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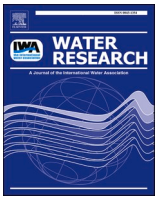

Hot summers raise public awareness of toxic cyanobacterial blooms

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ABSTRACT

Water quality of eutrophic lakes is threatened by harmful cyanobacterial blooms, which are favored by summer heatwaves and expected to intensify with global warming. Societal demands on surface water for drinking, irrigation and recreation are also highest in summer, especially during dry and warm conditions. Here, we analyzed trends in online searches to investigate how public awareness of cyanobacterial blooms is impacted by temperature in nine different countries over almost twenty years. Our findings reveal large seasonal and inter-annual variation, with more online searches for harmful cyanobacteria in temperate regions during hot summers. Online searches and media attention increased even more steeply with temperature than the incidence of cyanobacterial blooms, presumably because lakes attract more people during warm weather. Overall, our study indicates that warmer summers not only increase cyanobacterial bloom incidence, but also lead to a pronounced increase of the public awareness of toxic cyanobacterial blooms.

1. Introduction

Harmful cyanobacterial blooms are a major threat to ecosystem, animal, and human health (Huisman et al., 2018; Chorus and Welker, 2021). Blooms are promoted by eutrophication, and are expected to benefit from climate change, most notably global warming (Paerl and Huisman, 2008; Kosten et al., 2012; Smucker et al., 2021). Many bloom-forming cyanobacteria exhibit high temperature growth optima (Lürling et al., 2013), favoring rapid growth in warm waters. Warming is also expected to increase internal nutrient loading of shallow lakes through increased remineralization rates, further promoting cyanobacterial blooms (Søndergaard et al., 2013). Furthermore, warming may increase water column stability, which can enhance the development and proliferation of cyanobacterial blooms, as many bloom-forming taxa can regulate their buoyancy and thereby competitively exploit incoming light from above and nutrients from below (Jöhnk et al., 2008).

The human health risk of bloom-forming cyanobacteria is associated with their production of toxic secondary metabolites, with dense blooms often leading to high concentrations of these toxins (Chorus and Welker, 2021). Toxic cyanobacterial blooms have a substantial impact on a range of ecosystem services associated with surface waters, including the provisioning of clean water for drinking, fishing, irrigation, and recreation (Janssen et al., 2021). Because of the human health risk associated with cyanobacterial toxins and their disruptive consequences for aquatic system functioning, water quality monitoring programs often include assessment of cyanobacterial biomass or toxin concentrations, leading to management actions when guideline values are exceeded (Chorus and Welker, 2021; Ibelings et al., 2015). Possible actions include the placement of warning signs informing lake visitors about the presence of toxic cyanobacteria, closure of lakes for recreation, bans on aquaculture and fisheries, and implementation of additional treatments for safe drinking water production. These actions will affect public awareness of toxic cyanobacterial blooms, which we define here as the public's general interest to collect information about the existence of cyanobacterial blooms and their associated risks. We expect that public awareness will be raised by the occurrence of cyanobacterial blooms, especially if this involves placement of warning signs and closure of recreational waters.

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Online search engines have become a valuable tool to study public awareness, as they provide long-term data on the public interest in specific topics, cover broad spatial scales, and include many search results. As such, data from search engines have been used for analyzing, tracking, and predicting trends of a wide range of topics in, e.g., economy (Choi and Varian, 2012), epidemiology (Ginsberg et al., 2009), and nature conservation (Burivalova et al., 2018; Nghiem et al., 2016). For example, search data from Google Trends were shown to correlate with various economic indicators, and may possibly support short-term predictions of product sales (Choi and Varian, 2012). Moreover, relative frequencies of Google searches on influenza were correlated with the relative frequencies of influenza-related visits to physicians, and were therefore indicative of weekly influenza activity in each region of the USA (Ginsberg et al., 2009). While using Google search data to forecast influenza outbreaks did not always lead to accurate prediction (Butler, 2013), it still led to promising forecasts when combined with an autoregression model (Yang et al., 2015). Google searches were also shown to closely follow recurrent dynamics of natural events such as elevated levels of pollen and mosquitoes (Proulx et al., 2014), were associated to increased outdoor recreation activities during the COVID-19 pandemic (Armstrong et al., 2022), and have been used as indicators of climate change awareness (Archibald and Butt, 2018). Lastly, a shutdown of drinking water supply in Toledo, Ohio (USA), due to a toxic cyanobacterial bloom in western Lake Erie in 2014, caused a distinct peak in Google searches for 'Toledo water crisis' matching searches for 'algae' (Cha and Stow, 2015).

Here, we test whether public awareness of harmful cyanobacteria, based on online searches, exhibited a seasonal and interannual pattern that matched the occurrence of cyanobacterial blooms. We further assessed how seasonal and annual variation in public awareness of cyanobacterial blooms corresponded to variation in temperature and precipitation. Lastly, we hypothesized that public awareness is influenced directly by the occurrence of cyanobacterial blooms in lakes and indirectly through e.g. media attention (Arlt et al., 2011). We therefore also tested relationships between online searches, the occurrence of cyanobacterial blooms in lakes, and online media coverage.

2. Methods

2.1. Data collection

We used freely available data from the Google Trends website (Google LLC 2023) to explore annual trends in toxic cyanobacteria searches on Google, as this is the most used web search engine globally (Statcounter Global Stats 2022). We collected trend data using the term 'blue green algae', or analogues in various languages (see Table 1), as this is a commonly known term used by the public and media to refer to toxic cyanobacterial blooms. We selected those countries and/or states and periods that returned clear annual patterns. Please note that our intention was not to give a full report on web search results across countries in the world, but rather provide examples of annual recurring trends in searches for cyanobacteria-related terms. Data in Google Trends may show minor day to day variation as it is compiled based on search data using a sampling method (Choi and Varian, 2012). Google Trends only produces numbers for searches above a certain threshold that is set for privacy considerations. Searches in Google Trends are normalized to the highest number of searches found in the requested period. Values thus range from 0 to 100 %, where a value indicated by <1 was set at 0.5. Because several large lakes in China experience annually recurring blooms (Huo et al., 2021), we also recovered search volumes for equivalent search terms in Baidu (Baidu Inc. 2023), as this is the most popular web search engine in China (Statcounter Global Stats 2022). The number of searches from Baidu were normalized to the highest number of searches, similar to Google Trends data.

We also collected monthly mean air temperature and monthly total precipitation data from meteorological stations (Table 1), where changes in air temperature are assumed to reflect changes in water temperature. Stations were selected based on their central location or on their location close to lakes or reservoirs known for their annually recurring harmful cyanobacterial blooms. For China, Indonesia, and Brazil we collected monthly data on temperature and precipitation from the Climate Change Knowledge Portal of the World Bank Group (https://climateknowledgeportal.worldbank.org). In addition, we used the Netherlands as case study for further comparison of search data with temperature, number of affected lakes and number of media items. For the number of affected lakes, we refer to lakes where cyanobacterial biomass exceeded guideline values and received a warning sign at designated bathing water sites. This was based on the Dutch Cyanobacterial Protocol 2012 (Ibelings et al., 2012), which assigns a warning if cyanobacterial biovolumes exceed 2.5 $mm^3\ L^{-1}$ and a negative bathing advice if cyanobacterial biovolumes exceed 15 $mm^3\ L^{-1}$. For each month, the sum of all lakes receiving a warning or negative bathing advice was taken to indicate the total number of affected lakes. We obtained this data through BIJ12, which is part of the Association of Provinces of the Netherlands and responsible for a national information portal (www.zwemwater.nl) that reports on the quality of bathing water sites. We limited the period to 2013–2019 for which the same monitoring and risk assessment protocol was applied. The data of the number of online media items that mention the Dutch term for cyanobacteria (see Table 1) was acquired through the online media monitoring company Meltwater, which we recovered for the same period as the number of affected lakes.

2.2. Data analysis

All statistical analyses were performed using R Statistical Software

Table 1
Applied search terms by country and state (between brackets[a]), with locations of weather stations and providers (between brackets) for long-term temperature and precipitation data in selected countries.

Country and state	Search term	Period	Weather station and source
USA (Kansas)	*"Blue green algae"*	2011–2022	Milford Lake, KS (National Oceanic and Atmospheric Administration); calculated mean of monthly mean min/max temperatures
Canada (Alberta)		2011–2022	Oliver AGDM, Edmonton (Government of Canada)[b]
United Kingdom		2010–2022	Bradford (Met-Office)
Australia (Victoria)		2011–2022	Hume reservoir (Bureau of Meteorology); calculated mean of monthly mean min/max temperatures
The Netherlands	*"Blauwalg"*	2004–2022	De Bilt (Royal Netherlands Meteorological Institute)
Germany	*"Blaualgen"*	2004–2022	Thuringia (German Weather Service)
Brazil	*"Algas azuis"*	2012–2022	Climate Change Knowledge Portal (World Bank Group)[b]
Indonesia	*"Ganggang biru"*	2011–2022	Climate Change Knowledge Portal (World Bank Group)[c]
China	"蓝藻"	2011–2022	Climate Change Knowledge Portal (World Bank Group)[c]

[a] Data was limited to indicated state for testing relationships between online searches and temperature or precipitation.
[b] Precipitation data for the period 2013–2022 was retrieved from https://edmonton.weatherstats.ca.
[c] Temperature and precipitation data was obtained for the period 2011–2021.

version 4.2.2 (R-Core-Team 2022). Figures were plotted using the 'ggplot2' package (Wickham, 2016). For testing the relationships between online searches and temperature or precipitation (Table 1; Fig. 2, Fig. S1), and for the various months in the Netherlands (Fig. S2), we first standardized the data by z-scoring each value x according to $(x - \mu)/\sigma$, where μ is the overall mean with standard deviation σ. To disentangle seasonal variation from interannual variation in search data, temperatures, and precipitation, we seasonally adjusted the monthly data by fitting a LOESS function and retrieving the residuals for further calculations using the function *stl* in the 'bfast' package (Verbesselt et al., 2010). These residuals show months that are above or below the overall average for that specific month over the entire timeseries, and therefore indicate whether a month is warmer or cooler than the interannual mean for that month. The association between seasonally adjusted online searches and temperature or precipitation was then assessed by a Spearman rank correlation on $\log_{10}(x + 1)$ transformed data, as the dataset contained zero values and data was non-normally distributed based on the Shapiro-Wilk test. Significance of all correlations were confirmed by a Theil-Sen regression which reduces the influence of outliers on the slope of the relationship, using the 'mblm' package (Komsta, 2019). To gain better insight into patterns by month, we used the case study of the Netherlands to explore the slope of the relationship between relative means of online searches and summer temperature per month (May–September).

To test the relationship between relative mean temperatures and normalized online searches, number of affected lakes, and media attention in the Dutch dataset, all data were aggregated to monthly means and $\log_{10}$ transformed. Then the relationship between monthly summer temperatures and log normalized searches (Fig. 3a), log media items (Fig. 3b) and log number of affected lakes (Fig. 3c) was assessed by a log-linear regression model. The slopes of these log-linear relationships were compared using an ANCOVA, by testing for significant interaction effects between the categorical factor (log online searches, log media items, log number of affected lakes) and the covariate temperature. Additionally, we tested the relationships between normalized searches (Fig. S3a) and media items (Fig. S3b) and the number of affected lakes, as well as the relationship between normalized searches and media items (Fig. S3c) using a log-log linear regression model.

3. Results & discussion

3.1. Annual trends in online searches

We first analyzed temporal variation in the frequency of online searches for harmful cyanobacteria using data from Google Trends and Baidu (for China), applying the common public term 'blue-green algae', or analogous terms in languages of tested countries (Table 1). We observed clear annual patterns with peaks in searches for harmful cyanobacteria during summer in temperate climate regions, and during wet seasons in tropical climate regions (Fig. 1). These trends were particularly evident in temperate regions, where 67–90 % of the total number of normalized searches were found during the summer months in six out of seven countries (i.e., May-September in the USA, Canada, UK, the Netherlands, and Germany; and November–March in Australia). For

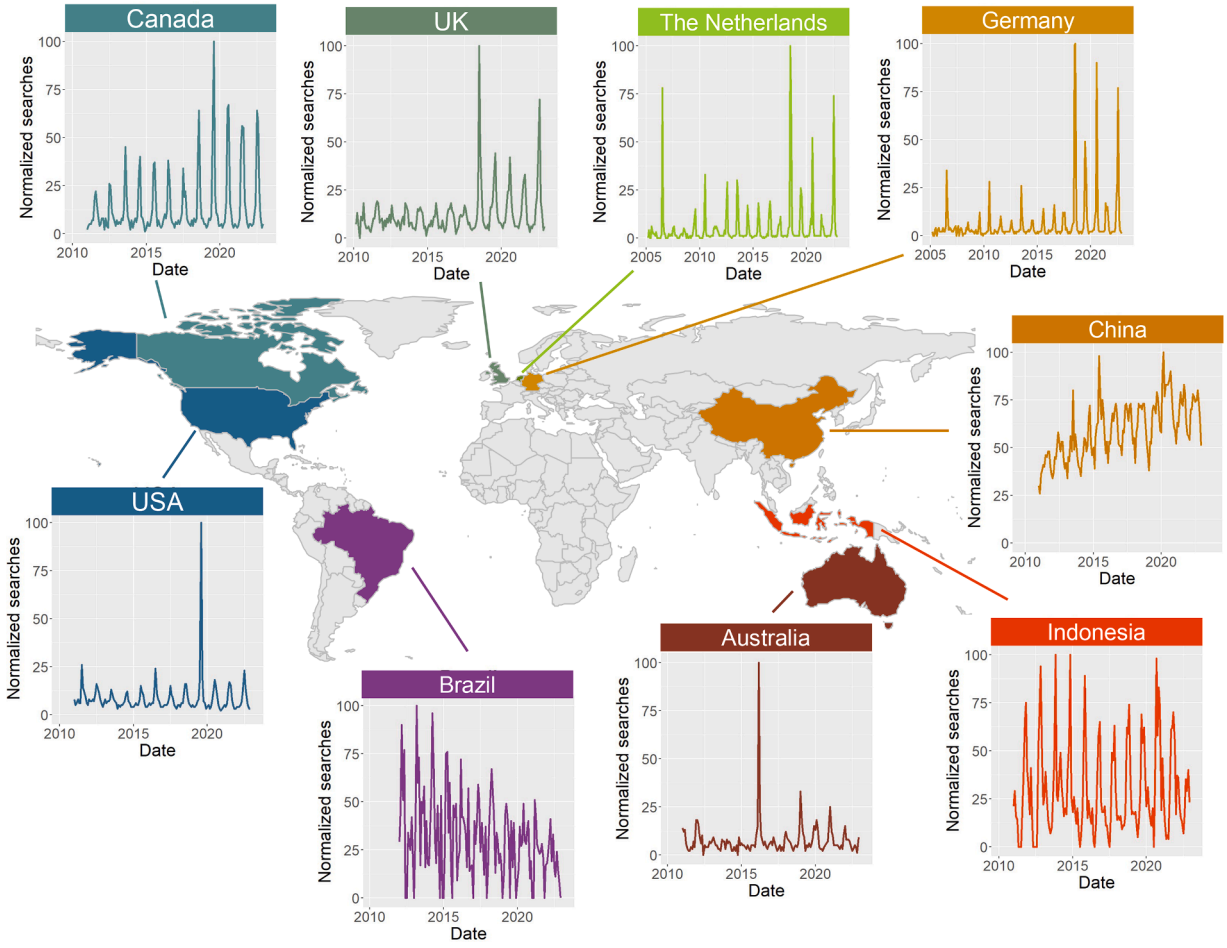

Fig. 1. World map with seasonal variation in online searches for harmful cyanobacteria in different countries, using the layman's term 'blue-green algae' or its analogues in other languages as search terms. Search data are normalized to highest values in targeted period. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

China, 47 % of the total number of normalized searches were found in summer, and in the countries with a tropical climate these percentages were 54 % and 36 % during the wet season for Indonesia and Brazil, respectively. These findings show that, in countries with a temperate climate, public awareness of harmful cyanobacteria is generally higher during summer periods, whereas public awareness shows a less distinct annual pattern in countries with a tropical climate. The observed trends in temperate regions are very likely linked to both the predominant presence of cyanobacterial blooms and the more intense use of surface waters during the summer period.

3.2. Warming effects on online searches

The reported trends also show interannual variation in peak height, indicating raised awareness in some years relative to others. We tested whether this pattern follows the interannual variation in summer temperatures in temperate regions. Our analyses confirmed that relatively warmer summers yielded significantly more online searches in six of the seven investigated countries with a temperate climate (Fig. 2a–f,h), but not in the two countries with a tropical climate (i.e. Indonesia and Brazil; Fig. 2g, i). To account for potential bias by temporal autocorrelation between months within the same year, we also tested the relationships between online searches and temperature for each individual

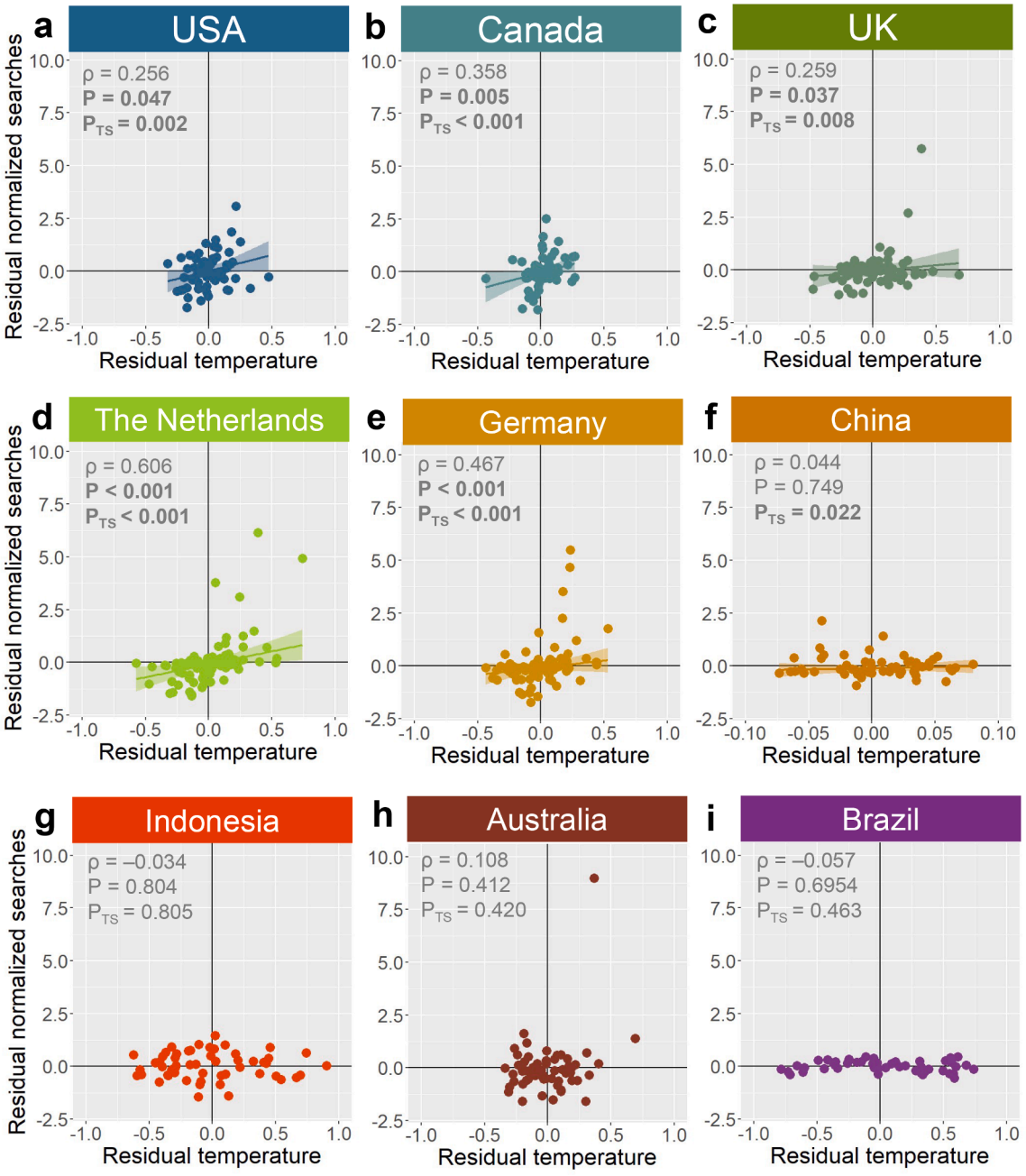

Fig. 2. Relationship between deviations from the mean of normalized monthly number of searches for harmful cyanobacteria and of the mean normalized monthly air temperature for Kansas, United States (a), Alberta, Canada (b), the United Kingdom (c), the Netherlands (d), Germany (e), China, (f), Indonesia (g), Victoria, Australia (h), and Brazil (i). Symbols indicate mean values of summer months from May to September on the northern hemisphere (a–f), and from November to March on the southern hemisphere (g–i). The statistics show the Spearman rank correlation coefficient (σ), its significance (P), and the significance of the Theil-Sen regression (P_{TS}). Regression lines are shown when $P_{TS} < 0.05$.

month for the Netherlands (Fig. S2). This largely confirmed the overall trends, with particularly strong correlations in the summer months July and August (Fig. S2c and d). Thus, our findings indicate that relatively hotter summers in temperate regions are accompanied by an increased public awareness of harmful cyanobacterial blooms compared to the overall mean, while online searches diminish in relatively cooler summers. There are multiple explanations for the increased public awareness during warmer summers; 1) the frequency and magnitude of harmful cyanobacterial blooms is higher in warmer summers, 2) the likelihood of people (interested in) bathing and swimming in lakes, and thereby seeing warning signs, will be higher, and 3) with more harmful cyanobacterial blooms and more people (interested in) visiting lakes the overall media attention for harmful cyanobacterial blooms will be higher.

For the countries with a tropical climate, i.e. Indonesia and Brazil, we did not observe a relationship between online searches and temperature. This is not surprising, since temperature is often not the main driver for cyanobacterial blooms in tropical regions (dos Santos Machado et al., 2022; Mowe et al., 2015). Instead, blooms have been linked to other factors, including nutrients and precipitation patterns (Mowe et al., 2015; Zapata-Anzola et al., 2009). We therefore also tested the relationship between online searches and precipitation, and our results show that the number of searches decreased slightly but significantly with total monthly precipitation in Indonesia and Brazil, the two tropical countries tested in our analyses (Figs. S1g,i). Comparable negative relationships with precipitation were found for only two of the countries in temperate regions (i.e. The Netherlands and Germany; Fig. S1d and e), while a slightly positive relationship was observed for China (Fig. S1f). Our results thus suggest that online searches follow the key climatic factors driving cyanobacterial blooms, where warmer and/or drier periods cause a relative increase in online searches.

3.3. Temperature dependence in online searches, media coverage, and harmful cyanobacteria

To investigate the different potential causes for increased public awareness in warmer summers, we used detailed data available in the Netherlands on the number of cyanobacteria-affected lakes, evidenced by the issued warning signs when blooms exceeded guideline values, as well as on the number of online media items containing the Dutch analogue to the common term 'blue-green algae' (Table 1). Our findings show that the number of affected lakes, media appearances, and online searches all increased significantly with temperature (Fig. 3). Remarkably, the observed patterns are best described by a log-linear model, which pointed to an exponential increase in the number of online searches along the investigated temperature range (Fig. 3a). While we also found a log-linear relation for the number of affected lakes (Fig. 3c), the slopes for both media attention and online searches along the temperature gradient were significantly steeper than the affected lakes – temperature relation (i.e. compare slopes in Fig. 3a and b, with Fig. 3c; ANCOVA, $F_{1,66} = 5.5$, $P = 0.022$, and $F_{1,66} = 25.0$, $P < 0.001$, respectively). This implies that the public awareness of cyanobacterial blooms shows an even stronger exponential increase with temperature than the incidence of harmful cyanobacterial blooms. Specifically, the slopes of the log-linear regressions correspond to a 1.17-fold increase of the number of affected lakes for every 1 °C rise in temperature, but a 1.34-fold and 1.62-fold increase of media items and online searches per 1 °C, respectively. These patterns support our hypothesis of a synergistic interaction, where public awareness of cyanobacterial blooms is raised by direct effects of warming on the incidence of blooms (Fig. 3c), and further amplified by indirect effects of warmer summers on the general interest to spend time at recreational lakes for bathing and swimming (as reflected by the increase in searches with increasing number of lakes affected by blooms (Fig. S3a)). This synergistic interaction may be mediated by the strongly increased media coverage with temperature, which indeed is correlated to the incidence of cyanobacterial blooms and, particularly, the number of online searches (Fig. S3b and c). While we cannot fully disentangle these underlying causes for an increased public awareness, our results clearly demonstrate that the online searches for cyanobacterial blooms and their coverage by online media increase more steeply during warmer summers than the number of affected lakes. We note that this was tested only for the Netherlands. Additional comparisons of online searches, media attention, and bloom incidences with temperature will be required to confirm the observed relationship for other countries.

3.4. Use of online search engines to study awareness

Our findings show the potential for using Google Trends to retrieve long-term data indicative for public awareness of cyanobacterial blooms across a wide range of geographic locations. Similar patterns of public awareness may possibly also apply to other water quality-related issues. There are also some limitations to consider when using search engine data as a proxy for public awareness. First, the data only reflect the number of searches, and not necessarily the reason why people are searching for these terms. To link the search terms to public awareness of harmful cyanobacteria, we applied common popular terms (such as 'blue green algae') that are typically only used by the public and media when referring to harmful cyanobacterial blooms. As such, we expect that the number of searches will reflect the interest of the general public in cyanobacterial blooms in lakes, and that this is indicative of their awareness of this issue. Second, the privacy threshold for number of searches in Google Trends may possibly mask potential trends when the number of searches is limited. Such a limited number of searches, in

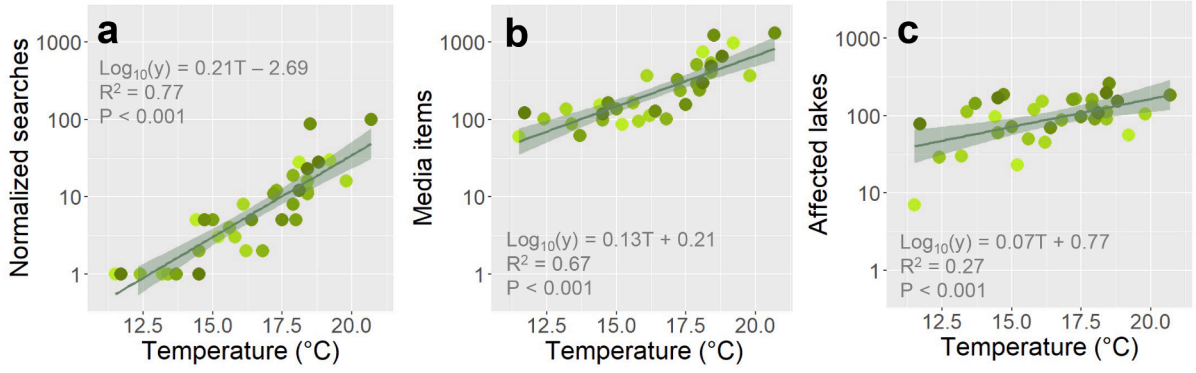

Fig. 3. Number of normalized searches (a), media items (b), and affected lakes (c) in relation to mean monthly air temperatures (T) in the Netherlands. Symbols indicate mean values of summer months from May to September over the period 2013–2019, where the shading indicates different years from light (2013) to dark (2019) shades. The statistics show the adjusted R^2 and significance of a log-linear regression.

turn, may have various reasons. For example, not all population groups may have access to the internet or use internet search engines for information acquisition. Moreover, instead of Google, there could be other, more dominant search engines in some countries. Comparative trend analysis between data from different search engines, however, showed similar trends between different types of search engines (Jun et al., 2017; Jun et al., 2018), suggesting that while absolute numbers may vary, the shown trends are reflective for overall online search behavior.

3.5. Implications for the study and management of harmful cyanobacteria

The annually recurring trends in online searches for harmful cyanobacteria suggest that online search records can provide valuable insights into the occurrence of cyanobacterial blooms, particularly in regions where the resources required for full-scale monitoring programs are limited. However, our current analyses focused on seasonal and multi-annual trends using monthly data, which is of insufficient frequency to timely inform water management authorities about potentially occurring cyanobacterial blooms. Higher frequency data with weekly or even daily analyses could possibly inform water management about regions with an elevated risk for harmful cyanobacterial blooms. In combination with responsive sampling schemes, this may support the development of tailored risk assessments. Moreover, higher frequency search data may support the development of an early warning system. For example, Google Trends data with a temporal resolution of a week or less have provided reasonable forecasting abilities for early detection of infectious disease outbreaks such as Lyme, HIV, and influenza, as well as for changes in health-related behaviors (Yang et al., 2015; Arora et al., 2019), or as input for early warning systems of financial market turbulence (Petropoulos et al., 2022). Such forecasting abilities could be further optimized when online search data are complemented with cyanobacterial bloom occurrence and analyzed using deep learning techniques (Arora et al., 2019; Petropoulos et al., 2022).

3.6. Interacting global change factors

Increases in cyanobacterial blooms, number of online searches, and media attention are typically not affected by temperature alone, but by a complex interplay with other global change factors (Richardson et al., 2019). For example, in temperate climate regions, global change also involves more extreme droughts, a higher frequency of storms and more intense rainfall events (IPCC 2021). When such combined changes in global change factors lead to new occurrences of blooms, or blooms of uncommon (e.g. invasive) species, this may particularly spark media attention and thereby raise public awareness. One example is the outbreak of cyanobacterial blooms in the hypereutrophic Milford Reservoir in Kansas, US. The initial 2011 bloom caused illnesses of humans and animals, including five dog deaths, which led to increased press coverage (Trevino-Garrison et al., 2015) and likely underlies the annual recurring summer peaks in Kansas since 2011. The cyanobacterial blooms in Milford Reservoir have been attributed to a combination of warming, promoting increases in microbially-mediated internal nutrient loading, and increased nutrient run-off from extreme rainfall events in spring, followed by more extensive droughts (Graham et al., 2012). Such local combinations of interacting global change factors may provide “the perfect storm” for ecological surprises (Filbee-Dexter et al., 2017; Haig et al., 2022), including the development of intense cyanobacterial blooms (Huisman et al., 2018; Paerl et al., 2016). An increased occurrence of local bloom events, in turn, may cause a societal response reflected by unexpected shifts in search dynamics, such as sudden increases in number of searches in a particular year or the start of annually recurring dynamics in online searches.

4. Conclusions

Warmer summers are expected to promote the occurrence, frequency, and magnitude of harmful cyanobacterial blooms. Our findings, for the first time, document online patterns of public awareness of cyanobacterial blooms, with pronounced increases in online searches every summer. Importantly, our analyses revealed climate-related trends in search behavior, where warmer and/or drier summers elicited a stronger interest by the public. This is likely caused by a synergistic combination of direct temperature effects on cyanobacterial blooms, as an increasing number of lakes and reservoirs experience blooms exceeding guideline values in warmer summers, and indirect temperature effects because warmer weather stimulates more outdoor activities and therefore raises people’s interest in the water quality of recreational lakes. Thus, the public is likely to become more aware of the potential problems caused by harmful cyanobacterial blooms when summers get warmer. In the future, online search patterns for harmful cyanobacteria may help to highlight regions or seasons with deteriorating water quality, especially in areas that are not monitored closely, and may thereby act as part of an early warning system for management action.

CRediT authorship contribution statement

Dedmer B. Van de Waal: Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Alena S. Gsell:** Formal analysis, Writing – review & editing. **Ted Harris:** Writing – review & editing. **Hans W. Paerl:** Writing – review & editing. **Lisette N. de Senerpont Domis:** Writing – review & editing. **Jef Huisman:** Formal analysis, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The data used in this study are available in the open data repository DataverseNL at https://doi.org/10.34894/JCTL8U.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2023.120817.

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