Revealing Chemical Trends: Insights from Data-Driven Visualisation and Patent Analysis in Exposomics Research

Dagny Aurich*[1], Emma L. Schymanski*[1], Flavio de Jesus Matias[1,2], Paul A. Thiessen[3], Jun Pang[2]

[1] *Luxembourg Centre for Systems Biomedicine (LCSB), University of Luxembourg, 6 Avenue du Swing, Belvaux L-4367, Luxembourg.*

[2] *Faculty of Science, Technology and Medicine (FSTM), University of Luxembourg, 6 Avenue de la Fonte, L-4364 Esch-sur-Alzette, Luxembourg.*

[3]*National Center for Biotechnology Information, National Library of Medicine, National Institutes of Health, Bethesda, MD 20894, USA.*

ORCIDs: DA: 0000-0001-8823-0596; ELS: 0000-0001-6868-8145; FdJM: 0009-0008-8585-7690*; PAT: 0000-0002-1992-2086; JP: 0000-0002-4521-4112.*

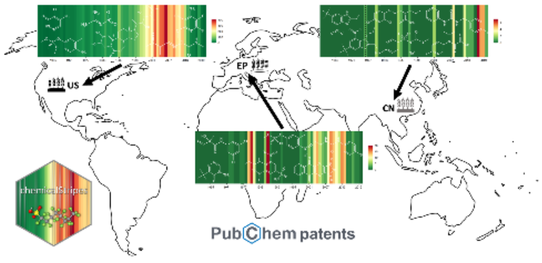
*Corresponding & co-first authors: dagny.aurich@uni.lu, emma.schymanski@uni.lu

Abstract

Understanding historical chemical usage is crucial for assessing current and past impacts on human health and the environment and informing future regulatory decisions. However, past monitoring data is often limited in scope and number of chemicals, while suitable sample types are not always available for remeasurement. Data-driven cheminformatics methods on patent and literature data offer several opportunities to fill this gap. The *chemical stripes* were developed as an interactive, open source tool for visualising patent and literature trends over time, inspired by the global warming and biodiversity stripes. This paper details the underlying code and datasets behind the visualisation, with a major focus on the patent data sourced from PubChem, including patent origins, uses, and countries. Overall trends and specific examples are investigated in greater detail to explore both the promise and caveats that such data offers in assessing the trends and patterns of chemical patents over time and across different geographic regions. Despite a number of potential artefacts associated with patent data extraction, the integration of cheminformatics, statistical analysis, and data visualisation tools can help generate valuable insights that can both illuminate the chemical past and potentially serve towards an early warning system for the future.

Keywords: Chemical Stripes, PubChem, Cheminformatics, Data Visualisation, Exposomics, Early Warning System, Patent Analysis

TOC Graphic:



Synopsis: Patent data trends provide insights into chemical use, highlighting past, present and future threats to environmental ecosystems and human health.

Introduction

While studying historical and current chemical exposures can provide insights into their health and environmental impacts, the re-creation of historical exposures to investigate past, present or future health effects using analytical data is severely limited by several factors. These include the past focus on only a few dozen target chemicals (primarily legacy pollutants), in many cases a lack of suitable historical samples for remeasurement with modern analytical methods, as well as the sheer immensity of chemical space under consideration. Patent data, accessible through platforms like the World Intellectual Property Organization (WIPO) and linked to chemical structures in open databases such as PubChem[1], offers an alternative data-mining approach for examining past and potential chemical exposures.

PubChem is an open database of chemical structures, properties and associated information, providing tools for searching and analysing chemical information[1]. Approximately 40 million of the 118 million compounds in PubChem (June 2024) are linked to ~51 million patent files[2]. This Google Patents dataset covers 120 million patent publications from >100 patent offices including the European (EPO), Japanese (JPO), Korean (KIPO) and US patent offices (USPTO) plus WIPO. Each *patent* record provides details on the chemicals referenced in that patent, along with patent title, abstract, application and publication dates, applicant, inventor, and patent classification, but without context about why particular chemicals are mentioned. Individual PubChem *compound* pages contain information about each patent linked to that compound (chemical) in the Patent subsection. A single invention may be described across multiple patent documents (*e.g.*, patent applications, grants, and re-examination certificates) identified with a unique patent identifier suffixed with a code (*e.g.*, A1, A2, B1, B2). The same patent may also be filed in multiple national agencies, which can be grouped together into patent families.

Patent data has been used to prioritize compounds in non-target environmental studies in a complementary manner to literature counts, aiding in the identification of potential contaminants with known commercial uses[3]. A recent viewpoint highlighted a concerning upward trend in chemical numbers across databases over time frames much shorter than the typical time for regulatory actions[4]. The *chemical stripes* visualisation included in that viewpoint[4] sparked extensive debate, drawing significant attention, feedback and questions from various audiences. The subsequent sonification[5] and accompanying video[6] by J. Perera further intensified the discussion, leaving viewers in a state of shock or deep contemplation. Combining international legislation, patent filing dates and region information could potentially reveal various trends in patent numbers, as well as the effectiveness of regulatory measures and the necessity for timely interventions. However, beyond the general upward trend in chemical and patent numbers, deviating patterns in the stripes visualisation were observed for various chemicals, while several potential artefacts and limitations became apparent. This feedback motivated this article, which presents the data, code and methods behind the *chemical stripes* visualisation and corresponding *chemicalStripes* R package[7] and performs a more detailed analysis of the patent data in PubChem for this particular context.

Materials and Methods

Chemical Stripes Visualisation

The open source *chemicalStripes*[7] R package is available on GitLab and was developed to create the *chemical stripes* figure for one or more specific chemicals by PubChem Compound IDs (CIDs). CIDs can be obtained easily from multiple starting queries using PubChem search functionality. In addition to the input CID(s), users can specify a date range (default 1960-2023), mode (patent or literature) and opt for a colourblind friendly version. The patent data is retrieved from the "Depositor Supplied Patent Identifiers" section[8] of the respective CIDs, while the literature data is retrieved from the "Consolidated References" section[9]. The default colour range is green through yellow to red (Figure 1A, C, D), reproducing a traffic-light scheme distinctive from both the *warming*[10] and *biodiversity stripes*[11] already produced, whereas the colourblind friendly version is blue to red (Figure 1B), very similar to the *warming stripes* (and hence not the preferred default). The (`chemical_stripes`) function begins by checking package dependencies and loading necessary libraries. It then retrieves compound information, including the compound name, molecular formula, and number of patents filed. If patent data is available, this is then downloaded and processed, generating the stripe plot using the ggplot2 package[12], both displaying and saving the output as PNG, see examples in Figure 1. For further details see the *chemicalStripes* repository[7].

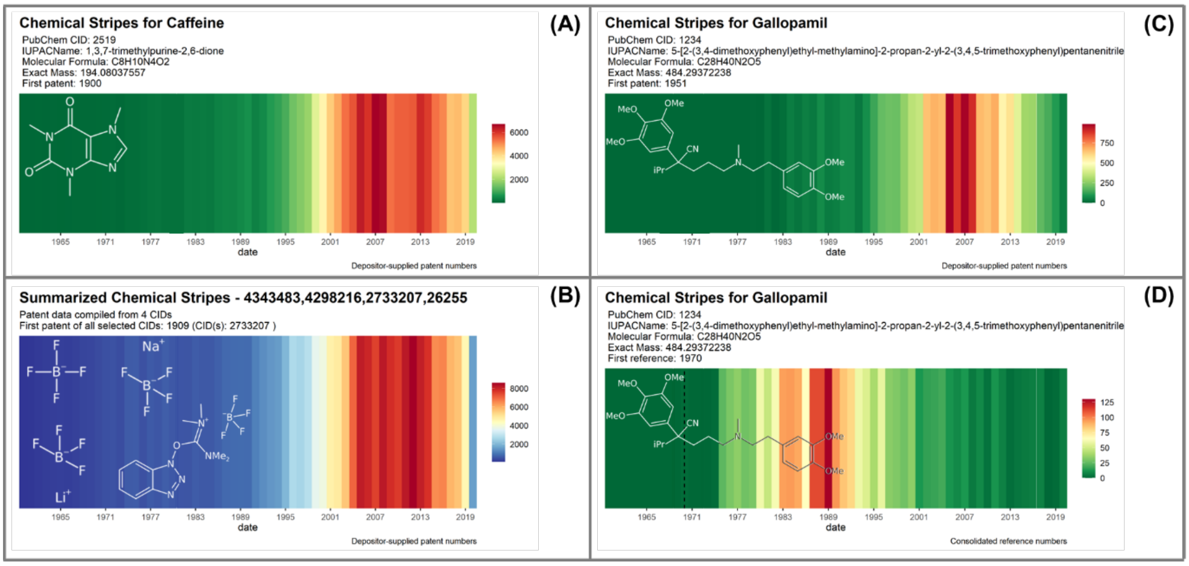


Figure 1: Several examples of Chemical Stripes from 1960-2020; structures generated in CDK Depict[13] are overlaid. A: Patent stripes for caffeine, showing the typical pattern. B: Summarized patent stripes for 4 species related to tetrafluoroborate in "colour-blind friendly" mode. C: Patent stripes and D: Literature stripes for gallopamil, with atypical patterns.

Statistical Analysis

Since a general trend was obvious (Figure 1A, B) with clear outliers (C), the patent dataset was analysed in more detail. Time series clustering was performed to systematically identify outliers, inspired by examples such as the abrupt decrease in patents for gallopamil (Figure 1C). Region-based analysis was performed by inventor region to identify chemicals exclusive to certain regions, or regions with similar patenting activities, while specific trends related to chemical classes such as pharmaceuticals, pesticides or persistent compounds like per-and polyfluorinated substances (PFAS) were also explored. Network analysis was used to find relationships and connectivity patterns between chemicals in the patent dataset. Further details are available as open source code in the *ULPatentTrends*[14] repository.

Since the patent dataset in PubChem is huge (>4 TB of data), subsets were used to perform these analyses. Several chemical lists were selected from the NORMAN Suspect List Exchange (NORMAN-SLE)[15–17], CompTox[18–20], the PubChem PFAS Tree[21,22] and the PubChem Compound Table of Contents (TOC) Tree[2] in the PubChem Classification Browser. The lists were chosen by subject areas including agrochemicals (the "Agrochemical Information", "EU Pesticides Data" and "USDA Pesticides Program" sections from the PubChem TOC Tree[2] and S28 EUBIOCIDES[23] from the NORMAN-SLE), bisphenols (S20 BISPHENOLS[24] and S97 UBABPAALT[25] from the NORMAN-SLE), polychlorinated biphenyls (PCBs) from CompTox[26]. For PFAS: S102 PARCPFAS[27] and S111 PMTPFAS[28] from the NORMAN-SLE plus four Stockholm Convention lists from the regulatory section of the PubChem PFAS Tree: the initial and updated perfluorooctanoic acid (PFOA) listing[29], the initial perfluorohexane sulfonic acid (PFHxS) list[30] and the proposed C9-C21 long chain perfluoroalkylcarboxylic acids (LC-PFCAs) listing[31–33].

Results and Discussion

Overall and Regional Trends by Chemical Lists

Information was available for 103 separate regions, with most data generally available for the US, Europe, Japan, China, Korea and WIPO; the first 5 were chosen for a more detailed regional analysis. One example plot showing the top 20 of the 103 regions is shown in Figure S1; additional plots are included in the *ULPatentTrends* repository[14]. The overall trends in patent numbers over the different lists broken down by the five largest regions (with all others, including world, in the "other" category) reveal varying trends, with six of the thirteen examples shown in Figure 2 and explained below. More examples are given in the Supporting Information (SI) Figures S2-S6, including some breakdowns per CID, and in *ULPatentTrends*[14].

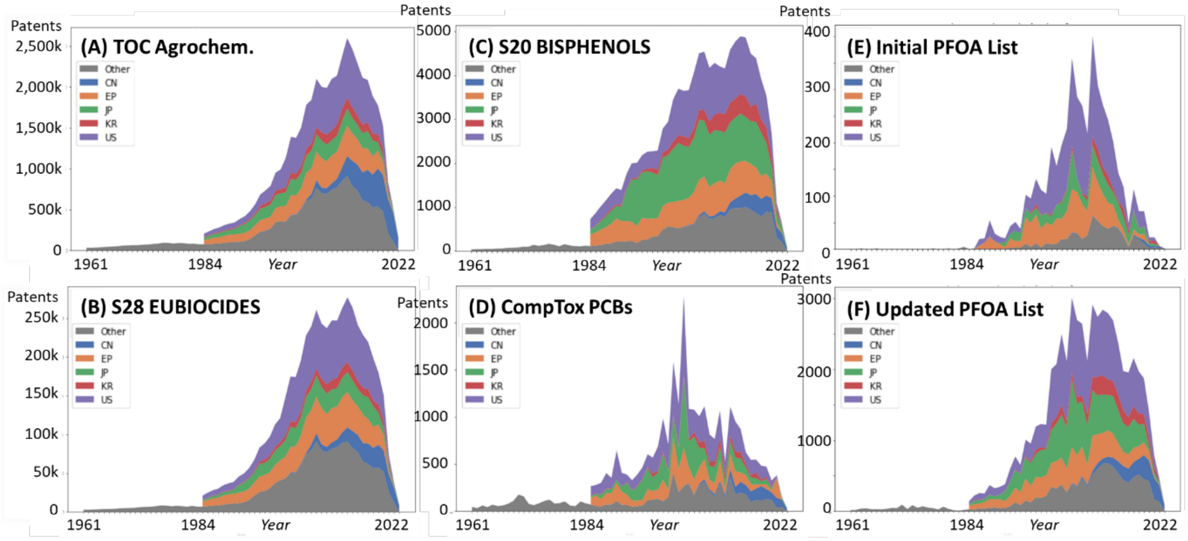


Figure 2: Patent counts for topic-based subsets of chemicals, with regional information. (A) The PubChem Table of Contents (TOC) Agrochemicals category. (B) The NORMAN-SLE S28 EUBIODICES list. (C) The NORMAN-SLE S20 BISPHENOLS list. (D) The CompTox Polychlorinated biphenyls (PCBs) list. (E) and (F) The initial and updated perfluorooctanoic acid (PFOA) listing in the Stockholm Convention. Purple=US, Red=Korea, Green=Japan, Orange=EU, Blue=China and Grey=Other regions.

The overall trends in the entire Agrochemicals category (Figure 2A) and the two EU and US subsets (SI Figure S2B&C) were quite similar, although the increase in patents from China was less pronounced for the US compared with the EU and overall agrochemical list. A slightly different pattern was observed for EUBIOCIDES (Figure 2B). Figure S3, a breakdown by compound, shows that this is driven primarily by benzoic acid, propanol and isopropanol. Further breakdowns per CID are included in *ULPatentTrends*[14]. The pattern for S20 BISPHENOLS (Figure 2C) and S97 UBABPAALT were almost identical, dominated by Bisphenol A (see Figure S4). The plot for CompTox PCBs (Figure 2D) reveals a markedly different pattern with a peak around 2001, potentially due to the impact of the Stockholm Convention signed in 2001 (effective 2004) – details by CID are given in Figure S5. This baseline is mainly 2-chlorobiphenyl, with 3,3',4,4',5-pentachlorobiphenyl and 3,3',4,4'-tetrachlorobiphenyl forming the peak around 2000 (see Figure S5). The difference in patent trends for the initial versus updated PFOA listings in the Stockholm Convention (Figure 2E vs. F), particularly in the last years (2009-2022), underscore the critical importance of updating regulatory lists, especially in light of the increasing proportion of Chinese patents. Regional plots for all six PFAS lists are included in Figure S6.

Discovering Important Chemicals in Lists via Centrality Analysis

Networks were constructed for CIDs from the chemical lists. Each (weighted) individual network consisted of the CIDs from a specific list as nodes. An edge connecting a pair of CIDs was established if both CIDs were mentioned by one patent. Each edge was further weighted by the number of co-appearances of the two CIDs in patents. These individual networks resulted in plots (see Figures S7-8 and *ULPatentTrends*[14] for examples) that were quite difficult to interpret. More detailed network analysis, shown in Figure 3 (including the US in Figures S9) helped isolate chemicals of particular interest to certain regions.

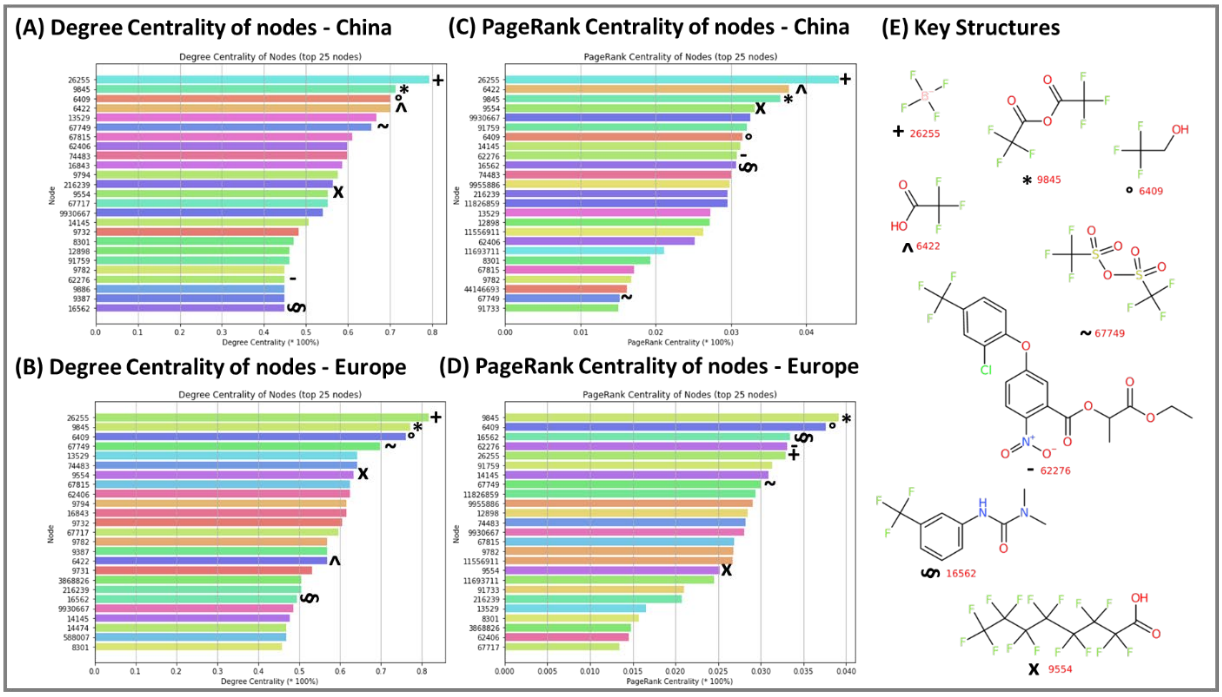


Figure 3: Network analysis on S111 PMTPFAS to find key structures of interest. (A) Degree centrality of nodes for China. (B) Degree centrality of nodes for Europe. (C) PageRank centrality of nodes for China. (D) PageRank centrality of nodes for Europe. (E) Key structures, the top four from (A)-(D), marked on each plot with respective symbols next to the CID.

Figure 3 shows a patent network analysis of the S111 PMTPFAS list, with nodes represented by their degree centrality for China (A) and Europe (B), and their PageRank centrality for China

(C) and Europe (D), each featuring the top 25 nodes. This analysis highlights differences in regional patent activity related to key PFAS compounds. In plots A, B, and C, the top candidate is tetrafluoroborate (CID 26255, see Figure 3E, top left, "+" symbol), which is used for electroplating and as an electrolyte additive for batteries. In the EU PageRank Centrality plot, it ranks only 5th, indicating a relatively lower number of patent applications involving this compound or within this sector compared to other regions or compounds. In plot D, the top compound is trifluoroacetic anhydride (TFAA, CID 9845, "*" in Figure 3E), which is second highest in A and B, third in C. TFAA serves as a recommended desiccant for trifluoroacetic acid (CID 6422, "^"), which is fourth in A and second in C, but is less prominent in Europe (B) and absent in D. Trifluoroethanol (CID 6409, "°"), a solvent used in organic chemistry, ranks third in A and B, second in D, and seventh in C. Fluometuron (CID 16562, sideways "§"), a herbicide, is second in D, tenth in C, and lower in both A and B. Lactofen (CID 62276, "-"), another herbicide, appears consistently across A, C and D, but is missing in B. PFOA (CID 9554, "X"), a well-known PFAS compound restricted by the Stockholm Convention since 2019, is present in all four plots, highest in Figure 3C (4th place). The differences between the plots underscore how regulatory environments, industrial needs, and research priorities shape the patenting activities related to PFAS compounds in the EU and China (and US - see Figure S9). The presence of compounds like PFOA in both regions highlights ongoing attention to regulated substances, but the specific applications and frequency of patent filings reveal divergent technological focuses and market demands between the two regions. A similar analysis for agrochemicals is included in the SI, Figure S10. Both examples show how investigating the patent data on various lists of chemicals could help isolate "stand-out" trends in chemical activity and act as (or help support) a potential early warning system for up and coming action.

The regional analysis of the patent dataset (see Figures S9&10) included CIDs that are unique to specific regions, such as agrochemicals present only in China, Europe or the US, or those unique to only two regions, such as China and Europe but not US. The analysis covering all possible regional subsets and can be found in *ULPatentTrends*[14]; custom queries can be formed from the CID lists. Examples for the agrochemical list are given in the TOC graphic.

Potential and Limitations of Patent Data

There are several challenges and limitations associated with analysing the chemical stripes visualizations and patent dataset. The patent dataset, while comprehensive, may not always be current or complete and seems to contain historical depositions that have been discontinued (potentially partially explaining some "blips" seen around 2007 and 2016), posing significant hurdles for accurate data (and trend) analysis. Extracting chemical information via image recognition or text mining from patents is challenging, since older patent documents are lower quality and are thus quite noisy and error prone[34,35]. Often, chemicals mentioned in the introduction of patents are not actually used in the application, leading to potential misinterpretation of their relevance, while any chemicals that happen to appear in Markush structures defined for drug discovery purposes may be overrepresented. Chemicals can be mistakenly identified due to their appearance in unrelated contexts, such as being part of an inventor's name. Such an error, reported for the 1913 patent linked to PFOS (US-1257524-A), based on a figure in the earlier viewpoint, led to a suggestion to use a higher threshold in the cut-off applied to the scoring of name recognition in future applications. The two earliest PFOS patents currently in PubChem (as of 29 June 2024) are due to misrecognised names: US-1257524-A was invented by Adolf **Pfos**er, while US-2290705-A was invented by Wilhelm **Pfos**t – the first genuine PFOS patent is 1953 (see Figure S11). The tabular view of the patent data in PubChem allows a quick check of the linked patents, assisting with rapid verification (see Figure S12); this can also be downloaded for offline use.

The timeliness of patent data is a major issue. Patent records from recent years, particularly post-2020, are often incomplete, which can skew analysis and trends; it can take 1-2 years for the data to filter through more completely. This gap highlights the need for rapid updates of data sources to ensure that recent innovations and filings are accurately represented. The accuracy of the dataset is heavily reliant on the efficiency and precision of literature mining and image recognition algorithms, which is an area of active research[34,36–39]. Adjustments to the extraction workflows can result in the exclusion of several patents from the dataset or the omission of information such as priority dates (which, if absent, cannot be included in the chemical stripes).

Future research directions could include exploring different patent sources, such as using AI applications such as DeepSearch by IBM to collect and curate documents, which may offer more reliable and comprehensive data. Refining the data mining tools would also help in managing and interpreting the patent dataset more effectively.

The chemical stripes package (*ChemicalStripes*[7]) and Jupyter notebooks (*ULPatentTrends*[14]) provided as part of this work are designed to help environmental researchers explore the possibilities of using patent data to address their environmental questions. This will help facilitate a deeper understanding of regional trends, regulatory impacts, and innovation landscapes in the chemical sector, as well as limitations in this data. Users are encouraged to report any artefacts, since such feedback is crucial for refining the dataset and approaches.[40] Incorporating more sophisticated classification methods in data extraction may help further enhance the accuracy and usability of this data in the future.

Declarations

Supporting Information

Supporting information available: brief text describing the repository, figures showing patent count by region (Figure S1), regional patent counts for agrochemicals, biocides, bisphenols, PCBs, PFAS (Figures S2-6), connected and disconnected networks (Figures S7-8), centrality results for China, EU and US for PFAS and Agrochemicals (Figures S9-10), screenshots of verifying patent information in PubChem (Figures S11-12). Code is available online at https://gitlab.com/uniluxembourg/lcsb/eci/chemicalstripes (Chemical Striptes) and https://gitlab.com/uniluxembourg/lcsb/eci/ULPatentTrends (ULPatentTrends notebooks).

Acknowledgements

We thank Lutz Weber (OntoChem / MolGenie) for discussions related to extraction artefacts, Evan Bolton (PubChem, NCBI/NLM/NIH) for earlier discussions as well as the other

Environmental Cheminformatics and PubChem team members and other colleagues and collaborators who contributed to this work indirectly via other collaborative and scientific activities.

Funding

DA, ELS and FdJM acknowledge funding support from the Luxembourg National Research Fund (FNR) for project A18/BM/12341006 (DA, ELS, FdJM) and the University of Luxembourg Institute for Advanced Studies (IAS) for the Audacity project “LuxTIME” (DA, ELS). The work of PAT was supported by the National Center for Biotechnology Information of the National Library of Medicine (NLM), National Institutes of Health.

Author Contributions

Dagny Aurich: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software (lead), Validation, Visualization, Writing original draft preparation (joint lead), Writing review and editing. Emma L. Schymanski: Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing original draft preparation (joint lead), Writing review and editing. Flavio de Jesus Matias: Data curation, Investigation, Methodology, Software (lead), Writing review and editing. Paul A. Thiessen: Data curation, Methodology, Software, Writing review and editing. Jun Pang: Conceptualization, Methodology, Resources, Software, Supervision, Writing review and editing.

Conflict of Interest Disclosure

The authors declare no competing financial interest

References

(1) Kim, S.; Chen, J.; Cheng, T.; Gindulyte, A.; He, J.; He, S.; Li, Q.; Shoemaker, B. A.; Thiessen, P. A.; Yu, B.; Zaslavsky, L.; Zhang, J.; Bolton, E. E. PubChem 2023 Update. *Nucleic Acids Res.* **2022**, gkac956. https://doi.org/10.1093/nar/gkac956.

(2) NCBI/NLM/NIH. *PubChem Table of Contents Classification Browser*. https://pubchem.ncbi.nlm.nih.gov/classification/#hid=72 (accessed 2024-07-08).

(3) Ruttkies, C.; Schymanski, E. L.; Wolf, S.; Hollender, J.; Neumann, S. MetFrag Relaunched: Incorporating Strategies beyond in Silico Fragmentation. *J. Cheminformatics* **2016**, *8* (1), 3. https://doi.org/10.1186/s13321-016-0115-9.

(4) Arp, H. P. H.; Aurich, D.; Schymanski, E. L.; Sims, K.; Hale, S. E. Avoiding the Next Silent Spring: Our Chemical Past, Present, and Future. *Environ. Sci. Technol.* **2023**, *57* (16), 6355–6359. https://doi.org/10.1021/acs.est.3c01735.

(5) Perera, J. *Our Chemical Past, Present And Future*; London, 2023. https://soundcloud.com/jamieperera/our-chemical-past-present-and-future.

(6) Perera, J. *Our Chemical Past, Present and Future*. https://vimeo.com/jpmlmusic/ourchemicalpastpresentandfuture (accessed 2024-06-18).

(7) Aurich, D.; Schymanski, E. L.; Thiessen, P. A. *GitLab repository “Environmental Cheminformatics / chemicalstripes.”* GitLab. https://gitlab.com/uniluxembourg/lcsb/eci/chemicalstripes (accessed 2023-06-12).

(8) NCBI/NLM/NIH. *Patents - PubChem Documentation*. https://pubchem.ncbi.nlm.nih.gov/docs/patents (accessed 2024-06-19).

(9) NCBI/NLM/NIH. *Consolidated References - PubChem Documentation*. https://pubchem.ncbi.nlm.nih.gov/docs/literature#section=Consolidated-Literature-Table (accessed 2024-06-19).

(10) Hawkins, E. *2018 visualisation update, Climate Lab Book*. Climate Lab Book. https://www.climate-lab-book.ac.uk/2018/2018-visualisation-update/ (accessed 2022-10-25).

(11) Richardson, M. *Biodiversity Stripes – A Journey from Green to Grey*. Finding Nature. https://findingnature.org.uk/2022/08/10/biodiversity-stripes/ (accessed 2022-12-14).

(12) Wickham, H. *Ggplot2: Elegant Graphics for Data Analysis*, 2nd ed. 2016.; Use R!; Springer International Publishing : Imprint: Springer: Cham, 2016. https://doi.org/10.1007/978-3-319-24277-4.

(13) Mayfield, J. *CDK Depict Web Interface*. https://www.simolecule.com/cdkdepict/depict.html (accessed 2023-03-09).

(14) de Jesus Matias, F. Uniluxembourg / LCSB / Environmental Cheminformatics / ULPatentTrends · GitLab, 2024. https://gitlab.com/uniluxembourg/lcsb/eci/ULPatentTrends (accessed 2024-07-08).

(15) Mohammed Taha, H.; Aalizadeh, R.; Alygizakis, N.; Antignac, J.-P.; Arp, H. P. H.; Bade, R.; Baker, N.; Belova, L.; Bijlsma, L.; Bolton, E. E.; Brack, W.; Celma, A.; Chen, W.-L.; Cheng, T.; Chirsir, P.; Čirka, Ľ.; D'Agostino, L. A.; Djoumbou Feunang, Y.; Dulio, V.; Fischer, S.; Gago-Ferrero, P.; Galani, A.; Geueke, B.; Głowacka, N.; Glüge, J.; Groh, K.; Grosse, S.; Haglund, P.; Hakkinen, P. J.; Hale, S. E.; Hernandez, F.; Janssen, E. M.-L.; Jonkers, T.; Kiefer, K.; Kirchner, M.; Koschorreck, J.; Krauss, M.; Krier, J.; Lamoree, M. H.; Letzel, M.; Letzel, T.; Li, Q.; Little, J.; Liu, Y.; Lunderberg, D. M.; Martin, J. W.; McEachran, A. D.; McLean, J. A.; Meier, C.; Meijer, J.; Menger, F.; Merino, C.; Muncke, J.; Muschket, M.; Neumann, M.; Neveu, V.; Ng, K.; Oberacher, H.; O'Brien, J.; Oswald, P.; Oswaldova, M.; Picache, J. A.; Postigo, C.; Ramirez, N.; Reemtsma, T.; Renaud, J.; Rostkowski, P.; Rüdel, H.; Salek, R. M.; Samanipour, S.; Scheringer, M.; Schliebner, I.; Schulz, W.; Schulze, T.; Sengl, M.; Shoemaker, B. A.; Sims, K.; Singer, H.; Singh, R. R.; Sumarah, M.; Thiessen, P. A.; Thomas, K. V.; Torres, S.; Trier, X.; van Wezel, A. P.; Vermeulen, R. C. H.; Vlaanderen, J. J.; von der Ohe, P. C.; Wang, Z.; Williams, A. J.; Willighagen, E. L.; Wishart, D. S.; Zhang, J.; Thomaidis, N. S.; Hollender, J.; Slobodnik, J.; Schymanski, E. L. The NORMAN Suspect List Exchange (NORMAN-SLE): Facilitating European and Worldwide Collaboration on Suspect Screening in High Resolution Mass Spectrometry. *Environ. Sci. Eur.* **2022**, *34* (1), 104. https://doi.org/10.1186/s12302-022-00680-6.

(16) NORMAN Association; NCBI/NLM/NIH. *PubChem Classification Browser: NORMAN Suspect List Exchange Tree (PubChem NORMAN-SLE Tree)*. https://pubchem.ncbi.nlm.nih.gov/classification/#hid=101 (accessed 2024-07-08).

(17) NORMAN Association. *NORMAN Suspect List Exchange (NORMAN-SLE) Website*. https://www.norman-network.com/nds/SLE/ (accessed 2024-07-08).

(18) US Environmental Protection Agency. *CompTox Chemicals Dashboard: Chemical Lists Page*. https://comptox.epa.gov/dashboard/chemical-lists (accessed 2024-07-08).

(19) Williams, A. J.; Grulke, C. M.; Edwards, J.; McEachran, A. D.; Mansouri, K.; Baker, N. C.; Patlewicz, G.; Shah, I.; Wambaugh, J. F.; Judson, R. S.; Richard, A. M. The CompTox

Chemistry Dashboard: A Community Data Resource for Environmental Chemistry. *J. Cheminformatics* **2017**, *9* (1), 61. https://doi.org/10.1186/s13321-017-0247-6.

(20) US EPA; NCBI/NLM/NIH. *PubChem Classification Browser: EPA DSSTox Tree (PubChem CompTox Chemicals Dashboard Chemical Lists Tree)*. https://pubchem.ncbi.nlm.nih.gov/classification/#hid=105 (accessed 2024-07-08).

(21) Schymanski, E. L.; Zhang, J.; Thiessen, P. A.; Chirsir, P.; Kondic, T.; Bolton, E. E. Per- and Polyfluoroalkyl Substances (PFAS) in PubChem: 7 Million and Growing. *Environ. Sci. Technol.* **2023**, *57* (44), 16918–16928. https://doi.org/10.1021/acs.est.3c04855.

(22) NCBI/NLM/NIH; LCSB-ECI. *PubChem Classification Browser: PFAS and Fluorinated Compounds in PubChem Tree*. https://pubchem.ncbi.nlm.nih.gov/classification/#hid=120 (accessed 2024-07-08).

(23) Rüdel, H. S28 | EUBIOCIDES | Biocides from the NORMAN Priority List. *Zenodo*, 2018, *DOI: 10.5281/zenodo.2648820*. https://doi.org/10.5281/zenodo.2648820.

(24) Rostkowski, P.; Fischer, S. S20 | BISPHENOLS | Bisphenols. *Zenodo*, 2017, *DOI: 10.5281/zenodo.2631745*. https://doi.org/10.5281/zenodo.2631745.

(25) German Environment Agency (UBA). S97 | UBABPAALT | List of Bisphenol A Alternatives from UBA. *Zenodo*, 2022, *DOI: 10.5281/zenodo.6405325*. https://doi.org/10.5281/zenodo.6405325.

(26) US EPA. *CompTox Chemicals Dashboard | PCBCHEMICALS - Polychlorinated biphenyl (PCB) collection*. https://comptox.epa.gov/dashboard/chemical-lists/PCBCHEMICALS (accessed 2024-06-20).

(27) Polesello, S.; Valsecchi, S. S102 | PARCPFAS | List of PFAS from PARC WP4. *Zenodo* **2023**, *DOI:10.5281/zenodo.10252414*. https://doi.org/10.5281/zenodo.10252414.

(28) Schymanski, E. S111 | PMTPFAS | Fluorine-Containing Compounds in PMT Suspect Lists. *Zenodo* **2023**, *NORMAN-SLE-S111.0.1.0*. https://doi.org/10.5281/zenodo.8417075.

(29) United Nations. *Updated Indicative List of Substances Covered by the Listing of Perfluorooctanoic Acid (PFOA), Its Salts and PFOA-Related Compounds*; Stockholm Convention on Persistent Organic Pollutants; Persistent Organic Pollutants Review Committee Seventeenth meeting UNEP/POPS/POPRC.17/INF/14/Rev.1; Geneva, Switzerland, 2022; p 57. https://chm.pops.int/TheConvention/POPsReviewCommittee/Meetings/POPRC17/Overview/tabid/8900/Default.aspx (accessed 2023-06-11).

(30) United Nations. *Draft Decision SC-10/[--]: Listing of Perfluorohexane Sulfonic Acid (PFHxS), Its Salts and PFHxS-Related Compounds*; Stockholm Convention on Persistent Organic Pollutants; Persistent Organic Pollutants Review Committee Tenth meeting UNEP/POPS/COP.10/CRP.10; Geneva, Switzerland, 2021; p 1. https://www.pops.int/TheConvention/POPsReviewCommittee/Meetings/POPRC10/Overview/tabid/3779/mctl/ViewDetails/EventModID/871/EventID/514/xmid/11873/Default.aspx (accessed 2023-06-10).

(31) United Nations. *Proposal to List Long-Chain Perfluorocarboxylic Acids, Their Salts and Related Compounds in Annexes A, B and/or C to the Stockholm Convention on Persistent Organic Pollutants*; Stockholm Convention on Persistent Organic Pollutants; Persistent Organic Pollutants Review Committee Seventeenth meeting UNEP/POPS/POPRC.17/7; Geneva, Switzerland, 2021; p 24. https://www.pops.int/TheConvention/POPsReviewCommittee/Meetings/POPRC17/Overview/tabid/8900/Default.aspx (accessed 2023-06-10).

(32) United Nations. *Draft Indicative List of Long-Chain Perfluorocarboxylic Acids, Their Salts and Related Compounds*; Stockholm Convention on Persistent Organic Pollutants; Persistent Organic Pollutants Review Committee Eighteenth meeting UNEP/POPS/POPRC.18/INF/14; Rome, 2022; p 24. https://www.pops.int/tabid/9165 (accessed 2023-06-10).

(33) United Nations. *Draft Risk Profile: Long-Chain Perfluorocarboxylic Acids, Their Salts and Related Compounds*; Stockholm Convention on Persistent Organic Pollutants; Persistent Organic Pollutants Review Committee Eighteenth meeting UNEP/POPS/POPRC.18/6/Add.1*; Rome, 2022; p 56. https://www.pops.int/tabid/9165 (accessed 2023-06-10).

(34) Morin, L. DS4SD/PatCID, 2024. https://github.com/DS4SD/PatCID (accessed 2024-06-29).

(35) Morin, L.; Weber, V.; Meijer, I.; Yu, F.; Staar, P. Document to Chemical Structure Benchmarks (D2C-RND and D2C-UNI). *Zenodo* **2024**. https://doi.org/10.5281/ZENODO.10978811.

(36) Rajan, K.; Zielesny, A.; Steinbeck, C. DECIMER: Towards Deep Learning for Chemical Image Recognition. *J. Cheminformatics* **2020**, *12* (1), 65. https://doi.org/10.1186/s13321-020-00469-w.

(37) Rajan, K.; Brinkhaus, H. O.; Sorokina, M.; Zielesny, A.; Steinbeck, C. DECIMER-Segmentation: Automated Extraction of Chemical Structure Depictions from Scientific Literature. *J. Cheminformatics* **2021**, *13* (1), 20. https://doi.org/10.1186/s13321-021-00496-1.

(38) Morin, L.; Weber, V.; Meijer, I.; Yu, F.; Staar, P. PatCID: An Open-Access Database of Chemical Structures in Patent Documents. *Zenodo* **2024**. https://doi.org/10.5281/ZENODO.10572869.

(39) Barnabas, S. J.; Böhme, T.; Boyer, S. K.; Irmer, M.; Ruttkies, C.; Wetherbee, I.; Kondić, T.; Schymanski, E. L.; Weber, L. Extraction of Chemical Structures from Literature and Patent Documents Using Open Access Chemistry Toolkits: A Case Study with PFAS. *Digit. Discov.* **2022**, *1* (4), 490–501. https://doi.org/10.1039/D2DD00019A.

(40) Kosonocky, C. W.; Wilke, C. O.; Marcotte, E. M.; Ellington, A. D. Mining Patents with Large Language Models Elucidates the Chemical Function Landscape. *Digit. Discov.* **2024**, *3* (6), 1150–1159. https://doi.org/10.1039/D4DD00011K.