Presumptive Contamination: A New Approach to PFAS Contamination Based on Likely Sources

Derrick Salvatore, Kira Mok, Kimberly K. Garrett, Grace Poudrier, Phil Brown, Linda S. Birnbaum, Gretta Goldenman, Mark F. Miller, Sharyle Patton, Maddy Poehlein, Julia Varshavsky, and Alissa Cordner*

Cite This: https://doi.org/10.1021/acs.estlett.2c00502

ABSTRACT: While research and regulatory attention to per- and polyfluoroalkyl substances (PFAS) has increased exponentially in recent years, data are uneven and incomplete about the scale, scope, and severity of PFAS releases and resulting contamination in the United States. This paper argues that in the absence of high-quality testing data, PFAS contamination can be presumed around three types of facilities: (1) fluorinated aqueous film-forming foam (AFFF) discharge sites, (2) certain industrial facilities, and (3) sites related to PFAS-containing waste. While data are incomplete on all three types of presumptive PFAS contamination sites, we integrate available geocoded, nationwide data sets into a single map of presumptive contamination sites in the United States, identifying 57,412 sites of presumptive PFAS contamination: 49,145 industrial facilities, 4,255 wastewater treatment plants, 3,493 current or former military sites, and 519 major airports. This conceptual approach allows governments, industries, and communities to rapidly and systematically identify potential exposure sources.

KEYWORDS: per- and polyfluoroalkyl substances (PFAS), presumptive contamination, PFAS testing and investigation, AFFF, PFAS waste and disposal

INTRODUCTION

Per- and polyfluoroalkyl substances (PFAS) are a class of over 12,000 chemicals widely used in consumer and industrial applications.1,2 With production origins in the U.S. Manhattan Project, manufacturers have known of health risks of certain PFAS since the 1960s.3−5 There is growing attention to PFAS as a chemical class because many share similar adverse health effects, modes of action, and physical and biochemical properties.6−8 PFAS are present in at least 200 use categories ranging from aerosol propellants to wire insulation.9 Many PFAS are highly mobile in ground and surface water, and contamination of drinking water, air, and other media is a growing concern.10 The economic and social impacts of PFAS contamination include health impacts, testing and remediation costs, agricultural and real estate impacts, and burdens on local and state governments.11,12

An estimated 200 million U.S. residents receive PFAS-contaminated drinking water, and state-level testing indicates widespread contamination of environmental media,13 yet tremendous data gaps exist related to PFAS contamination and human exposure.2,14 The only federal drinking water testing initiative with PFAS data to date, the Environmental Protection Agency’s (EPA) Unregulated Contaminant Monitoring Rule 3 (UCMR3), focused on large drinking water systems, had high reporting thresholds (10−90 ng/L), and excluded private wells.15 The EPA has developed nonbinding Health Advisory Levels (HALs) for four PFAS, including updated HALs for PFOA and PFOS at “near zero” levels,16 but no federal limits on PFAS in public drinking water currently exist.1

To date, 19 states have enacted guidance or regulatory limits on PFAS in drinking water, and others have policies in development.17 Some states have systematically tested drinking water and then looked “upstream” for contamination sources; while this approach provides substantial data, it is time-consuming, resource-intensive, excludes PFAS not commonly analyzed, and potentially misses contamination that has not yet reached drinking water sources. State agencies differ in levels of relevant expertise and face disincentives to testing for PFAS without a mandate, including testing costs, liability concerns, risk communication challenges, time and resource constraints, and remediation challenges.11 Thus, known PFAS contami-
nation underrepresents the scope of contamination and is biased toward locations with rigorous testing programs.

In the absence of comprehensive testing data, locations of presumptive PFAS contamination can be identified based on proximity to certain types of identified facilities. Proximity to contamination is consistently associated with higher PFAS levels in drinking water, and consuming contaminated water is associated with higher PFAS blood levels.18,19 Our analysis builds on prior research identifying suspected industrial PFAS dischargers,20 state-based studies that use PFAS testing data to identify suspected categories of contamination,21 self-reported PFAS release data from industrial users,21 and numerous studies on specific PFAS-contaminated sites. This paper presents a conceptual argument for presumptive contamination and a methodological approach that conservatively identifies specific locations of likely contamination to guide interventions, resulting in a publicly available map of presumptive PFAS contamination locations in the United States. Absent high-quality sampling data, agencies can use this approach to prioritize investigative testing and remediation resources, and interested stakeholders in can identify their proximity to potential PFAS contamination.

PRESUMPTIVE PFAS CONTAMINATION

A presumptive contamination approach posits that, in the absence of high-quality data to the contrary, PFAS contamination is probable near facilities known to produce, use, and/or release PFAS, and to protect public health, the existence of PFAS in these locations should be presumed until high-quality testing data is available. The goal of this approach is not to identify every possible location of PFAS contamination but rather to develop a conservative and actionable model based on the best available data regarding sources of PFAS contamination. Several state and federal agencies already use a similar model that targets sampling for PFAS contamination based on facility type.22

Existing research suggests that in the absence of high-quality testing, the potential for PFAS contamination should be presumed at three types of sites: (1) AFFF discharge sites; (2) certain industrial facilities; and (3) sites related to PFAS-containing waste (Figure 1). As we discuss below, publicly available, high-quality, nationwide data exists for some, but not all, of these facility types (“Observable” in Figure 1). Other types of sites described by our conceptual model lack high-quality, nationwide data sets, so they are not included in our map (“Expected” in Figure 1).

1. AFFF Discharge Sites. Fluorinated AFFF has been used extensively for fire training and extinguishing fuel-based fires.24 PFAS contamination is expected wherever AFFF has been discharged, including military sites, major airports, fire training areas, and some fire suppression locations.

Military Sites. AFFF has been routinely discharged at Department of Defense (DOD) sites since 1967 as part of training, testing, and firefighting operations.25 Numerous military installations remain unassessed, including many Formerly Used Defense Sites (FUDS) abandoned or returned to private or public use.26

Major Airports. Airports serving scheduled carrier operations with more than nine seats require certification under Title 14 Code of Federal Regulation Part 139, which includes regular testing and AFFF discharge.27 In 2018, Congress directed the Federal Aviation Agency (FAA) to stop requiring fluorinated AFFF use by 2021.28 but no fluorine-free foams have been certified by DOD.24 Airports continue to use fluorinated AFFF, though training activities no longer necessarily result in fluorinated AFFF releases.27

Other Firefighting Training Sites. PFAS contamination is expected at locations where AFFF was discharged during firefighting training.24 Since 2018, 13 states have legislatively restricted the use of fluorinated AFFF for training and testing,29 and fire departments elsewhere have voluntarily stopped using AFFF in training, though storage and disposal concerns remain.30 In 2020, DOD released guidance prohibiting AFFF use in testing and training at most facilities.31

High-Hazard Flammable Liquid Fire Sites. PFAS contamination should also be expected at fire suppression locations where fluorinated AFFF was deployed. Although airplane crashes are rare and the majority take place at or near
airports. AFFF would be expected to be discharged. Additionally, AFFF is used to extinguish fires at railroad crash sites, oil and gas extraction sites, petroleum refineries, bulk storage facilities, and chemical manufacturing plants.

2. Industrial Facilities That Produce and/or Use PFAS. PFAS are used in numerous manufacturing and industrial processes. The EPA requires facilities in certain industries to report the release or treatment of 175 nonproprietary PFAS, mostly PFAS included in the EPA’s PFOA Stewardship Program and/or existing Significant New Use Rules, to the Toxics Release Inventory (TRI). In 2020, only 39 unique facilities reported PFAS TRI emissions, likely a huge underestimation. Thus, TRI disclosures are an incomplete portrait of PFAS emissions, and facility type is a better predictor of PFAS discharges.

Industrial facilities are identified by North American Industry Classification System (NAICS) codes. Researchers, state environmental agencies, and the EPA have all used NAICS codes to identify facilities suspected of using PFAS, although approaches vary. Our method, described below, synthesizes previous approaches into a single set of NAICS codes that are likely sources of PFAS contamination.

3. Sites Related to PFAS-Containing Waste. PFAS are often present in wastewater, resulting in contaminated effluent and sludge from wastewater treatment plants (WWTPs). When WWTP sludge is applied to agricultural land, it can contaminate soil and agricultural products. Facilities handling solid waste can generate additional PFAS-contaminated media, such as landfill leachate or incinerator ash. Complete combustion of certain PFAS requires a minimum temperature of 1000 °C, raising concerns about airborne emissions from incinerators.

Materials and Methods

Identifying all locations of presumptive PFAS contamination would require high-quality, nationwide data for the three categories of sites described above. In the absence of such data, we combined available public data sets described below into a single spatial analysis.

We identified Military Sites using the Military Installations, Ranges, and Training Areas (MIRTA) data set from the DOD’s Defense Installations Spatial Data Infrastructure Program (retrieved from U.S. Army Corps of Engineers Geospatial Open Data) and the FUDS data set from the DOD’s Defense Environmental Restoration Program Annual Report to Congress (retrieved from U.S. Army Corps of Engineers Geospatial Open Data). We filtered the FUDS data set to only include FUDS with at least one cleanup “project”.

We identified Major Airports by downloading the FAA Part 139 Airport Certification Status Table data set. We assigned coordinates for each AFFF-certified airport using a Google Maps API.

We identified 11 lists of Industrial Facility NAICS codes previously used by regulatory agencies and academic researchers to link PFAS contamination to facility type: the primary NAICS codes of facilities reporting TRI PFAS emissions, NAICS codes used in two academic studies that quantitatively linked facility type to PFAS contamination, and NAICS codes from eight regulatory lists used for testing and site prioritization by state or federal agencies. To reliably identify industry facilities that are presumptive sources of PFAS contamination across the resulting 191 distinct NAICS codes, we included only 38 NAICS codes that were present on at least four lists (Table S-1).

Data about facilities self-reporting within these NAICS codes were downloaded from the EPA’s Facility Registry Service (FRS) EZ Query. To remove poorly geocoded data, we excluded 23.5% of industrial facilities (n = 21,316) with FRS geolocation accuracy scores ≥1,000 m or missing geolocation data. Included NAICS codes also capture some AFFF discharge sites, including petroleum refineries, and some sites related to PFAS-containing waste, including solid waste landfills and incinerators.

We identified WWTPs using the Clean Watershed Needs Survey, which collected nutrient load data every four years from 1972 to 2012. These data were downloaded and filtered to include only “major” WWTPs, which have a design flow of ≥1 million gallons per day or an industrial pretreatment program.

High-quality, nationwide data on many other presumptive contamination sites, including locations of firefighting training, airplane and railroad crashes, and sludge application, are not publicly available.

Analysis. Analysis was conducted using R version 4.1.2 and RStudio version 2021.09.2. Presumptive contamination sites were combined into a single data set. We transformed all coordinates to match a uniform reference system (NAD83) and removed sites with duplicate entries or missing geocoded information. We downloaded the U.S. Census Bureau’s Cartographic Boundary shapefile for states, and used the R package sf to locate each site within states. The PFAS Project Lab, Silent Spring Institute, and PFAS-REACH maintain an interactive map in ArcGIS Experience Builder to visually display sites of presumptive contamination. Unlike some existing PFAS screening tools, we did not assign any weighting to site types.

We used a manual validation process to assess whether our conceptual model fully captured known PFAS contamination sites. Briefly, we identified known PFAS contamination sites using the PFAS Project Lab’s PFAS Contamination Site Tracker. To be conservative in our validation process, our validation method prioritized locations with more PFAS testing. We selected four counties from each of the five states with the highest numbers of known contamination sites and the five states closest to the median number of known contamination sites. For each of the selected 40 counties, we searched the presumptive contamination data set for sites that were in the known contamination data set. We calculated three accuracy measurements in our validation process: the percent of known contamination sites that were captured by our presumptive contamination data set (observed); the percent of known contamination sites that were included in our conceptual model but were not captured by our data set (expected); and the percent of total known contamination sites (observed or expected) that were included in our data set or our conceptual model (total).

The Supporting Information Document accompanying this paper includes a justification for and in-depth description of this validation process, as well as additional details regarding validation in New Hampshire. Table S-1 lists the 38 NAICS codes included in our presumptive contamination model. Table S-2 presents county-level results from our validation model, Table S-3 separates validation results by states with high versus median number of known contamination sites, and Table S-4 separates validation results by counties with high...
versus median number of known contamination sites. Table S-5 presents validation results excluding known contamination sites from New Hampshire. Table S-6 includes site-by-site validation results for 503 sites.

### RESULTS AND DISCUSSION

We identified 57,412 sites of presumptive PFAS contamination in the United States, including 49,145 industrial facilities, 4,255 WWTPs, 3,493 military sites (762 MIRTA and 2,731 FUDS), and 519 major airports (Figure 2). These sites are displayed in the publicly available PFAS Contamination Site and Community Resources map (available at [www.pfasproject.com](http://www.pfasproject.com)).

Our validation sample included 503 known contamination sites from 40 counties in 10 states. Of these, 176 (35%) were observed in the map, and another 187 (37%) were expected by the model but were not mapped due to data limitations, bringing the total validation accuracy to 72% (Table 1, Table S-2). The 28% of known contamination sites not captured by our model were generally of three types: (1) sites where PFAS contamination is comprehensible but whose NAICS codes are not presumptive within our conservative model, including septage businesses, car washes, and textile cleaners; (2) sites not logically associated with PFAS contamination, such as convenience stores, senior centers, and restaurants; and (3) sites with relatively low levels of PFAS, perhaps suggesting background contamination rather than a specific source. A full list of all 503 sites and their classification is available in Table S-6.

As expected, our conceptual model was more predictive in locations with median levels of known PFAS contamination (Table S-3 and S-4). Accuracy varied by state, reflecting differences in testing approaches. For example, New Hampshire’s robust PFAS testing has identified 469 known contamination sites, while our model identifies only 380 presumptive sites (Table S-5).

Our nationwide map provides an underestimation of presumptive PFAS contamination because of data quality and availability issues. 23.5% of identified industrial facilities ($n = 21,316$) were excluded because they lacked high-quality geolocation information. NAICS codes are self-reported, leading to possible misclassification. Despite being documented as possible PFAS sources, other facilities that likely produce or use PFAS are also excluded, such as dry cleaners, car washes, or ski shops, because we are not confident that every facility of its type should be considered presumptive. For example, although some dry cleaning processes use and release PFAS, other dry cleaners are water-based or send cleaning to off-site facilities, so including all dry cleaners would be inappropriate.

High-quality nationwide data on other sites of presumptive PFAS contamination, including firefighting training sites, railroad and airplane crash sites with AFFF use, oil and gas hydraulic fracturing sites, bulk fuel storage facilities, and sewage sludge application sites, are not publicly available. Our map also excludes U.S. territories because of data limitations. State and local efforts have developed data on additional presumptive contamination sites that are not included in this nationwide map. Subnational analyses could incorpor-
Table 1. Presumptive Contamination Model Validation by Selected States⁶

<table>
<thead>
<tr>
<th>State</th>
<th>Known contamination sites, n</th>
<th>Consolidated county known contamination sites, n</th>
<th>Observed matches, n (%)</th>
<th>Expected matches (not observed), n (%)</th>
<th>Total matches, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Hampshire</td>
<td>469</td>
<td>2 Highest</td>
<td>189</td>
<td>30 (16%)</td>
<td>69 (37%)</td>
</tr>
<tr>
<td>California</td>
<td>253</td>
<td>2 Highest</td>
<td>52</td>
<td>39 (75%)</td>
<td>11 (21%)</td>
</tr>
<tr>
<td>Michigan</td>
<td>188</td>
<td>2 Highest</td>
<td>57</td>
<td>30 (53%)</td>
<td>22 (39%)</td>
</tr>
<tr>
<td>Minnesota</td>
<td>101</td>
<td>2 Highest</td>
<td>17</td>
<td>9 (53%)</td>
<td>6 (35%)</td>
</tr>
<tr>
<td>Maine</td>
<td>99</td>
<td>2 Highest</td>
<td>28</td>
<td>9 (32%)</td>
<td>11 (39%)</td>
</tr>
<tr>
<td>Vermont</td>
<td>62</td>
<td>2 Highest</td>
<td>30</td>
<td>15 (50%)</td>
<td>15 (50%)</td>
</tr>
<tr>
<td>Mississippi</td>
<td>9</td>
<td>2 Highest</td>
<td>7</td>
<td>2 (29%)</td>
<td>5 (71%)</td>
</tr>
<tr>
<td>Rhode Island</td>
<td>8</td>
<td>2 Highest</td>
<td>5</td>
<td>5 (100%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>Washington</td>
<td>8</td>
<td>2 Median</td>
<td>3</td>
<td>2 (67%)</td>
<td>1 (33%)</td>
</tr>
<tr>
<td>Tennessee</td>
<td>6</td>
<td>2 Median</td>
<td>2</td>
<td>2 (100%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>Total</td>
<td>503</td>
<td>176</td>
<td>187</td>
<td>176 (35%)</td>
<td>187 (37%)</td>
</tr>
</tbody>
</table>

Notes: All county results included in Table S2.⁶ Consolidated data from two counties with the highest and two counties with the median levels of known contamination sites within the state. Number of presumptive contamination sites with matched known contamination sites within the counties. Numbers of known contamination sites without presumptive contamination matches but are included in model parameters. Total known contamination sites incorporated by model parameters (observed matches + expected matches). Percentages may not add to 100 due to rounding.

Sources: Author’s analysis.⁶¹,⁶²

Our presumptive contamination data set excludes known PFAS contamination sites because the model’s purpose is to fill data gaps and drive future surveillance and action. Because testing requirements and technical capacity of PFAS contamination vary between states, the identification of known contamination reflects the scale of testing conducted in that state, not necessarily the extent of underlying PFAS contamination. We also did not include facilities with TRI discharge reports as presumptive PFAS contamination sites, though our data set captures 32 of the 39 unique facilities that reported PFAS emissions to EPA in 2020. (The seven TRI-reporting facilities not identified by our model include facilities related to cement, fertilizer, industrial gas, analytical laboratory instruments, and fats/oils refining and blending.)

Applications and Next Steps. PFAS contamination may increase exposure for proximate populations. By developing the concept of presumptive contamination and validating that model against known contamination sites, this paper provides a rigorous advancement to previous academic and regulatory models using NAICS codes alone or in limited geographic areas. This standardized methodology allows researchers, regulators, and other decision-makers at various geographic scales to identify presumptive PFAS contamination using publicly available data, addressing several “urgent questions” described by leading PFAS scholars, including the identification of PFAS contamination hotspots and the need for accessible PFAS measurement tools.⁶⁹

State and federal agencies can use a presumptive contamination approach to identify and prioritize locations for monitoring, regulation, and remediation. Decision-makers working at smaller geographic scales could conduct site-by-site verification of sites excluded from our data set due to poor geolocation, potentially locating many for inclusion in local efforts. Future prioritization could evaluate PFAS risks associated with facility type and/or density of sites. For example, the Minnesota Pollution Control Agency evaluates facility types codes on a scale of 1–4 based on assessed likelihood of PFAS use.⁴¹ Additional research could determine the proximity of presumptive contamination sites to prioritized locations, such as public water supplies, Tribal lands, environmental justice communities, public parks, and population-dense areas.

While all data described in this analysis are publicly available, other PFAS data are hard to utilize, inaccessible to the public, or not nationally aggregated. We recommend that federal and state agencies develop, aggregate, and broadly disseminate information on the many sources of presumptive PFAS contamination identified in this paper. Planned nationwide testing for PFAS in public drinking water sources⁶₈ will exclude the 43 million U.S. residents who rely on private wells.⁶⁹ States can use PFAS-specific task forces and investigative orders to identify contamination and target action using our presumptive contamination categories. Surveys to facilities identified by NAICS codes could investigate PFAS use and inform further testing and action. When nationwide data sets do not exist, local and/or state data on permits, industrial activity, and application sites could be aggregated.

Our presumptive contamination approach focuses only on proximity to locations of PFAS use, release, or disposal, ignoring other exposure routes including occupation, diet, or consumer products. Future research could expand this site-
based model to residence- and occupation-based models of presumptive exposure, similar to existing models of occupation-based presumptive illness. Since NAICS codes can identify industries where workers are likely exposed, our approach can support occupational exposure monitoring. Identification of PFAS in consumer products could further inform an occupation-based presumptive exposure model.

In the absence of widespread testing data, this presumptive contamination model allows governments, industries, and communities to identify potential sources expediently and take data-informed steps to investigate and address PFAS contamination. While the scale of presumptive contamination we identified is large, it likely underestimates PFAS contamination in the United States. The high costs of PFAS contamination to human health, municipalities, and the environment demand swift regulation, reformulation, and exposure reduction.1

ASSOCIATED CONTENT
Supporting Information
The Supporting Information is available free of charge at https://pubs.acs.org/10.1021/acs.estlett.2c00502.

Description of Presumptive Contamination Validation Process; Table S-1. NAICS codes included in presumptive contamination model; Table S-2. Presumptive contamination model validation, county level analysis; Table S-3. Presumptive model validation, state comparison by known contamination level; Table S-4. Presumptive model validation, county comparison by known contamination level; Model Validation discussion; Table S-5. Presumptive contamination model validation, county level analysis, excluding New Hampshire; Table S-6. Presumptive contamination model validation – known contamination data (PDF).

AUTHOR INFORMATION

Corresponding Author
Alissa Cordner – Department of Sociology, Whitman College, Walla Walla, Washington 99362, United States; orcid.org/0000-0001-5223-2848; Email: cordneaa@whitman.edu

Authors
Derrick Salvatore – Department of Marine and Environmental Sciences, Northeastern University, Boston, Massachusetts 02215, United States; orcid.org/0000-0003-3909-9311
Kira Mok – Department of Sociology and Anthropology and Department of Health Sciences, Northeastern University, Boston, Massachusetts 02215, United States; orcid.org/0000-0003-4289-819X
Kimberly K. Garrett – Department of Sociology and Anthropology and Department of Health Sciences, Northeastern University, Boston, Massachusetts 02215, United States
Grace Poudrier – Department of Sociology and Anthropology and Department of Health Sciences, Northeastern University, Boston, Massachusetts 02215, United States; orcid.org/0000-0001-5568-3062
Phil Brown – Department of Sociology and Anthropology and Department of Health Sciences and Department of Health Sciences, Northeastern University, Boston, Massachusetts 02215, United States
Linda S. Birnbaum – National Institute of Environmental Health Sciences, Research Triangle Park, North Carolina 27709, United States; Duke University, Durham, North Carolina 27708, United States
Gretta Goldenman – Milieu Consulting, 1060 Brussels, Belgium
Mark F. Miller – National Institute of Environmental Health Sciences and U.S. Public Health Service, Research Triangle Park, North Carolina 27709, United States
Sharyle Patton – Health and Environment Program, Commonwealth, Bolinas, California 94924, United States
Maddy Pochlein – PFAS Project Lab, Northeastern University, Boston, Massachusetts 02215, United States
Julia Varshavsky – Department of Health Sciences and Department of Civil and Environmental Engineering, Northeastern University, Boston, Massachusetts 02215, United States

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.estlett.2c00502

Funding
We acknowledge funding from the National Science Foundation (SES-1827817 and SES-2120510: P.B., A.C., K.M., G.P., and D.H.S.), the National Institute of Environmental Health Sciences (2-T32-ES023769-06 and R01ES028311: P.B. and G.P.), the Marisla Foundation (S.P.); and the Tides Foundation (TF2101-096968; G.G., S.P., and D.H.S.).

Notes
The authors declare no competing financial interest.

ACKNOWLEDGMENTS
We are grateful to the Reviewers and Editor for thoughtful comments that greatly improved this manuscript, including the suggestion of validating known contamination sites. We are grateful to Andrew Lindstrom for invaluable comments and suggestions, and to Laurel Schaider, Courtney Carignan, Maia Fitzstevens, Alex Goho, and Erik Haugsjaa for collaborative work on the PFAS Sites and Community Resources map. We are grateful to members of the PFAS Project Lab, including Lauren Richter, Jennifer Ohayon, Rosie Mueller, Marina Atlas, Miranda Dodson, Lílyana Ibañez, and Mya Heard, for their support of this project.

REFERENCES


(60) Pebesma, E.; Bivand, R.; Racine, E.; Sumner, M.; Cook, I.; Keitt, T.; Lovelace, R.; Wickham, H.; Ooms, J.; Müller, K.; Pedersen, T. L.; Baston, D.; Dunnington, D. *Sf: Simple Features for R*. 2021.

(61) PFAS Project Lab; PFAS Exchange. *PFAS Sites and Community Resources*. [https://experience.arcgis.com/experience/12412ab41b3141598e0bb48523a7c940/](https://experience.arcgis.com/experience/12412ab41b3141598e0bb48523a7c940/) (accessed 2022−01−12).


(64) Per- and Polyfluoroalkyl Substances (PFAS); California State Water Resources Control Board. [https://www.waterboards.ca.gov/pfas/](https://www.waterboards.ca.gov/pfas/) (accessed 2022−07−14).


