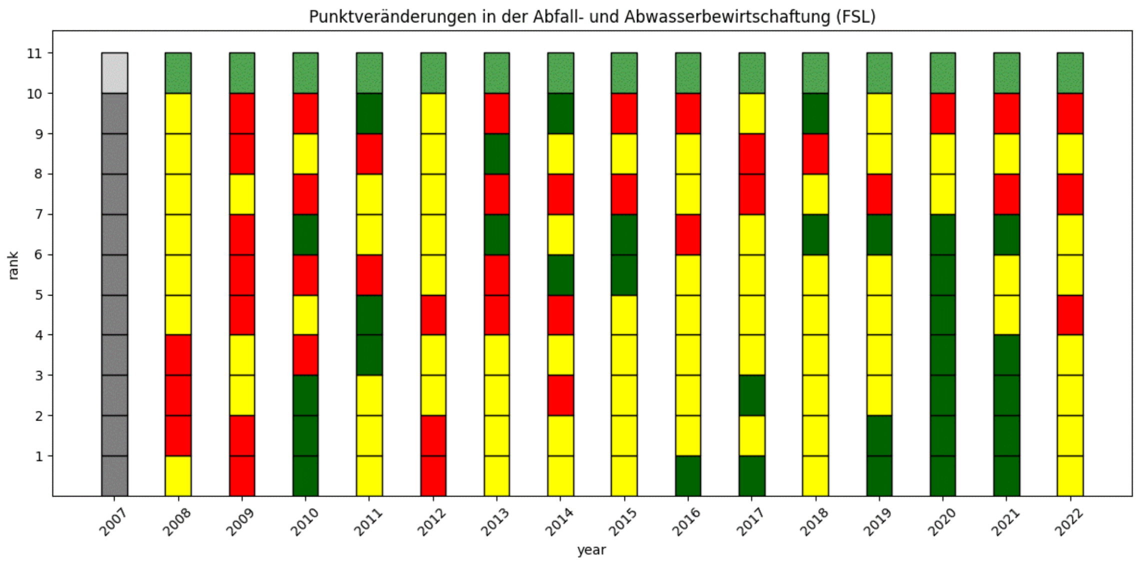


**Figure 7:** Variation analysis of branch waste and wastewater management regarding releases of GHG into the air.

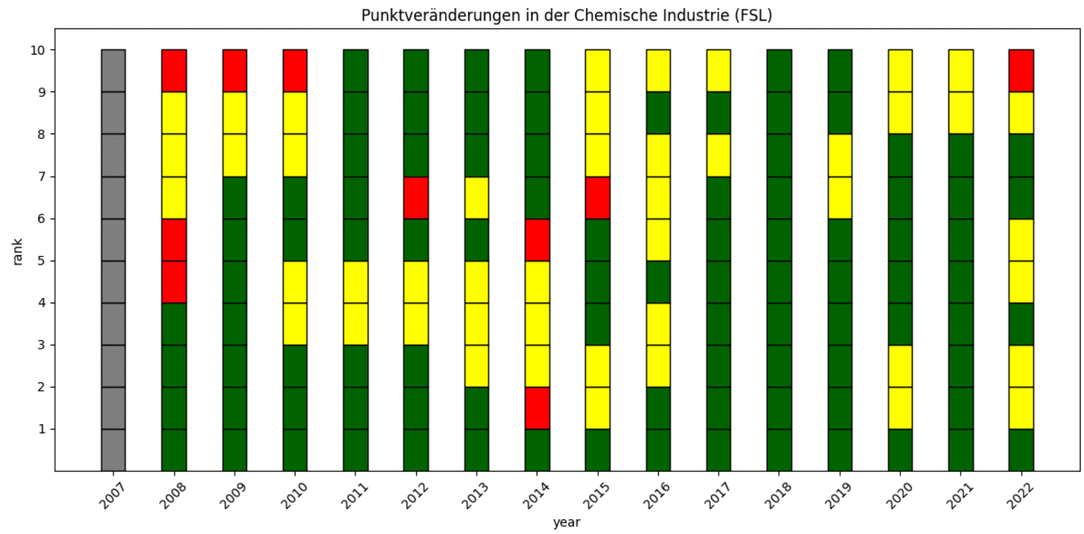


**Figure 8:** Variation analysis of branch chemical industries regarding releases of GHG into the air.

### 4.3. Further Use Cases

The proposed method offers a range of options for practical application beyond the generation and analysis of standard corporate pollution rankings. It supports story telling with intuitive diagrams as useful for different stakeholder groups. Regulatory authorities can leverage the method to monitor the long-term environmental performance of industrial sectors, identifying persistent top polluters and assessing the effectiveness of regulatory measures over time. Industry associations can apply the method to benchmark companies within their sector, encouraging competition for improved environmental performance without directly disclosing individual identities.

Moreover, the method has the potential to serve as a pressure instrument for business entities, promoting greater accountability and transparency. By visualizing the dynamics of top polluters over time, the method can help reveal cases where companies repeatedly appear in top polluter rankings or exhibit insufficient progress in reducing emissions. This transparency can motivate companies to enhance their environmental performance, as consistently high rankings may attract scrutiny from regulators, investors, and the public. Additionally, the method can help expose instances of greenwashing by highlighting discrepancies between reported sustainability efforts and actual pollution data. The practical relevance of this potential can be further amplified by enhancing online versions of the visualizations with easy access to company information, allowing stakeholders to quickly identify rank holders within top polluter lists.

Financial institutions and investors may use the method to evaluate the environmental risk profiles of companies, incorporating pollution dynamics into sustainability assessments and investment decisions. Likewise, environmental NGOs and the general public can apply the method to advocate for stronger environmental regulations and corporate accountability by highlighting trends and shifts in pollution rankings.

The method’s visualization capabilities, including intuitive color-coded diagrams with the time dimension on the y-axis and ranks on the x-axis, ensure that complex temporal dynamics are conveyed in an accessible manner. By complementing the previously described color codes with an additional grey code to mark the ranks of the earliest ranking list within the time interval, stakeholders can easily identify trends and variations over time. Overall, the method's flexibility, simplicity, and focus on anonymized data make it a valuable tool for promoting environmental transparency and accountability while respecting corporate confidentiality.

## 5. Outlook and Conclusions

This study introduced a straightforward method for analyzing and visualizing the variation dynamics of corporate top polluter rankings using public pollution data, exemplified by the German PRTR register. The proposed approach provides stakeholders with a practical tool to assess ranking stability, shifts over time, and industry-specific performance. By quantifying rank changes and visualizing dynamic patterns, the method enhances transparency and supports data-driven decision-making in environmental monitoring and regulation.

However, while pollution rankings based on reported substance amounts are useful, several critical issues should be considered to ensure accurate and fair assessments. One limitation is that rankings based solely on the quantity of pollutants may not fully reflect the environmental and health impacts of different substances. For example, smaller quantities of highly toxic substances can have more severe consequences than larger amounts of less harmful substances. Future research should explore methods that incorporate substance toxicity levels, such as weighting reported amounts by their potential environmental and health effects. This approach would provide a more comprehensive and meaningful ranking system, aligning with sustainability goals and public health priorities.
Another key consideration is the accuracy and reliability of reported data. Inaccurate pollution rankings can lead to false accusations, damaging corporate reputations and undermining stakeholder trust. Ensuring the integrity of pollution data requires robust reporting regulations, independent verification mechanisms, and advanced data validation techniques. Moreover, future research should investigate methods to account for data inconsistencies and reporting errors, ensuring that rankings are both fair and scientifically sound.

Looking ahead, integrating advanced machine learning techniques and data analytics can further enhance the analysis of ranking dynamics. Predictive models could help forecast future ranking trends, enabling proactive measures to reduce environmental impact. Additionally, visual analytics tools with interactive features could make the results more accessible and engaging for stakeholders, including regulators, industry representatives, investors, and the general public.

## 6. Conclusion

In conclusion, the proposed method offers a practical and transparent approach to exploring the temporal dynamics of pollution rankings. By addressing current limitations and leveraging emerging technologies, future research can further improve the accuracy, fairness, and interpretability of pollution assessments, contributing to more effective environmental regulation and corporate accountability.

## Declarations

### Ethics approval and consent to participate

Not applicable

### Consent for publication

Not applicable

### Availability of data and material

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

### Competing interests

The authors declare that they have no competing interests.

### Funding

Not applicable

### Authors' contributions

HT was a major contributor in designing the research framework and writing the manuscript. VS was a major contributor in conducting the data preparation, the model development, and model validation using the Python programming language. VS also read and approved the final manuscript

### Acknowledgements

Not applicable.

## Publication bibliography

1. European Commission (2006): The European Pollutant Release and Transfer Register (E-PRTR). Edited by The European Pollutant Release and Transfer Register (E-PRTR). The European Pollutant Release and Transfer Register (E-PRTR). Available online at https://environment.ec.europa.eu/topics/industrial-emissions-and-safety/european-pollutant-release-and-transfer-register-e-prtr_en, checked on 7/10/2024.
2. Kolominskas, Chaim; Sullivan, Rory (2004): Improving cleaner production through pollutant release and transfer register reporting processes. In Journal of Cleaner Production 12 (7), pp. 713–724. DOI: 10.1016/S0959-6526(03)00057-X.
3. MacDonald, Karen (2008): The European Pollutant Release and Transfer Register - A Case Study of Bosnia-Herzegovina. In European Journal of Law Reform X (1), pp. 21–49.
4. OECD (2023): Uses of PRTR Data and Tools for their Presentation. Edited by OECD. OECD. Paris (OECD Environment, Health and Safety Publications Series on Pollutant Release and Transfer Registers, 27). Available online at https://one.oecd.org/document/ENV/CBC/MONO(2023)9/en/pdf, checked on 20th October 2024.
5. Kuo, Yun-Hsin; Fujiwara, Takanori; Chou, Charles C.-K.; Chen, Chun-houh; Ma, Kwan-Liu (2022): A Machine-Learning-Aided Visual Analysis Workflow for Investigating Air Pollution Data.
6. Kuppardt-Kirmse, Anke; Grimm, Sabine (2024): Pollutants of the PRTR - Situation in Germany - Reporting years 2007 - 2022. Edited by German Federal Environmental Agency. German Federal Environmental Agency. Dessau. Available online at https://www.umweltbundesamt.de/publikationen/pollutants-of-the-prtr-situation-in-germany, checked on February 18th, 2025.
7. Melnikov, Oleg; Raun, Loren H.; Ensor, Katherine B. (2016): Dynamic Principal Component Analysis: Identifying the Relationship between Multiple Air Pollutants.
8. Plocoste, T.; Carmona-Cabezas, R.; Jimenez-Hornero, F. J.; Rave, E. Gutierrez de; Calif, R. (2023): Multifractal characterisation of particulate matter (PM10) time series in the Caribbean basin using visibility graphs. DOI: 10.48550/arXiv.2311.12072.
9. Varapongpisan, T.; Ingsrisawang, L.; Frank, T. D. (2019): Taking drift-diffusion analysis from the study of turbulent flows to the study of particulate matter smog and air pollutants dynamics. DOI: 10.48550/arXiv.1907.01477.
10. Erhart, Szilárd; Erhart, Kornél (2023): Environmental ranking of European industrial facilities by toxicity and global warming potentials. In Scientific reports 13 (1), p. 1772. DOI: 10.1038/s41598-022-25750-w.
11. Shaw, Henry (1992): Pollution ranking of new technologies. In Journal of Systems Integration 2 (3), pp. 249–261. DOI: 10.1007/BF02265077.
12. C.M. Payus; M.S. Nur Syazni; J. Sentian (2022): Extended air pollution index (API) as tool of sustainable indicator in the air quality assessment: El-Nino events with climate change driven. In Heliyon 8 (3), pp. 1–12. Available online at https://www.cell.com/heliyon/fulltext/S2405-8440(22)00445-5, checked on 2/23/2025.
13. Deng, Zikun; Di Weng; Chen, Jiahui; Liu, Ren; Wang, Zhibin; Bao, Jie et al. (2020): AirVis: Visual Analytics of Air Pollution Propagation. In IEEE transactions on visualization and computer graphics 26 (1), pp. 800–810. DOI: 10.1109/TVCG.2019.2934670.
14. European Commission (2022): Regulation (EC) No 1893/2006, Statistical classification of economic activities NACE Revision 2. Available online at https://eur-lex.europa.eu/eli/reg_del/2023/137/oj, checked on 8/4/2024.