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Spatiotemporal dynamics of PFAS contamination around industrial and military facilities in U.S. Regions

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Abstract

Spatiotemporal dynamics of per and polyfluoroalkyl substances PFAS contamination around industrial and military facilities across United States regions present a complex environmental and public health challenge. This study synthesizes monitoring data, regulatory reports, and peer reviewed literature to characterize how PFAS concentrations vary across space and time in high risk operational landscapes. Emphasis is placed on legacy and active sources, including firefighting training areas, chemical manufacturing plants, metal plating sites, and logistics hubs, where repeated releases have created persistent soil, groundwater, and surface water plumes. Evidence shows that contamination patterns are strongly shaped by facility age, waste handling practices, hydrogeology, regulatory history, and remediation timing. Temporal trend analyses indicate that while some locations show gradual declines following intervention, others exhibit stable or expanding footprints due to ongoing inputs and subsurface migration. Seasonal variability is also observed, with precipitation, recharge, and hydrologic connectivity influencing PFAS transport and detection frequency. Advanced geospatial modeling and time series methods reveal clustered hotspots near discharge zones and downgradient communities, highlighting disproportionate exposure risks for nearby populations. Comparative regional assessment further suggests uneven monitoring coverage and data resolution, limiting early warning capacity in several jurisdictions. The integration of remote sensing, high resolution sampling, and predictive analytics improves plume tracking and supports risk informed decision making for site prioritization. Results underscore the need for standardized longitudinal surveillance, transparent reporting, and adaptive remediation strategies tailored to site specific transport pathways. Strengthening regulatory thresholds, infrastructure audits, and cross agency coordination will be critical for reducing long term exposure burdens and guiding equitable resource allocation. Overall, a spatiotemporal perspective provides a more accurate basis for intervention design, liability assessment, and community protection in PFAS affected U.S. regions. Future research should couple sensor based networks with biomonitoring and health outcome datasets to better link environmental gradients with human exposure patterns and disease indicators. Such integrated frameworks can enhance accountability, accelerate cleanup performance, and inform safer chemical substitution and procurement policies nationwide. Coordinated federal, state, and local data sharing platforms will be essential to sustain comparable long term spatiotemporal PFAS risk mapping and evidence based regulatory action. Across vulnerable industrial and defense adjacent communities nationwide today and into future planning cycles and protection strategies ahead overall nationally.

Keywords: PFAS, Spatiotemporal Analysis, Groundwater Contamination, Industrial Facilities, Military Sites, Environmental Monitoring, Geospatial Modeling, Public Health Risk.

INTRODUCTION

Introduction to PFAS and the Need for Spatiotemporal Analysis

Per- and polyfluoroalkyl substances (PFAS) are a large class of synthetic fluorinated compounds that have been widely used since the mid-twentieth century because of their exceptional resistance to heat, water, oil, and chemical degradation. Their strong carbon–fluorine bonds make them highly stable in both industrial applications and environmental conditions. This same stability, however, also makes them extremely persistent once released, earning them the label “forever chemicals (Attah & Osuashi Sanni, 2023, Sanusi, Bayeroju & Nwokediegwu, 2023, Uduokhai, et al., 2023).” PFAS have been extensively applied in firefighting foams, nonstick and stain-resistant coatings, textiles, food packaging, electronics manufacturing, metal plating, and numerous defense and aerospace operations. As a result, industrial complexes and military installations have become some of the most significant point sources of PFAS contamination across many regions of the United States (Liadi, 2024, Okonkwo, et al., 2024).

The environmental behavior of PFAS is complex because these compounds do not readily break down through natural biological or chemical processes. Instead, they tend to accumulate in soils, sediments, surface waters, groundwater systems, and living organisms. Their mobility varies by chain length and functional group, with some PFAS traveling long distances through aquifers and watershed networks (Akinrinoye, et al., 2025, Ezeh, et al., 2025, Nwafor, et al., 2025, Ukamaka, et al., 2025). This creates contamination plumes that can extend far beyond the original release point, affecting municipal water supplies and nearby communities. Conventional site assessment approaches that rely on single time point measurements often fail to capture the evolving extent and intensity of such plumes, leading to underestimation of exposure risk (Anioke & Atima, 2023, Ogunboye, et al., 2023, Okonkwo, Mayo & Okeke, 2023).

A spatiotemporal perspective is therefore essential for accurately characterizing PFAS contamination patterns around industrial and military facilities. Spatial analysis helps identify hotspots, transport corridors, and exposure zones, while temporal analysis reveals trends in concentration levels, plume migration, seasonal variability, and the effects of regulatory controls or remediation actions (Osuashi Sanni, et al., 2022, Seyi-Lande, Arowogbadamu & Oziri, 2022, Uduokhai, et al., 2022). When combined, spatial and temporal assessments provide a more complete understanding of how contamination originates, spreads, and persists over time. This integrated approach supports better monitoring design, more precise risk evaluation, and more effective intervention strategies across diverse U.S. regions where PFAS releases have occurred (Atima & Anioke, 2020, Okonkwo, et al., 2020).

METHODOLOGY

This study adopts an integrated spatiotemporal environmental surveillance design that combines longitudinal evidence synthesis, geospatial decision-support modeling, and predictive analytics to characterize PFAS contamination patterns around industrial and military facilities across U.S. regions. The approach is structured to mirror best practices for working with large, time-indexed datasets and building reproducible predictive pipelines, drawing methodological cues from longitudinal machine-learning evidence reviews and risk-aware analytics frameworks (Adediran et al., 2025a; Adediran et al., 2025b; Badmus & Olamide, 2020; Badmus & Olamide, 2025).

Facility inventory development begins by compiling a geo-referenced registry of PFAS-relevant sites, including military installations (e.g., airfields, training areas), industrial PFAS users and manufacturers, metal finishing clusters, landfills, and wastewater infrastructure nodes. Each facility is assigned attributes describing facility type, operational timeline, likely PFAS use mechanisms, and potential release pathways to enable stratified analysis by source profile and operational history (Dako, et al., 2019, Nwafor, et al., 2019, Oguntegbe, Farounbi & Okafor, 2019). The study domain is then partitioned into hydrologically meaningful units (watersheds and aquifers) and administrative units (state/county) to support cross-region comparability and policy interpretation. A risk-oriented scoping step is used to prioritize investigation areas where receptors (drinking-water wells, surface-water intakes, schools, sensitive ecosystems) are plausibly connected to sources through groundwater flow or surface drainage, reflecting structured risk-prioritization logic used in complex systems planning (Agbabiaka et al., 2019; Badmus & Olamide, 2023).

Environmental data assembly integrates multi-source measurements and contextual covariates. PFAS concentration records are collated for groundwater, surface water, soil/sediment where available, and drinking-water compliance datasets, preserving sampling date/time, method, detection limits, and analyte lists to ensure temporal comparability. Remote sensing and GIS covariates are added to support transport interpretation and spatial prediction, including land use, impervious surface fraction, drainage density, elevation/slope, surface-water proximity, precipitation proxies, and indicators of hydrologic change, consistent with remote-sensing–enabled regulatory surveillance concepts (Badmus & Olamide, 2025; Olamide & Badmus, 2019). Where repeated observations exist at fixed locations (monitoring wells, stations), the records are curated into longitudinal panels to enable trend detection and change-point analysis (Adediran et al., 2025a; Ajayi et al., 2023).

Data preparation is handled through a quality-assurance pipeline emphasizing contamination control, comparability, and bias reduction. Standardization includes harmonizing units, censoring rules for non-detects, and aligning analyte names across laboratories. Duplicate handling, outlier screening, and metadata completeness checks are performed to reduce spurious trend signals. Bias and integrity controls are embedded to limit systematic distortions from inconsistent sampling effort, shifting detection limits, and uneven coverage, borrowing principles from bias-countermeasure thinking in modern analytics systems (Adeniyi et al., 2025). The final analytic dataset is organized into (i) space–time point observations, (ii) facility-centered distance and flow-path features, and (iii) regional context layers for interpretation.

Spatiotemporal characterization proceeds in two linked stages. First, descriptive mapping is conducted using GIS to identify clusters, hotspot cores, and downgradient plume corridors via facility-buffer analysis, watershed overlays, and receptor proximity. Second, formal space–time modeling is applied to estimate continuous contamination surfaces and their evolution (Ezeh, et al., 2025, Oparah, et al., 2025, Sanusi, 2025, Ukasoanya, et al., 2025). Depending on data density, the study uses space–time kriging or Bayesian hierarchical spatiotemporal models with covariates capturing hydrogeologic controls, land-use, and infrastructure connectivity. Predictive components can incorporate hybrid machine-learning and process-informed features to better represent soil–water transport pathways under variable hydrologic conditions (Badmus & Olamide, 2021; Olamide & Badmus, 2018). Temporal behavior is assessed using longitudinal trend tests, seasonal decomposition, and change-point detection to distinguish legacy tailing, ongoing inputs, and hydrologically driven variability (Adediran et al., 2025b; Ajayi et al., 2023).

Risk mapping translates modeled concentrations into decision-relevant outputs. A multi-criteria risk index is constructed that combines (a) modeled concentration magnitude and trend direction, (b) pathway connectivity (groundwater gradient alignment, surface-water linkage), (c) receptor density and vulnerability proxies, and (d) uncertainty penalties where monitoring coverage is weak (Okafor, et al., 2024, Oparah, et al., 2024, Uduokhai, et al., 2024). This index is rendered as regional risk tiers to support prioritization of monitoring expansion, treatment interventions, and remediation sequencing. Dashboard-style reporting outputs are designed to support transparent, repeatable oversight and scenario testing, aligned with data-driven governance and performance-monitoring approaches used in other complex regulatory environments (Anioke & Atima, 2019; Oparah et al., 2023; Oparah et al., 2025).

Model performance and robustness are evaluated using spatial cross-validation (holding out clusters or watersheds), temporal back-testing (training on earlier periods and predicting later samples), and sensitivity analysis for censoring assumptions and covariate selection. Outputs include uncertainty maps, hotspot persistence metrics, plume migration indicators, and prioritized monitoring recommendations. The overall methodology is designed to be auditable, reproducible, and adaptable as new PFAS analytes, detection methods, and regulatory thresholds evolve (Badmus & Olamide, 2020; Adediran et al., 2025a).

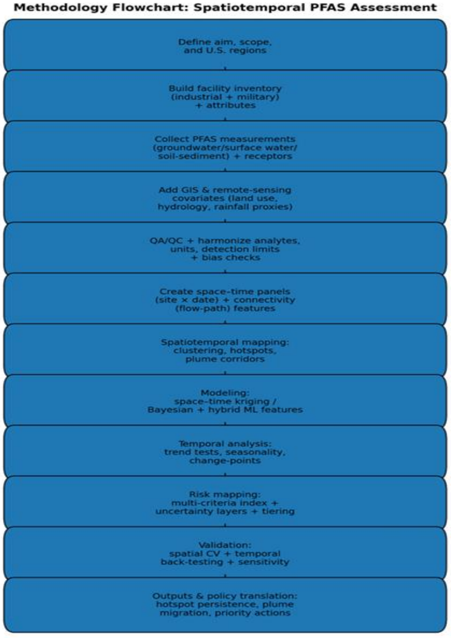

Figure 1: Flowchart of the Study Methodology

Major PFAS Sources in Industrial and Military Settings

Per- and polyfluoroalkyl substances (PFAS) contamination around industrial and military facilities in U.S. regions is strongly linked to a relatively defined but highly impactful set of source activities. These compounds were not typically produced for a single narrow use but rather incorporated into many operational materials because of their thermal stability, surfactant behavior, and resistance to chemical breakdown (Arowogbadamu, Oziri & Seyi-

Lande, 2022, Fatimetu, et al., 2022, Umoren, et al., 2022). As a result, PFAS releases have occurred through repeated, routine practices rather than isolated accidents. Understanding the dominant release sources requires attention not only to facility type but also to operational history, material handling practices, and the specific pathways through which PFAS enter soil and water systems over time (Liadi, 2022, Owoade, et al., 2022).

One of the most significant PFAS release sources in military and certain civilian industrial settings is the use of aqueous film forming foam, commonly known as AFFF. This specialized firefighting foam has been widely used for decades to suppress high intensity fuel fires, especially those involving jet fuel and petroleum products. Military airfields, naval bases, airport fire training centers, and petroleum storage terminals relied heavily on AFFF for emergency response readiness and routine training exercises (Okonkwo, Ogunwole & Okeke, 2018). Historically, repeated discharge during training drills allowed large volumes of foam to infiltrate soil and unlined ground surfaces. Because many training areas were designed for rapid drainage rather than containment, PFAS compounds readily migrated downward into subsurface layers and laterally into nearby groundwater and surface water bodies. Operational history is critical here, since facilities with long running fire training programs from the 1970s through the early 2000s often show broader and deeper PFAS plumes than newer sites that adopted containment measures earlier. Even where AFFF use has been reduced or reformulated, legacy residues remain a continuing source through slow desorption and subsurface transport (Anioke & Atima, 2019, Badmus & Olamide, 2019).

Chemical manufacturing facilities represent another primary source category, especially plants that historically produced PFAS or used them as processing aids. These facilities handled large precursor volumes and generated PFAS containing wastes, off gases, and wastewater streams. Earlier regulatory frameworks did not always require advanced treatment for fluorinated compounds, so process water and residual sludges were sometimes discharged into nearby rivers, infiltration basins, or landfills. Air emissions from high temperature operations also contributed to atmospheric deposition, followed by rainfall driven transfer into soils and surface waters across surrounding areas (Ahmed, Odejobi & Oshoba, 2021, Dako, et al., 2021, Ogunsola & Michael, 2021). The spatial footprint of contamination near manufacturing sites is often complex, reflecting multiple release points such as discharge pipes, storage areas, waste lagoons, and accidental spill locations. Temporal patterns also vary, with older production eras typically associated with higher emission intensity and fewer controls. Facility upgrades, product phaseouts, and process changes over time can produce layered contamination signatures that reflect different PFAS chemistries across decades of operation (Olude & Badmus, 2015, Kolndadacha, et al., 2013).

Metal finishing and electroplating operations have also contributed meaningfully to PFAS releases, particularly through the use of fluorinated surfactants in mist suppression and surface treatment baths. These substances were added to reduce aerosol formation and improve coating uniformity. During routine operations, PFAS containing solutions could be lost through drag out on parts, bath overflow, filter backwash, and spent solution disposal. Smaller plating shops often operated with limited wastewater pretreatment infrastructure, increasing the likelihood that PFAS entered municipal sewer systems or on site disposal units (Akinrinoye, et al., 2015, Aminu-Ibrahim, Ogbete & Ambali, 2019). Even when routed through treatment plants, conventional processes were not designed to remove PFAS effectively, allowing downstream discharge into rivers and biosolids. Over time, biosolids application on land created a secondary pathway for PFAS entry into agricultural soils and shallow groundwater. The operational scale of these facilities matters, but so does duration, since decades of low level releases can generate significant cumulative loading in nearby environmental media (Liadi, 2022, Osuashi Sanni, et al., 2023). Figure 2 shows average $\sum$ 4-

23 PFAS concentrations in surface water and fish at Site 4 presented by Reinikainen, et al., 2022.

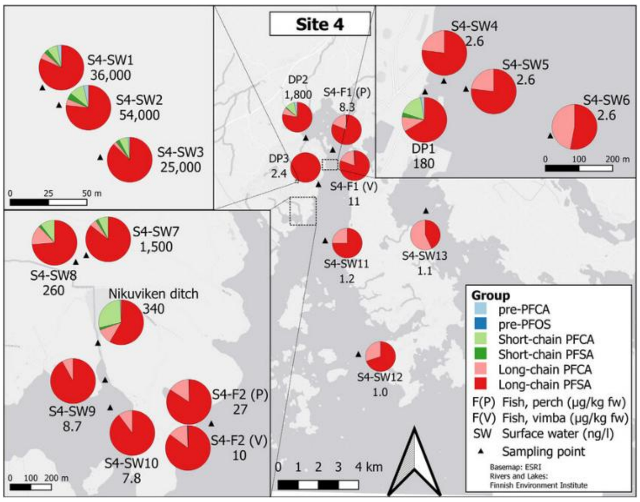

Figure 2: Average ∑ 4-23 PFAS Concentrations in Surface Water and Fish at SITE 4 (Reinikainen, et al., 2022)

Waste disposal practices form a cross cutting source pathway that links many industrial and military PFAS uses. Landfills that accepted PFAS containing wastes, including sludge, spent filters, contaminated soils, textiles, and packaging materials, often became long term secondary sources. In unlined or poorly lined landfills, leachate carrying dissolved PFAS migrated into surrounding soils and aquifers (Farounbi, et al., 2021, Olatunji, et al., 2021, Oparah, et al., 2021). Even modern lined facilities can act as ongoing point sources when leachate collection systems route contaminated liquids to treatment plants not equipped for PFAS removal. Military bases and industrial campuses frequently operated on site disposal areas, burn pits, or burial trenches in earlier decades, creating localized but persistent source zones. These disposal areas may be poorly documented, making later site investigations more difficult and contributing to delayed recognition of contamination (Badmus & Olamide, 2025, Yusuff, et al., 2025).

Operational history plays a central role in interpreting PFAS source strength and distribution. Facilities with continuous high intensity PFAS use over many years generally produce broader and more stable plumes than sites with short term or intermittent use. Changes in product formulation, such as shifts from long chain to shorter chain PFAS, introduce additional temporal complexity because different compounds move and persist differently in the environment (Osuashi Sanni, Atima & Attah, 2022). Historical record gaps, contractor changes, and evolving safety standards further complicate reconstruction of release timelines. As a result, spatiotemporal analysis must often combine archival research, interviews, and environmental forensics to map likely release periods and pathways (Okonkwo, Ogunwole & Okeke, 2018, Olamide & Badmus, 2018).

Release pathways from these dominant sources typically include direct surface discharge, subsurface infiltration, sewer and wastewater routing, atmospheric deposition, and solid waste leaching. Surface discharge occurs when PFAS containing liquids are released to ground or water bodies during training, washing, or process overflow. Subsurface infiltration follows when these liquids penetrate permeable soils and move downward into aquifers (Oguntegbe, Farounbi & Okafor, 2023, Oshoba, Ahmed & Odejobi, 2023, Uduokhai, et al., 2023). Sewer routing transfers PFAS to treatment plants, which often pass them through to receiving waters or concentrate them in sludge. Atmospheric pathways arise from volatilization or particle bound emissions during high temperature processes, followed by regional deposition. Solid waste leaching occurs when PFAS treated materials break down in disposal environments and release soluble fractions into percolating water (Okonkwo, et al., 2024). Figure 3 shows potential sources, pathways, and impacts of PFAS in soil and sediments presented by Ehsan, et al., 2024.

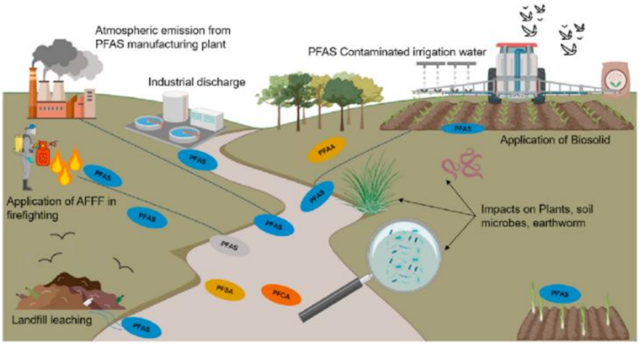

Figure 3: Potential Sources, Pathways, and impacts of PFAS in Soil and Sediments (Ehsan, et al., 2024).

Taken together, aqueous film forming foam use, chemical manufacturing, metal finishing operations, and diverse waste disposal practices account for a large share of PFAS loading around industrial and military facilities in U.S. regions. Their combined impact is shaped by facility function, infrastructure design, and decades of operational decisions made before PFAS persistence was fully recognized. A spatiotemporal perspective that integrates facility history with environmental transport pathways is therefore essential for accurately identifying dominant sources, predicting plume behavior, and prioritizing investigation and remediation efforts (Badmus & Olamide, 2021, Olamide & Badmus, 2021).

Environmental Transport Pathways and Fate Mechanisms

Per- and polyfluoroalkyl substances (PFAS) display distinctive environmental transport behavior that sets them apart from many conventional organic pollutants. Their strong carbon–fluorine bonds make them resistant to thermal, chemical, and biological degradation, which means that once they are released from industrial and military facilities, they tend to persist and move through multiple environmental compartments rather than breaking down in place (Adenuga, et al., 2025, Michael & Ogunsola, 2025, Oparah, et al., 2025). The spatiotemporal dynamics of PFAS contamination are therefore governed not only by source strength and release history but also by the interacting transport pathways across soil, groundwater, surface water, and the atmosphere. Understanding these pathways and fate mechanisms is essential for predicting plume growth, identifying exposure zones, and designing effective monitoring and remediation strategies in U.S. regions affected by PFAS releases (Adediran, et al., 2025, Okonkwo, et al., 2025).

Following release at the ground surface, PFAS commonly enter the soil system first. Their migration through soil depends on compound specific properties such as chain length and functional group, as well as soil characteristics including texture, organic carbon content, mineral composition, and moisture conditions. Shorter chain PFAS tend to be more water soluble and less strongly sorbed to soil particles, allowing them to move more rapidly downward with infiltrating water (Dako, Okafor & Osuji, 2021, Ezeh, et al., 2021, Ogunsola & Michael, 2021). Longer chain PFAS often show stronger sorption to organic matter and fine grained soils, which can slow vertical movement but also create long term secondary reservoirs that gradually release contaminants back into pore water. This sorption behavior is reversible, so changes in groundwater chemistry, pH, or ionic strength can remobilize previously retained PFAS. Repeated wetting and drying cycles, common in many U.S. climates, further influence retention and release patterns over time (Anioke & Atima, 2020, Badmus & Olamide, 2020). Figure 4 shows schematic for per- and polyfluoroalkyl substances (PFAS), adsorption of PFAS at air–water interfaces and mass transfer of PFAS between bulk presented by Chen & Guo, 2023.

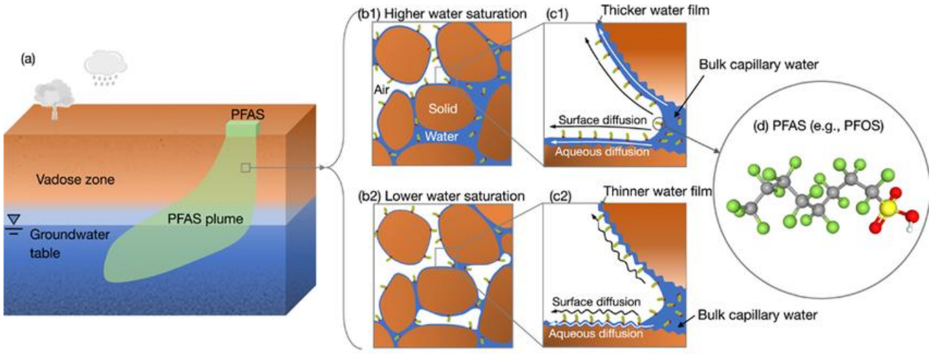

Figure 4: Schematic for per- and polyfluoroalkyl substances (PFAS), adsorption of PFAS at air–water interfaces and mass transfer of PFAS between bulk (Chen & Guo, 2023).

Hydrogeologic controls play a decisive role in determining how PFAS migrate once they pass below the root zone and enter the vadose and saturated zones. Soil permeability, stratigraphy, fracture networks, and aquifer type all shape transport speed and direction. In sandy or gravelly formations with high hydraulic conductivity, PFAS can move relatively quickly with groundwater flow, forming elongated plumes that extend downgradient from industrial plants or military training areas (Oguntegbe, Farounbi & Okafor, 2019, Michael & Ogunsola, 2019, Oziri, Seyi-Lande & Arowogbadamu, 2019). In contrast, clay rich or layered formations may slow vertical migration but promote lateral spreading along preferential pathways such as sand lenses or fractures. Karst terrains, characterized by solution channels and conduits, can transmit PFAS rapidly over long distances with limited natural attenuation. Groundwater recharge rates, driven by precipitation and land surface conditions, influence how quickly PFAS are flushed downward from contaminated surface zones into aquifers (Olamide & Badmus, 2020, Patrick, et al., 2020).

Groundwater transport is often the dominant long term pathway for PFAS plume expansion. Because PFAS do not readily degrade under typical subsurface conditions, they can persist in aquifers for decades. Advective transport carries dissolved PFAS along hydraulic gradients, while dispersion spreads the plume laterally and vertically. Matrix diffusion can move PFAS into low permeability zones adjacent to main flow channels, creating storage zones that later release contaminants back into flowing groundwater (Ogunsola & Michael, 2023, Osuji, Okafor & Dako, 2023, Uduokhai, et al., 2023). This back diffusion effect contributes to extended tailing in concentration time series, where levels decline slowly even after the primary source is removed. Pumping from water supply wells can further modify flow fields, sometimes drawing PFAS plumes toward municipal or private wells and altering their spatial footprint (Liadi, 2023, Ogunboye, et al., 2023, Okonkwo, et al., 2023).

Surface water systems also function as major transport corridors for PFAS. When contaminated groundwater discharges into streams, rivers, lakes, or wetlands, PFAS are transferred into surface water bodies and can travel far beyond the original release area. Direct surface releases from industrial outfalls, wastewater treatment plant discharges, and fire training runoff add additional loading (Ogunsola & Michael, 2022, Olatunji, et al., 2022, Oparah, et al., 2022). Within rivers and streams, PFAS are transported primarily in dissolved form, although some fraction may associate with suspended particles or sediments, especially for longer chain compounds. Hydrologic variability introduces strong temporal dynamics. High flow events such as storms and snowmelt can mobilize PFAS stored in soils, sediments, and floodplains, producing concentration pulses downstream. During low flow periods, dilution decreases and measured concentrations may rise even without new releases (Badmus, et al., 2021, Ogunwole, et al., 2021, Okonkwo, et al., 2021).

Lakes and reservoirs can act as both sinks and secondary sources. PFAS entering these systems may remain in the water column for long periods because they resist degradation and are not easily removed by natural processes. Some PFAS accumulate in sediments or biota, while others remain largely dissolved and subject to outflow transport (Ahmed, Odejobi & Oshoba, 2020, Nwafor, Ajirotutu & Uduokhai, 2020). Stratification and seasonal mixing cycles influence vertical distribution, with turnover events redistributing PFAS through the water column. Where surface waters are used for drinking water supply, this creates a direct pathway from distant industrial or military sources to human exposure points (Adediran, et al., 2025).

Atmospheric transport and deposition provide an additional pathway that expands the spatial reach of PFAS contamination. Certain PFAS and precursor compounds can enter the atmosphere through volatilization, aerosol formation, or stack emissions from manufacturing and high temperature processes. Once airborne, these substances or their transformation products can travel regionally before being deposited through wet or dry deposition (Akinrinoye, et al., 2020, Odejobi, Hammed & Ahmed, 2020, Oguntegbe, Farounbi & Okafor, 2020). Rain and snow can scavenge PFAS from the atmosphere and deliver them to soils and surface waters far from the original source. Atmospheric oxidation of volatile precursors can also generate more persistent PFAS that then deposit onto land and water surfaces. This mechanism helps explain detections in remote areas and contributes to diffuse background contamination patterns that overlay point source plumes (Anioke & Atima, 2023, Badmus & Olamide, 2023).

Persistence is a defining feature of PFAS fate, but mobility varies widely across the compound class. Factors influencing persistence and mobility over time include molecular structure, co contaminant chemistry, temperature, redox conditions, and biological activity. While most terminal PFAS resist degradation, some precursor compounds can transform through chemical or biological pathways into more stable end products (Michael & Ogunsola, 2023, Ogunsola & Michael, 2023, Uduokhai, et al., 2023). These transformation processes may occur in soils, sediments, wastewater systems, or the atmosphere, effectively extending the contamination timeline as new persistent PFAS are generated after the initial release. Temperature and sunlight can influence certain transformation reactions at the surface, while subsurface conditions generally favor persistence (Agbabiaka, et al., 2019, Olamide & Badmus, 2019).

Interactions with engineered systems also shape PFAS fate. Wastewater treatment plants, stormwater systems, and landfill leachate networks often redistribute PFAS rather than destroy them. Treatment processes may transfer PFAS from water to sludge or from sludge to land applied biosolids, shifting contamination from one environmental compartment to another. Over time, these redistributed reservoirs become secondary sources that feed PFAS back into soil and water systems through leaching and runoff (Liadi, 2022, Osuashi Sanni, et al., 2024, Wedraogo & Osuashi Sanni, 2024).

The combined effect of soil retention and release, groundwater advection and storage, surface water transport, atmospheric deposition, and precursor transformation produces complex spatiotemporal contamination patterns around industrial and military facilities. Plumes evolve, branch, and sometimes re intensify as hydrologic conditions change or secondary sources activate (Akinola, et al., 2020, Nwafor, Uduokhai & Ajirotutu, 2020, Osuashi Sanni, Ajiga & Atima, 2020). A detailed understanding of these transport pathways and fate mechanisms is therefore essential for interpreting monitoring data, forecasting plume behavior, and selecting control measures that address not just the original source but the full environmental system through which PFAS move and persist over time (Patrick, et al., 2021).

Spatial Distribution Patterns and Regional Hotspots

Spatial distribution patterns of per- and polyfluoroalkyl substances (PFAS) contamination around industrial and military facilities in U.S. regions reveal strong geographic clustering, distinct hotspot formation, and complex downgradient plume behavior shaped by both natural and built environment factors. Unlike contaminants that degrade relatively quickly, PFAS tend to persist and migrate, which allows their spatial footprint to expand over time and produce layered patterns of contamination (Ajayi, et al., 2023, Odejobi, Hammed & Ahmed, 2023, Onyelucheya, et al., 2023). These patterns are rarely uniform. Instead, they reflect the interaction between source intensity, release history, hydrogeology, land use, and infrastructure networks. A spatiotemporal perspective shows that PFAS contamination is best understood not as isolated point pollution but as evolving regional mosaics of concentrated hotspots and extended transport corridors (Anioke & Atima, 2020, Badmus & Olamide, 2020).

Geographic clustering is one of the most consistent features observed in PFAS monitoring datasets. Elevated concentrations are commonly found near known source facilities such as military airfields, firefighting training grounds, fluorochemical manufacturing plants, metal finishing clusters, and large logistics or fuel storage hubs. These clusters often correspond with historical use of PFAS containing materials, especially aqueous film forming foam and specialty industrial surfactants (Ajayi, et al., 2023, Olatunji, et al., 2023, Oshoba, Ahmed & Odejobi, 2023). Because these activities are not randomly distributed across the landscape, PFAS contamination also appears in nonrandom spatial groupings. Regions with dense industrial corridors or multiple defense installations tend to show overlapping zones of concern, where several facilities contribute to cumulative loading. Over time, clustered releases can merge into broader contamination zones, complicating source attribution and response planning (Badmus, et al., 2021, Okonkwo, et al., 2021).

Hotspot formation near facilities is driven by repeated releases at specific operational locations combined with limited early containment measures. Fire training areas, foam testing pads, chemical handling zones, waste lagoons, and discharge outfalls often function as primary hotspot cores. In these areas, PFAS concentrations in soil and shallow groundwater can be orders of magnitude higher than regional background levels (Michael & Ogunsola, 2024, Ogunsola & Michael, 2024, Okafor, Osuji & Dako, 2024). Spatial mapping frequently shows steep concentration gradients radiating outward from these cores, with levels declining with distance but remaining detectable far beyond facility boundaries. The geometry of hotspots is rarely circular. Instead, it often follows site drainage patterns, surface grading, and subsurface flow directions. Where stormwater channels or infiltration basins are present, elongated hotspot shapes may form along these engineered pathways (Ezeh, et al., 2024, Liadi, 2024, Okonkwo, et al., 2024, Olamide & Badmus, 2024).

Downgradient plume behavior adds another layer of spatial complexity. Once PFAS enter groundwater, they tend to follow hydraulic gradients, creating plumes that extend away from the source along preferred flow directions. These plumes can travel hundreds to several thousands of meters depending on aquifer properties and time since release. Spatially, this produces asymmetric contamination footprints, with relatively clean conditions upgradient and laterally displaced but elevated concentrations downgradient (Ezeh, et al., 2022, Onyelucheya, et al., 2021, Oparah, et al., 2021). Monitoring well networks often reveal narrow, finger like extensions where high permeability zones accelerate transport, alongside broader, lower concentration halos where dispersion dominates. Over time, plumes may bifurcate when encountering heterogeneity in subsurface materials, forming multiple downgradient branches rather than a single continuous body (Badmus, 2019, Okonkwo, et al., 2019).

Regional contrasts in PFAS spatial patterns are strongly influenced by geology. In unconsolidated sand and gravel aquifers common in parts of the Midwest and Northeast, high permeability allows faster groundwater velocities and longer plume migration distances. This tends to produce elongated regional plumes and wider spatial impact zones. In contrast, regions dominated by clay rich sediments may show more vertically constrained contamination with slower lateral spread but stronger local retention, leading to intense but more localized hotspots (Ogbete & Aminu-Ibrahim, 2024). Fractured bedrock settings introduce additional variability, since PFAS may move rapidly along fractures while leaving adjacent rock matrix less affected. Karst regions with solution channels and sinkholes can exhibit highly irregular spatial patterns, including rapid long distance transport and unexpected emergence points at springs or surface waters (Liadi, 2024, Okonkwo, et al., 2024, Opara, et al., 2024).

Land use patterns also shape spatial distribution. Urban and industrial landscapes typically contain dense networks of storm drains, sewers, and engineered channels that can redirect PFAS laden water away from original release points. This redistribution can create secondary hotspots at outfalls, detention basins, and downstream receiving waters (Onyelucheya, et al., 2023, Sanusi, Bayeroju & Nwokediegwu, 2023, Uduokhai, et al., 2023). Suburban areas near military bases or airports may show patchy contamination patterns tied to private well use, lawn irrigation, and localized recharge conditions. Agricultural areas that received PFAS contaminated biosolids or irrigation water can develop diffuse but widespread soil and shallow groundwater contamination, creating broader spatial footprints with lower peak concentrations but larger affected areas (Anioke & Atima, 2018, Badmus & Olamide, 2018).

Infrastructure plays a critical role in determining where PFAS accumulate and how hotspots evolve. Drinking water supply wells, irrigation wells, and dewatering systems can alter groundwater flow fields, effectively pulling plumes toward pumping centers. This creates capture zones where contamination becomes concentrated near well fields, sometimes shifting hotspot locations over time (Akinola, et al., 2025, Odejobi, Hammed & Ahmed, 2019, Oshoba, Hammed & Odejobi, 2019). Surface water infrastructure such as reservoirs, canals, and diversion channels can similarly influence spatial patterns by storing, mixing, or rerouting contaminated water. Wastewater treatment plants often act as spatial nodes where PFAS from multiple upstream sources converge, after which treated effluent and biosolids distribute contamination along new pathways. The spatial signature downstream of such facilities may therefore reflect mixed source inputs rather than a single origin (Olamide & Badmus, 2026).

Hotspot persistence and evolution are also time dependent. Some hotspots remain stable for years where source zones continue to release PFAS slowly from contaminated soils and sediments. Others gradually weaken following source control and remediation, though residual subsurface storage can sustain moderate concentrations for extended periods (Akinrinoye, et al., 2023, Sanusi, Bayeroju & Nwokediegwu, 2023, Umoren, et al., 2023). Spatial monitoring over multiple sampling rounds often shows shrinking high concentration cores but expanding low concentration fringes, as plumes spread and dilute. In certain cases, new hotspots appear downgradient years after the original release due to delayed transport through low permeability layers or seasonal flow reversals (Anioke & Atima, 2024, Badmus & Olamide, 2024, Liadi, 2024, Okonkwo, et al., 2024).

Regional monitoring intensity further affects the apparent spatial distribution. Areas with comprehensive sampling programs tend to show more detailed hotspot maps and more detected clusters, while under sampled regions may appear cleaner simply due to data gaps. This creates an uneven national picture in which observed spatial patterns partly reflect surveillance effort. As monitoring networks expand, previously unrecognized clusters and transport corridors are often identified, refining understanding of regional PFAS geography (Badmus, et al., 2021, Olamide & Badmus, 2021).

Taken together, geographic clustering near source facilities, concentrated hotspot cores, directional downgradient plumes, and strong regional contrasts driven by geology, land use, and infrastructure define the spatial character of PFAS contamination around industrial and military sites in U.S. regions. These patterns are dynamic rather than static, changing as plumes migrate, infrastructure alters flow, and remediation progresses. Spatiotemporal mapping that integrates facility history with environmental and infrastructural context provides the most reliable basis for identifying priority areas, forecasting plume movement, and protecting exposed communities (Liadi, 2023, Okonkwo, et al., 2023).

Temporal Trends and Longitudinal Monitoring Evidence

Temporal trends in per- and polyfluoroalkyl substances (PFAS) contamination around industrial and military facilities in U.S. regions reveal patterns that are closely tied to operational history, regulatory change, environmental transport processes, and remediation efforts. Because PFAS are highly persistent and often mobile, their concentration profiles over time rarely show rapid natural decline. Instead, longitudinal monitoring records typically display extended plateaus, delayed peaks, multi-phase declines, or even secondary increases long after primary releases occurred (Anioke & Atima, 2023, Liadi, 2023, Olamide & Badmus, 2023). A spatiotemporal understanding of PFAS therefore depends heavily on time series data from repeated sampling of groundwater, surface water, soil, and drinking water systems, allowing analysts to distinguish between legacy contamination, ongoing inputs, and hydrologically driven fluctuations (Aransi, et al., 2018, Farounbi, et al., 2018, Odejobi & Ahmed, 2018).

Legacy releases represent one of the dominant drivers of long term PFAS trends near military and industrial sites. For several decades, activities such as firefighting foam training, fluorochemical production, and specialized manufacturing used PFAS intensively with limited containment. In many locations, the highest mass loading occurred years or decades before systematic monitoring began. As a result, early sampling rounds often captured only the later stages of plume development rather than the initial rise (Aminu-Ibrahim, Ogbete & Iwuanyanwu, 2025, Osuashi Sanni, Iwuanyanwu & Essien, 2025). Longitudinal datasets frequently show that even after source use has stopped, PFAS concentrations in groundwater remain stable or decline only slowly. This persistence reflects continued leaching from contaminated soils, vadose zone storage, and low permeability layers that act as long term reservoirs. Time lag between surface release and groundwater detection can be substantial, meaning that measured peaks in wells may occur long after operational changes at the surface (Ezeh, et al., 2024, Michael & Ogunsola, 2024, Oparah, et al., 2024).

In contrast, ongoing releases produce different temporal signatures. Where PFAS containing materials are still used or where contaminated infrastructure continues to discharge, monitoring records often show relatively steady or gradually increasing concentration trends. These upward or flat high level trends can signal active inputs from process wastewater, leachate systems, or residual foam stocks (Ezeh, et al., 2023, Oguntegbe, Farounbi & Okafor, 2023, Odejobi, Hammed & Ahmed, 2023). Distinguishing ongoing releases from legacy tailing requires careful alignment of monitoring data with facility operational timelines, chemical usage records, and regulatory interventions. In some cases, compound specific trends help clarify the picture. A shift in the relative proportions of different PFAS compounds over time can indicate transition from older product formulations to newer ones, suggesting more recent inputs layered onto older contamination (Akinrinoye, et al., 2024, Seyi-Lande, Arowogbadamu & Oziri, 2024, Uduokhai, et al., 2024).

Seasonal variability introduces additional temporal structure into PFAS datasets. Although PFAS are chemically stable, their measured concentrations in water systems often fluctuate with hydrologic cycles. During wet seasons, increased precipitation and recharge can mobilize PFAS from soils and shallow source zones, producing concentration pulses in groundwater and surface water. At the same time, higher flow volumes may dilute concentrations at certain monitoring points, creating apparent decreases that reflect dilution rather than reduced mass (Michael & Ogunsola, 2025, Onyelucheya, et al., 2025, Oparah, et al., 2025). Dry seasons may show the opposite effect, with lower water volumes leading to higher measured concentrations even when mass loading is unchanged. Snowmelt periods in colder U.S. regions can generate pronounced seasonal spikes as accumulated atmospheric deposition and surface residues are flushed into streams and recharge zones. Longitudinal analysis must therefore interpret short term rises and falls within the context of seasonal hydrology rather than treating them as purely source driven changes (Okafor, et al., 2021, Oshoba, Hammed & Odejobi, 2021, Umoren, et al., 2021).

Remediation activities leave recognizable signatures in temporal PFAS trends, though the response is often slower and more complex than for degradable contaminants. Source control measures, such as discontinuing certain firefighting foams, lining training areas, or diverting waste streams, may reduce new inputs relatively quickly. However, concentration declines in downgradient groundwater frequently lag behind these actions because stored PFAS mass continues to migrate (Arowogbadamu, Oziri & Seyi-Lande, 2023, Dako, Okafor & Osuji, 2022, Umoren, et al., 2022). Pump and treat systems, adsorption barriers, and advanced treatment installations can produce gradual downward trends in monitored concentrations, but rebound effects are common when treatment is paused or when back diffusion from low permeability zones replenishes the plume. Longitudinal datasets often show an initial drop following remediation startup, followed by a slower decline phase or partial rebound before stabilization (Olatunji, et al., 2023, Oparah, et al., 2023, Uduokhai, et al., 2023). This multi stage temporal behavior highlights the importance of sustained monitoring over many years rather than relying on short post-remediation observation windows.

Long term monitoring datasets from federal and state programs, as well as site specific investigations, provide critical evidence for interpreting PFAS temporal dynamics. Repeated sampling of fixed monitoring wells and surface water stations allows construction of time series that reveal whether concentrations are trending upward, downward, or remaining stable. Statistical trend analysis methods are increasingly applied to these datasets to separate signal from noise, accounting for seasonal cycles and sampling variability (Akinrinoye, et al., 2020, Rukh, Seyi-Lande & Oziri, 2023, Sanusi, Bayeroju & Nwokediegwu, 2023). Multi year records are especially valuable for identifying delayed plume arrival at new locations. A well that initially tests below detection may show measurable PFAS years later as the plume front advances, underscoring the need for ongoing surveillance beyond initial baseline studies (Ezeh, et al., 2025, Michael & Ogunsola, 2025, Sanusi, 2025, Oziri, Arowogbadamu & Seyi-Lande, 2025).

Temporal resolution also matters. High frequency sampling during certain periods, such as storm seasons or remediation transitions, can capture short term variability that would be missed by annual or semiannual sampling. Event based monitoring has shown that PFAS concentrations in runoff and receiving waters can spike sharply during major storms, contributing disproportionately to annual mass transport. Without time resolved data, these episodic contributions may be underestimated. Conversely, overly sparse sampling can create misleading impressions of stability or decline by missing intermittent peaks (Ajayi, et al., 2025, Okafor, et al., 2025, Ukamaka, et al., 2025).

Another important temporal feature is the evolution of analytical methods and detection limits. Over the past two decades, laboratory techniques for PFAS measurement have improved significantly, allowing detection at much lower concentrations and for a broader range of compounds. Apparent upward trends in some long term datasets partly reflect better detection rather than actual increases in environmental levels (Bayeroju, Sanusi & Nwokediegwu, 2019, Filani, Fasawe & Umoren, 2019, Nwafor, et al., 2019). Careful data harmonization is required when comparing older and newer records, including adjustment for reporting limits and compound lists. Expanded analyte panels have also revealed that while some well known PFAS decline, other previously unmonitored compounds remain steady or increase, changing the overall temporal risk profile (Osuashi Sanni, Ajiga & Atima, 2020, Oshoba, Hammed & Odejobi, 2020, Oziri, et al., 2020).

Compound specific behavior further shapes time based patterns. Shorter chain PFAS often move faster and appear earlier at downgradient points, producing earlier peaks and faster apparent turnover. Longer chain compounds may show delayed arrival but longer persistence near source zones due to stronger sorption (Seyi-Lande, Arowogbadamu & Oziri, 2021, Uduokhai, et al., 2021). Precursors that transform into terminal PFAS introduce delayed generation effects, where concentrations of stable end products rise over time even without new external inputs. This transformation driven increase complicates simple interpretations of trend direction (Ogunsola & Michael, 2021, Osuashi Sanni & Atima, 2021, Umoren, et al., 2021).

Taken together, temporal trends and longitudinal monitoring evidence show that PFAS contamination around industrial and military facilities follows extended, multi phase trajectories rather than simple rise and fall curves. Legacy releases create long tails, ongoing sources sustain plateaus or gradual increases, seasonal hydrology drives cyclic variability, and remediation produces slow, sometimes nonlinear declines. Only through consistent, long term, and methodologically stable monitoring can these patterns be resolved with confidence and used to guide effective management and protection strategies (Odejobi & Ahmed, 2018, Seyi-Lande, Arowogbadamu & Oziri, 2018).

Methods and Tools for Spatiotemporal Assessment

Assessing the spatiotemporal dynamics of PFAS contamination around industrial and military facilities in U.S. regions requires an integrated methodological framework that combines structured sampling, geospatial analysis, temporal modeling, and risk oriented interpretation tools. Because PFAS are persistent, mobile, and often unevenly distributed, no single method is sufficient to capture their behavior across space and time (Ahmed, Odejobi & Oshoba, 2019, Nwafor, et al., 2019, Oziri, Seyi-Lande & Arowogbadamu, 2019). Instead, effective assessment depends on coordinated use of field sampling frameworks, laboratory analytics, spatial mapping platforms, remote sensing support data, time series modeling techniques, and risk mapping approaches that translate measurements into decision relevant insights (Ahmed & Odejobi, 2018, Nwafor, et al., 2018, Seyi-Lande, Arowogbadamu & Oziri, 2018).

Robust sampling frameworks form the foundation of any spatiotemporal PFAS assessment. These frameworks typically combine targeted source area sampling with downgradient and background sampling to define both hotspot intensity and plume extent. Around industrial and military facilities, sampling designs often use a tiered structure. Initial screening focuses on high probability release zones such as fire training areas, storage yards, discharge points, and waste handling locations. Follow up phases expand outward along inferred groundwater flow paths and surface drainage networks (Akinrinoye, et al., 2019, Nwafor, et al., 2019, Sanusi, Bayeroju & Nwokediegwu, 2019). Monitoring networks usually include multiple environmental media, such as soil, vadose zone pore water, groundwater at different depths, surface water, sediment, and sometimes air deposition collectors. Well network design is especially important, with nested wells and transects installed to capture vertical and horizontal concentration gradients. Repeated sampling at fixed locations over months and years enables temporal trend detection, while rotating supplemental locations help refine spatial boundaries (Aransi, et al., 2019, Nwafor, et al., 2019, Oguntegbe, Farounbi & Okafor, 2019, Umoren, et al., 2019).

Analytical tools used in PFAS sampling have evolved significantly and are central to spatiotemporal characterization. High resolution liquid chromatography with mass spectrometry allows detection of multiple PFAS compounds at very low concentrations. Modern laboratory panels can quantify dozens of target analytes, while non targeted analysis and total organic fluorine methods provide broader screening for unknown or emerging PFAS (Ogbete, Aminu-Ibrahim & Iwuanyanwu, 2025). Consistency in laboratory methods across sampling rounds is critical for temporal comparability. Field quality assurance measures, including equipment blanks, trip blanks, and duplicate samples, are necessary because PFAS are common in many consumer materials and cross contamination risk is high (Oziri, et al., 2022, Rukh, Seyi-Lande & Oziri, 2022, Umoren, et al., 2022). Standardized protocols for sample containers, preservation, and transport reduce variability and improve confidence in spatial and temporal comparisons.

Geospatial mapping tools translate PFAS measurements into visual and analytical spatial patterns. Geographic information systems are widely used to integrate sampling results with facility layouts, hydrogeologic maps, land use layers, and infrastructure networks. Point measurements from wells and surface stations can be interpolated using spatial statistics methods to estimate continuous concentration surfaces and plume footprints. Techniques such as kriging and inverse distance weighting are commonly applied, with model choice depending on data density and spatial structure (Adeniyi, Odejobi & Taiwo, 2025, Sanusi, Chinwendu & Kehinde, 2025, Uduokhai, et al., 2025). Three dimensional geospatial models are increasingly used to represent vertical plume structure, especially where multiple aquifer layers are involved. Time enabled GIS layers allow analysts to animate plume evolution across sampling rounds, revealing directional migration, hotspot persistence, or contraction following remediation (Michael & Ogunsola, 2019, Seyi-Lande, Arowogbadamu & Oziri, 2019, Umoren, et al., 2019).

Remote sensing does not directly measure PFAS concentrations but provides valuable supporting data that strengthen spatiotemporal assessments. Satellite and aerial imagery help identify land use patterns, surface water networks, soil moisture conditions, and landscape changes that influence PFAS transport. Thermal imagery and multispectral data can detect surface disturbances, waste lagoons, and hydrologic connectivity features that may correspond to release or migration pathways (Arowogbadamu, Oziri & Seyi-Lande, 2024, Umoren, et al., 2021). Remote sensing derived elevation models support watershed and runoff modeling, which is important for understanding how PFAS move from source zones into streams and recharge areas. Time series of satellite imagery also reveal temporal changes in facility operations, construction, and land cover that may align with shifts in contamination patterns (Ahmed & Odejobi, 2018, Seyi-Lande, Arowogbadamu & Oziri, 2018).

Time series modeling is essential for interpreting PFAS concentration data collected repeatedly at the same locations. Simple trend plots often show variability that reflects both true change and environmental noise. Statistical time series methods help separate these components and identify meaningful trends. Approaches include seasonal decomposition, regression with time and hydrologic covariates, and nonparametric trend tests designed for environmental monitoring data (Ezeh, et al., 2024, Uduokhai, et al., 2024, Umoren, et al., 2024). Where sampling frequency is high enough, autoregressive and state space models can be used to forecast short term concentration behavior and detect anomalies. Time series analysis is particularly useful for distinguishing seasonal hydrologic effects from long term increases or decreases related to source control or remediation. Compound specific time trends can also be compared to detect shifts in PFAS mixtures that signal changing source profiles (Nwafor, Uduokhai & Ajirotutu, 2020, Sanusi, Bayeroju & Nwokediegwu, 2020).

Spatiotemporal modeling approaches extend beyond separate spatial and temporal analyses by integrating both dimensions in a unified framework. Space time kriging and Bayesian hierarchical models are examples of methods that estimate concentration fields that vary across both coordinates and time. These models can incorporate hydrogeologic parameters, flow direction, recharge rates, and source history as explanatory variables. The result is a dynamic representation of plume behavior that can be updated as new monitoring data become available. Such models support scenario analysis, allowing investigators to test how plumes may evolve under different remediation or pumping conditions (Osuashi Sanni & Adumaza, 2023, Oziri, et al., 2023, Umoren, et al., 2023).

Risk mapping approaches build on sampling and modeling outputs to translate PFAS distributions into exposure and hazard insights. Risk maps typically overlay concentration surfaces with population distribution, drinking water well locations, ecological receptors, and land use categories (Akinrinoye, et al., 2020, Sanusi, Bayeroju & Nwokediegwu, 2021). Threshold based mapping highlights zones where concentrations exceed regulatory or advisory levels. More advanced approaches use weighted indices that combine concentration, persistence, pathway connectivity, and receptor proximity into composite risk scores. These maps help prioritize investigation and cleanup by identifying areas where contamination and vulnerability intersect (Adenuga, et al., 2025, Baalah, et al., 2025, Sanusi, 2025, Uduokhai, et al., 2025). Time enabled risk maps show how priority zones expand or contract over successive monitoring rounds, supporting adaptive management.

Decision support tools increasingly integrate these methods into interactive platforms. Web based dashboards allow regulators and facility managers to view sampling results, plume maps, trend graphs, and risk indicators in near real time. These platforms often include query and filtering functions that let users explore compound specific patterns or time windows. Linking monitoring databases with geospatial and statistical engines improves consistency and speeds interpretation. Machine learning methods are beginning to be applied to large PFAS datasets to detect hidden spatial clusters, predict plume pathways, and optimize monitoring network design, though careful validation is needed (Ogbete, Aminu-Ibrahim & Ambali, 2020, Seyi-Lande, Arowogbadamu & Oziri, 2020).

Effective spatiotemporal assessment of PFAS around industrial and military facilities therefore depends on coordinated use of structured sampling, advanced analytics, geospatial mapping, remote sensing context, time series modeling, and risk mapping. Each tool contributes a different lens, and their integration produces a more complete and reliable picture than any single method alone. This combined methodological approach supports earlier detection, clearer trend interpretation, and more targeted protection of affected communities and environments (Oziri, et al., 2023, Rukh, Oziri & Seyi-Lande, 2023, Umoren, et al., 2023).

Human and Ecological Risk Implications

The human and ecological risk implications of PFAS contamination around industrial and military facilities in U.S. regions are closely tied to the way these substances move and persist across space and time. Because PFAS are durable, mobile, and capable of bioaccumulation for certain compounds, their risk profile cannot be understood through single location or single time measurements alone (Nwaigbo, et al., 2025, Shah, Oziri & Seyi-Lande, 2025, Umoren, et al., 2025). Instead, spatiotemporal dynamics determine who is exposed, through which pathways, at what concentrations, and for how long. Industrial plants, defense installations, airports, and specialized manufacturing sites often function as long term source zones, while surrounding communities and ecosystems experience varying exposure intensity depending on hydrogeology, infrastructure, land use, and monitoring coverage (Osuashi Sanni, Ajiga & Atima, 2020, Seyi-Lande, Arowogbadamu & Oziri, 2020).

Human exposure pathways are multiple and often overlapping. Drinking water is widely recognized as the dominant pathway near contaminated facilities, especially where groundwater wells or surface water intakes lie downgradient of PFAS source areas. As plumes migrate over time, previously unaffected wells may become impacted, creating delayed exposure scenarios. Private wells are particularly vulnerable because they are less frequently monitored than municipal systems and may lack advanced treatment (Osuashi Sanni, 2026). Surface water exposures also matter where rivers and lakes receiving contaminated discharge are used for drinking water, recreation, or irrigation. Food pathway exposure can occur through crops grown on contaminated soils, use of impacted irrigation water, and consumption of fish from affected water bodies. Certain PFAS compounds accumulate in fish and wildlife, increasing dietary intake for subsistence and recreational fishers. Indoor exposure may also occur indirectly where PFAS contaminated dust, consumer products, or building materials contribute to background body burden, adding to water and food sources (Bayeroju, Sanusi & Nwokediegwu, 2021, Osuji, Okafor & Dako, 2021, Uduokhai, et al., 2021).

Temporal variability significantly shapes exposure risk. Short term sampling may underestimate true risk if it misses seasonal peaks or delayed plume arrival. Communities located at the edge of plumes may show low or nondetect levels for years and then experience rising concentrations as groundwater transport progresses. Conversely, remediation or source control may reduce concentrations, but human body burdens decline more slowly because some PFAS remain in the body for years (Arowogbadamu, Oziri & Seyi-Lande, 2021, Umoren, et al., 2021). This lag between environmental improvement and biological response complicates risk communication and health tracking. Spatiotemporal monitoring helps identify these lag patterns and supports more realistic exposure assessments that account for duration as well as concentration (Michael & Ogunsola, 2022, Uduokhai, et al., 2022, Umoren, et al., 2022).

Community vulnerability near industrial and defense facilities is influenced by proximity, dependence on local water resources, socioeconomic status, and institutional capacity. Populations living close to bases, manufacturing corridors, and fire training sites are more likely to rely on local groundwater or small water systems that may be impacted. Rural communities often depend on private wells and have limited resources for testing and treatment (Nwafor, et al., 2018, Seyi-Lande, Arowogbadamu & Oziri, 2018). Transient populations, renters, and informal housing clusters may be missed by outreach and sampling programs, increasing unnoticed exposure risk. Occupational groups, including firefighters, maintenance crews, and plant workers, may experience higher direct exposure through contact with PFAS containing materials and contaminated environments, adding a workplace dimension to community risk (Oguntegbe, Farounbi & Okafor, 2023, Sanusi, Bayeroju & Nwokediegwu, 2023, Uduokhai, et al., 2023).

Ecological risks follow similar spatiotemporal logic but involve additional pathways through habitat and food webs. PFAS entering soils and waters near industrial and military facilities can affect plants, invertebrates, fish, birds, and mammals. Aquatic ecosystems are particularly vulnerable because PFAS are water soluble and persistent (Bayeroju, Sanusi & Nwokediegwu, 2022, Umoren, et al., 2021). Fish and amphibians can accumulate certain PFAS, which then move up the food chain to predatory species. Wetlands and riparian zones that receive contaminated groundwater discharge may function as long term exposure hubs for wildlife. Temporal persistence means that even if releases stop, ecological exposure can continue across multiple breeding cycles, potentially affecting reproduction, growth, and immune function in sensitive species. Migratory species can also transport PFAS body burdens beyond the original contamination region, extending ecological implications spatially (Akinrinoye, et al., 2020, Oziri, Seyi-Lande & Arowogbadamu, 2020).

Environmental justice concerns are strongly connected to PFAS spatiotemporal patterns. Industrial and military facilities are often located near communities with historical economic disadvantage or limited political influence. These communities may face cumulative exposure from multiple pollution sources in addition to PFAS. Uneven monitoring coverage can produce inequitable protection, where well resourced areas receive frequent testing and rapid response while underserved areas remain under sampled (Bayeroju, Sanusi & Nwokediegwu, 2023, Umoren, et al., 2021). Language barriers, limited technical literacy, and distrust of institutions can further reduce access to information and mitigation resources. Where contamination plumes spread across jurisdictional boundaries, fragmented governance may delay coordinated action, leaving certain populations exposed longer. A spatiotemporal lens helps reveal these disparities by mapping contamination alongside demographic and infrastructure data, showing where risk and vulnerability overlap (Aminu-Ibrahim, Ogbete & Iwuanyanwu, 2020).

Risk prioritization benefits directly from spatiotemporal insight. Instead of treating all contaminated sites as equal, regulators and investigators can rank areas based on plume movement, exposure pathway connectivity, receptor density, and trend direction. A site with stable low concentrations far from receptors may be lower priority than a site with rising concentrations moving toward a municipal well field (Sanusi, Bayeroju & Nwokediegwu, 2020, Umoren, et al., 2021). Time trend data help distinguish declining legacy plumes from active source zones that demand urgent intervention. Spatial modeling identifies hotspot cores where source removal or containment would produce the greatest long term benefit. Integrating time and space also improves sampling efficiency by guiding where new wells or surface stations should be placed to detect early plume migration (Atima, Osuashi Sanni & Attah, 2022, Bayeroju, Sanusi & Nwokediegwu, 2022, Uduokhai, et al., 2022).

Regulatory response is increasingly shaped by these spatiotemporal assessments. Monitoring requirements often expand outward from confirmed hotspots and include repeated sampling to establish trends. Adaptive management approaches adjust cleanup targets and timelines based on observed temporal behavior rather than fixed assumptions about decay. Early warning trigger levels can be set for sentinel wells located between source zones and community receptors. Spatiotemporal data also support more transparent public communication by showing not only where contamination exists but how it is changing. This helps communities understand both current risk and expected future trajectories (Rukh, Seyi-Lande & Oziri, 2024, Seyi-Lande & Onaolapo, 2024, Uduokhai, et al., 2024).

Ecological and human health risk assessments are also being updated to incorporate time weighted exposure estimates rather than single point concentrations. Models that combine concentration histories with intake rates and toxicity values produce more realistic dose estimates. For ecosystems, repeated sampling across seasons and years captures chronic exposure patterns that matter more than isolated peaks. Restoration and remediation planning can then be aligned with exposure duration and pathway dominance rather than static snapshots (Bayeroju, Sanusi & Nwokediegwu, 2023, Seyi-Lande, Arowogbadamu & Oziri, 2023, Umoren, et al., 2023).

Overall, the human and ecological risk implications of PFAS contamination near industrial and military facilities are inseparable from their spatiotemporal dynamics. Exposure pathways shift as plumes migrate, vulnerability varies across communities and habitats, and justice concerns emerge where contamination and disadvantage intersect. Methods that integrate spatial mapping with long term trend analysis provide a stronger basis for prioritizing action, allocating resources, and designing fair and effective regulatory responses (Ezeh, et al., 2025, Oziri, Seyi-Lande & Arowogbadamu, 2020, Umoren, et al., 2025).

CONCLUSION AND POLICY DIRECTIONS

The spatiotemporal dynamics of PFAS contamination around industrial and military facilities in U.S. regions demonstrate that these pollutants behave in ways that challenge conventional site assessment and cleanup models. Their persistence, mobility, and chemical diversity produce contamination patterns that evolve over long time horizons and across wide geographic areas. Rather than remaining confined to facility boundaries, PFAS frequently form clustered hotspots near release zones and elongated plumes that migrate through groundwater and surface water systems. Temporal evidence shows that concentrations often remain stable or decline slowly even after source control, while seasonal hydrologic cycles and delayed subsurface transport can produce fluctuating or rising trends at downgradient locations. These combined spatial and temporal features mean that PFAS risk cannot be accurately defined using isolated samples or short monitoring windows.

Key insights from spatiotemporal analysis highlight the importance of integrating source history, hydrogeology, land use, and infrastructure into contamination evaluation. Legacy releases continue to influence present day exposure because stored PFAS mass in soils and low permeability layers acts as a long term secondary source. Ongoing inputs from certain operational and waste systems can sustain elevated levels despite partial controls. Spatial mapping reveals that plume geometry is shaped by flow pathways, engineered drainage, and pumping patterns, while longitudinal monitoring shows multi phase trends that include lag, rebound, and tailing effects. Together, these findings support a shift away from static site snapshots toward dynamic plume tracking and trend based decision making.

Monitoring strategy must therefore be designed around both space and time. Networks should extend beyond known source areas along predicted transport pathways and include vertical as well as horizontal coverage. Repeated sampling at consistent locations is essential for detecting trends, seasonal variability, and delayed plume arrival. Analytical consistency and expanded compound lists improve temporal comparability and source interpretation. High resolution geospatial tools, time enabled mapping, and integrated databases strengthen interpretation and communication. Monitoring programs that combine environmental media with drinking water and, where appropriate, biomonitoring data provide a more complete picture of exposure evolution.

Remediation strategy also benefits from a spatiotemporal framework. Source zone control remains critical, but expectations for rapid plume disappearance are unrealistic in many settings. Long term containment, hydraulic control, and treatment systems must be evaluated using trend data rather than single performance checks. Designs should account for back diffusion, secondary sources, and infrastructure driven flow changes. Adaptive remediation, supported by continuous data review, allows adjustment of methods and boundaries as plume behavior becomes clearer over time.

Policy direction should emphasize coordinated, data driven regulatory and management frameworks across U.S. regions. Standardized monitoring protocols, shared geospatial data platforms, and consistent reporting thresholds improve comparability and equity. Cross agency coordination between environmental, defense, water, and public health authorities reduces fragmentation and speeds response. Prioritization models that integrate concentration, trend, pathway connectivity, and population vulnerability support fairer resource allocation. A unified spatiotemporal approach ultimately provides the strongest foundation for effective PFAS risk reduction, transparent governance, and long term community and ecosystem protection.

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