Understanding Microplastics Discourse Through Social Sensing: Insights from Geotagged Social Media

Tracking Microplastics Discourse with Social Sensing

Xi Gong[1,2,*], Parastou Fahim[3], Yujian Lu[4], Zhenlong Li[5], Yan Lin[5,6], and Joseph Hoover[7]

[1] Department of Biobehavioral Health, The Pennsylvania State University, University Park, PA 16802, USA

[2] Institute for Computational and Data Sciences (ICDS), The Pennsylvania State University, University Park, PA 16802, USA

[3] Department of Electrical Engineering and Computer Science, The Pennsylvania State University, University Park, PA 16802, USA

[4] Department of Geography & Environmental Studies, University of New Mexico, Albuquerque, NM 87131, USA

[5] Department of Geography, The Pennsylvania State University, University Park, PA 16802, USA

[6] Social Science Research Institute (SSRI), The Pennsylvania State University, University Park, PA 16802, USA

[7] Department of Environmental Science, University of Arizona, Tucson, AZ 85721, USA

*Corresponding author

Email: xigong@psu.edu (XG)

Abstract

Microplastics have emerged as a growing global environmental and public health concern due to their widespread presence and increasing potential for human exposure through food, water, and air. Recent scientific evidence and expanding media coverage have heightened public awareness and debate surrounding their ecological and health impacts. However, a systematic understanding of how public attention and discourse related to microplastics vary across time and regions remains limited. Social sensing provides a promising framework to address this gap by leveraging large-scale digital trace data to capture collective attention and perception. This study analyzed geotagged microplastics-related tweets between 2017 and 2022 to characterize spatiotemporal patterns of public attention, dominant themes, and sentiment across global and regional contexts. Using an integrated spatiotemporal and content-based approach, we identified shifts in discussion intensity, thematic emphasis, and regional engagement, and examined their associations with local sociodemographic characteristics. Results show that public attention follows an issue-attention cycle rather than a steady increase. Three dominant themes emerged: Advocacy, Risk and Exposure, and Scientific Communication, with advocacy-related discussions consistently dominant. Across all themes, the proportion of neutral tweets declined over time, suggesting a shift toward more evaluative and opinion-oriented discourse. In the United States, neutral-sentiment discourse exhibited significant spatial heterogeneity and varies with education, race/ethnicity, and income. Overall, this study presents a scalable social sensing framework that leverages geotagged social media big data to track how environmental issues are discussed across time and space, with broader applications for studying public communication related to other emerging and controversial issues.

Keywords: microplastics, social media, social sensing, spatiotemporal analysis, public discourse, spatial heterogeneity.

Introduction

Plastic production has increase significantly over the last 70 years because plastics are inexpensive, durable, and resistant to corrosion, which makes them widely used in everyday applications such as packaging, food services, construction, and personal-care products (1–4). As plastic waste accumulates in the environment, it fragments into macroplastics (larger items) and microplastics (small particles) (5,6). Microplastics (MPs) are generally defined as synthetic polymer particles smaller than 5 mm (7). They originate from both primary sources and secondary sources: primary microplastics are intentionally manufactured at small sizes and released directly (e.g., microbeads and industrial pellets), while secondary microplastics form through the fragmentation of larger plastic items via weathering and aging processes accelerated by ultraviolet (UV) radiation, thermal oxidation, and mechanical abrasion (2–4). Microplastics also vary in polymer composition, with common types including polyethylene (PE), polypropylene (PP), and polystyrene (PS) (8–10). Microplastics have now been detected across marine, terrestrial, and atmospheric environments (7–11), including remote regions such as Arctic sea ice (12). Their widespread distribution creates multiple potential human exposure pathways, including ingestion through food and drinking water and inhalation via air (13). As scientific evidence of environmental persistence and potential health implications accumulates, microplastics have increasingly become not only an environmental pollution issue but also a subject of public debate, media attention, and policy discussion (8,14–17).

Understanding how environmental risks are perceived, interpreted, and communicated is critical because public perception influences behavioral responses, regulatory support, and broader governance processes (18–20). Prior work has examined public perceptions of microplastics through survey- and interview-based studies, as well as analyses of traditional media coverage, with an emphasis on awareness levels, perceived environmental and health risks, and willingness to support mitigation or policy (21–25). These studies provide important contextual depth. For example, Cammalleri et al. surveyed future public-health professionals at Sapienza University of Rome to assess baseline knowledge and concern, and then reassessed awareness after exposure to an informational brochure on microplastics, demonstrating how survey designs can capture both initial perceptions and changes in awareness or concern following targeted communication (21). A face-to-face survey in coastal Bangladesh applied an ordered logistic regression model to examine willingness to restrict microplastics pollution and its predictors, finding low baseline awareness and variation in readiness to act across demographic and household characteristics as well as familiarity with plastics and microplastics (26). In Nigeria, survey evidence from stakeholders around Lagos Lagoon reported relatively high awareness but limited knowledge and weaker perceived ecological and health implications, although respondents expressed willingness to learn more and support cleanup and advocacy efforts (27). One study combined expert interviews with analysis of Reddit discussions (seven Reddit posts and 781 associated comments) to examine perceptions of microplastic and nanoplastic pollution across Canadian provinces and sectors (25). Another study used print media coverage of microplastics in Germany to analyze public environmental and health concerns related to microplastics from 2004 to 2018 (22). Cross-national qualitative studies have also examined how people reason about microplastics and how this reasoning differs across contexts. Cross-national interview research in Germany and Italy applied a mental-models approach to explore how citizens construct perceptions of microplastics risks, emphasizing the importance of communicating scientific uncertainty and clarifying potential environmental and health impacts (24).

Although these approaches provide valuable and often in-depth insights, many are constrained by sample size, cross-sectional designs, or geographically specific case studies. As a result, they face limitations in capturing how public discourse evolves over time and varies across spatial contexts. Moreover, since microplastics are largely invisible in everyday experience, public understanding is shaped primarily through mediated information such as news coverage, institutional communication, and online discussion rather than through direct personal experience (14,15,28). This situation highlights a broader methodological challenge: how can researchers systematically capture and interpret large-scale, geographically distributed discourse as it evolves over time?

In recent years, the increasing availability of digital trace data has enabled new approaches to studying public discourse. Social sensing provides a conceptual and analytical framework that treats user-generated digital content, typically from social media platforms, as distributed sensors of social processes (29). By aggregating large volumes of time-stamped and, in some cases, geo-referenced content, social sensing allows researchers to examine temporal trends, sentiment dynamics, thematic structures, and spatial heterogeneity in public discussion. In this framework, social media platforms function as socio-technical infrastructures through which public discussion is expressed and circulated, enabling researchers to examine discourse dynamics at scales that are difficult to achieve with traditional methods (15). As Web 2.0-based systems, they support the creation and exchange of user-generated content, with some platforms incorporating georeferenced information that facilitates spatial pattern exploration (30–32). Compared with conventional data sources, social media data offer lower acquisition costs, near–real-time availability, and larger, more diverse samples (30). Twitter (now X) is particularly well suited for public discourse research due to its rapid information diffusion, standardized short-text format, and interaction mechanisms such as retweeting and following (33). Geotagged tweets add an explicit spatial dimension to online discourse, enabling researchers to link what people say with where and when they say it. As a result, geotagged tweets have been widely applied in event detection, topic identification, perception measurement, and spatial behavior analysis at large scales (34–38). Collectively, these studies demonstrate the utility of georeferenced social media data as a scalable empirical foundation for analyzing public discourse across temporal and spatial dimensions.

Despite these advances, applications of social sensing to microplastics remain limited. More broadly, there remains a need for systematic approaches that can capture how public discourse evolves across time and geographic contexts using large-scale digital trace data. In this study, we implement a social sensing framework that integrates temporal analysis, sentiment classification, thematic clustering, and spatial modeling to examine patterns of public discourse. Social sensing serves as the conceptual foundation of the study, while social media data provides empirical observations used to operationalize the framework. Specifically, this study addresses the following research question: how does microplastics-related discourse evolve across time and geographic contexts? Using geotagged microplastics-related tweets posted between 2017 and 2022 as a demonstration case, the framework enables us to (1) characterize temporal fluctuations in public attention, (2) examine sentiment shifts across space and time, (3) identify dominant themes in the discourse, and (4) analyze spatial heterogeneity in public sentiment and its association with regional sociodemographic characteristics. By integrating these components, the study advances understanding of public discourse on microplastics while demonstrating a generalizable approach for studying other emerging or controversial social, environmental, and public health issues.

The remainder of this paper is organized as follows. Section 2 describes the data and preprocessing. Section 3 presents the integrated analytical approach. Section 4 reports the results and related discussions. Section 5 concludes with key findings as well as implications and limitations.

Data Collection and Preprocessing

This study used a multilingual dataset of geotagged tweets discussing microplastics collected worldwide between 2017 and 2022. The geotagged tweets were collected worldwide using the Twitter Application Programming Interface for Academic Research (API v2) (39) between 2017 and 2022 in previous work (40). From this global corpus of geotagged tweets, we filtered the dataset using a curated multilingual lexicon of microplastics-related terms as keywords (Table S1). The inclusion lexicon covered core microplastics-related terms and their common variants (e.g., microplastic(s), nano-plastic(s), meso-plastic(s), including plural and hyphenated forms), frequently referenced sources and forms (e.g., microbead(s), nurdles, plastic/resin pellets, fragments, fibers/fibres, films, and foams), and commonly used advocacy hashtags and concatenated variants (e.g., #banmicrobeads, #stopmicroplastics, #breakfreefromplastic, plasticpellets) across multiple languages. To further improve precision, contextual exclusion patterns were applied to remove systematic false positives associated with unrelated uses of terms such as “plastic” and “glitter,” including references to toys and models, cosmetics and beauty content, plastic surgery, and other recurring non-environmental themes.

After filtering, standard text preprocessing steps were applied to prepare the dataset for analysis. URLs and user mentions were removed, hashtag markers were stripped while preserving lexical content, text was converted to lowercase, and common stopwords (e.g. the, a, an, is, are, that) were removed to reduce noise and improve downstream topic and sentiment analysis. The final dataset consists of 19,751 unique geotagged tweets from 139 countries that directly reference microplastics across environmental, social, health-related, and policy contexts.

Methodology

Building on the social sensing framework introduced above, we operationalize the analysis using geotagged social media data to examine temporal trends, thematic structures, sentiment patterns, and spatial heterogeneity in microplastics-related discourse.

To characterize temporal dynamics, geotagged microplastics-related tweets were aggregated by calendar year (2017–2022). Annual tweet counts were used to examine fluctuations in discussion intensity and identify periods of increased or decreased attention. This aggregation provides a consistent temporal scale for comparing discourse trends across years and geographic regions.

To assess the emotional tone of microplastics-related discourse, we conducted sentiment analysis on the tweet corpus using a multilingual transformer model fine-tuned for Twitter sentiment classification (CardiffNLP Twitter-XLM-RoBERTa-base-sentiment) (41).

The model was trained on eight languages (Arabic, English, French, German, Hindi, Italian, Spanish, and Portuguese) and classifies tweets into negative, neutral, or positive categories. Because language tags were missing for some tweets in the dataset, we re-estimated the language of each tweet using the lingua-language-detector library (42), which provides probabilistic identification across a wide range of languages. The resulting distribution shows that English, Spanish, German, French, Italian, and Portuguese together account for over 91% of the dataset. Since these languages are among the eight languages used to fine-tune the sentiment model, the model is well aligned with the language profile of the dataset. For subsequent analysis, the three sentiment categories were further aggregated into a binary indicator distinguishing neutral tweets, which generally represent informational content, from non-neutral tweets that express an evaluative stance or emotional response in either positive or negative form.

To examine how microplastics are framed in online discussions, we analyzed frequently used words and hashtags and constructed a term co-occurrence network. Terms that frequently appear together were grouped using the VOS clustering algorithm implemented in VOSviewer (43). This approach identifies clusters of related terms that represent dominant discussion themes within the dataset. To track how these themes evolve over time, we calculate yearly percentages of tweets associated with each cluster from 2017 to 2022.

To explore spatial heterogeneity in microplastics-related discourse, we focus on state-level variation within the United States and link geotagged tweets to sociodemographic indicators from the U.S. Census Bureau. Comparable census-based sociodemographic indicators are not consistently available worldwide at a similar geographic resolution, so the spatial analysis is restricted to the United States. State-level variables for 2022 were obtained from the U.S. Census Bureau and include gender ratio, educational attainment, racial and ethnic composition, age structure, unemployment rate, and per capita income. To mitigate multicollinearity among covariates, we conducted a variance inflation factor (VIF) analysis and excluded highly correlated variables, including non-Hispanic White population percentage, population aged 18 and younger, and poverty rate. The remaining indicators were used as explanatory variables in a geographically weighted regression (GWR) model to evaluate how local sociodemographic and demographic characteristics are associated with the spatial variation in the distribution and sentiment of microplastics-related tweets across U.S. states.

Results and Discussion

Temporal and Spatial Patterns of Microplastics Tweets

Our findings are derived from 19,751 geotagged tweets discussing microplastics between 2017 and 2022. The geographic distribution of these tweets reveals a highly uneven spatial footprint. Geotagged tweets are concentrated in North America and Europe, while many countries in the Global South show relatively low activity in microplastics-related tweets in (Fig 1). Europe accounts for approximately 44% of tweets and the United States 28%, making these two regions the dominant contributors to the dataset. This pattern likely reflects differences in internet access, platform use, language coverage, and the likelihood that users enable geotags, rather than the true geographic distribution of microplastic pollution (44). Analyses based on geotagged tweets inevitably reflect sampling biases related to platform use and location-sharing behavior (45). Nevertheless, they provide a useful observational window into where microplastics-related discussions are most visible on Twitter platform.

Fig 1. Global distribution of geotagged microplastics-related tweets by country

We next examine temporal trends in tweet activity across Europe, the United States, and the global datasets. Globally, tweet volume fluctuates over time rather than following a steady upward trend (Fig 2). Periods of increased activity likely correspond to bursts of public attention driven by media coverage, scientific publications, or advocacy campaigns related to plastic pollution. Tweets geotagged to the United States also exhibit broadly similar temporal patterns, with the highest tweet volume observed in 2019. This pattern is consistent with the issue-attention cycle often observed in environmental discourse, where public attention rises rapidly around particular events and then declines (46). Together, the spatial distribution and temporal trends establish the basic footprint of the dataset and provide context for examining how microplastics are discussed on social media.

Fig 2 Annual volume of geotagged microplastics-related tweets (2017–2022) globally, in the U.S., and in Europe

Sentiment Dynamics of Microplastics Tweets

Across the full dataset, 50.0% of tweets are classified as neutral, while the remaining 50.0% expresses non-neutral sentiment (either positive or negative). Within this non-neutral subset, sentiment is predominantly negative, with 32.5% of all tweets classified as negative and 17.5% as positive. Nonetheless, these polarity labels should be interpreted with caution because they do not necessarily reflect attitudes toward microplastics themselves. Positive sentiment may reflect optimism about solutions or mitigation efforts, while negative sentiment might capture concern, urgency, or criticism related to environmental impacts. As a result, we focus primarily on the neutral versus non-neutral distinction, which differentiates informational tweets from those expressing an evaluative stance.

Globally, the share of neutral tweets declines over time, suggesting that discussions increasingly express opinions or emotional reactions rather than remaining purely descriptive (Fig 3). Although the pattern is not strictly monotonic, with a brief increase in neutrality around 2020, the overall trend indicates a gradual shift toward more evaluative discourse. This variability is consistent with the event-driven dynamics of social media communication; specifically, bursts of advocacy, media coverage, or public campaigns can temporarily amplify emotional or opinionated discourse (47,48). Changes in the composition of participating users may also contribute to these fluctuations (49), as advocacy-oriented participation can reduce neutrality in some periods while informational content increases it in others.

Fig 3 Annual proportion of neutral microplastics-related geotagged tweets (2017–2022) globally, in the U.S., and in Europe

Thematic Structure of Microplastics Discourse

Tables Table **1** summarize the top 15 most frequent terms (e.g., microplastic, plastic, pollution, water, and ocean) and hashtags (e.g., #plasticpollution, #plasticfree, #breakfreefromplastic), providing a descriptive overview of the corpus. The prevalence of terms and hashtags related to pollution, oceans, and plastic-reduction campaigns suggest that many discussions are framed around environmental impacts and advocacy.

Table 1 Top 15 most frequent terms and hashtags in microplastic-related tweets

Term	Frequency	Hashtag	Frequency
microplastic	12,056	#microplastic	4152
plastic	9339	#breakfreefromplastic	1301
micro	2983	#plasticpollution	858
water	1762	#plastic	795
ocean	1754	#microbead	391
microbead	1520	#plasticfree	322
breakfreefromplastic	1240	#pollution	261
pollution	1207	#environment	226
film	988	#ocean	216
environment	900	#beachcleanup	168
found	884	#sustainability	133
plasticpollution	859	#zerowaste	128
food	740	#climatechange	125
beach	715	#beach	118
time	671	#singleuseplastic	110

While frequency statistics provide a descriptive overview of commonly used terms, they do not reveal how words are connected within broader narratives. The co-occurrence network of frequently used terms helps identify groups of words that frequently appear together, representing dominant themes in the discourse. The network reveals three major clusters of discussion: Advocacy, Risk and Exposure, and Scientific Communication (Fig 4). The first cluster (Advocacy) reflects activism and public advocacy, characterized by terms such as breakfreefromplastic, plasticfree, and ban, which emphasize campaigns and behavior-change initiatives. The second cluster (Risk and Exposure) focuses on exposure pathways and environmental or health impacts, including terms such as ocean, water, food, human, and health. The third cluster (Scientific Communication) reflects scientific investigation, containing terms such as research, science, sample, and paper, which correspond to tweets sharing research findings or scientific reports about microplastics. These clusters provide a higher-level interpretation of the discourse structure and align with the themes suggested by the most frequent words and hashtags.

Fig 4 Co-occurrence network of frequently used terms in microplastics-related tweets

Fig 5 further illustrates the annual proportion of tweets associated with each cluster, both globally and through a comparison between the United States and Europe. Globally, the advocacy cluster consistently represents the highest percentage of tweets across the study period (Fig 5a). This dominance likely reflects the tendency for microplastics to be framed on social media within broader plastic pollution debates, where mobilization and policy-oriented messaging are common. Prior studies of plastic and marine plastic discourse on Twitter similarly report that campaign-style messaging and “call-to-action” vocabulary (e.g., plasticfree, plasticpollution, bans, and organized hashtag campaigns) are highly prevalent and often structure online conversations around plastics (48,50,51).

Fig 5b compares theme distributions between the United States (solid lines) and Europe (dashed lines). Europe consistently shows a lower proportion of tweets in the Advocacy cluster than the United States, suggesting relatively less campaign-oriented messaging in the European subset. The Risk and Exposure cluster exhibits similar proportions in both regions in 2017, but after 2018, the United States generally shows a higher proportion than Europe, indicating greater emphasis on environmental and health-related risk discussions. The Scientific Communication cluster remains relatively small in both regions during 2017–2018 but diverges in 2019 when the United States shows a noticeable increase before declining again toward 2022. This temporary divergence may reflect heightened attention to scientific findings or media reporting on microplastics research during that period. These patterns indicate that the dominance and temporal dynamics of microplastics-related themes vary between the United States and Europe, suggesting regional variations in how the issue is discussed and framed on social media.

(a) (b)

Fig 5 Annual percentage of tweets assigned to each theme cluster. (a) Worldwide dataset; (b) Comparison between the United States and Europe

To further examine how sentiment interacts with topic structure, we compute the annual proportion of neutral tweets within each cluster (Fig 6). Neutral percentages generally decrease over time in all three clusters, which means that tweets in each cluster increasingly contain evaluative language or expressed opinions (non-neutral) rather than being purely informational. In other words, for the three thematic categories (Advocacy, Risk and Exposure, and Scientific Communication), the tone of discussion becomes progressively more opinionated in online conversations.

Fig 6 Annual percentage of neutral microplastics-related tweets within each topic cluster (2017–2022)

Sociodemographic Drivers of U.S. Microplastics Discourse

Fig 7 illustrates the associations between the proportion of neutral microplastics-related tweets and selected sociodemographic characteristics across contiguous U.S. states. The maps display local t-values from the GWR analysis, where the sign indicates the direction of the relationship and color intensity represents the magnitude of the association. Gray shading indicates statistically non-significant relationships ($p \geq 0.05$).

Fig 7 Associations between the proportion of neutral microplastics-related tweets and selected sociodemographic characteristics across contiguous U.S. states: (a) population without a high school diploma, (b) African American population percentage, (c) Hispanic/Latino population percentage, and (d) per capita income. Gray areas indicate non-significant relationships ($p \geq 0.05$)

Several notable regional relationships emerge from the spatial patterns shown in Fig 7. In several western U.S. states, there is a positive association between the proportion of residents without a high school diploma and the share of neutral tweets (Fig 7a), suggesting that lower educational attainment may be linked to more informational or less opinionated engagement with microplastics discussions. This pattern aligns with previous research indicating that lower science literacy can be associated with less polarized engagement in environmental debates (52,53), although the underlying mechanisms cannot be directly assessed here. In contrast, higher proportions of African American residents are associated with lower shares of neutral microplastics-related tweets in several western states (Fig 7b). This negative association may reflect, in part, greater engagement with environmental risks and justice-related concerns, as suggested in prior studies (54), though these relationships are likely shaped by broader historical and regional contexts. Fig 7c reveals contrasting regional patterns for the Hispanic and Latino population percentage. In western states, higher Hispanic and Latino population percentages are associated with decreased neutral tweet proportions, whereas the opposite pattern appears in several eastern states. These regional differences may reflect variation in regional sociopolitical context and communication environments, particularly differences in Spanish- versus English-language media use, media platform preferences, and information pathways (55), as well as broader contextual factors that shape how environmental issues are interpreted and discussed. Finally, in parts of the western United States, higher per capita income is associated with increased proportions of neutral microplastic-related tweets (Fig 7d). This pattern suggests that higher-income areas may exhibit more informational or observational engagement with microplastics discussions. This pattern may be related to differences in access to information and exposure to technical, scientific, or policy-oriented content (56), although these associations should be interpreted cautiously given the aggregate nature of the data.

Taken together, these findings suggest that sociodemographic characteristics are unevenly associated with patterns of neutral microplastics-related discourse across U.S. states. Associations with education, racial and ethnic composition, and income indicate that local social context may influence whether discussions appear more informational or more opinion driven. The observed spatial heterogeneity highlights the importance of considering geographic and sociodemographic context when interpreting social media signals related to environmental issues.

Study Limitations and Future Research

Interpretation of the findings should consider some limitations related to sampling, measurement, and data availability. First, the analysis relies on geotagged tweets, which represent only a small fraction of all social media posts and are unevenly distributed across users and regions. Consequently, the spatial patterns observed here reflect geotag-enabled participation rather than population-wide public opinion (57,58). Nevertheless, compared to traditional data collection methods, geotagged tweets from social sensing provide useful signals for identifying broad spatial patterns in online discourse when analyzed across large geographic areas and multiple years. Future work could incorporate additional social media platforms or complementary data sources to improve coverage and representativeness.

Second, the sentiment classifier used in this study is a general-purpose model that is not specifically trained on environmental discourse. Although transformer-based models enable scalable analysis of large datasets, some classification uncertainty may remain when applied to domain-specific topics. Future research could improve accuracy by developing domain-specific sentiment classifiers or validating results using manually labeled tweet samples.

Third, linking tweet content with aggregated sociodemographic indicators introduces potential ecological inference limitations, since state-level characteristics may not represent individual users. However, this contextual approach still provides insight into how local social conditions relate to patterns of online environmental discourse. Future work could explore methods for estimating user-level sociodemographic factors while maintaining privacy protections.

Finally, ethical considerations remain important when using publicly accessible social media data. Although tweets are publicly available, they are not necessarily created with the expectation of being used for research. To reduce privacy risks, this study focuses on aggregated patterns rather than individual accounts and avoids quoting identifiable content.

Future work could extend this analytical framework to other controversial environmental topics and public debates across multiple social media platforms. Integrating social media signals with complementary traditional data sources, such as surveys, interviews, news coverage, and policy timelines, would help triangulate findings and better interpret shifts in attention, theme, and sentiment over time. Further research could move beyond observed associations to examine the underlying drivers and mechanisms shaping microplastics-related discourse, including the roles of information exposure, media environments, and communication channels. Such work would help explain regional differences in thematic emphasis and sentiment dynamics.

Conclusion

This study applies a social sensing framework to examine how microplastics are discussed in online public discourse. Using geotagged microplastics-related tweets posted between 2017 and 2022, we combined temporal analysis, sentiment classification, thematic clustering, and spatial modeling to characterize patterns of discussion across time and geographic regions. By integrating these analytical components, the study provides a large-scale empirical perspective on how environmental issues are framed and communicated in social media environments.

Several patterns emerge from the analysis. The geographic distribution of microplastics-related tweets is highly uneven, with discussions concentrated in Europe and the United States. Temporal trends show that online attention fluctuates over time rather than increasing steadily, suggesting that public discourse follows an issue-attention cycle influenced by events such as media coverage, scientific publications, and advocacy campaigns. Thematic analysis identifies three major themes in microplastics discussions: Advocacy, Risk and Exposure, and Scientific Communication. Advocacy-related discussions consistently represent the highest percentage of tweets, highlighting the prominence of environmental campaigns and policy-oriented messaging in social media conversations about microplastics. While these thematic categories remain relatively stable over time, the tone of discussion within each theme becomes increasingly evaluative rather than purely informational. Finally, spatial analysis of data within the United States shows that the prevalence of neutral-sentiment discourse varies geographically and is associated with local sociodemographic characteristics (including education, race/ethnicity, and income), suggesting that regional social contexts influence how environmental issues are discussed on social media.

Together, these findings illustrate the potential of social sensing to capture the dynamics of environmental discourse on microplastics at large spatial and temporal scales. Beyond microplastics, this framework offers a generalizable strategy for studying public communication related to other emerging environmental and societal challenges using social media big data.

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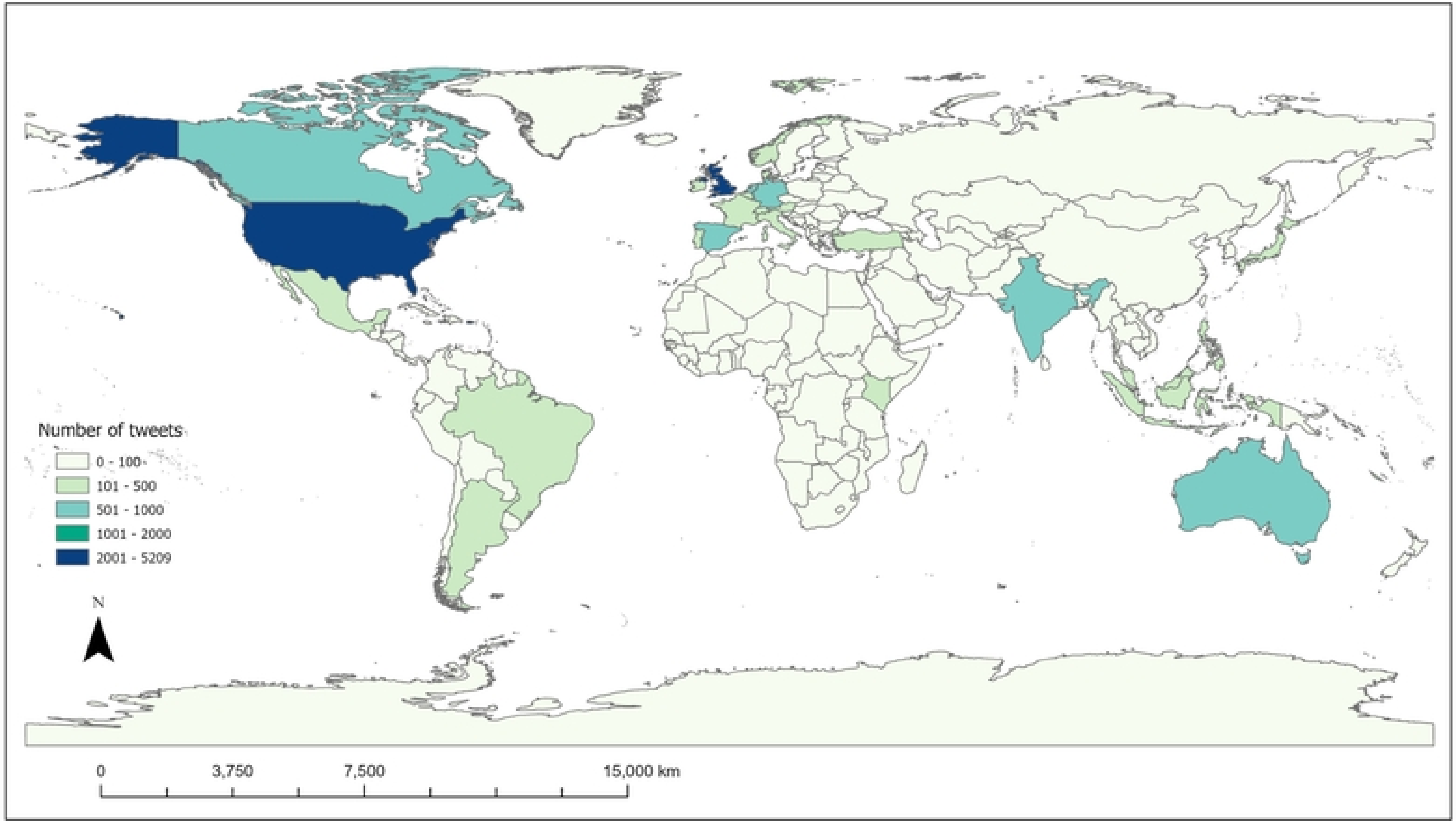
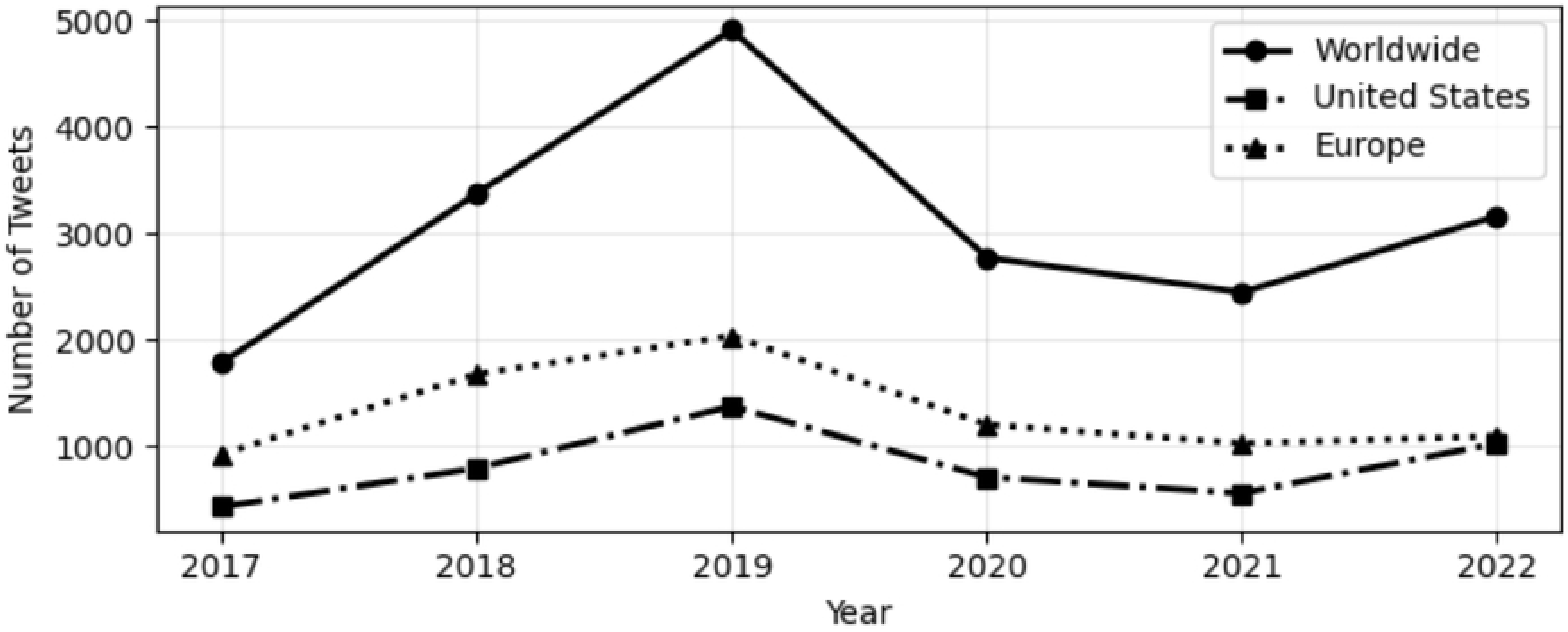
Supporting information

Table S1 Keyword categories for microplastics-related social media data filtering

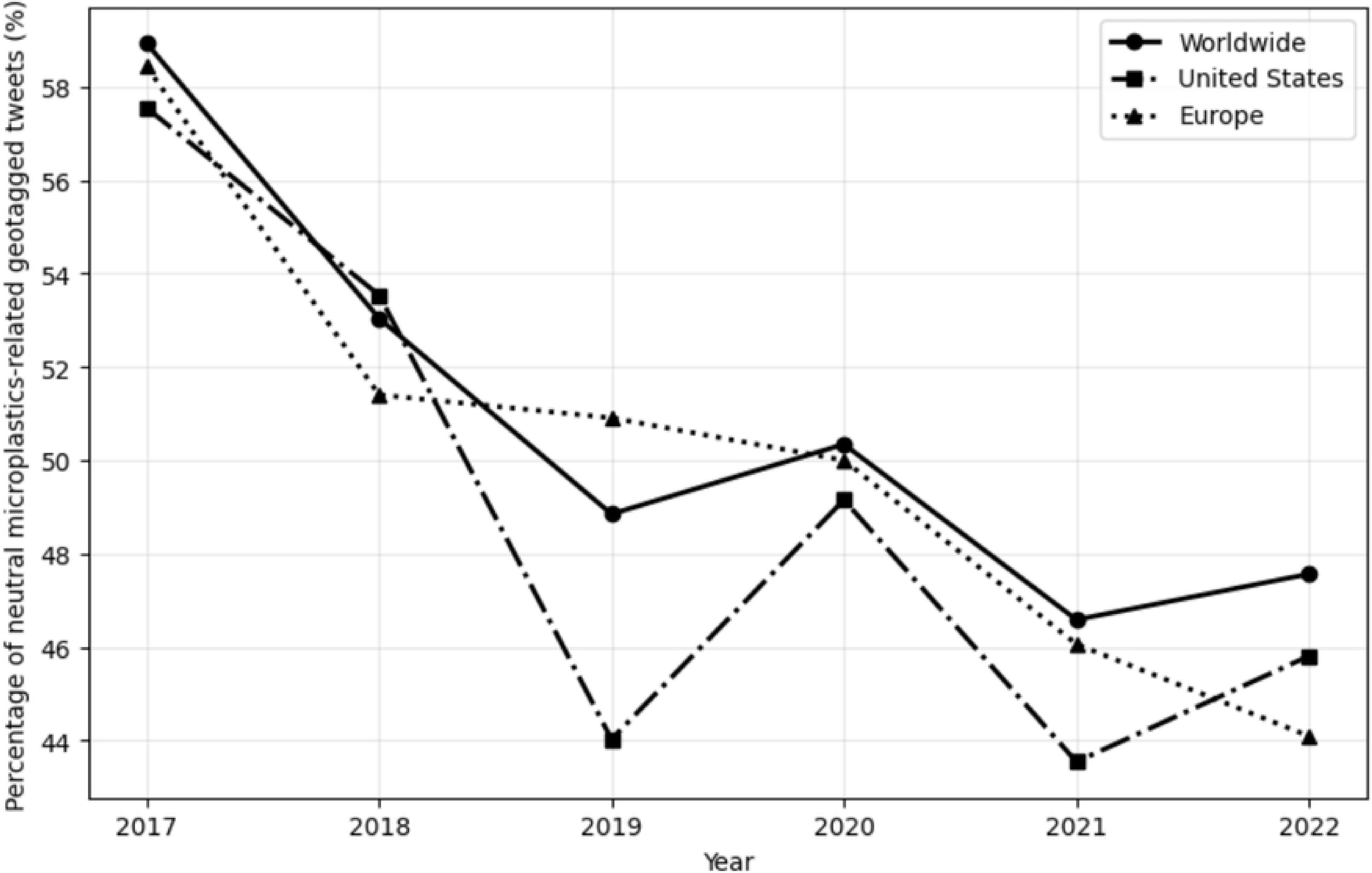

Number of tweets
0 - 100
101 - 500
501 - 1000
1001 - 2000
2001 - 5209
N
0
3,750
7,500
15,000 km

Figure

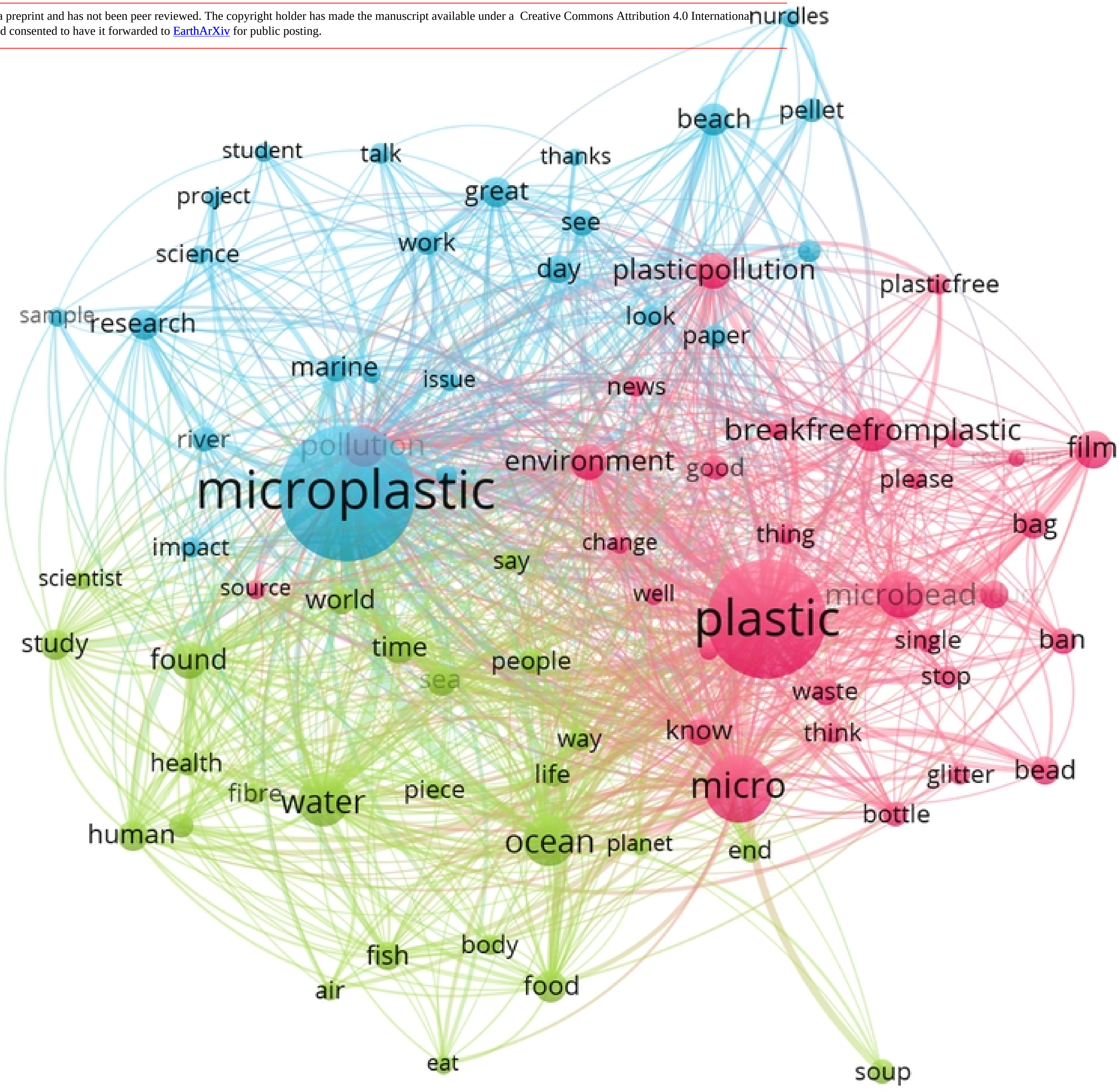


Worldwide
United States
Europe
Number of Tweets
5000
4000
3000
2000
1000
2017
2018
2019
2020
2021
2022
Year

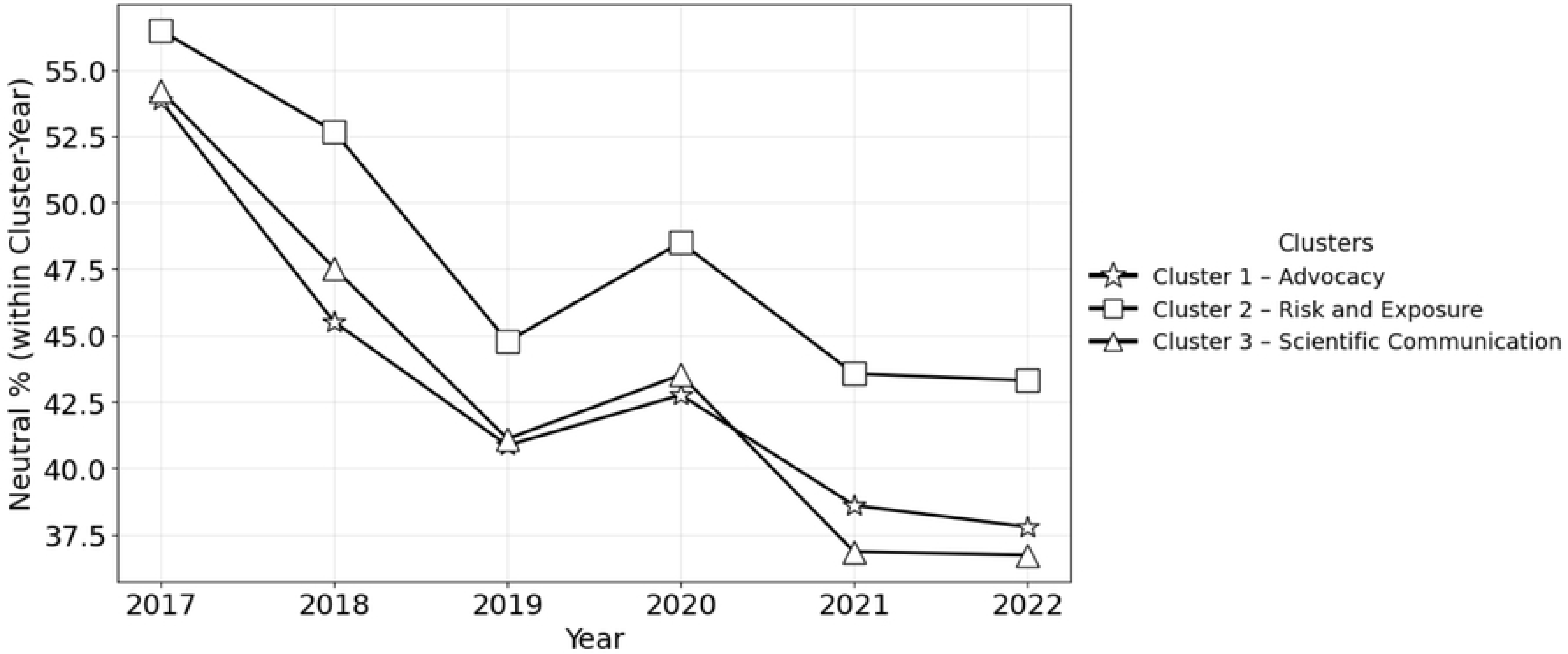
Figure


Worldwide
United States
Europe
Percentage of neutral microplastics-related geotagged tweets (%)
58
56
54
52
50
48
46
44
2017
2018
2019
2020
2021
2022
Year

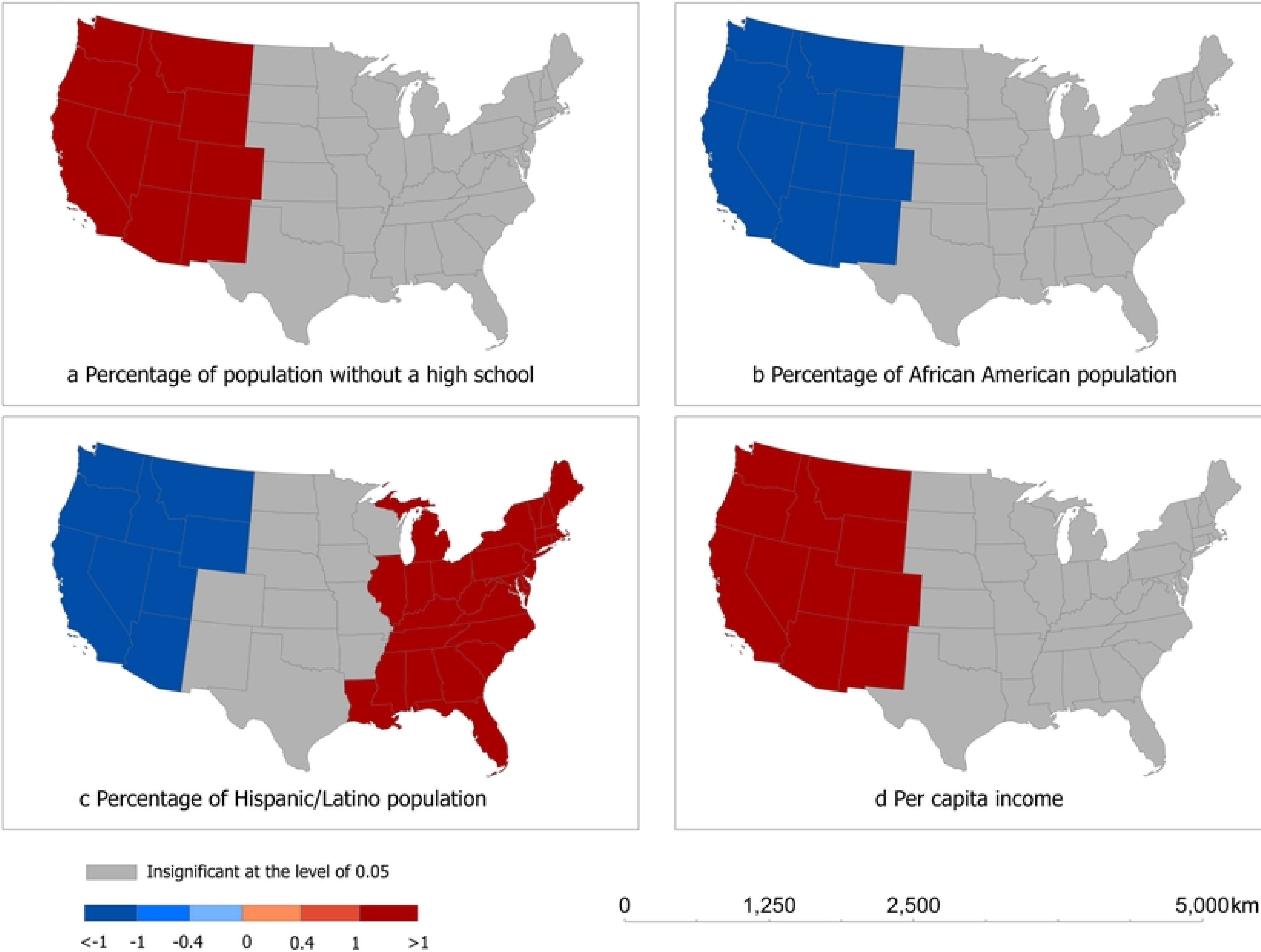
Figure


nurdles
beach
pellet
student
talk
thanks
project
great
see
science
work
day
plasticpollution
plasticfree
sample
research
look
paper
marine
issue
news
breakfreefromplastic
river
pollution
environment
good
film
microplastic
please
impact
change
thing
bag
say
scientist
source
well
microbead
world
plastic
study
single
ban
found
time
people
stop
sea
waste
know
way
think
health
life
glitter
bead
fibre
water
piece
micro
bottle
human
ocean
planet
end
body
fish
food
air
eat
soup

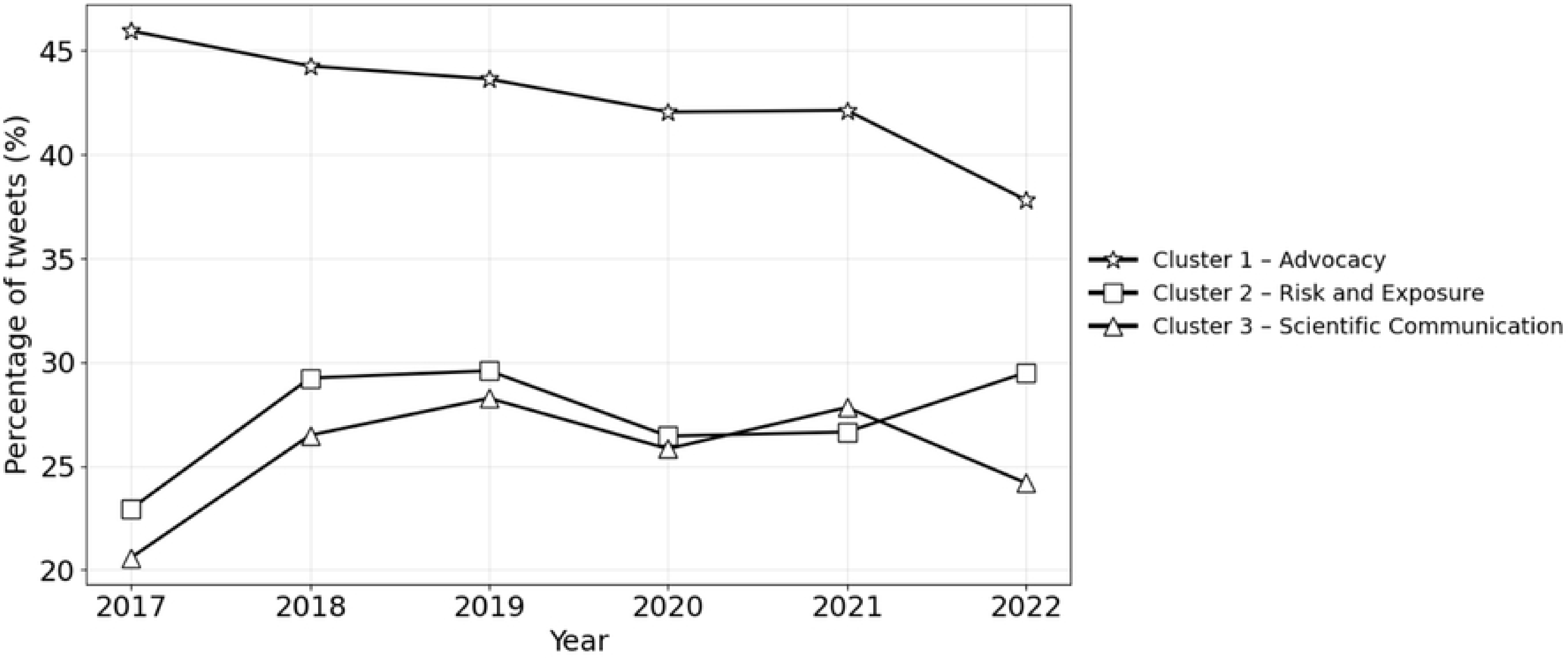
Figure


Neutral % (within Cluster-Year)
55.0
52.5
50.0
47.5
45.0
42.5
40.0
37.5
2017
2018
2019
2020
2021
2022
Year
Clusters
Cluster 1 – Advocacy
Cluster 2 – Risk and Exposure
Cluster 3 – Scientific Communication

Figure

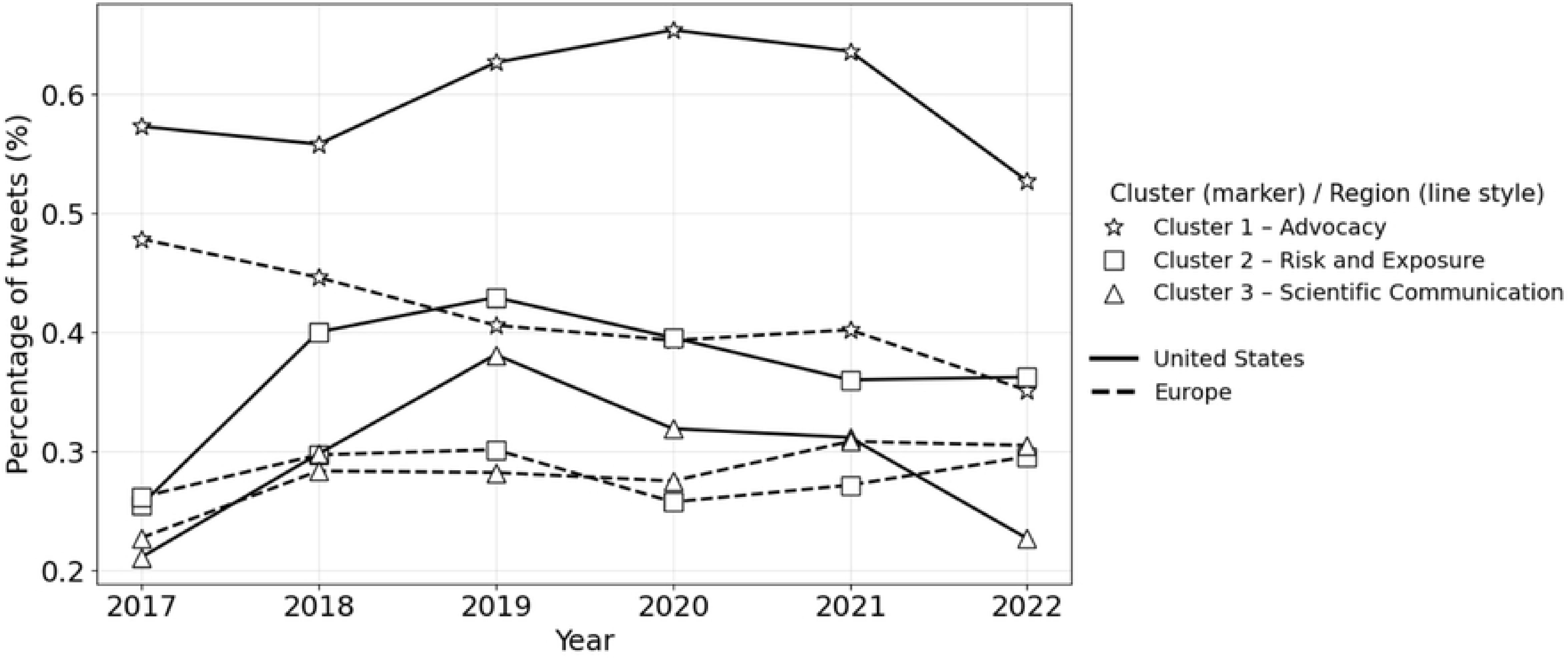

a Percentage of population without a high school
b Percentage of African American population
c Percentage of Hispanic/Latino population
d Per capita income
Insignificant at the level of 0.05
<-1
-1
-0.4
0
0.4
1
>1
0
1,250
2,500
5,000km

Figure



Percentage of tweets (%)
45
40
35
30
25
20
2017
2018
2019
2020
2021
2022
Year
Cluster 1 – Advocacy
Cluster 2 – Risk and Exposure
Cluster 3 – Scientific Communication

Figure



Percentage of tweets (%)
0.6
0.5
0.4
0.3
0.2
2017
2018
2019
2020
2021
2022
Year
Cluster (marker) / Region (line style)
Cluster 1 – Advocacy
Cluster 2 – Risk and Exposure
Cluster 3 – Scientific Communication
United States
Europe

Figure