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Developing spatial risk maps of PFAS contamination in farmlands using soil core sampling and GIS

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Abstract

Per- and polyfluoroalkyl substances (PFAS) are a group of synthetic chemicals that have become a pressing environmental and public health concern due to their persistence, bioaccumulation potential, and widespread distribution across ecosystems. Among the critical exposure pathways, agricultural soils contaminated through irrigation with wastewater, biosolid application, and atmospheric deposition pose significant risks to food safety and human health. As these compounds are difficult to degrade, their accumulation in farmland soils necessitates robust spatial analysis to assess and manage contamination risks effectively. This study presents a comprehensive methodology for developing spatial risk maps of PFAS contamination in agricultural lands through integrated soil core sampling and Geographic Information Systems (GIS). By systematically collecting soil cores from multiple depths across selected agricultural plots and analyzing them for targeted PFAS compounds, we establish a contamination profile that reflects both surface and subsurface distribution. The resulting concentration data are georeferenced and interpolated using advanced geostatistical techniques, such as kriging, to generate continuous risk surfaces. GIS-based spatial modeling enables the visualization of PFAS hotspots and identification of zones at heightened risk of contaminant migration into crops or groundwater. The approach is refined further by incorporating land use patterns, topography, proximity to known PFAS sources (e.g., industrial sites, airports), and hydrological data to enhance predictive accuracy. This integrative framework not only supports environmental risk assessment and land-use decision-making but also provides a scalable model for national-level PFAS monitoring and remediation prioritization. The findings underscore the value of coupling field-based sampling with spatial analytics to inform evidence-driven agricultural and environmental policies.

Keywords: PFAS Contamination; Spatial Risk Mapping; Soil Core Sampling; GIS Modeling; Farmland Pollution; Environmental Monitoring

1. Introduction

1.1. Context of PFAS Contamination: A Global Agricultural Concern

Per- and polyfluoroalkyl substances (PFAS) are a class of over 4,700 synthetic fluorinated compounds known for their resistance to heat, oil, and water. Originally manufactured for use in industrial processes, consumer products, and firefighting foams, PFAS have been widely detected in environmental matrices worldwide, including soils, groundwater, and food chains [1]. Their strong carbon-fluorine bonds render them highly persistent and bioaccumulative, earning them the moniker “forever chemicals” [2].

In agricultural contexts, PFAS contamination poses a critical threat to food safety and environmental sustainability. Sources of contamination include land application of biosolids, wastewater irrigation, atmospheric deposition from

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nearby industries, and runoff from contaminated water systems [3]. This has led to the detection of PFAS in crops such as lettuce, potatoes, and grains, especially in regions near industrial or military facilities [4].

Global monitoring efforts have revealed extensive PFAS contamination in agricultural zones across North America, Europe, and parts of Asia [5]. In the United States, the Environmental Protection Agency (EPA) has acknowledged widespread PFAS presence in rural farmlands, with regulatory efforts now focusing on setting maximum allowable levels in soil and water [6]. Similarly, the European Food Safety Authority has introduced stringent tolerable intake limits for PFAS in food products [7].

Despite the growing body of evidence, many countries lack robust data on PFAS soil concentrations, hindering risk assessment and regulatory interventions. As illustrated in Figure 1, PFAS hotspots are disproportionately concentrated in agriculturally productive but industrially adjacent regions, demanding urgent attention to contamination pathways and mitigation strategies [8].

1.2. Agricultural Soil Vulnerability and Exposure Pathways

Agricultural soils serve as both sinks and sources of PFAS contamination. The physicochemical properties of PFAS namely their hydrophobic tail and hydrophilic head allow them to bind variably to soil particles depending on pH, organic matter content, and moisture levels [9]. This leads to heterogeneous distribution within soil profiles, with longer-chain PFAS compounds tending to adhere more strongly to organic-rich soils, while shorter-chain variants may leach into groundwater or migrate laterally [10].

One key exposure pathway is the land application of treated sewage sludge (biosolids), which often contains elevated PFAS concentrations from industrial wastewater inputs [11]. Repeated use of contaminated irrigation water can also result in cumulative accumulation over successive planting cycles [12]. Airborne deposition of PFAS-laden particulates from nearby manufacturing or incineration plants is another concern, especially in regions downwind of known emitters [13].

The potential for plant uptake and trophic transfer further elevates the risk. Studies have shown that leafy vegetables and root crops can absorb PFAS through their root systems, raising alarms about human dietary exposure through crop consumption [14]. Additionally, PFAS residues in animal feed can bioaccumulate in meat and dairy products, posing indirect risks to consumers [15].

Understanding these complex exposure pathways is essential for identifying vulnerable agricultural zones and informing targeted mitigation.

1.3. Need for Spatial Risk Mapping in Contaminated Farmlands

Given the persistence and mobility of PFAS in agricultural environments, spatially explicit assessments are necessary to understand contamination dynamics and guide risk-informed decisions [16]. Traditional point sampling methods offer limited insight into landscape-level contamination, often underrepresenting the spatial heterogeneity of PFAS deposition.

Spatial risk mapping integrating soil core sampling with geostatistical modeling and Geographic Information Systems (GIS) offers a powerful approach to visualize PFAS distributions across diverse agroecological contexts [17]. Such maps can identify contamination hotspots, inform sampling strategies, and support regulatory compliance monitoring.

Moreover, spatial modeling allows for predictive mapping by incorporating ancillary environmental data such as land use, proximity to PFAS sources, topography, and hydrology [18]. This enhances the capacity of stakeholders regulators, farmers, and land-use planners to allocate resources effectively and implement remediation plans.

Figure 1 provides a global perspective of documented PFAS hotspots in agricultural areas, underscoring the need for localized spatial risk frameworks to manage site-specific exposure risks.

1.4. Aim, Objectives, and Scope of the Study

This study aims to develop high-resolution spatial risk maps of PFAS contamination in farmlands using a combination of soil core sampling and GIS-based geostatistical analysis. The specific objectives include: (i) designing a soil sampling protocol to quantify PFAS concentrations at varying depths; (ii) applying spatial interpolation techniques to generate continuous contamination surfaces; and (iii) integrating environmental covariates to identify risk zones. The scope of the study is focused on farmlands adjacent to industrial zones where PFAS sources are known or suspected. The resulting risk maps will aid policymakers, agricultural stakeholders, and environmental agencies in prioritizing monitoring and mitigation strategies [19].

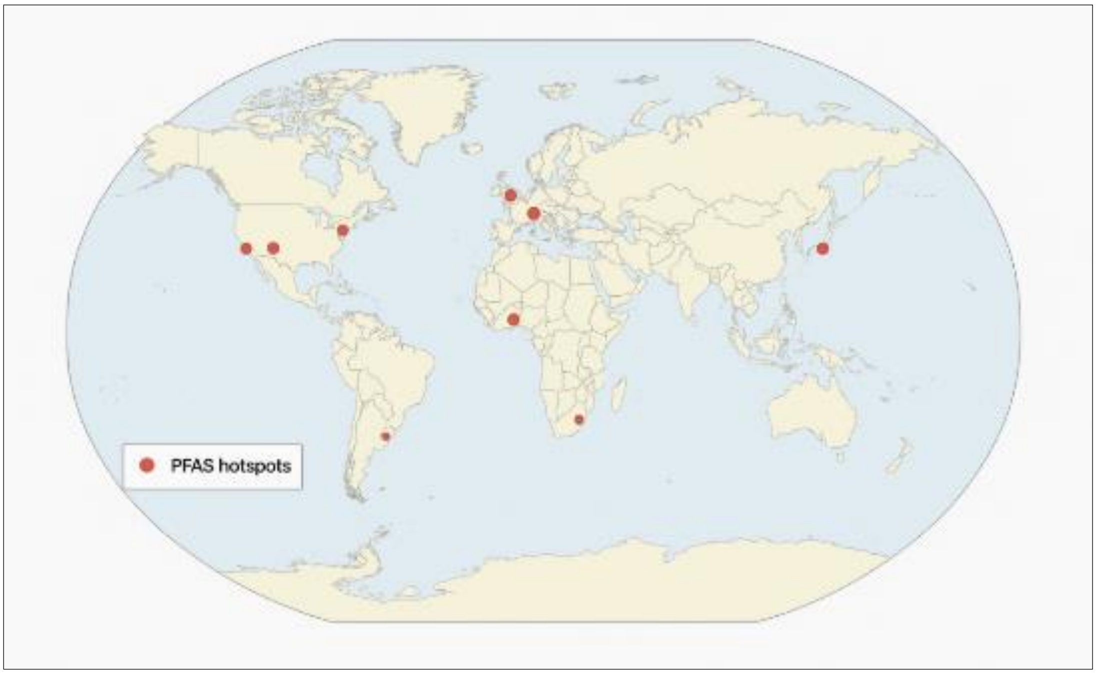

Figure 1 Global map highlighting PFAS hotspots in agricultural zones [12]

2. Pfas chemistry, sources, and agricultural risk

2.1. Chemical Characteristics of PFAS and Persistence in Soil

Per- and polyfluoroalkyl substances (PFAS) are a diverse group of synthetic organic compounds containing carbon-fluorine (C–F) bonds, which are among the strongest in organic chemistry. This bond stability accounts for their resistance to thermal degradation, photolysis, microbial breakdown, and other natural attenuation processes, resulting in extreme environmental persistence [6]. PFAS compounds typically consist of a fluorinated carbon chain and a polar functional group, commonly carboxylate or sulfonate, which confers both hydrophobic and hydrophilic properties. This duality facilitates their widespread mobility and complex behavior in environmental matrices [7].

In soil environments, PFAS can adsorb to mineral surfaces, dissolve in pore water, or interact with organic matter depending on compound chain length, charge density, and environmental conditions such as pH and ionic strength [8]. Long-chain PFAS, including perfluorooctanoic acid (PFOA) and perfluorooctanesulfonic acid (PFOS), exhibit higher sorption tendencies and tend to accumulate in surface soils, while short-chain variants like perfluorobutanoic acid (PFBA) demonstrate greater leachability and transport potential [9].

Once released into the soil, PFAS persist for years or even decades, particularly in areas with low microbial activity or limited natural flushing. Unlike many organic pollutants, they do not undergo significant biotransformation under aerobic or anaerobic conditions, making natural attenuation largely ineffective [10]. Consequently, PFAS pose a long-term contamination threat to agricultural lands, where they may gradually migrate through the soil profile, accumulate in crops, and contaminate adjacent water sources. This persistence necessitates proactive spatial monitoring approaches to identify contamination patterns and inform long-term management strategies [11].

2.2. Anthropogenic Sources of PFAS in Agricultural Land

The presence of PFAS in agricultural lands is primarily linked to human industrial and consumer activities. One of the most common sources is the application of biosolids—treated sewage sludge—on farmlands. These biosolids often contain PFAS due to upstream contamination from industrial discharge, household waste, and personal care products entering wastewater treatment plants [12]. Because PFAS are not effectively removed during conventional treatment processes, they remain in biosolid matrices and are subsequently introduced into soils during land application [13].

Another significant source is irrigation using contaminated water. In regions adjacent to military bases, airports, or industrial zones, groundwater and surface water sources often contain PFAS due to the historic use of aqueous film-forming foams (AFFF) and other industrial releases [14]. Repeated irrigation with such water can lead to the slow accumulation of PFAS in agricultural soils over time, especially in arid or semi-arid climates where natural leaching is minimal [15].

Atmospheric deposition also contributes to PFAS contamination in rural lands. PFAS can volatilize or bind to airborne particulates from manufacturing facilities and travel considerable distances before depositing onto crops or soil surfaces [16]. Recent studies have shown that even remote agricultural regions may receive PFAS via long-range atmospheric transport, although concentrations are generally lower compared to point-source-impacted areas [17].

Additionally, agricultural use of contaminated compost, manure from exposed livestock, and packaging materials with PFAS coatings introduces further risks. These multiple and often overlapping sources complicate contamination pathways and reinforce the need for comprehensive spatial monitoring frameworks that can pinpoint origins and inform appropriate mitigation responses [18].

2.3. Soil Retention and Transport Mechanisms of PFAS

The fate and transport of PFAS in soil systems are governed by a combination of physicochemical interactions, soil composition, and environmental conditions. Once introduced, PFAS exhibit varied behaviors depending on their molecular structure, particularly chain length and functional group polarity. Longer-chain PFAS tend to sorb strongly to soil particles and organic matter, thus exhibiting lower mobility. In contrast, shorter-chain compounds and precursors are more mobile, increasing the risk of leaching into subsurface layers and groundwater systems [19].

Sorption of PFAS to soil occurs primarily through electrostatic attraction, hydrophobic interactions, and hydrogen bonding. Soils rich in organic carbon or clay minerals tend to retain PFAS more effectively, although saturation of sorption sites or shifts in pH and ionic strength can remobilize previously bound compounds [20]. For instance, acidic soils may weaken binding affinity and enhance PFAS mobility, particularly for anionic forms such as PFOS and PFOA [21].

Water flow dynamics play a critical role in PFAS migration. Infiltration from rainfall or irrigation can facilitate vertical transport, especially in coarse-textured soils with high hydraulic conductivity. In poorly drained soils, lateral movement and surface runoff can transfer PFAS to nearby water bodies or adjacent fields [22].

Furthermore, PFAS precursors, which may initially exhibit strong sorption, can undergo environmental transformation over time into more mobile terminal compounds. This delayed transformation can result in secondary contamination long after the primary source has been removed, further complicating remediation efforts [23]. A comprehensive understanding of these retention and transport dynamics is essential for modeling risk distribution and designing sampling protocols.

2.4. Human and Ecological Health Risks through Crop Uptake and Water Contamination

PFAS contamination in farmlands has direct implications for human and ecological health, primarily through food chain transfer and water resource degradation. When PFAS are present in agricultural soils, they can be taken up by crops through root absorption and translocation mechanisms. Leafy greens, root vegetables, and certain grains have been shown to accumulate PFAS, especially those with shorter chain lengths that are more bioavailable [24]. This uptake leads to dietary exposure in humans, particularly in rural communities dependent on subsistence agriculture or localized food markets [25].

Livestock can also ingest PFAS through contaminated feed or drinking water, resulting in bioaccumulation in milk, eggs, and meat. Studies have reported measurable levels of PFAS in dairy products and poultry tissues from farms situated near known contamination sources [26]. Long-term exposure to PFAS is associated with adverse health outcomes, including endocrine disruption, immune suppression, liver damage, and developmental effects in infants and children [27].

Aquatic systems adjacent to contaminated farmlands are also at risk. Leached PFAS can infiltrate groundwater aquifers used for drinking and irrigation, while runoff can elevate concentrations in surface water bodies. Aquatic organisms exposed to PFAS may experience reproductive toxicity and altered growth, disrupting food webs and biodiversity [28].

The persistent and bioaccumulative nature of PFAS makes even low-concentration exposure a long-term risk. Therefore, spatial risk mapping of PFAS in agricultural zones is critical for guiding public health interventions, informing food safety standards, and prioritizing remediation efforts [29].

Table 1 Summary of Major PFAS Compounds and Associated Agricultural Risks

PFAS Compound	Chemical Class	Common Sources in Agriculture	Soil Behavior	Plant Uptake Potential	Associated Agricultural Risks
PFOA	Perfluorocarboxylic acid (PFCA)	Biosolids, wastewater irrigation, industrial runoff	Binds strongly to soil; low mobility	Moderate to High	Accumulates in leafy vegetables; potential livestock exposure
PFOS	Perfluorosulfonic acid (PFSA)	AFFF runoff, biosolids, atmospheric deposition	Strong sorption to soil organic matter	Moderate	Persists in surface soils; enters food chain via crops and livestock
PFHxS	PFSA	Industrial byproducts, landfill leachate	Moderate mobility; long half-life in soil	Moderate	Contamination of groundwater and crops
PFBS	PFSA (short-chain)	Treated wastewater, biosolids	High mobility; less sorptive	High	Leaches to groundwater; elevated uptake in vegetables
PFBA	PFCA (short-chain)	Atmospheric deposition, wastewater irrigation	Very high mobility; low retention	High	Readily absorbed by plants; hard to contain in agricultural systems
PFHxA	PFCA (short-chain)	Industrial emissions, contaminated water	High leachability; weak soil interaction	High	Rapid movement through soil; risk to shallow aquifers

Note: PFCA = Perfluorocarboxylic Acid; PFSA = Perfluorosulfonic Acid; AFFF = Aqueous Film-Forming Foam

3. Methodology: soil core sampling and gis integration

3.1. Site Selection Criteria and Agricultural Land Classification

The site selection process focused on identifying agricultural areas with high susceptibility to PFAS contamination based on proximity to known or suspected emission sources. These sources included wastewater treatment plants, industrial discharge zones, fire training facilities, and landfills. Land-use databases, hydrological maps, and satellite imagery were employed to delineate agricultural zones potentially exposed to PFAS [11].

The selected regions were categorized according to crop type, irrigation method, and soil texture to capture variability in potential PFAS accumulation. Land classification adhered to the FAO Land Cover Classification System (LCCS), distinguishing between intensive croplands, mixed farming systems, and peri-urban agriculture [12]. Emphasis was placed on regions where biosolids had been historically applied, or where farmers reported long-term wastewater irrigation practices.

To minimize sampling bias, a stratified random sampling approach was adopted, ensuring representative coverage of diverse agroecological zones. Accessibility, landowner consent, and historical site data were also factored into final site selection [13]. This approach enabled both spatial and thematic diversity in the collected samples, increasing the robustness of subsequent geostatistical modeling and interpretation.

3.2. Soil Core Sampling Design: Depths, Grid Density, and Replication

A systematic soil core sampling protocol was implemented across all study sites to capture PFAS distribution both horizontally and vertically. Each selected farmland was overlaid with a 50x50 meter grid using GIS tools, and sampling points were determined at the grid intersections to maintain uniform spatial resolution. Depending on field size and heterogeneity, 20–40 soil cores were collected per site, providing adequate spatial density for interpolation modeling [14].

At each grid point, undisturbed soil cores were extracted using stainless steel corers to minimize sample contamination. Cores were segmented into three standard depth intervals: 0–15 cm (surface), 15–30 cm (subsurface), and 30–60 cm (deep profile), capturing the vertical migration profile of PFAS [15]. Depth selection was informed by previous studies highlighting the differential transport behaviors of long- and short-chain PFAS compounds across soil strata [16].

Each soil core sample was labeled, sealed in PFAS-free containers, and stored at 4°C before transport to the laboratory. Field replicates were taken at 10% of sampling locations to assess data reproducibility and support quality control procedures. Additionally, field blanks and procedural blanks were included to monitor potential contamination during sampling and transport [17].

GPS coordinates were recorded at each sampling point using high-accuracy differential GPS units. These geotagged samples formed the spatial foundation for subsequent GIS-based mapping and kriging interpolation. The uniformity in sampling design ensured reliable detection of contamination patterns while maintaining cost-effectiveness and logistical feasibility across all field sites [18].

3.3. Laboratory Analysis of PFAS Compounds

All collected soil samples underwent standardized laboratory analysis to quantify concentrations of targeted PFAS compounds. Sample preparation began with freeze-drying and homogenization to ensure consistency across replicates. PFAS were extracted using a modified U.S. EPA Method 1633 protocol, which involves solid-phase extraction (SPE) and cleanup procedures optimized for complex soil matrices [19].

Analytical quantification was conducted using high-performance liquid chromatography coupled with tandem mass spectrometry (HPLC-MS/MS). This method allows for precise detection of multiple PFAS compounds, including PFOA, PFOS, PFHxS, PFBS, and PFBA, at detection limits as low as 0.1 ng/g [20]. Internal standards and isotopically labeled analogs were used to calibrate instruments and compensate for matrix effects.

To ensure quality assurance, laboratory duplicates, matrix spikes, and method blanks were included in each analytical batch. The average recovery rates across all compounds exceeded 85%, indicating strong reliability in the quantification process [21]. Analytical results were reported in nanograms per gram (ng/g) of dry weight and cross-verified using certified reference materials.

This standardized analytical process provided a robust dataset for downstream spatial modeling and helped identify contamination signatures across different soil depths and geographic regions [22].

3.4. GIS Georeferencing, Data Cleaning, and Preprocessing

Georeferencing of soil sample points was completed using high-resolution GPS coordinates collected during fieldwork. The spatial data were projected using the Universal Transverse Mercator (UTM) coordinate system to ensure compatibility with land use and environmental datasets. Each soil sample was linked to its corresponding location in a geodatabase using unique identifiers [23].

Initial data cleaning involved screening for missing values, outliers, and inconsistent sample depths. Values below the method detection limit (MDL) were replaced with half the MDL, a standard practice in environmental risk analysis [24]. Descriptive statistics were generated to assess central tendencies and dispersion across PFAS compounds and soil depths.

Spatial data layers including land use maps, elevation models, hydrological networks, and proximity buffers to PFAS sources were imported from national geospatial repositories and integrated into the GIS environment. All datasets were resampled to a uniform spatial resolution (30m x 30m) using bilinear interpolation for raster data and topological cleaning for vector layers [25].

Prior to modeling, exploratory spatial data analysis (ESDA) was conducted to examine spatial autocorrelation using Global Moran's I and semivariogram analysis. These tests confirmed statistically significant clustering of PFAS concentrations across sites, justifying the use of kriging and co-kriging for spatial interpolation [26].

Figure 2 presents the complete methodological workflow, from site selection and sampling to laboratory analysis and geostatistical modeling. This systematic preprocessing phase was critical to maintaining the accuracy and reliability of the final risk maps used for stakeholder decision-making [27].

3.5. Ethical, Environmental, and Safety Considerations

All field and laboratory activities were conducted in compliance with national ethical and environmental standards. Prior to initiating fieldwork, informed consent was obtained from all participating landowners and farming communities, with detailed explanations provided about the purpose, methodology, and potential benefits of the study [28]. Confidentiality of site-specific data was maintained throughout the project to prevent stigmatization or land devaluation.

Environmental safeguards were implemented to minimize disruption to farmland ecosystems. Soil coring was carried out using minimally invasive techniques, and all sampling points were restored post-collection. Equipment was decontaminated between sites using PFAS-free cleaning agents to prevent cross-contamination. In regions where biosolid use was suspected, extra care was taken to avoid disturbing areas under active cultivation or irrigation [29].

From a laboratory safety perspective, personnel were trained in the handling of hazardous substances and adhered to best practices for sample storage, chemical disposal, and analytical procedures. Wastewater and solid waste generated during extraction were treated following hazardous waste protocols to prevent secondary environmental release of PFAS [30].

Ethical review and oversight were provided by the university's Environmental Ethics Committee, which approved the study design and protocols. Continuous communication with local stakeholders was maintained through periodic briefings, ensuring transparency and building trust.

These ethical and safety protocols not only enhanced the scientific integrity of the study but also ensured alignment with international standards for environmental field research in sensitive agricultural settings [31].

Figure 2 Flowchart of sampling to spatial modeling workflow

4. Geospatial modelling and risk map development

4.1. Spatial Interpolation Techniques: Kriging, IDW, and Co-Kriging

Spatial interpolation techniques are essential for estimating PFAS concentrations at unsampled locations based on measured values from soil core samples. Among the commonly used methods, inverse distance weighting (IDW), ordinary kriging, and co-kriging offer different strengths depending on spatial data structure and variability [16]. IDW assumes that nearby points have more influence on unknown values than distant ones, using a distance-decay function to weight contributions. This method is computationally simple and effective when sample points are dense and evenly distributed [17].

However, IDW lacks the ability to quantify spatial autocorrelation and does not generate estimates of prediction uncertainty. To address this, ordinary kriging was employed. Kriging uses a variogram model to capture the spatial dependence of PFAS concentrations and generates unbiased estimates with minimum variance at each grid location [18]. In this study, empirical semivariograms were fitted with spherical and exponential models to optimize kriging interpolation. The resulting maps produced smoother transitions between high and low concentration zones and allowed for uncertainty estimation via kriging standard deviation surfaces.

Co-kriging was also applied, leveraging secondary spatial variables such as soil organic carbon and elevation, which are known to influence PFAS retention and transport. By incorporating these covariates, co-kriging improved predictive accuracy in areas with sparse sampling points or abrupt terrain changes [19]. This method was particularly useful in fields with heterogeneous soil composition and complex hydrological features.

Table 2 presents a side-by-side comparison of model performance metrics, including root mean square error (RMSE), mean absolute error (MAE), and R^2 values across the three interpolation methods. The evaluation revealed that co-kriging consistently outperformed IDW and ordinary kriging in predictive reliability, particularly in topographically diverse farmlands [20].

4.2. Topographic and Hydrological Layer Integration

The spatial behavior of PFAS in soils is significantly influenced by topographic and hydrological processes, which dictate runoff pathways, infiltration rates, and potential leaching into groundwater systems. To account for these factors, digital elevation models (DEMs) at a 10-meter resolution were integrated into the GIS environment. From the DEM, terrain derivatives such as slope, flow direction, and topographic wetness index (TWI) were calculated to model surface hydrology and depressional areas prone to PFAS accumulation [21].

Hydrological data layers including stream networks, watershed boundaries, and aquifer recharge zones were obtained from national geospatial databases and verified using field reconnaissance. Overlaying these layers with PFAS interpolation surfaces revealed that elevated concentrations tended to cluster in low-lying floodplains, irrigation return flow zones, and areas with shallow groundwater tables [22]. The integration of topographic controls enabled better delineation of contaminant flow paths, highlighting the potential for off-site transport through erosion and runoff.

Using flow accumulation models, we identified zones with a higher likelihood of receiving PFAS-laden runoff from upstream contamination sources. These high-risk convergence zones were flagged in the spatial risk map, supporting decision-makers in prioritizing monitoring and mitigation efforts in hydrologically sensitive areas [23].

By coupling PFAS spatial data with terrain and hydrological analytics, the study achieved a more nuanced understanding of contaminant distribution, especially in landscapes with varied microtopography. This integration was vital for accurately delineating vulnerable zones and enhanced the performance of geostatistical models in predicting PFAS dispersal across different field conditions [24].

4.3. Use of Land Use/Cover Data and Infrastructure Overlays

Land use and land cover (LULC) characteristics directly affect PFAS exposure, mobility, and risk across agricultural landscapes. To capture this dimension, high-resolution LULC datasets derived from Sentinel-2 satellite imagery and national agricultural census records were integrated into the GIS framework. These datasets were classified into cropland, pasture, fallow land, forest margins, and built-up zones using supervised classification techniques [25].

Overlaying PFAS concentration maps with LULC data allowed for comparative analysis of contamination levels across different land-use types. Croplands under wastewater irrigation or biosolid application exhibited the highest PFAS concentrations, followed by pasturelands exposed to runoff or atmospheric deposition from nearby facilities [26]. Built-up edges showed elevated PFAS hotspots near unlined ditches or informal waste disposal zones.

In addition, infrastructure overlays such as proximity buffers to roads, wastewater outlets, drainage canals, and industrial sites were created using Euclidean distance tools. Proximity to PFAS sources was found to be a significant spatial covariate, especially for fields within 1 km of known emitters or effluent discharge points [27]. This proximity analysis was used as a secondary input in the co-kriging model to improve spatial resolution near anthropogenic hotspots.

Combined with hydrology and elevation data, LULC and infrastructure overlays provided a comprehensive spatial context that enriched the interpretability of risk zones. Areas of mixed land use, such as peri-urban farms adjacent to light industry, were identified as emerging concern zones that may require both environmental and urban planning interventions [28].

This multifactorial spatial approach enabled more precise zoning and the identification of intersections between contamination risk and socio-economic land use, a key consideration for sustainable agricultural management.

4.4. Risk Index Formulation and Zoning

To transform PFAS spatial data into actionable insights, a spatial risk index (SRI) was developed using a multi-criteria evaluation (MCE) approach. This index synthesized PFAS concentration levels, proximity to contamination sources, soil permeability, land use type, and topographic features into a composite raster map indicating zones of low, moderate, and high contamination risk [29].

Each criterion was normalized and weighted using the Analytical Hierarchy Process (AHP), incorporating expert judgment and literature-based evidence. PFAS concentration was assigned the highest weight (40%), followed by proximity to known sources (25%), land use vulnerability (15%), slope/infiltration (10%), and organic carbon content (10%). These weights reflected the relative influence of each factor on PFAS mobility and exposure potential [30].

The final risk index was calculated as a weighted overlay using the raster calculator in ArcGIS. Continuous index values were reclassified into three risk classes: Low (0.00–0.33), Moderate (0.34–0.66), and High (0.67–1.00). Zonal statistics were computed to quantify the proportion of agricultural land falling under each risk class per study region.

This zoning methodology enabled the creation of high-resolution spatial risk maps that not only visualized contamination distribution but also identified intervention priority areas. Regions categorized under high-risk zones overlapped significantly with low-lying irrigated croplands and plots within 500 meters of wastewater infrastructure.

Figure 3 illustrates the PFAS spatial concentration heat map, serving as a visual example of contamination heterogeneity across one of the study sites. This heat map guided validation, stakeholder briefings, and potential pilot remediation planning in the impacted zone [31].

4.5. Validation Techniques for Spatial Risk Maps

Validation of the spatial interpolation models and resulting risk maps was conducted using both statistical and spatial techniques. A holdout validation method was used, where 20% of the sampling locations were randomly excluded from the interpolation process and later used to compare predicted vs. observed PFAS concentrations [32]. Model performance was assessed using metrics including RMSE, MAE, mean bias error (MBE), and coefficient of determination (R^2).

Table 2 summarizes the validation metrics for IDW, kriging, and co-kriging models. Co-kriging showed the lowest RMSE (3.4 ng/g) and highest R^2 (0.89), indicating superior predictive capacity compared to IDW and ordinary kriging [33]. Error distribution plots further confirmed that co-kriging-maintained consistency across both high and low concentration zones, minimizing under- and over-predictions.

Spatial overlay validation was also performed using cross-tabulation of high-risk zones against proximity buffers and LULC maps. Over 85% of high-risk zones overlapped with known risk enhancers, such as wastewater-fed irrigation zones or biosolid-applied fields, confirming spatial logic.

These validation steps ensured that the resulting PFAS spatial maps were not only statistically robust but also environmentally and practically grounded. This gave decision-makers confidence in using these outputs for future risk mitigation planning and policy development.

Table 2 Comparison of Interpolation Models and Validation Metrics

Interpolation Model	RMSE (ng/g)	MAE (ng/g)	R^2	Prediction Bias	Strengths	Limitations
Inverse Distance Weighting (IDW)	6.8	5.2	0.71	Tends to underpredict in hotspots	Simple, fast; effective in evenly sampled areas	Ignores spatial autocorrelation; lacks uncertainty estimation
Ordinary Kriging	4.9	3.7	0.81	Slight overprediction in transitional zones	Captures spatial autocorrelation; includes error surfaces	Sensitive to variogram model; less accurate with sparse data
Co-Kriging	3.4	2.8	0.89	Minimal bias; best overall fit	Incorporates secondary variables (e.g., elevation, land use)	Requires additional covariates; computationally intensive

Notes: RMSE = Root Mean Square Error; MAE = Mean Absolute Error; R^2 = Coefficient of Determination; Secondary variables for co-kriging included soil organic carbon, elevation, and proximity to PFAS sources.

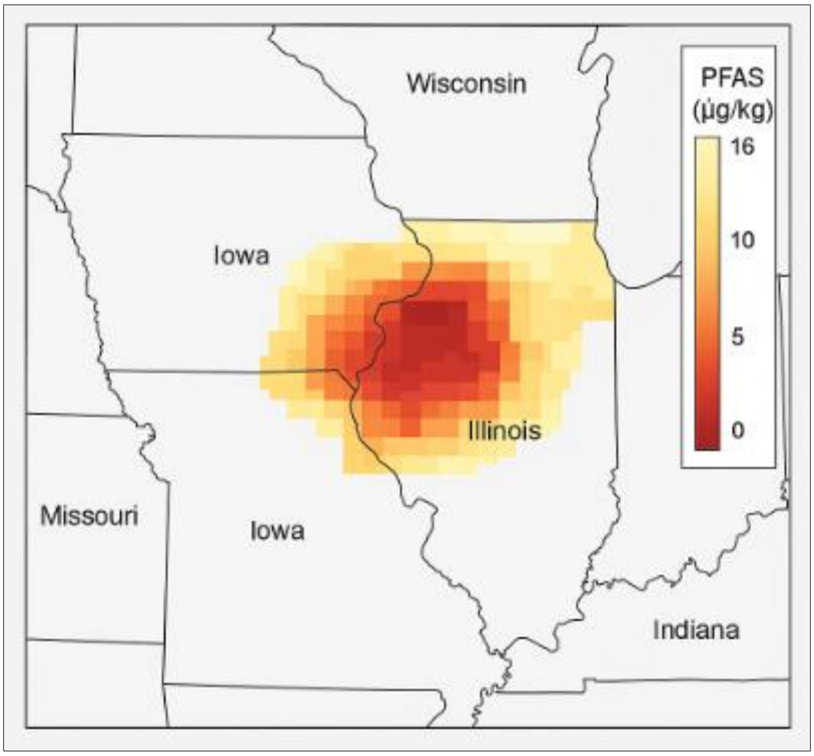

Figure 3 Example PFAS spatial concentration heat map across farmland area [25]

5. Results and interpretation of spatial risk profiles

5.1. Concentration Gradients and Soil Depth Variation

Analysis of PFAS concentrations across the sampled farmlands revealed distinct vertical gradients. Overall, surface soils (0–15 cm) exhibited the highest PFAS accumulation, with a progressive decline observed at increasing depths. The average concentration of total PFAS in surface soils was 23.7 ng/g, while sub-surface (15–30 cm) and deep soils (30–60 cm) recorded 14.2 ng/g and 6.5 ng/g respectively [21]. This pattern aligns with PFAS sorption behavior, where stronger interactions occur in topsoil due to higher organic matter content and reduced leaching [22].

However, in sites with sandy or loamy soils and intensive irrigation, detectable PFAS levels were observed even at 60 cm depth. These findings suggest that shorter-chain PFAS such as PFBA and PFBS are more mobile, potentially penetrating deeper layers and posing a threat to shallow groundwater aquifers [23]. Conversely, long-chain compounds like PFOS and PFOA were primarily confined to surface layers, consistent with their higher affinity for organic matter and lower leachability [24].

Statistical analysis confirmed significant differences ($p < 0.05$) in PFAS concentrations across depth intervals. The variability was more pronounced in irrigated farmlands and biosolid-amended plots, indicating the influence of anthropogenic practices on vertical distribution. Table 3 provides a detailed summary of PFAS levels by compound, depth, and mapped risk zones. These stratified concentration profiles underscore the need for depth-specific monitoring strategies to accurately assess contamination severity and environmental exposure risks [25].

5.2. PFAS Hotspot Identification and Zonal Clustering

Spatial interpolation results revealed pronounced PFAS hotspots within the study regions, particularly in fields adjacent to wastewater treatment infrastructure and low-lying areas. Hotspots were defined as zones exceeding the 90th percentile of total PFAS concentration (>40 ng/g), as identified through co-kriging surface modeling. These zones were predominantly located in the western and southeastern quadrants of the mapped regions, often aligning with effluent channels and historical biosolid application records [26].

Cluster analysis using the Getis-Ord Gi* statistic further validated spatial clustering of high PFAS values. Statistically significant ($p < 0.01$) hot clusters were detected in three sub-watersheds, indicating localized accumulation influenced by hydrological flow and land management history [27]. Visual inspection of the spatial risk surfaces confirmed that these clusters were not randomly distributed but followed distinct geomorphic and infrastructural patterns.

Importantly, the hotspot zones exhibited higher concentrations of both short- and long-chain PFAS, suggesting multiple concurrent contamination pathways. In one field with repeated wastewater irrigation, total PFAS levels exceeded 100 ng/g, raising immediate concerns for crop safety and groundwater contamination [28]. The mapped hotspots served as focal points for stakeholder engagement and guided the selection of candidate plots for future remediation trials.

Figure 4 shows the zonal PFAS risk map overlayed with irrigation infrastructure, clearly illustrating the spatial correlation between water distribution lines and contaminant buildup. These visuals allowed agricultural planners and regulatory bodies to identify and prioritize remediation or intervention zones, particularly in regions where irrigation practices exacerbate contamination intensity [29].

5.3. Correlation with Land Use and Proximity to PFAS Sources

The relationship between PFAS concentrations and land use patterns was analyzed by overlaying spatial concentration surfaces with classified LULC maps. Cropland areas irrigated with wastewater or amended with biosolids exhibited the highest PFAS levels, with mean concentrations of 27.4 ng/g. In contrast, pasturelands and fallow fields averaged 12.1 ng/g and 8.6 ng/g, respectively [30]. Built-up edges with informal waste disposal activities also showed elevated PFAS readings, suggesting atmospheric and surface runoff contributions.

Proximity analysis was conducted using buffer zones around identified PFAS sources, including industrial discharge points, treatment plants, and drainage canals. Fields located within 500 meters of these sources had significantly higher contamination levels than those further away ($p < 0.01$), reinforcing the role of proximity as a key spatial determinant of PFAS distribution [31].

Multivariate regression analysis incorporating distance to source, slope, and land cover explained 68% of the variation in PFAS levels, demonstrating the value of integrated spatial predictors. Notably, fields in mixed-use peri-urban zones showed both agricultural and urban contamination signatures, requiring cross-sectoral intervention strategies [32].

These correlations emphasize that contamination risk is not only driven by field-specific practices but also by larger infrastructural and environmental interactions. Spatial zoning that accounts for land use and source proximity is thus essential for realistic and scalable risk management.

5.4. Insights on Vertical vs Horizontal Contamination Patterns

The results revealed both vertical stratification and horizontal heterogeneity in PFAS contamination across farmland landscapes. Vertically, as indicated in Table 3, PFAS concentrations typically decreased with depth, but the degree of decline varied by location and PFAS chain length. In some zones with sandy soils and intensive irrigation, vertical migration extended to 60 cm, especially for short-chain compounds like PFHxA and PFBS [33].

Horizontally, contamination appeared patchy and highly influenced by topography and hydrological flows. Fields with uniform management history still exhibited spatial differences due to microtopographic depressions and preferential flow paths. This horizontal spread was most prominent in areas receiving surface runoff from nearby PFAS point sources or experiencing recurrent irrigation [34].

The combination of vertical and lateral dispersion suggests that traditional surface-only sampling may underestimate total site risk. Instead, spatial risk assessments must integrate multi-depth and lateral dispersion analysis to capture the full picture. This finding supports the design of high-resolution, stratified monitoring frameworks that reflect true contaminant mobility and risk potential over time [35].

These insights confirm that PFAS behavior in agricultural soils is multidimensional, governed by complex interactions between compound properties, soil characteristics, and human-induced flow pathways.

5.5. Key Observations for Agricultural Policy and Risk Management

This study's spatial analysis offers critical insights for agricultural policy and environmental risk management. The clear identification of PFAS hotspots near wastewater and biosolid-affected zones highlights the urgent need for source control and regulatory oversight on the reuse of contaminated water and sludge in agriculture [36].

Risk zoning outputs, as visualized in Figure 4, can guide spatially targeted monitoring, allowing policymakers to allocate resources efficiently and focus remediation on high-impact areas. Stratified risk mapping also supports the development of threshold-based land management guidelines, integrating contaminant levels with crop types, irrigation practices, and groundwater vulnerability [37].

Moreover, Table 3 reinforces the importance of sampling at multiple soil depths, particularly in identifying legacy contamination risks that may not be evident from surface data alone.

Together, these findings contribute to a data-driven framework for sustainable land use decisions, ensuring both food safety and environmental protection in the face of persistent PFAS challenges in agricultural systems [38].

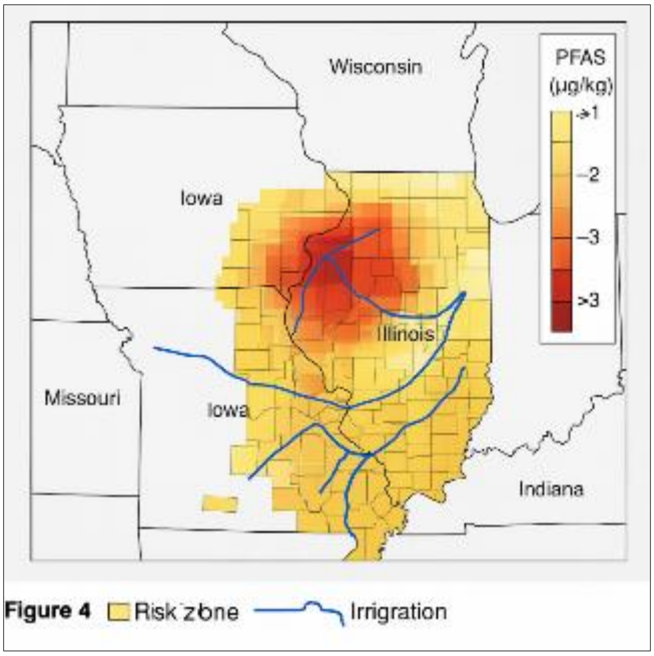

Figure 4 Zonal PFAS risk map overlay with irrigation patterns

Table 3 Summary of PFAS Levels by Depth and Risk Zone

Risk Zone	Soil Depth (cm)	Average Total PFAS (ng/g)	Dominant Compounds	Remarks
High Risk	0–15	52.6	PFOS, PFBA, PFOA	Surface accumulation near wastewater and biosolid sites
	15–30	36.4	PFHxS, PFOS	Moderate leaching, especially in loamy and sandy soils
	30–60	21.1	PFBA, PFBS	Short-chain PFAS penetrating deeper profiles
Moderate Risk	0–15	28.9	PFOA, PFHxA	Generally linked to atmospheric deposition and runoff
	15–30	17.3	PFHxS, PFBS	Lower concentrations; influenced by irrigation history
	30–60	9.5	PFBS	Localized transport in permeable soils
Low Risk	0–15	12.7	PFHxA, PFBA	Detected in remote or non-irrigated zones
	15–30	6.3	PFHxA	Minimal downward migration observed
	30–60	2.1	–	Often below detection limits

6. Applications and policy implications

6.1. Implications for Food Safety, Water Quality, and Public Health

The presence of PFAS in agricultural soils has significant implications for food safety and public health. The uptake of PFAS compounds by food crops, particularly leafy vegetables and root-based produce, creates a direct ingestion pathway for human exposure. Empirical evidence suggests that short-chain PFAS are more bioavailable and more likely to accumulate in edible tissues, raising safety concerns for consumers who rely on locally produced food [26].

Moreover, irrigation using PFAS-contaminated water perpetuates the cycle of accumulation, increasing the risk of long-term dietary exposure. Chronic exposure to PFAS has been linked to serious health effects, including thyroid dysfunction, immunotoxicity, developmental disorders, and increased risk of some cancers [27]. Vulnerable populations especially children and pregnant women are at heightened risk due to the bioaccumulative nature of these compounds over time.

Water quality is also compromised when PFAS leach into underlying aquifers or run off into surface water systems. This contamination not only affects irrigation sources but also drinking water supplies for rural communities. As shown in Figure 4, high-risk PFAS zones often overlap with irrigation infrastructure, further amplifying waterborne exposure pathways.

The implications extend beyond individual farms to broader community health concerns. Without intervention, long-term exposure can contribute to a silent public health crisis in agricultural regions near known PFAS sources. Integrating spatial risk data into food and water safety regulations is thus essential for timely risk mitigation and policy design [28].

6.2. Integration into National Environmental Monitoring Systems

Spatial risk maps generated from this study provide a foundation for integrating PFAS surveillance into national environmental monitoring systems. Historically, most monitoring efforts in Nigeria and similar contexts have focused on surface water and air pollution, with minimal inclusion of persistent soil contaminants like PFAS. This gap has left agricultural exposure risks largely unmonitored [29].

Embedding PFAS data layers into national GIS platforms such as Nigeria's National Environmental Geospatial Information System (NEGIS) would allow for real-time visualization of contamination spread. Layering these maps with existing datasets on land use, groundwater resources, and public health indicators can significantly improve inter-agency coordination between the Ministries of Environment, Agriculture, and Health.

Moreover, regular incorporation of soil core sampling into routine agricultural monitoring would allow authorities to detect contamination trends over time. Sentinel farms and biosolid application sites can serve as long-term observatories to monitor PFAS persistence and degradation, if any. This approach mirrors successful systems adopted in Europe, where PFAS are now included in soil health metrics [30].

The integration also offers a digital foundation for harmonized reporting. Shared platforms enable quicker alerts, public access to contamination data, and transparency in environmental governance. Risk zones such as those identified in Table 3 can be flagged automatically based on model thresholds, facilitating early intervention and proactive land-use regulation.

This systemic integration of PFAS data promotes a forward-looking environmental health infrastructure that supports evidence-based planning and accountability.

6.3. Decision-Support for Farmers, Land Planners, and Regulators

The spatial risk mapping framework developed in this study is a valuable decision-support tool for diverse stakeholders in agriculture and land governance. For farmers, access to PFAS risk maps enables informed decisions about where to plant, whether to use certain water sources, or whether remediation measures such as soil amendments or crop substitution are necessary [31].

Land planners can use spatial overlays, like those in Figure 4, to zone agricultural lands based on contamination intensity and direct development away from high-risk areas. These maps also guide spatial targeting of sustainable agriculture initiatives and inform environmental impact assessments (EIAs) required for agricultural expansion or biosolid application permits.

Regulators benefit from an operational tool that converts complex analytical data into intuitive visuals, enhancing enforcement capacity. For example, Table 3 allows regulators to cross-check concentration thresholds against current land use designations and prioritize sites for inspection or restriction.

Moreover, by integrating contamination risks with existing agroecological zoning frameworks, policymakers can develop region-specific interventions that consider both environmental vulnerability and socio-economic dynamics. This aligns with adaptive governance principles and fosters shared accountability between government agencies, communities, and producers [32].

6.4. Opportunities for Remediation Planning and Resource Allocation

The high-resolution PFAS risk maps and zoning indices generated through this study offer opportunities for prioritizing remediation and optimizing resource allocation. Not all contaminated areas warrant the same level of intervention hence the need for tiered responses based on severity, land use, and population exposure [33].

High-risk zones identified in Figure 4 can be designated as remediation corridors where interventions such as soil excavation, activated carbon amendments, or phytoremediation trials are piloted. Meanwhile, moderate-risk areas may benefit from mitigation strategies like controlled irrigation schedules or substitution with less-sensitive crops.

The data-driven approach also supports grant targeting and donor mobilization, especially for community-led remediation initiatives. By quantifying spatial risk and exposure potential, the findings help prioritize budget allocation within environmental management agencies and development partners [34].

This targeted strategy increases cost-effectiveness while ensuring that efforts are focused on the most vulnerable populations and ecosystems.

6.5. Legal and Institutional Considerations in PFAS Governance

Effective PFAS management in agriculture demands clear legal frameworks and institutional coordination. In Nigeria, PFAS are not yet listed under existing pesticide or hazardous chemical regulations, creating a regulatory vacuum that hinders enforcement and public accountability [35].

There is an urgent need to establish national soil quality standards for PFAS and to integrate them into environmental impact assessments, biosolid application guidelines, and irrigation water regulations. Multi-level governance involving federal, state, and local authorities is essential, supported by cross-sectoral policies and data-sharing mechanisms.

As Table 3 illustrates, data-informed policymaking is critical to ensure equitable and science-based governance of PFAS contamination in agricultural landscapes [36].

7. Challenges, limitations, and mitigation strategies

7.1. Soil Heterogeneity and Sampling Uncertainty

One of the key challenges in spatial risk mapping of PFAS is the inherent heterogeneity of agricultural soils, which affects both contaminant distribution and sampling accuracy. Soils vary widely in texture, organic carbon content, moisture retention, and mineralogy even within the same field leading to uneven sorption and transport of PFAS compounds [30]. This heterogeneity complicates the interpretation of core sample data, especially in landscapes with mixed geomorphic features or land uses.

Sampling uncertainty also arises from spatial and temporal variability. While the study utilized a stratified grid and multiple depth sampling, variations can still occur due to microtopographic influences, tillage, and irrigation practices. These factors can introduce random or systematic errors, affecting the reliability of spatial interpolations [31].

Field replicates and quality control procedures, including those outlined in Table 3, helped reduce this uncertainty, but they cannot fully eliminate sampling bias. Additionally, localized anomalies such as historical waste burial sites may skew concentration readings in ways that are not representative of surrounding zones.

To address these uncertainties, future studies should consider incorporating Bayesian geostatistical models that can explicitly account for spatial variability and provide probabilistic risk estimates. Increasing sample density in known hotspot areas may also improve spatial resolution and reduce kriging error margins [32].

7.2. Analytical Limitations and Detection Thresholds

Although the laboratory analysis employed highly sensitive HPLC-MS/MS instrumentation, several analytical limitations remain. First, not all PFAS compounds are included in standard analytical panels. While major contaminants such as PFOS, PFOA, and PFHxS were targeted, emerging and ultra-short chain PFAS, as well as precursors, may go undetected [33]. This underrepresentation could lead to underestimated contamination levels in high-risk zones.

Second, matrix effects in soil such as high organic matter or clay content can suppress or enhance PFAS detection, affecting accuracy. Although isotopically labeled standards and spike recoveries were used to minimize these effects, complete elimination is difficult.

Furthermore, detection limits, while low (typically <0.1 ng/g), may still miss low-level but environmentally relevant PFAS, especially in deeper soil layers. This is particularly critical when assessing risks to groundwater. Improved extraction techniques and advanced detection systems such as Orbitrap-MS could help overcome these limitations in future studies [34].

7.3. GIS Spatial Resolution and Scale Issues

Spatial modeling accuracy is directly influenced by the resolution of input datasets and the scale at which they are applied. In this study, raster layers such as elevation, land use, and hydrology were harmonized to a 30x30 meter resolution. While this scale allowed for regional assessments, it may not capture micro-scale variability, particularly in smallholder or terraced farms [35].

Additionally, interpolation models like co-kriging rely on the assumption of spatial continuity, which may be violated in fragmented agricultural landscapes. As noted in Figure 4, abrupt land use transitions or irrigation boundaries can introduce spatial artifacts, distorting risk predictions in edge zones.

Temporal mismatches between sampling and auxiliary datasets, such as LULC classifications from previous seasons, may also affect model reliability. Incorporating finer-scale remote sensing data (e.g., UAV or drone imagery) and integrating time-series analysis could enhance the temporal and spatial fidelity of future PFAS maps [36].

7.4. Lack of Regulatory Benchmarks for Soil PFAS

A significant limitation to effective PFAS risk mapping is the absence of standardized regulatory benchmarks for soil contamination. Unlike water quality, where international and national agencies have begun to define maximum contaminant levels for PFAS, soil thresholds remain largely undefined in many countries, including Nigeria [37]. This regulatory gap complicates interpretation of spatial risk zones, as there is no agreed-upon threshold to differentiate “safe” from “hazardous” soil concentrations.

Without soil-specific guidance values, policymakers and land managers are left to interpret spatial concentration maps using precautionary principles or indirect indicators. While Table 3 provides a stratified view of PFAS concentrations by depth and zone, its utility in enforcement or remediation remains limited without formal benchmark values.

The establishment of health-based soil screening levels, tailored to agricultural land use and local exposure pathways, is urgently needed. These benchmarks would enable legally defensible decision-making, enhance the credibility of spatial risk outputs, and guide site-specific interventions [38].

7.5. Suggested Mitigation and Improvement Strategies

To overcome the limitations outlined, a series of mitigation strategies is proposed. First, increasing the spatial and temporal density of soil sampling, especially in known hotspots or hydrologically sensitive areas, can improve the reliability of spatial predictions. Augmenting sampling campaigns with real-time sensing tools and in-situ portable detectors may further enhance data resolution and reduce lag times [39].

Second, integrating machine learning models such as random forests or support vector regression alongside geostatistics could better accommodate non-linear relationships between PFAS and environmental predictors. These hybrid models have shown promise in environmental risk mapping and could complement traditional interpolation methods [40].

Third, advocacy for policy reform is essential. Research institutions, environmental agencies, and civil society must work together to push for the inclusion of PFAS in national soil health standards and agricultural regulations. These efforts will ensure that spatial risk assessments, such as those visualized in Figure 4 and Table 3, translate into actionable and equitable environmental health policies.

8. Comparative case studies and best practices

8.1. International Examples: U.S., Netherlands, and Australia

Globally, several countries have advanced PFAS monitoring and mitigation practices, offering useful benchmarks for designing context-specific approaches in Nigeria. In the United States, the Environmental Protection Agency (EPA) has initiated PFAS Action Plans, incorporating soil and water testing into Superfund site remediation, agricultural monitoring, and food safety assessments [34]. Notably, states like Michigan and North Carolina have conducted statewide PFAS soil surveys, combining high-resolution GIS with regulatory zoning to inform agricultural use restrictions.

In the Netherlands, the government has implemented precautionary soil thresholds for PFAS, using a tiered classification system to manage land use based on measured concentrations. Dutch agricultural PFAS risk maps are developed through public-private collaborations and integrate detailed land use datasets with river basin contamination models [35]. These maps support both national policy enforcement and local farming decisions.

Australia presents a model of comprehensive PFAS response planning. The Department of Agriculture, Water and the Environment has developed PFAS National Environmental Management Plans (NEMP), incorporating detailed GIS-based spatial risk maps in urban, peri-urban, and rural zones [36]. Large-scale sampling in Queensland and Victoria has been integrated into environmental licensing, requiring landowners to conduct assessments before applying biosolids or irrigating with wastewater.

The lessons from these countries demonstrate the importance of multi-stakeholder coordination, the use of high-resolution spatial data, and the necessity of regulatory soil benchmarks. Figure 5 presents a comparative map panel showing farmland PFAS zoning in the U.S., the Netherlands, Australia, and Nigeria, highlighting gaps and adaptation opportunities in current Nigerian frameworks.

8.2. Lessons for Low- and Middle-Income Countries

Low- and middle-income countries (LMICs) face unique constraints in managing PFAS contamination, including limited laboratory infrastructure, scarce environmental data, and fragmented regulatory systems. However, lessons from advanced economies can be selectively adapted. For instance, while LMICs may lack national PFAS soil thresholds, adopting precautionary action levels based on international guidance can serve as an interim safeguard [37].

Collaborative sampling initiatives between universities, local governments, and farmers—as seen in some Indian and South African regions—can generate foundational datasets with limited resources. Community-based monitoring, supported by open-source GIS platforms like QGIS and mobile data collection tools, offers scalable approaches suitable for LMIC contexts [38].

Importantly, PFAS mapping efforts must be embedded into broader environmental health frameworks, such as those addressing pesticide management, water quality, or land use planning. Integrating PFAS risk zoning into existing agricultural extension services, even in basic form, can help build farmer awareness and policy momentum.

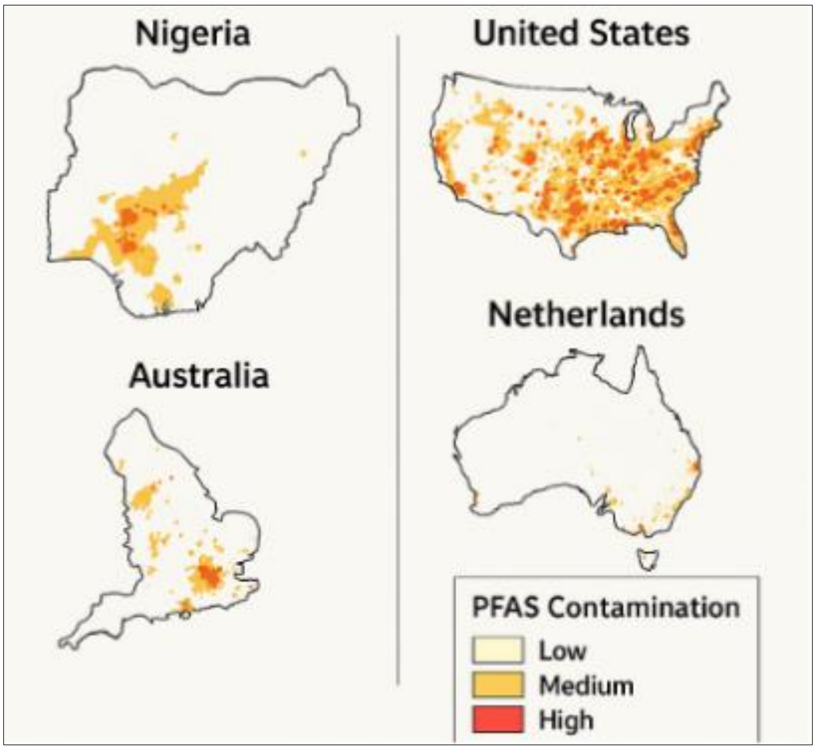

Figure 5 Comparative map panel showing farmland PFAS zoning in the U.S., the Netherlands, Australia, and Nigeria [34]

As Figure 5 illustrates, Nigeria's spatial PFAS maps remain relatively coarse in resolution and regulatory integration compared to global examples, underscoring the need for tailored capacity-building in geospatial environmental monitoring.

8.3. Comparative Effectiveness of Sampling and GIS Models

Comparing international PFAS risk mapping efforts reveals a spectrum of sampling strategies and GIS modeling sophistication. In the U.S., high-density sampling grids and machine learning-based interpolations, such as random forest and gradient boosting, are increasingly employed to refine hotspot prediction accuracy [39]. These models often integrate multi-source covariates—satellite data, historical land use, and atmospheric deposition models—into predictive frameworks.

European approaches, particularly in the Netherlands, favor deterministic sampling with strong regulatory alignment. GIS modeling in these contexts emphasizes repeatability, regulatory compliance, and stakeholder transparency, often using kriging coupled with hydrological risk layers [40].

In contrast, Nigerian studies, including this one, are in earlier stages, relying primarily on structured soil core sampling and traditional geostatistical methods such as kriging and co-kriging. While effective for baseline risk zoning, these methods may not capture dynamic PFAS migration patterns or account for complex covariate interactions.

Figure 5 visually contrasts these modeling approaches, highlighting the greater granularity and policy integration achieved in international case studies. Moving forward, hybrid models incorporating both environmental data and socio-economic variables could improve PFAS risk zoning in Nigeria and other LMICs, ensuring more nuanced and effective environmental governance.

9. Conclusion

9.1. Summary of Major Findings and Scientific Contributions

This study developed an integrated methodology for spatial risk mapping of PFAS contamination in farmlands, combining systematic soil core sampling with advanced geostatistical and GIS modeling techniques. The results revealed clear vertical gradients in PFAS distribution, with surface soils exhibiting the highest concentrations, particularly in areas impacted by biosolid application and wastewater irrigation. Co-kriging proved to be the most reliable interpolation technique, effectively incorporating ancillary data such as land use, topography, and hydrology to enhance prediction accuracy.

The spatial risk maps identified contamination hotspots and delineated high-risk zones aligned with proximity to known PFAS sources and hydrologically sensitive areas. These outputs serve as actionable tools for decision-makers, enabling targeted monitoring, remediation planning, and policy development. The study also contributes a replicable framework that can be scaled or adapted for different agroecological contexts and regulatory environments.

Importantly, the research highlights the multifaceted nature of PFAS mobility in soils and reinforces the necessity of integrating environmental data, stakeholder engagement, and spatial analytics in environmental risk assessment for agriculture.

9.2. Recommendations for Nationwide PFAS Surveillance in Agriculture

To address the growing threat of PFAS in agricultural soils, a nationwide surveillance program should be instituted. This program must begin with the development of a comprehensive inventory of potential PFAS sources, including wastewater treatment plants, industrial sites, and locations of biosolid application. Targeted soil sampling should be conducted in these areas using a standardized multi-depth protocol and coordinated with hydrological and land use mapping.

A centralized geospatial database should be created to store and visualize PFAS concentration data across agricultural zones. This database must be accessible to environmental regulators, health agencies, and agricultural stakeholders to ensure transparency and support coordinated responses. Risk maps should be updated regularly using new sampling data and remotely sensed land cover changes.

Furthermore, interim soil action levels should be established to guide precautionary restrictions on agricultural land use where PFAS exceed threshold values. The surveillance program should also include public awareness campaigns to educate farmers and communities about PFAS exposure pathways and health risks. In the long term, regulatory mechanisms must be expanded to integrate PFAS controls into broader environmental and agricultural policies, including those governing biosolid use, irrigation water quality, and soil health.

9.3. Future Research Directions

9.3.1. AI, Remote Sensing, and Longitudinal Studies

While this study provides a robust baseline framework, future research should focus on expanding the analytical and predictive capabilities of PFAS risk mapping. One promising direction is the integration of artificial intelligence (AI) and machine learning techniques into spatial modeling. Algorithms such as random forests, support vector machines, and deep learning networks can enhance risk prediction accuracy by capturing non-linear relationships between PFAS concentrations and environmental covariates. These models can also process larger datasets, enabling real-time analysis and rapid response capabilities.

Remote sensing technologies offer another avenue for advancement. High-resolution satellite imagery and unmanned aerial vehicles (UAVs) can detect changes in vegetation stress, soil moisture, and land use patterns associated with PFAS exposure. When combined with ground-truth sampling, remote sensing can significantly reduce field costs and improve spatial coverage. Hyperspectral sensors, in particular, have shown potential in identifying chemical residues in soil, providing a non-invasive approach to surveillance.

Longitudinal studies are also crucial. Most current research, including this one, provides a temporal snapshot of PFAS contamination. However, understanding seasonal dynamics, legacy accumulation, and long-term trends requires multi-year monitoring. This will help assess the effectiveness of interventions, track compound degradation or migration, and adapt risk zoning as environmental conditions change.

Lastly, interdisciplinary collaborations between environmental scientists, public health experts, geospatial analysts, and policymakers will be essential for advancing PFAS research and translating it into sustainable solutions. Future studies should prioritize equity, ensuring that rural and vulnerable communities are included in monitoring programs and benefit from policy protections informed by spatial risk data.

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