

Science and Democracy Under Siege

*Documenting Six Months of the Trump
Administration's Destructive Actions*

Methodology

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Documenting Attacks on Science

Definitions and examples for attacks on science (AOS) presence (or whether an article contains at least one AOS) and categories were developed using previous Union of Concerned Scientists (UCS) research on AOS—including the existing AOS database and accompanying peer-reviewed publication—and expert consultation. We define an AOS as an action, statement, or decision that originates from an elected official or political appointee in a federal agency that results in the censoring, manipulation, forging, or misinforming of scientific data, results, or conclusions conducted within the government or with federal funds.

Data collection for this report was conducted from a larger data collection and analysis, in which news articles were assessed for AOS presence, category, topic (that describes the public policy topic of the AOS, such as climate science or equity), completion stage (when an AOS is either threatened or completed, resulting in a tangible decision or policy), and reversal (whether an AOS was reversed or rescinded at time of news article publication). For this report, only AOS presence and category were described.

The definition of AOS presence and categories (which detail the types of AOS, such as censorship or altering study results) were reviewed by experts on the UCS Center for Science and Democracy research team before being finalized by the third author of this report.

Potential AOSs were identified via news coverage of the federal government's actions, decisions, and statements. The report's third author reviewed news articles for potential AOS against the definition of AOS presence. Any article that was identified as containing a potential AOS was compiled chronologically in a spreadsheet. If more than one news article was identified as containing the same AOS, only the first article was included in the spreadsheet as a potential AOS.

The process of coding news articles for AOS presence and categories followed methodological best practices of human content analyses. Up to four human coders were trained to code AOS presence and categories. Over a period of several weeks, the human coders read news articles that were marked as containing potential AOS. Coders met to discuss and resolve coding discrepancies.

In line with methodological best practices, before coders could begin to independently code news articles for AOS presence and categories, they must reach a Gwet's AC₁ intercoder reliability statistic of at least 0.70. This metric indicates an “acceptable” overlap of agreement between human coders. Coders reached reliability for AOS presence (Gwet's AC₁ ranging from .71 to .88) before coding for this variable independently. Coder training is still ongoing for AOS categories, including those described in the “Documenting Attacks on Science” section of the report. This means those specific numbers (e.g., “At least 39 instances of a federal agency...”) do not encompass the total number of attacks *by category*. As of June 30, 2025, we have categorized 119 out of 402 attacks on science through the process of human coding. Research to determine the category, topic, completion stage, and reversal of the remaining attacks is still ongoing.

The number of attacks on science represents the number of news articles that were deemed to have at least one unique attack on science described. Two notable limitations of this approach are that attacks can only be identified in news articles that are publicly available, and multiple AOS in one article are not accounted for in the final AOS count. For any questions related to

the list of attacks on science referenced in this section of the report, please contact the Center for Science and Democracy's Communications Officer, Lana Cohen (lcohen@ucs.org).

Evolving AOS Methodology in President Donald J. Trump's Second Term

Preceding President Trump's second term, AOSs were identified using a set of sequential criteria. The evolved definition departs from the previous characterization of AOS in three key ways.

First, we have expanded our AOS presence definition to include actions, statements, or decisions. This expansion allows us to capture when AOSs are publicly communicated or threatened before tangible policy decisions occur. Second, we assume that any action, statement, or decision of an elected or politically appointed person is politically motivated, regardless of whether that motivation stems from the desire to be reelected or to develop and pass policy. Third, our definition of AOS can involve the misuse (or noticeable absence) of science in the federal government or scientific work that receives federal funding. This expansion has allowed us to capture AOSs on academic and medical institutions that receive federal funding, such as from the National Institutes of Health (NIH).

Because we relied heavily on existing UCS research and analysis to inform our current definitions of AOS presence and category, there is a substantial amount of overlap between these variables and those used before President Trump's second term.

Regarding the types of AOS (for example, censorship and politicization of grants and funding), we divided categories that encompassed distinct AOS types (for example, "rolling back data collection or data accessibility") into separate AOS types (for example, "data collection," "data accessibility"). This is to ensure variable definitions are distinct so as to encourage data quality and validity.

We also added three new variables to capture AOSs: agency appointments, losing positions, and targeting scientists based on identity. Finally, we changed the name of one AOS type to capture any AOS on federal scientists' professional engagement (such as grant review panels and public forums) as opposed to tagging AOSs only on federal scientists' conference attendance. This means that the seven categories of AOSs used before President Trump's second inauguration have been expanded into 12 distinct categories.

As a result of this more comprehensive approach, our findings may include a larger number of attacks on science during January 20 through June 30, 2025 than if we had used the same methodology from previous presidential administrations.

How to Destroy Public Science That Keeps Us Safe—Lessons from the Second Trump Administration

Gutting Scientific Expertise

There are a variety of types of federal job loss: employees put on administrative leave, employees eliminated through reduction in force, and employees encouraged to retire early or leave voluntarily. Within each of these categories, federal administrations can announce their plans to eliminate positions and there is a formal notice to employees that their position is

eliminated and there is an effective elimination date. For example, the Trump administration announced plans to eliminate all environmental justice employees from the federal government; later, they put staff and leadership in the Environmental Protection Agency's (EPA) Office of Environmental Justice and External Civil Rights on administrative leave. On April 30, those employees were formally notified of termination if their positions were eliminated, and that elimination takes effect on July 31, 2025. Thus, the language in this section of the report is intentionally clear about “announced,” “effective,” and “confirmed.” The overall federal cuts discussed are “announced,” so there may be a lag until the employees are removed from federal service. To complicate this further, some of these announced layoffs have been or will be overturned in courts (and those court decisions are often followed by appeals). We have drawn the total cuts to the federal workforce from the *CNN* tracker, “[Tracking Trump’s Overhaul of the Federal Workforce](#)” and drawn the percent increase between the first quarter of 2024 and 2025 from *The Challenger Report* article “Federal Cuts Dominate March 2025 Total: 275,240 Announced Job Cuts, 216,670 from DOGE Actions.” There are multiple sources tracking the federal employee layoffs, and there is notable uncertainty as previously discussed. We chose to use the total number from *CNN* since their methods were available in the article and transparent. These estimates will become more certain over time as court cases are finalized.

The agency-specific layoff numbers are “confirmed cuts.” They do not include staff and leadership who accepted buyouts, nor do they include unconfirmed announced layoffs. They also do not include planned reductions, which may be, but are not necessarily, the same as announced layoffs. The data in Figure 2 are drawn directly from the *New York Times* article “[The Federal Work Force Cuts So Far, Agency by Agency](#).” These percent cuts are a total of confirmed layoffs with a denominator of the size of the agency at the beginning of the Trump administration.

1. Halting Science and Innovation

Publicly available funding data was exported from [USASpending.gov](#) using the Advanced Search feature. This feature includes many filters—such as time frame, type of funding award, and award recipients—that can be used to specify the type of data to export. Foremost, we included only project grants disseminated by the NIH. For the time frame filter, we pulled data from a specific time frame (January 1 through June 30) from the previous 10 years (2016 to 2025). Only new awards were exported, which means that only grants awarded within the specified time frame were included. USASpending.gov data exports include four separate CSV files; of these, we analyzed only the dataset including prime awards (the whole sum of monies disseminated per project). We used R Studio to clean and organize the data. To examine differences in project grants by year, we used the [Award Base Action Date](#), or the date on which the federal government signs the funding agreement to disseminate the federal funds for the award.

2. Ignoring Public Input

Using [data](#) obtained by the Environmental Defense Fund (EDF) of 532 facilities that would qualify for the Clean Air Act Section 112 [compliance exemption](#), we identified the location of these facilities by first joining the facility's name, city, and state with the EPA National Emissions Inventory (NEI) data (which includes facilities' latitude and longitude). Facility names often change, so we joined the remaining facilities by county and state; we then could

discern the latitude/longitude from the facilities within the same county by visually matching names. For example, some facilities had their owners' names, which were available in the EDF analysis. Joining by counties narrowed down the possible matches between the NEI data and the EDF facility list. Next, we completed this same process by zip code, congressional district, and cities. For the remaining unjoined facilities, we conducted a Google Maps search by facility or owner name and the state.

We then pulled EPA AirToxScreen 2020 [data](#), and, using R script, drew a five-mile spatial buffer around the 532 facilities, making the facilities a polygon (that is, not point spatial data). We then intersected the facility buffer polygons and the polygons of the modeled AirToxScreen results within census block groups. Next, we pulled the result from the census block group with the highest modeled AirToxScreen result for each facility. This was a professional judgment choice to ensure that impacts were not "averaged out" for communities, because five-mile buffers are much larger geographies than some overburdened and historically disinvested neighborhoods. Here is the final R script:

[01_airtoxscreen_dereg_fac_in_buffers.R](#)

Next, we pulled the demographics of the communities within a five-mile buffer around each facility from the US Census Bureau's 2022 American Community Survey. We used information about the percent of "non-White" people (everyone who is estimated to not identify as White in a census block group ("white alone, not hispanic or latino"). We also included data on people who are low-income within census block groups, which is defined as people who lived below 200 percent of the federal poverty level, and the estimated populations in census block groups who do not speak English well ("grepl("speak English", label), grepl("not at all|not well", label)).

Then we intersected the census polygons with the five-mile facility buffers. Many buffers crossed county and state borders. So, we weighted the populations by the area that the buffer covered in each census block group (for each county and state the buffer covered). Additionally, we located the [childcare centers](#) and [public](#) and [private](#) schools around these facilities using the linked data sources.

3. Cutting Out Independent Experts

We identified a full list of 208 fiscal year 2025 Scientific Technical Program Advisory Boards from the "committee function" field of the [Federal Advisory Committee Database](#), accessed July 1, 2025. We further categorized scientific technical federal advisory committees (FACs) by the "status" field ("terminated," "chartered," or "administratively inactive"). To identify the set of scientific technical FACs active at the beginning of the second Trump administration, we removed any FACs classified as administratively inactive before January 20, 2025 (15 FACs) or that did not have a reported end term or termination recommendation date in the "Recommendations/Justifications" section (6 FACs). No FACs in our dataset were terminated before February 2025, resulting in a set of 188 active FACs at the beginning of President Trump's second term.

To identify the number of FACs eliminated by the Trump administration, we examined the "Actual Termination Date" of terminated FACs and identified 51 FACs terminated since January 20, 2025. We also included two statutory FACs that were labeled as "administratively

inactive” but that cited [executive order 14217](#) in the “Recommendation Remarks” section of the database where the FAC was recommended for termination. The remaining chartered FACs were cross-referenced with news reports of FAC terminations and updated to reflect recent reporting.

To identify the number of FACs disrupted by the Trump administration, we examined daily LexisNexis alerts and crowdsourced news reports for references to any scientific or technical FACs. Reports of FAC member removal or meeting delays/cancellations of any of the remaining active FACs were noted and included as two separate categories of FAC disruptions. Lastly, we noted news reports of HHS considering the termination of eight additional chartered scientific FACs as “termination recommended” to highlight likely disruption and/or termination. No new information emerged from examining news reports of FAC terminations and disruptions, and all data used to inform Figure 5 is from the [Federal Advisory Committee Database](#).

4. Censoring and Suppressing Scientific Information

Our analysis used the Environmental Data and Governance Initiative’s (EDGI) [Federal Environmental Web Tracker](#). EDGI monitors more than 4,400 federal URLs related to climate, energy, and the environment, documenting changes to the webpage content, language, and links. EDGI provided UCS with data showing the number the federal environmental webpages that have been subject to content/substance changes, defined as “substantial change to the content of the webpage (e.g., language changes or alteration of sentences and paragraphs)” through June 30, 2025, as well we webpages subject to access changes, defined as “substantial change in access to information (e.g., removal of links or webpages)” for the first 100 days of President Trump’s second term. EDGI’s selection criteria for URLs and methods for documenting changes to federal webpages can be found [here](#).

Case Study: Attacking Climate Science and Policies to Benefit Fossil Fuel Companies

The analysis in this section used multiple sources to track several kinds of attacks by the Trump administration against five key agencies whose work helps generate federal climate science or is connected to climate or clean energy regulations and policy implementation. The agencies included are EPA, the National Oceanic and Atmospheric Administration (NOAA), the Department of Energy (DOE), the Federal Emergency Management Agency (FEMA), and the Department of the Interior (DOI). We defined attacks on climate science as: actions that boost fossil fuel use or permitting; attempts to undermine bedrock scientific determinations such as EPA’s Endangerment Finding; broadside attacks on agency science or research, funding, staffing, or programs; regulatory rollbacks or other reversions; mis/disinformation campaigns or appointments of candidates who proliferate anti-science rhetoric; and other actions that undercut scientific efforts.

We categorized these attacks by agency and created a table with a check mark against each category for which an agency had experienced an attack. The data sources used are listed on the following page.

Table 1. Figure 7 Sources

Science-Specific	Cumulative Attacks	Agency Websites
Science.org	CNN (executive orders)	epa.gov
Nature.org	NYTimes (firings)	noaa.gov
NIH grant tracker (Harvard)	NYTimes (first 100 days)	energy.gov
EJ tracker (Harvard Law)	Allsides.com	doi.gov
Silencing Science (Columbia Law)	IRA Funding tracker	fema.gov
Silencing Science Complements	Climate Action Campaign	
Web changes tracker from EDGI	Senate Appropriations Committee	
NSF grant tracker (Harvard)	Project 2025 progress tracker	
Sabin Center Climate Backtracker	CNN (workforce)	

Limitations

Given the rapidly shifting nature of the government changes documented in this report, coupled with the slow pace of updates to government databases, much of the report uses data collected by or documented in news reports. As a result, we are limited by relying often on nongovernment data to summarize government staffing, grants, and regulatory changes, among other data points.

Furthermore, given the time-bound nature of our report, our data analysis covers January 20 to June 30, 2025 (and in some cases, earlier) and therefore does not span the full six-month period following President Trump’s inauguration. As a result, our findings may underestimate or exclude new information collected or reported between July 1 and July 20, 2025.

Furthermore, the spatial analysis comparing facility locations with socioeconomic demographics from the US Census and American Community Survey applies a general assumption that people are evenly distributed within the comparison geography and includes all of the underlying limitations and uncertainties of these data sets. The comparisons of the facility locations and the modeled air toxic concentrations, schools, and socioeconomic data include all facilities potentially able to request an exemption from several environmental regulations. This analysis was not pared down to those facilities that have already requested such exemptions. There is also uncertainty in both the facility locations and the air pollutant emissions that each facility reports.