Defining plastic pollution hotspots

Paolo F. Tasseron[1,2], Tim H.M. van Emmerik[1], Paul Vriend[3], Rahel Hauk[1], Francesca Alberti[2], Yvette Mellink[4], and Martine van der Ploeg[1]

[1] Hydrology and Environmental Hydraulics Group, Wageningen University and Research, 6708 PB, Wageningen, The Netherlands.

[2] Amsterdam Institute for Advanced Metropolitan Solutions, 1018 JA Amsterdam, The Netherlands.

[3] Rijkswaterstaat, Ministry of Infrastructure and Water Management, 2515 XP, The Hague, Netherlands

[4] Aquatic Ecology and Water Quality Group, Wageningen University and Research, 6709 PB, Wageningen, The Netherlands.

Abstract

Plastic pollution in the natural environment poses a growing threat to ecosystems and human health, prompting urgent needs for monitoring, prevention and clean-up measures, and new policies. To effectively prioritize resource allocation and mitigation strategies, it is key to identify and define plastic hotspots. UNEP's draft global agreement on plastic pollution mandates prioritizing hotspots, suggesting a potential need for a defined term. Yet, the delineation of hotspots varies considerably across plastic pollution studies, and a definition is often lacking or inconsistent without a clear purpose and boundaries of the term. In this paper, we applied four common hotspot definitions to plastic pollution datasets ranging from urban areas to a global scale. Our findings reveal that these hotspot definitions encompass between 0.8% to 93.3% of the total plastic pollution, covering <0.1% to 50.3% of the total locations. Given this wide range of results and the possibility of temporal inconsistency in hotspots, we emphasize the need for fit-for-purpose criteria and a unified approach to defining plastic hotspots. Therefore, we designed a step-wise framework to define hotspots by determining the purpose, units, spatial scale, temporal scale, and threshold values. Incorporating these steps in research and policymaking yields a harmonized definition of hotspots, facilitating the development of effective plastic pollution prevention and reduction measures.

1 Introduction

Plastic pollution in natural environments has received significant attention from academia and policymakers in recent years, because of the potential detrimental impacts on ecosystems, economies, and human health (van Emmerik and Schwarz, 2020). Plastic pollution can enter the terrestrial and aquatic ecosystems from diverse sources, such as wastewater treatment plants, landfills, agricultural activities, and mismanaged waste in urban areas (Lechthaler et al., 2020; Li et al., 2021). Recent estimates of global plastic leakage to aquatic systems are uncertain and range between 4.8 and 23 million metric tons annually (Boucher and Billard, 2019; Borrelle et al., 2020; Roebroek et al., 2022). Yet, only a small fraction of this mismanaged plastic waste is transported to oceans (Meijer et al., 2021; van Emmerik et al., 2022b). Most mismanaged plastics can accumulate and be retained for decades in aquatic and terrestrial compartments of rivers (van Emmerik et al., 2022b; Kaandorp et al., 2023).

Yet, the driving factors and dynamics of plastic transport and accumulation in these compartments are largely unknown (Ford et al., 2022). Observations of plastic pollution are key to solving these unknowns. As such, multiple monitoring efforts were made to understand the transport and fate of plastics in urban areas (Tramoy et al., 2022; Tasseron et al., 2023a), river systems (González-Fernández and Hanke, 2017; Schwarz et al., 2019; Liro et al., 2020; van Emmerik and Schwarz, 2020), beaches (Morales-Caselles et al., 2021; Fruergaard et al., 2023), and oceans (Shim et al., 2022).

The methodologies and results from these studies are subsequently used to design effective policies and mitigation strategies to reduce and prevent plastic waste in the environment. Several of these focus on targeting "hotspot" areas. For example, the "National Guidance for Plastic Pollution Hotspotting and Shaping Action" was developed to present a structured framework for the identification of plastic leakage hotspots, assessments of their impacts across the entire plastic value chain, and subsequent prioritization of actions after hotspots are identified (Boucher and Initiative, 2020). Whilst such frameworks should provide relevant insights for policymakers to tackle plastic pollution, hotspots are not clearly defined, resulting in different definitions across plastic pollution studies. For example, Franceschini et al. (2021) used an inverse distance weighting interpolation method to obtain a map of marine zones where plastic litter tends to accumulate, and subsequently defined hotspots as areas where the number of particles exceeded the 90th percentile of all values. Schuyler et al. (2016) established a global risk map to highlight hotspot areas with a high probability of marine debris ingestion by sea turtles. In their study, hotspots are qualitatively defined as areas with high concentrations of marine debris and high turtle species diversity. Hotspots are occasionally restrained to specific spatial scales. Lessler et al. (2017) highlighted the importance of defining the spatial scale of hotspots based on various practical considerations, such as data availability and resources, or a specific scale at which the planned interventions are relevant to be implemented. Tasseron et al. (2020) proposed a seven-step approach for plastic hotspot mapping specifically designed for urban water systems, where hotspots were defined when an arbitrary threshold was exceeded. Another key aspect to consider is that hotspot locations might change over time. Temporal variability in plastic abundance can influence whether a hotspot is permanent, or occurs only in extreme events such as peak river discharges (van Emmerik et al., 2023). Lastly, plastic pollution can be reported in either item counts per unit length, area, volume, or mass, which might yield different hotspots based on the composition of the plastic litter. For example, de Lange et al. (2022) shows a strong divergence between the top ten most abundant items when assessed by item counts compared to assessments based on the mass of items.

While a common characteristic among these studies is the identification of areas in which plastics are abundantly concentrated, specific criteria and methodologies differ greatly in both temporal and spatial domains. Acknowledging these diverse perspectives and their influence on the reported hotspot areas is crucial for advancing the development of effective, targeted mitigation strategies and their cost-benefit analyses. The draft of UNEP's legally binding instrument to target plastic pollution worldwide states that government bodies and local parties should prioritize hotspots, and note a definition of the term may be required (UNEP, 2023). For example, in Bangladesh, at national and urban levels, an action plan for sustainable plastic management was developed, in which hotspots were defined as "A place where plastics leak into the environment, including land, air, water, and marine environment, where waste accumulates regularly and is not collected and transported to landfills for proper disposal" (Yoshijima et al., 2021). While this definition points out where pollution is happening, it resulted in over 1,200 hotspots in the city of Dhaka alone, which poses a challenge to efficient mitigation strategies. Another example concerns Queensland's Plastic Pollution Reduction Plan, which states that state-wide plastic pollution hotspots should be identified and monitored, without giving a hotspot definition (Queensland Government, 2019). It is evident that the concept of hotspots varies significantly across plastic pollution studies. Different concepts may lead to different amounts and localization of hotspots and can have strong impacts on the design and effectiveness of local, national, or international waste management strategies and plastic pollution treaties. Therefore, this study aims to compare four quantitative approaches to define hotspots using plastic pollution datasets on four different spatial scales: global (Meijer et al., 2021), continental (González-Fernández et al., 2021), national (van Emmerik et al., 2020a; Kiessling et al., 2021) and urban (van Emmerik et al., 2020b; Tasseron et al., 2023a). By exploring the similarities, differences, and limitations of these approaches, our study seeks to provide a comprehensive understanding of the definition of hotspots and their impact on hotspot identification. We propose a framework toward a harmonized definition of plastic hotspots that can be used to support local, national, and international ambitions to end plastic pollution.

2 Methods

2.1 Datasets

In this study, seven plastic pollution datasets on four different spatial scales were used. An overview of these datasets is shown in Table 1, and the distribution of values within each dataset in Figure 1. Firstly, a global dataset presented by Meijer et al. (2021) modeled over 100,000 outlets of rivers and streams, of which nearly 32,000 locations are reported to leak plastic litter into marine environments. In this study, the amount of plastic was quantified in million tonnes per year [MT yr^{-1}]. A subset of this dataset is taken that includes all plastic leaking locations in continental Europe, resulting in 2,626 locations (administrative areas obtained from `https://gadm.org/data.html/`). Next, a continental dataset presented by González-Fernández et al. (2021) modeled the annual floating macrolitter load (FML) from Europe into the ocean at over 32,500 locations in plastic items per year [items yr^{-1}]. Two datasets at the national scale are used. Firstly, the dataset presented by Kiessling et al. (2021) contains riverine floating macrolitter observations for nearly 150 sites in Germany conducted in the spring of 2017, reported in items per meter per sampling hour [items m^{-1} h^{-1}]. Secondly, another national dataset presented by van Emmerik et al. (2020a) includes over 500 sampling locations along riverbanks in the Dutch Rhine-Meuse delta. In the spring of 2021, the riverbank macrolitter was sampled and categorized using the River-OSPAR method [items m^{-1} riverbank] (van Emmerik et al., 2020a). Lastly, we used two datasets at the urban scale. One was a dataset of crowd-based observations of floating plastic in the city of Leiden, the Netherlands (van Emmerik et al., 2020b). The abundance of floating litter was registered for over 200 locations within the urban waterways [items]. The other dataset at the urban scale was collected in Amsterdam (Tasseron et al., 2023b). The abundance of litter was registered at 150 distinct locations in the canals of the historic city center [items]. Floating items were observed, counted, and categorized according to the River-OSPAR protocol. A map showing the locations and observed floating litter counts is found in Figure 6 in the Appendix.

Table 1: Datasets used in this study, including the reference, type of data, the spatial scale, type of water body, number of locations, and the unit of the measurements.

Reference	Type	Spatial scale	Water body	# locations	unit
Meijer et al. (2021)	Model output	Global	Outlets into ocean	31,820	MT yr^{-1}
Meijer et al. (2021)	Model output	Continental (Europe)	Outlets into ocean	2,626	MT yr^{-1}
González-Fernández et al. (2021)	Model output	Continental (Europe)	Outlets into ocean	32,652	items yr^{-1}
Kiessling et al. (2021)	Observations	National (Germany)	Rivers and streams	141	items m^{-1} h^{-1}
van Emmerik et al. (2020a)	Observations	National (Netherlands)	Riverbanks	512	items m^{-1}
van Emmerik et al. (2020b)	Observations	Urban (Leiden)	Waterways	217	items
Tasseron et al. (2023b)	Observations	Urban (Amsterdam)	Waterways	150	items

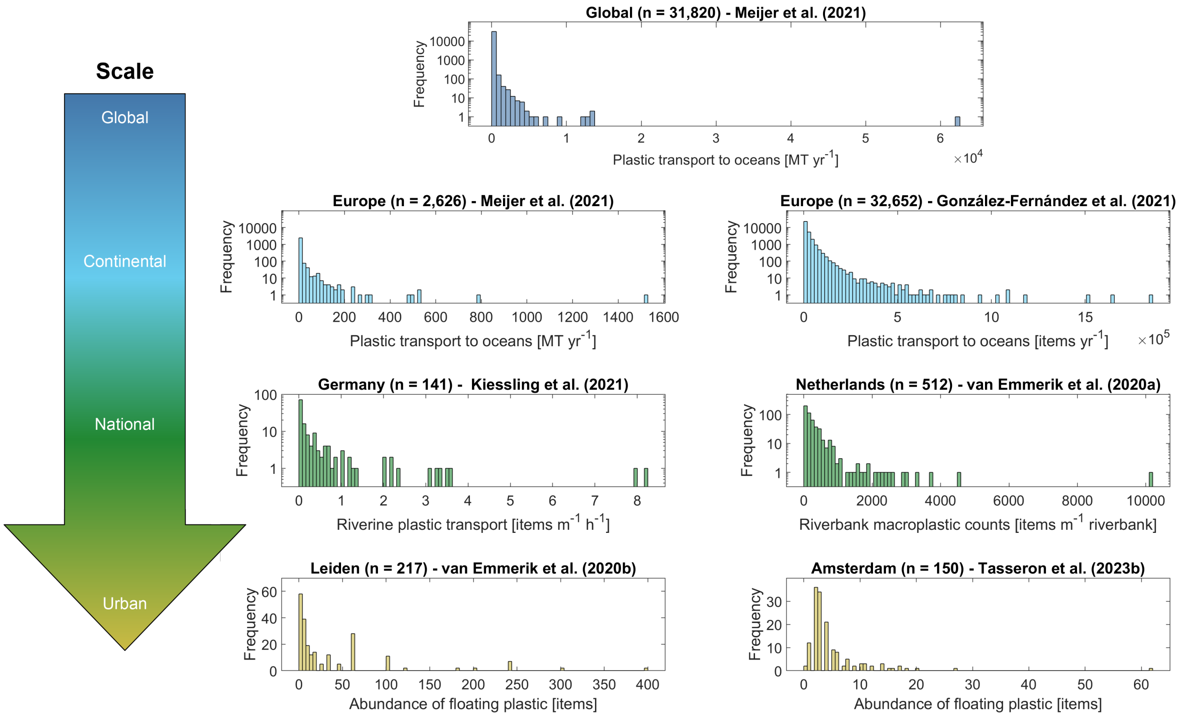

Figure 1: Distribution of plastic pollution values for each dataset used in this study. Note the difference in scale on both the y and x axes.

2.2 Hotspot definitions and statistical analyses

Four quantitative definitions were used based on the distribution of the values in the plastic pollution datasets. Values above these thresholds are defined as hotspots:

1. **Above average values.** With this approach, any value above the average value of the dataset is considered a hotspot. This definition is based on Fok and Cheung (2015), who identified microplastic pollution in Hong Kong to be higher than international averages, highlighting Hong Kong as a hotspot of marine plastic pollution. Another example of the above-average definition is used by Fruergaard et al. (2023), who determined that the Nha Thrang coast (Vietnam) is a global hotspot for plastic pollution because the mean abundance of plastic litter items found was higher than other beaches worldwide. The "above average" definition is also used in other disciplines, for example, in criminology, hotspots can be classified as areas with an above-average number of criminal indices or areas where the risk of becoming a crime victim is higher than average (Eck et al., 2005).

2. **Values in the highest interval.** Datasets can be divided into several (constant) intervals, in which the highest interval represents hotspots. For example, Tasseron et al. (2020) use five intervals for two urban plastic pollution datasets, in which the highest interval is depicted as a hotspot. These intervals can be chosen arbitrarily or with equal steps in between the intervals. Here, five equal intervals are used for each dataset, in which the highest interval represents hotspots.

3. **Outliers** Outlier values can be defined as hotspots. Extreme events such as high river discharge and (flash) floods can cause high rates of plastic transport (van Emmerik et al., 2022a). Aquatic systems with favorable hydrodynamic conditions for the accumulation of plastic litter can, in turn, be characterized by extreme levels of pollution, which are likely to be outliers in the dataset (Jayasiri et al., 2013). In our study, we use the common definition of outliers to describe hotspots, which are any values above the 3rd quantile plus 1.5 times the interquartile range (Q3 + 1.5 * IQR).

4. **Values in the top percentile.** Hotspots can be defined based on values within the upper

n-th percentile range (e.g. 90th, 95th, or 99th, depending on the desired number of hotspots). For example, Franceschini et al. (2021) identified microplastic hotspots as areas in which the number of particles exceeded the 90th percentile of all values. Here, we use the 90th percentile value to classify hotspots. The percentile threshold can be adjusted based on specific research objectives and context.

2.3 Temporal variability and consistency

Assessing the consistency and changes of hotspots over time can be crucial to effectively allocate resources for cleanup practices. Here, six monitoring rounds of plastic pollution along Dutch riverbanks and beaches are used to identify this consistency. Between the fall of 2020 and the spring of 2023, 101 locations were monitored twice a year using the River-OSPAR protocol (van Emmerik et al., 2020a). In the resulting six datasets, hotspots are defined as values above the 90th percentile, resulting in 10 hotspots for each dataset. The resulting hotspots are analyzed in terms of consistency, whether they are 1) consistently defined as hotspots for multiple monitoring rounds, 2) hotspots on just a single occurrence, or 3) not a hotspot.

3 Results

Applying four hotspot definitions on seven plastic pollution datasets resulted in widely different representations of hotspots (Figure 2). A large range was observed in the percentage of the total plastic pollution contained in hotspots (0.8-93.3%). Similarly, a large range in the percentage of the total locations defined as hotspots is present (<0.1-50.3%). Here, the findings for each definition and its implications are presented.

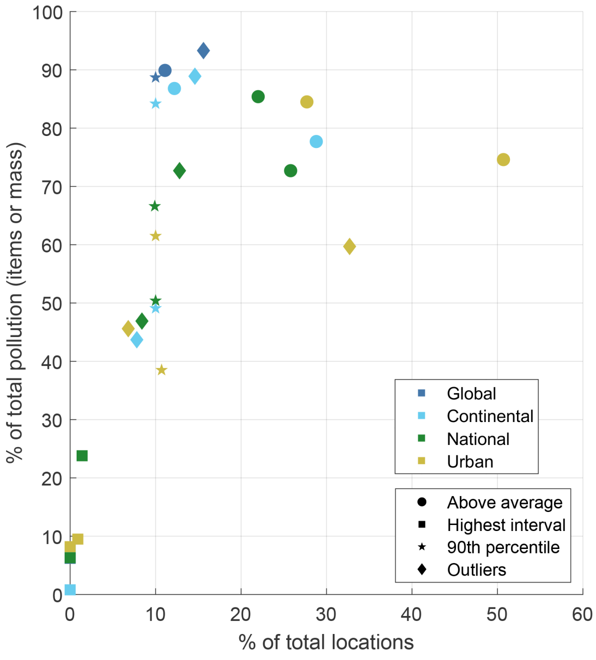

Figure 2: The four different hotspot definitions, and their effect on the percentage of total locations and total items/mass these definitions cover. The colors indicate spatial scale, where dark blue is global, light blue is continental, green is national, and yellow is urban. Different symbols indicate the four hotspot definitions, in which the circle is “Above average”, the square is “Highest interval”, the star is “90th percentile”, and the diamond is “Outliers”.

Defining hotspots as any value above the average value of the pollution dataset results in hotspots containing between 72.7% and 89.9% of the total plastic pollution across the four spatial scales (Figure 2). Out of all the locations in the datasets, between 11.1% (Global) and 50.7% (Urban, Leiden) are identified as hotspots. This suggests the above-average definition might not effectively pinpoint extremely polluted areas as hotspots, since certain regions with slightly elevated pollution levels could be overemphasized. When aiming to identify hotspots using this method, efforts and resources can be diverted away from areas with more pressing pollution concerns.

Dividing the data into five equal intervals and using the highest interval as the definition for hotspots results in a contrasting situation. Here, hotspots contain between 0.6% and 23.8% of the total pollution, distributed over <0.1%-1.4% of the total locations. In absolute numbers, this method identifies only 1-3 locations at each of the four spatial scales as hotspots. Since the intervals are strongly determined by the highest value in the dataset, an extreme outlier results in many data points in the lowest interval(s) and only a few in the highest. Therefore, given its highly selective nature, this method might not capture areas with moderate to high levels of pollution and may therefore not be suitable for offering comprehensive insights into the spatial distribution of hotspots.

Next, using outliers results in 43.3%-93.3% of the total plastic pollution to be included in hotspots. Between 6.8% and 15.6% of the total locations are classified as hotspots (Figure 2). Compared to "Above Average" hotspots and "highest interval" hotspots, the outlier-based method seems to capture a more balanced portion of the pollution, providing a broader spatial perspective. However, it is essential to consider that statistical outliers may not always be present in every dataset. In these rare instances, the outlier-based method is ineffective in pinpointing hotspots.

Lastly, using the 90th percentile as the threshold for hotspots, between 38.5% and 88.7% of the total plastic pollution is included for the different spatial scales. Since this statistical threshold is based on a certain percentage of the data, in all cases 10.0% of the total locations are defined as hotspots (Figure 2). This standardized proportion of hotspot locations is a valuable feature of this method, providing a consistent basis for hotspot identification irrespective of the dataset size. When the original number of locations included in monitoring or model outputs is not too large, this method effectively captures plastic hotspots while maintaining a reasonable number of locations for practical management purposes.

3.1 Arbitrary thresholds and spatial variability

In the absence of well-established guidelines for classifying plastic pollution hotspots, researchers and policymakers may resort to using arbitrary thresholds as a pragmatic approach to identify hotspots. In such cases, the threshold is often determined based on a combination of scientific judgment, data availability, and policy objectives (Bank et al., 2021; Lu et al., 2019). For example, an objective of cleanup strategies and actions can be to target the top ten most polluted locations in a city, or the top 50 most polluted global rivers. These thresholds can be based on several factors such as item count, concentration, plastic weight, or a specific number of locations. Contrary to using statistical thresholds, the use of arbitrary thresholds across different scales or studies can hinder meaningful comparisons between hotspots.

In Figure 3a, the cumulative distribution of pollution over the share of locations is shown. The curves of the different datasets and spatial scales do not overlap, implying a threshold set on a specific dataset - for example, the 15.0% most polluted locations are hotspots - covers an entirely different share of the total pollution for the "Amsterdam - Urban" dataset (56.0%), compared to the "Meijer et al. (2021) - Global" dataset (7.0%). This is a direct result of the diversity in data collection protocols, units, and various patterns at different spatial scales. For example, when comparing the two "Continental" datasets, it seems the plastic pollution in González-Fernández et al. (2021) is much more diffuse compared to Meijer et al. (2021). Even though the distribution is different at various spatial scales, at least 57.0% of the total pollution is concentrated in 25.0% of the total locations regardless of scale, protocol, and the number of locations. The share of pollution is even higher for 25.0% of the total locations when using a similar protocol, as depicted in Figure 3b. Here, cumulative plots of the pollution distribution across the share of locations are shown using subsets at different scales for the Meijer et al. (2021) dataset. In this case, at least 79.0% of the total pollution is concentrated in 25.0% of the locations, regardless of scale. These insights could be relevant for designing strategies tackling plastic pollution on multiple spatial scales simultaneously.

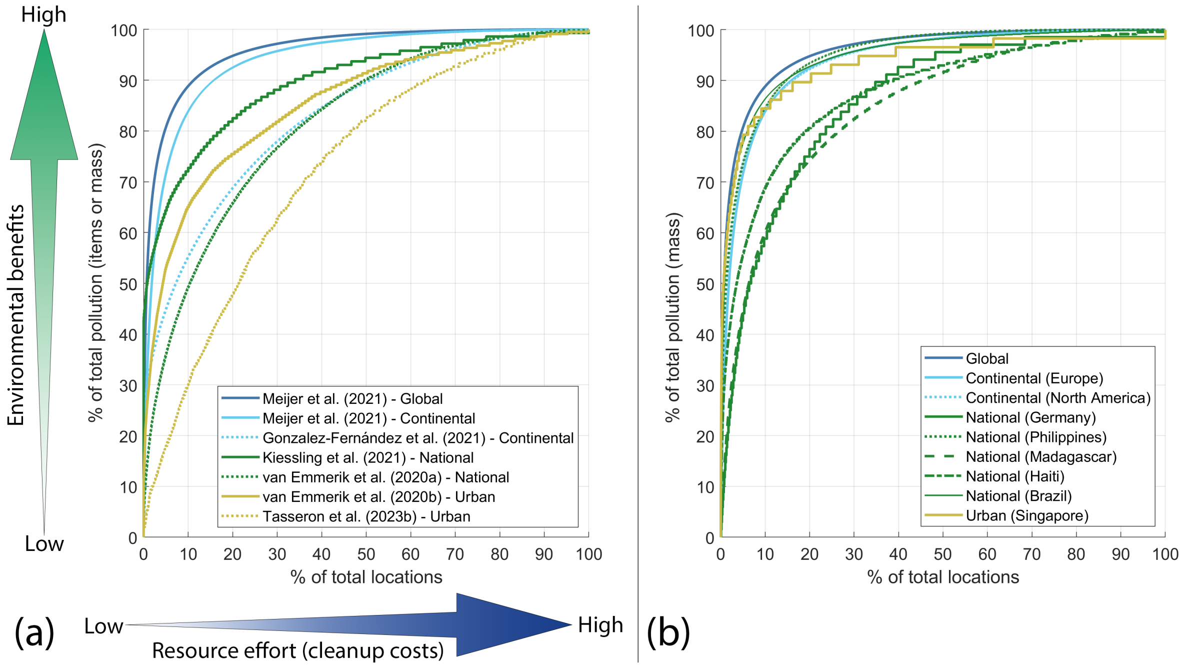

Figure 3: (a) Cumulative plots, expressing the percentage of total locations (x-axis) and percentage of total pollution (y-axis) using the seven different plastic datasets. For management purposes, a higher number of hotspot locations requires more resources, whereas targeting higher shares of plastic pollution for cleanups results in higher environmental benefits. (b) Cumulative plots using different continental, national, and urban subsets of the Meijer et al. (2021) dataset.

3.2 Temporal variability and consistency

Seasonal variability in hydrological and meteorological patterns can strongly impact the consistency and composition of plastic hotspots monitored in different periods. In Figure 4, an overview of the temporal consistency of hotspots along the Dutch riverbanks monitored between the fall of 2020 and the spring of 2023 is depicted. Figure 4a shows the consistency of hotspots over time, using the "Values in the top percentile" definition, resulting in ten hotspots per monitoring round. In total, 33 unique locations emerge as hotspots at least once in any of the monitoring rounds. Only one location is always classified as a hotspot, and just six locations are a hotspot in three or more monitoring rounds. In Figure 4b, an arbitrary threshold was chosen to define hotspots for the same six monitoring rounds. Defining hotspots as locations in which >500 plastic litter items per 100-meter riverbank are monitored results in a different number of hotspots for each season, ranging from one (Fall 2021) to fifteen (Spring 2021) hotspots. As hotspots change over time, tracking their dynamics is crucial for the effective allocation of resources for targeted cleanup practices. Continuous monitoring of longer timescales will yield further insights into hotspots driven by short-term fluctuations (such as floods (van Emmerik et al., 2023) or shipping cargo spills (Saliba et al., 2022)), and consistent hotspots characterized by persistent accumulation of plastic litter.

4 Discussion and outlook

4.1 Temporal variation and consistency of hotspots

The seven datasets used in this study to examine the influence of different hotspot definitions were static, containing plastic pollution values of either model outputs, single observations, or observations

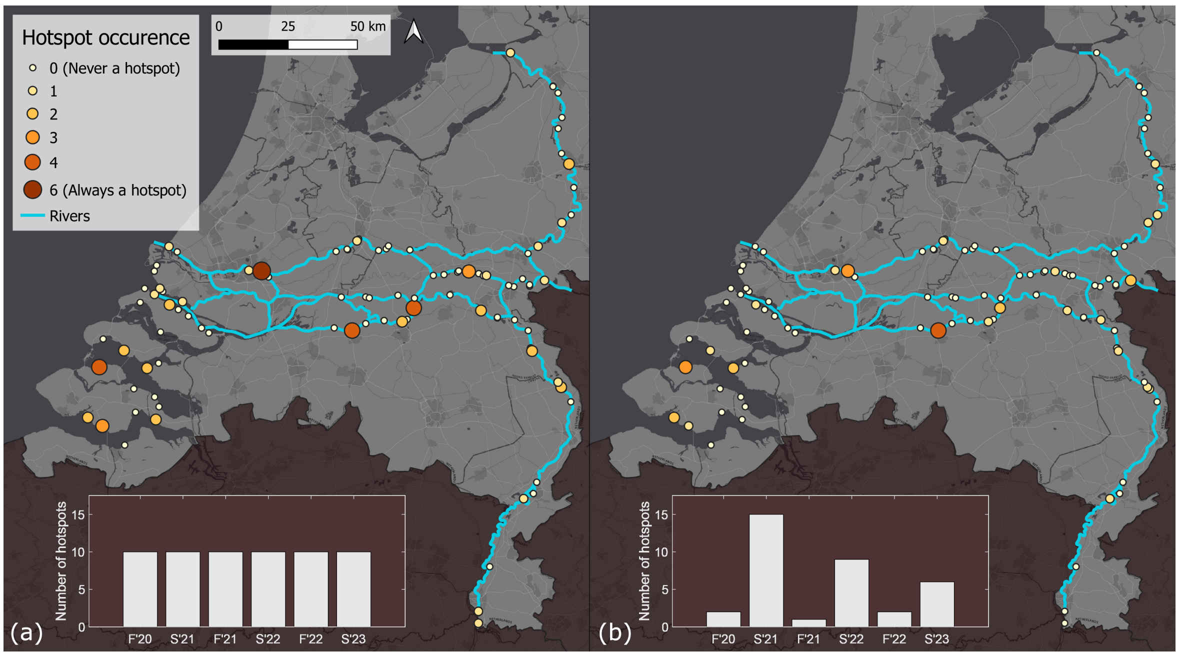

Figure 4: Temporal differences and consistency of hotspot occurrence of plastic pollution along Dutch riverbanks between Fall (F) 2020 and Spring (S) 2023. (a) Shows the hotspots defined according to values above the 90th percentile, resulting in ten hotspots for each monitoring round. (b) Shows the hotspots using an arbitrary threshold, in which hotspots are locations with >500 monitored plastic items per 100-meter riverbank, resulting in a different number of hotspots for each monitoring round. Basemap: Esri, HERE, DeLorme, MapmyIndia.

averaged over time. By using time-series data, for instance, twenty years of beach plastic litter data (Grundlehner et al., 2023), emerging hotspots can be identified and the evolution of previously identified ones can be tracked (Piacenza et al., 2015). Monitoring pollution hotspots over temporal timescales helps to distinguish between short-term fluctuations such as floods (van Emmerik et al., 2023) or areas in which pollution is recurring and consistent, such as accumulation zones (Schwarz et al., 2019; van Emmerik et al., 2022b). The latter may contribute to the efficient allocation of resources and cleanup practices. For instance, areas that are characterized by consistent hotspots may require continuous monitoring and a sustained allocation of resources, whereas regions experiencing occasional hotspots might demand more targeted interventions during peak pollution periods. Hotspot monitoring over time might benefit from utilizing a fixed threshold as opposed to statistical thresholds. Statistical thresholds such as "above average" and "values in the top percentile" will always lead to hotspots, even when litter abundance can reduce over time due to targeted cleanups. In these situations, using a definition that can result in the absence of hotspots might better describe the limited level of pollution. Lastly, monitoring the change of hotspots over time allows the determination of how effective specific mitigation measures are once implemented.

4.2 Qualitative elements and non-measurable components

Within plastic pollution research, the identification of hotspots has initially been associated with quantitative measurements, reporting either an abundance, density, or concentration of pollution in aquatic compartments. Yet, as introduced by Boucher and Initiative (2020) hotspots can encompass qualitative and non-measureable components that contribute significantly to their characterization and complexity. While quantitative data remains fundamental in hotspot identification, qualitative aspects play a vital role in understanding the broader context of sources, sinks, and dynamics and their impact on the environment and communities. For example, the quality of waste management infrastructure, recycling capacities, or the frequency of (informal) cleanups can have a critical influence on plastic leakage and abundance (Boucher and Initiative, 2020; Mihai et al., 2021). The latter can also influence the definition of hotspots, for instance when a criterion is required that hotspot locations have good access to infrastructure or are easily accessible for waste management personnel. Other non-measurable components that potentially influence hotspots include societal attitudes, local policies, and cultural practices. Therefore, Boucher and Initiative (2020) recommends formulating "actionable" hotspots to provide a comprehensive view of hotspots across the plastic value chain. These actionable hotspots should concisely specify the type of plastic involved, identify the expected source of leakage, and pinpoint potential key drivers for leakage within the waste management system. By combining measurable data with qualitative insights and non-measurable components, an integrated perspective emerges that fosters more efficient decision-making and facilitates targeted interventions.

4.3 Recommendations for future efforts

We recommend using the term "hotspot" in an explicit and meaningful way that is tailored to specific research objectives or demands for management strategies. While some studies report a detailed definition of hotspots, it is frequently employed in an imprecise manner as an evocative term to draw attention to a study (Lessler et al., 2017). Therefore, we propose a step-wise framework, which includes five main steps to use hotspots in plastic pollution research. These steps are 1) define the purpose, 2) determine units of interest, 3) determine the spatial scale, 4) determine the temporal scale, and 5) determine and report threshold values (Figure 5).

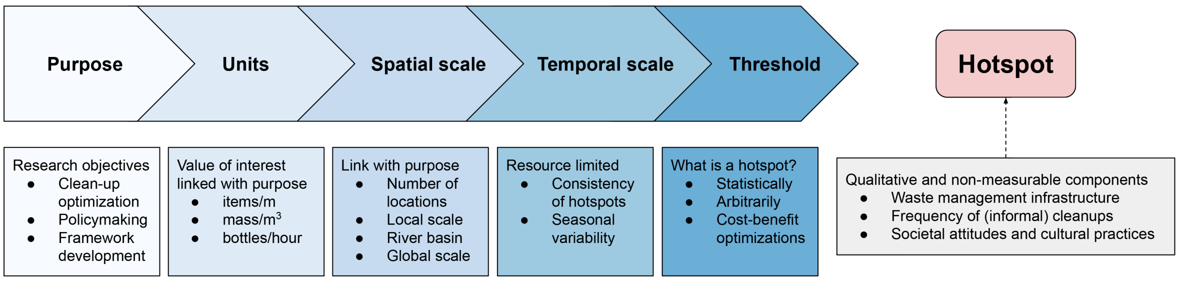

Figure 5: Framework with the recommended steps to be taken when using the term "hotspot" in plastic pollution research. The terms in bullet points are possible definitions for each step and are not limited to these examples.

1. **Define the purpose of hotspot mapping.** Before proceeding with hotspot identification, the research objectives and intended use of the hotspot data should be clearly defined. For example, the purpose could be to prioritize resource allocation for clean-up efforts (Prata et al., 2019). Another purpose could be to guide (international) policymaking and unified frameworks to target the most effective mitigative actions (Boucher and Initiative, 2020). Defining the purpose allows subsequent hotspot definitions to align with desired outcomes. While a unified hotspot definition is useful in terms of comparability, the purpose of the research might require specific definitions that differ.

2. **Determine units of interest** Next, appropriate units that align with the purpose of hotspots should be defined. For example, when a clean-up effort is designed to reduce the abundance of plastic mass on riverbanks, an appropriate unit would be [kg/m^2 riverbank]. Another purpose could focus very specifically on identifying the transport of PET bottles, in which the appropriate unit could be [PET bottles/hour] flowing past a measurement location. By selecting the correct units, goals linked to the purpose of hotspots will be measurable and quantifiable.

3. **Determine the spatial scale.** As evident from the results presented here, a specific hotspot definition might contain an entirely different percentage of the total pollution for datasets with other spatial extents. When assessing hotspots on a local scale, the number of included locations can be relatively low (Vriend et al., 2020), whereas achieving a more comprehensive understand-

ing of hotspots on (multi) river basin scales or even global scale, the number of required sampling sites increases.

4. **Determine the temporal scale.** Assessing whether hotspots are persistent or transient might be relevant in the formulation of effective management strategies. Seasonal variability, floods, and various hydrodynamic conditions might all influence the abundance and accumulation of plastic in aquatic environments (Cheung et al., 2016; van Emmerik et al., 2023; Roebroek et al., 2021). Therefore, reporting the temporal scale (period, frequency, structure, and duration) is key to assessing whether hotspots are consistent through time, or whether they are just temporary as a result of specific or unique events. This assessment could be resource-limited, especially when (pilot) monitoring efforts have limited funds available to facilitate high-frequency monitoring.

5. **Selecting and reporting the threshold values.** Lastly, researchers and policymakers need to establish and report threshold values in a transparent way that is based on sound scientific reasoning. They can be chosen arbitrarily, statistically, or result from complex cost-benefit optimizations. For example, Christensen et al. (2021) introduced and illustrated a spatial cost-benefit optimization framework allowing the prioritization of limited cleanup efforts of plastic pollution, maximizing the environmental benefits. Another example includes a threshold that could be directed by the development of a global legally binding treaty by the UN to end plastic pollution (March et al., 2022). Such treaties would incentivize policymakers to first target the most heavily polluted hotspots on multiple spatial scales with limited resources, influencing the threshold of when a location is classified as a hotspot.

Conclusion

Hotspots in plastic pollution research and policymaking are often used to highlight areas in which plastics are concentrated and should be prioritized in monitoring, prevention, and reduction actions. Yet, the definition and characterization of key aspects related to plastic hotspots is often lacking or inconsistent, without a clear purpose and boundaries of the term. Here, we compared different quantitative ways of how hotspots can be defined, and shown they vary significantly on four different spatial scales ranging from urban to global datasets. All hotspot definitions combined encompass between 0.8-93.3% of the total pollution, distributed across <0.1-50.3% of the total locations. Furthermore, we highlighted hotspots can be dynamic over time, in which the temporal consistency varies greatly per monitored location. Classifying hotspots appropriately is particularly relevant for resource allocation and management strategies to target pollution hotspots. Therefore, we designed a five-step framework for defining hotspots in plastic pollution research. By determining the purpose, units, spatial scale, temporal scale, and threshold values, hotspots are defined in an explicit and meaningful way that is suitable for specific research objectives or management strategies. Ultimately, the ability to define, target, and address plastic hotspots effectively is necessary to safeguard our environments and ecosystems and achieve the ambitions to end plastic pollution.

Author Contributions

Conceptualization, PT, TvE, PV, RH, YM; Data curation, PT; Formal analysis, PT; Funding acquisition TvE, MvdP; Investigation, PT; Methodology, PT, PV, TvE, MvdP; Resources, TvE; Supervision, TvE, MvdP; Visualization, PT; Writing – original draft, PT; Writing – review & editing, All authors.

Declaration of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Funding

The work of PT was supported by the project Solving the Urban Plastic Soup, which is (partly) funded by the the SESA programme (Subsidie Economische Structuur en Arbeidsmarktversterking) of the City of Amsterdam, the directie Stadswerken (Programma Plastic Smart City) of the City of Amsterdam, the Netherlands Ministry of Infrastructure and Water Management, Directorate-General for Public Works and Water Management (Rijkswaterstaat), and Waternet. The work of MvdP was supported by the 4TU.Federation Plantenna project. The work of TvE was supported by the Veni research program The River Plastic Monitoring Project with project number 18211, which is (partly) funded by the Dutch Research Council (NWO).

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Appendix

Figure 6: 150 locations within the historic city center of Amsterdam in which the abundance of plastic pollution was monitored using the River-OSPAR item categorization. The data sheet is available online (https://doi.org/10.4121/6ee9946f-9ff5-4019-9d91-03e1c5283210) (Tasseron et al., 2023b). Basemap: Esri, HERE, DeLorme, MapmyIndia.