

GIS and multi-temporal remote sensing assessment of heavy-metal redistribution susceptibility and monitoring priorities around the KAT refinery, Kirkuk, Iraq

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ABSTRACT

Industrial soil contamination may persist long after initial deposition, yet the spatial conditions favoring subsequent redistribution are rarely evaluated together with historical chemical measurements. This study integrates an archived 2021 soil dataset from 21 locations around the KAT refinery in Kirkuk, Iraq, with multi-temporal Landsat 8 observations (2017, 2021, and 2025), SRTM terrain analysis, modeled surface-flow connectivity, and scenario-based susceptibility mapping. Eleven metals were available, with a pronounced Zn-Cu-Pb hotspot in the northwestern waste-valley sector. A standardized Zn-Cu-Pb hotspot composite (HCS) represented this multimetal pattern. SRTM elevations agreed strongly with an independent contour-derived terrain surface (Spearman rho approximately 0.962; RMSE approximately 1.82 m). Between 2017 and 2025, median NDVI declined from 0.127 to 0.112 and SAVI from 0.107 to 0.092, whereas NDBI increased from 0.039 to approximately 0.059. Long-term SAVI and NDVI changes showed the strongest exploratory associations with HCS (rho approximately 0.592 and 0.567), although neither crossed the multiple-testing-adjusted 0.05 threshold. Direct quantitative forecasting was rejected after poor leave-one-out cross-validation. Instead, a Pollution Redistribution Susceptibility Index (PESI) integrated source pressure, terrain/connectivity, and long-term surface response under alternative weighting scenarios. Consensus PESI showed moderate internal spatial agreement with HCS (rho approximately 0.468, p approximately 0.033), but this is not independent validation because the documented MA-MB-MC sector contributes to source-pressure definition. The final 30-m priority raster covered 99.8001 km². Tier 1 occupied 8.7282 km² (8.746%) and Tier 2 occupied 2.9520 km² (2.958%), totaling 11.6802 km² (11.704%); MA-MB-MC occurred within Tier 1. The framework does not predict future metal concentrations; it identifies areas where documented contamination, environmental connectivity, and surface change jointly indicate greater susceptibility to persistence or redistribution. Independent repeat soil sampling is required for external validation. The study converts a sparse archived contamination baseline into a testable susceptibility framework without treating remote-sensing indices as direct metal measurements.

Keywords: heavy metals, GIS, Landsat 8, SRTM, pollution susceptibility, environmental monitoring, Kirkuk, industrial contamination.

INTRODUCTION

Contaminant accumulation in industrial soils is inherently spatially heterogeneous and depends not only on the location of emission or waste sources, but also on production processes, waste-management practices, topography, run-off connectivity, soil properties, and subsequent

land-surface disturbance. Recent studies of industrial sites demonstrate that delineation of heavy-metal risk zones depends on source information and environmental controls rather than on distance or concentration alone (Lin et al., 2024). Heavy metals are of particular concern because they persist in soil and may remain available for redistribution long after initial deposition.

Integrating site-specific field chemistry with GIS, remote sensing, and environmental covariates can strengthen monitoring and management of contaminated sites (Wang et al., 2022; Wang et al., 2024a; Zou et al., 2026). Remote sensing and GIS therefore provide a complementary framework for examining contaminated industrial landscapes in space and time.

Multi-temporal imagery can document changes in vegetation, exposed soil, moisture, and built surfaces, whereas DEM-derived variables can represent terrain-controlled transport pathways. At the site scale, identifying heavy-metal sources and hotspots and understanding source-sink relationships and surface-runoff pathways are important for interpreting potential redistribution (Wang et al., 2024b). However, spectral indices cannot directly quantify heavy-metal concentrations. A 2024 review of 529 publications found that remote-sensing inversion of soil heavy metals remains dependent on indirect spectral associations and scenario-specific calibration and recommended a mechanism-data-model-application framework (Wang et al., 2024a). Recent synthesis of machine-learning applications at industrially contaminated sites reaches a similar conclusion: predictive performance depends strongly on sample design, environmental covariates, and independent validation (Zou et al., 2026). Multi-temporal environmental monitoring is also important for distinguishing changes associated with shifts in anthropogenic pressure from short-term spatial snapshots; for example, Ali et al. (2024) documented measurable changes in particulate and noise pollution by comparing conditions before and during a major reduction in urban activity.

The KAT refinery area in Kirkuk provides an appropriate setting for such an assessment because archived soil measurements are available from a spatial network surrounding the refinery, including samples collected from a northwestern waste-valley sector and from locations inside and around the facility. The archived dataset establishes a historical chemical baseline, while Landsat observations before, near, and after the sampling period allow environmental surface changes to be evaluated over a longer temporal window.

The central methodological problem is therefore not to extrapolate a single chemical sampling campaign into precise future concentrations. Instead, the objective is to determine whether measured contamination, terrain-controlled connectivity, and remotely sensed environmental change

can be integrated to identify areas with comparatively greater susceptibility to future persistence or redistribution of pollution pressure.

The novelty of the present study lies in separating three questions that are often conflated in contaminated-site mapping: where contamination was actually observed, which landscape processes could support its redistribution, and where future monitoring should be prioritized. Spatial prediction at contaminated sites is sensitive to sampling density and design; studies using advanced interpolation or optimized sampling demonstrate that reliable concentration mapping requires substantially stronger spatial support than a small legacy dataset can provide (Man et al., 2022; Man et al., 2023). Rather than interpolating 21 archived measurements into a deterministic future concentration surface, the workflow therefore first tests whether quantitative prediction is defensible and then, only after that test fails, constructs a process-based susceptibility framework. This distinction reduces the risk of presenting remotely sensed change or terrain connectivity as chemical evidence. This conservative choice is further justified by recent industrial-site work showing that high-resolution three-dimensional prediction of multiple metals relies on substantially richer multisource covariate and training data than are available for KAT (Peng et al., 2024).

Accordingly, this study aims to: (i) characterize the spatial structure of the archived heavy-metal dataset; (ii) evaluate terrain and modeled surface-flow conditions around the observed hotspots; (iii) quantify multi-temporal environmental change using Landsat observations from 2017, 2021, and 2025; (iv) test associations between the contamination baseline and environmental predictors; (v) evaluate whether direct concentration prediction is statistically defensible; and (vi) develop and sensitivity-test a Pollution Redistribution Susceptibility Index (PESI) for identifying future monitoring priorities.

STUDY AREA

The study focuses on the KAT private petroleum/asphalt refinery area in Kirkuk Governorate, northern Iraq. The archived sampling network comprises 21 surface-soil locations distributed north, east, south, and west of the refinery, together with samples from the northwestern waste-valley sector (MA–MC) and two locations inside the

refinery (MS and MN). The sampling network extends approximately between 35.6003–35.6078° N and 44.3700–44.3867° E. A wider approximately 5-km environmental analysis zone was used for terrain, drainage, and remote-sensing assessment so that potential pathways were not artificially truncated at the original sampling footprint. The study-area setting and sampling coordinates are summarized in Table 1 and illustrated in Figures 1 and 2.

MATERIALS AND METHODS

Table 2 summarizes the datasets, processing sequence, and analytical role of each evidence stream.

Archived soil and heavy-metal data

The chemical baseline was obtained from the archived field campaign reported by Al-Taey (2022). Twenty-one surface-soil samples were collected around and within the KAT refinery in January 2021 from a depth of 0–20 cm using a hand auger. Approximately 1 kg of soil was collected at each location, stored in sealed polyethylene bags, labeled, and georeferenced using GPS. The sampling network included locations around the refinery, two samples inside the facility, and three samples (MA–MB–MC) documented in the

Table 1. Coordinates of the 21 archived KAT soil sampling locations

Sample	Latitude	Longitude
M1	35.605833	44.378056
M2	35.605556	44.380556
M3	35.606667	44.380833
M4	35.607778	44.380000
M5	35.601667	44.385000
M6	35.601667	44.385278
M7	35.601389	44.385833
M8	35.600833	44.386667
M9	35.601389	44.382222
M10	35.601111	44.382222
M11	35.600556	44.382222
M12	35.600278	44.382222
M13	35.604167	44.371944
M14	35.604167	44.371111
M15	35.604167	44.370556
M16	35.603889	44.370000
MA	35.605278	44.371944
MB	35.605278	44.371667
MC	35.605278	44.371389
MS	35.603236	44.376417
MN	35.602142	44.383447

original source as a waste-valley sector northwest of the refinery. Laboratory preparation in the archival study included drying, disaggregation, grinding, and sieving through a 200-mesh sieve, followed by acid digestion and ICP-MS

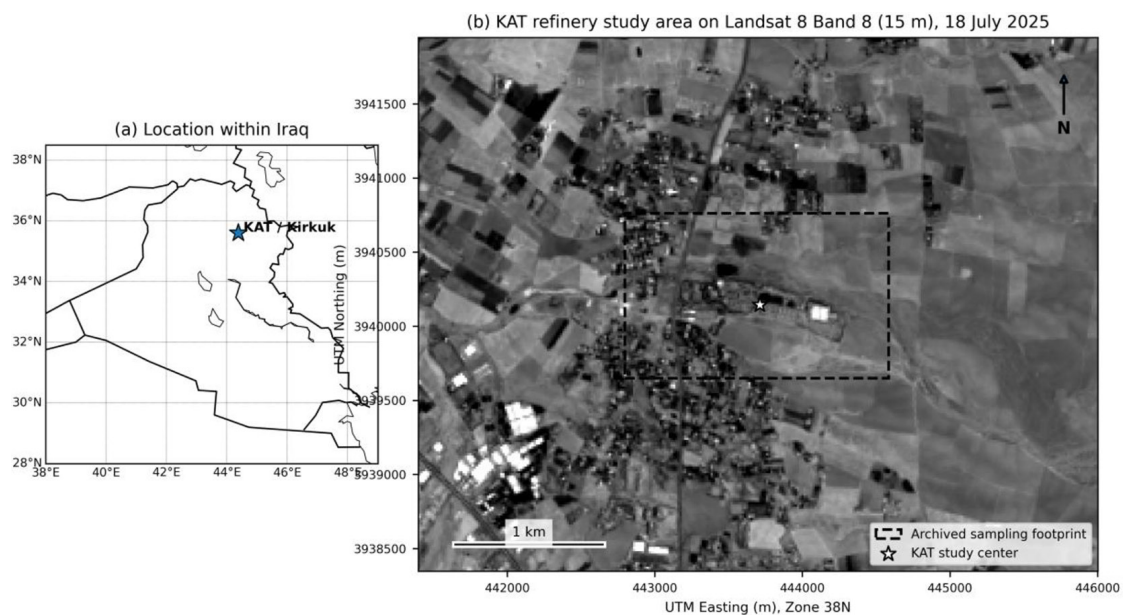


Figure 1. Location of the KAT refinery study area in Kirkuk, Iraq, with the archived sampling footprint shown on the native 15-m Landsat 8 panchromatic image

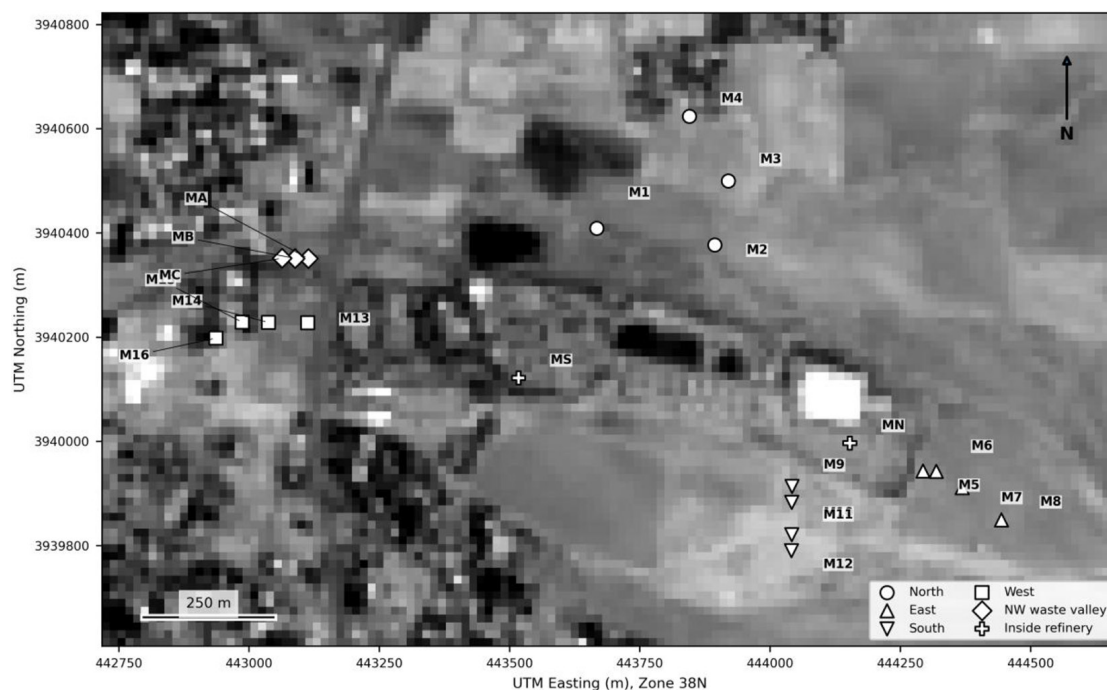


Figure 2. Detailed distribution of the 21 archived soil-sampling locations around and within the KAT refinery area, grouped by sampling sector

Table 2. Summary of datasets, processing steps, and analytical roles used in the integrated GIS–remote-sensing workflow

Component	Source / year	Spatial basis	Processing	Role in study
Archived soil chemistry	Al-Taey thesis; field campaign 2021	21 surface-soil samples	Descriptive statistics; HCS; rank associations	Observed contamination baseline / internal spatial comparison only
Landsat 8	28 Jul 2017: LC08_L1TP_169035_20170728_20200903_02_T1; 23 Jul 2021: LC08_L1TP_169035_20210723_20210729_02_T1; 18 Jul 2025: LC08_L1TP_169035_20250718_20250726_02_T1	WRS-2 169/35; common 30-m UTM grid	TOA reflectance; QA masking; NDVI, SAVI, NDBI, NDWI; temporal differences	Multi-temporal surface-response evidence
SRTM DEM	1 Arc-Second Global	30-m UTM Zone 38N	Elevation; slope; D8 flow accumulation; drainage distance	Terrain and transport-connectivity evidence
Statistical screening	Derived point variables	n = 21	Spearman; BH-FDR; redundancy screening; LOOCV	Test associations and reject unsupported direct forecasting
PESI scenarios	Integrated raster factors	333 × 333 cells; 30 m; 9.99 × 9.99 km (99.8001 km ²)	Source pressure + connectivity + surface response; 3 weight scenarios	Process-based susceptibility and sensitivity mapping
Priority zoning	Consensus / robust-high PESI	30-m grid	Tier 1 and Tier 2 decision rules	Field-monitoring prioritization

elemental analysis. The source thesis reports minimum detection limits of 0.2 mg kg^{−1} for Co and Ni, 0.1 mg kg^{−1} for Cu, Zn, Mo, Cd and Pb, 1 mg kg^{−1} for As, and 5 µg kg^{−1} for Hg. Analytical quality control reported in the source included

comparison with a reference soil material and duplicate analysis of a soil sample. Separate LOQ values and method-blank results were not explicitly reported in the archived thesis and are therefore not inferred here. These measurements are

treated as historical secondary observations; no new soil sampling or laboratory analysis was performed for the present study.

Exploratory contamination analysis and HCS

Descriptive statistics, rank correlations, and zone-level comparisons were used to identify metals showing strong spatial heterogeneity. Zn, Cu, and Pb displayed a coherent hotspot pattern centered particularly on sample MB and the northwestern waste-valley sector. To summarize this co-occurring pattern without replacing the original concentrations, a hotspot composite was calculated as:

$$HCS = (Z_{Zn} + Z_{Cu} + Z_{Pb})/3 \quad (1)$$

where: Z denotes the standardized concentration of each metal across the 21 samples; HCS is therefore an analytical composite, not a concentration unit or a regulatory pollution index.

All descriptive statistics reported in the present study were recalculated from the 21 individual archived KAT measurements rather than copied from summary statistics reported in the source thesis. This distinction is stated to preserve traceability between Appendix A and the calculations used here.

Multi-temporal Landsat analysis

Three seasonally matched Landsat 8 Collection 2 Tier 1 Level-1 L1TP scenes from WRS-2 path/row 169/35 were used: LC08_L1TP_169035_20170728_20200903_02_T1 (28 July 2017), LC08_L1TP_169035_20210723_20210729_02_T1 (23 July 2021), and LC08_L1TP_169035_20250718_20250726_02_T1 (18 July 2025). The same sensor, path/row, and late-July acquisition window were selected to reduce phenological and sensor-related inconsistency. Level-1 digital numbers were converted to top-of-atmosphere (TOA) reflectance using the Collection 2 radiometric rescaling coefficients and per-pixel solar-zenith correction following USGS guidance. Pixels flagged by QA_PIXEL for fill, dilated cloud, cirrus, cloud, cloud shadow, or snow were excluded. The NDVI, SAVI ($L = 0.5$), NDBI, and NDWI were then calculated using standard formulations (Huete, 1988; McFeeters, 1996; Zha et al., 2003), and change layers for 2017–2021, 2021–2025, and 2017–2025

were produced. All analyses were performed on a common 30-m UTM Zone 38N grid. Spectral indices were interpreted as land-surface response indicators rather than direct measurements of heavy-metal contamination. The Landsat scenes are part of the Landsat 8–9 OLI/TIRS Level-1, Collection 2 dataset (Earth Resources Observation and Science (EROS) Center, 2020), and processing followed current USGS Level-1 guidance (U.S. Geological Survey, 2026).

The spectral indices were calculated as follows:

$$NDVI = (NIR - Red)/(NIR + Red) \quad (2)$$

$$SAVI = 1.5(NIR - Red)/(NIR + Red + 0.5) \quad (3)$$

$$NDBI = (SWIR1 - NIR)/(SWIR1 + NIR) \quad (4)$$

$$NDWI = (Green - NIR)/(Green + NIR) \quad (5)$$

Terrain and modeled surface-flow connectivity

Topographic analysis used the SRTM 1 Arc-Second Global DEM (~30 m) covering the KAT area. The DEM was reprojected to UTM Zone 38N and processed to derive elevation, slope, D8 flow direction, flow accumulation, drainage networks, and distance-to-drainage surfaces. The final common terrain/susceptibility raster comprised 333×333 cells at 30-m resolution, corresponding to 9.99×9.99 km (99.8001 km²). Drainage extraction was evaluated using multiple accumulation thresholds (100, 250, 500, and 1000 cells) to assess threshold sensitivity. A locally available 10-m contour-interval dataset was independently converted to a TIN-style terrain surface over the portion where it overlapped the sampling network and was used to evaluate the consistency of SRTM elevations. The SRTM 1 arc-second elevation product was sourced from the U.S. Geological Survey archive (Earth Resources Observation and Science (EROS) Center, 2019).

Statistical screening and predictive-model check

Spearman rank correlations were used because the sample size was small ($n = 21$) and several variables were strongly skewed by localized hotspot behavior. False-discovery-rate sensitivity was evaluated with the Benjamini-Hochberg procedure (Benjamini, 2010). Predictor redundancy

was screened before modeling; highly collinear spectral variables were not entered together. Two deliberately parsimonious models were evaluated with leave-one-out cross-validation (LOOCV). The proximity-only model used refinery-center distance (m) as its single predictor. The integrated environmental model used four explicitly documented predictors: (i) Dist_WasteValleyProxy_m, the Euclidean distance (m) from the documented MA-MB-MC waste-valley source proxy; (ii) Slope_deg, SRTM-derived terrain slope in degrees; (iii) dSAVI_2017_2025, the dimensionless SAVI change calculated as SAVI2025 - SAVI2017; and (iv) Dist_Drain_1000_m, the Euclidean distance (m) to the drainage network extracted using the 1000-cell flow-accumulation threshold. Ridge regression ($\alpha = 1$) was fitted with predictor standardization performed within each training fold. In each LOOCV iteration, one observation was withheld, the scaler and model coefficients were re-estimated from the remaining 20 observations, and HCS for the withheld location was predicted; the procedure was repeated for all 21 locations. Model adequacy was judged from the complete set of out-of-fold predictions using cross-validated R^2 and RMSE rather than in-sample fit. Recalculation using these documented predictors reproduced the archived results: $R^2 = -0.0387$ and RMSE = 0.9768 for the refinery-distance model, and $R^2 = -0.2391$ and RMSE = 1.0669 for the four-predictor integrated model. Negative cross-validated R^2 values were interpreted as failure to outperform a mean-response benchmark and therefore as evidence against direct quantitative forecasting.

Pollution redistribution susceptibility index (PESI)

Following the predictive-model check, the analysis was reformulated as susceptibility mapping rather than concentration forecasting. PESI integrates three process families: source pressure (S), transport connectivity (C), and long-term surface response (R). Source pressure was represented by inverse distance from the independently documented MA-MB-MC waste-valley sector. Connectivity combined normalized slope and inverse distance to the selected 1000-cell drainage network, while surface response used the non-redundant 2017–2025 SAVI change layer. Robust percentile scaling used the 2nd and 98th percentiles (P2-P98), with values clipped to 0–1 outside

those limits. For positively oriented factors, $N(x) = \text{clip}[(x-P2)/(P98-P2), 0, 1]$; inverse-distance factors used $1-N(x)$. The recovered raster cut-points were: source-proxy distance, P2 = 795.897984 m and P98 = 6558.834037 m; slope, P2 = 0.335902° and P98 = 6.742862°; distance to the 1000-cell drainage network, P2 = 0.000000 m and P98 = 1154.216621 m; and dSAVI_2017_2025, P2 = -0.100108 and P98 = 0.071444. Connectivity was formed from normalized slope and inverse normalized drainage distance, while R was the normalized dSAVI layer. The three a priori scenarios were: Balanced PESI = $0.40S + 0.35C + 0.25R$; Source-dominant PESI = $0.55S + 0.30C + 0.15R$; and Connectivity-dominant PESI = $0.35S + 0.45C + 0.20R$. The consensus surface was the arithmetic mean of the three scenario scores, while scenario standard deviation represented weighting sensitivity. HCS was not interpolated into the PESI raster and was retained only for point-based internal-consistency assessment. Recalculation with the documented P2-P98 cut-points reproduced the archived consensus raster to numerical precision (Pearson $r > 0.99999999$; RMSE approximately 1.2×10^{-5}), confirming that the reported PESI results and interpretations remain unchanged.

Susceptibility-based monitoring priority zones

General susceptibility was further converted into operational monitoring priorities. Tier 1 core-priority areas were required to remain high under all PESI scenarios and to show jointly elevated source pressure and connectivity. Tier 2 represented secondary-priority areas supported by high consensus susceptibility and at least one of the source/connectivity dimensions. Very small isolated patches were removed to avoid interpreting single-pixel artifacts as meaningful management zones. These classes represent monitoring priority, not certainty of future contamination.

RESULTS

Spatial characteristics of the archived heavy-metal dataset

The 21-sample dataset showed high spatial heterogeneity. Zn, Mo, Pb and Cu were among the most heterogeneous metals while Ni and Fe

Table 3. Descriptive statistics and mean-to-reference ratios for the archived heavy-metal dataset

Metal	Mean	Median	SD	Min	Max	Mean/Ref.
Mn	697	709	79.242	496	881	0.970752
Ni	111.695	111.9	8.48678	99	130.8	5.07706
Zn	70.6667	61.4	42.2703	46.3	248.9	1.12169
Co	32.1905	31.4	6.27367	22.4	46.5	4.02381
Cu	26.581	24.8	8.54527	19	59.7	1.32905
Pb	12.9857	11.6	4.21157	9.9	28.5	0.865714
As	6.41905	6.9	1.17415	3.4	7.8	2.56762
Mo	4.61905	3.9	1.96128	2.6	10.6	2.56614
Cd	0.833333	0.9	0.0966092	0.5	0.9	1.66667
Hg	0.0454271	0.045	0.00892863	0.0273	0.06692	1.13568
Fe	33701.7	33795	2546.74	27549	37593	0.962906

were relatively homogeneous. The strongest multimetal anomaly occurred at MB, where Zn, Cu, and Pb reached 248.9, 59.7, and 28.5 mg/kg, respectively. MA was also elevated within the same northwestern sector. HCS ranked MB first (3.93) and MA second (1.29), clearly separating the northwestern waste-valley signal from most other sampling locations. The descriptive statistics are summarized in Table 3, and the spatial HCS pattern is shown in Figure 3.

Terrain and hydrological context

SRTM and the independent contour-derived terrain surface showed strong agreement at 13 overlapping sample locations (Spearman $\rho \approx 0.962$; Pearson $r \approx 0.967$; RMSE ≈ 1.82 m). The MA–MB–MC sector was relatively low lying, with a median elevation of approximately 387.3 m compared with approximately 398.6 m for the remaining samples. Although the hotspot sector

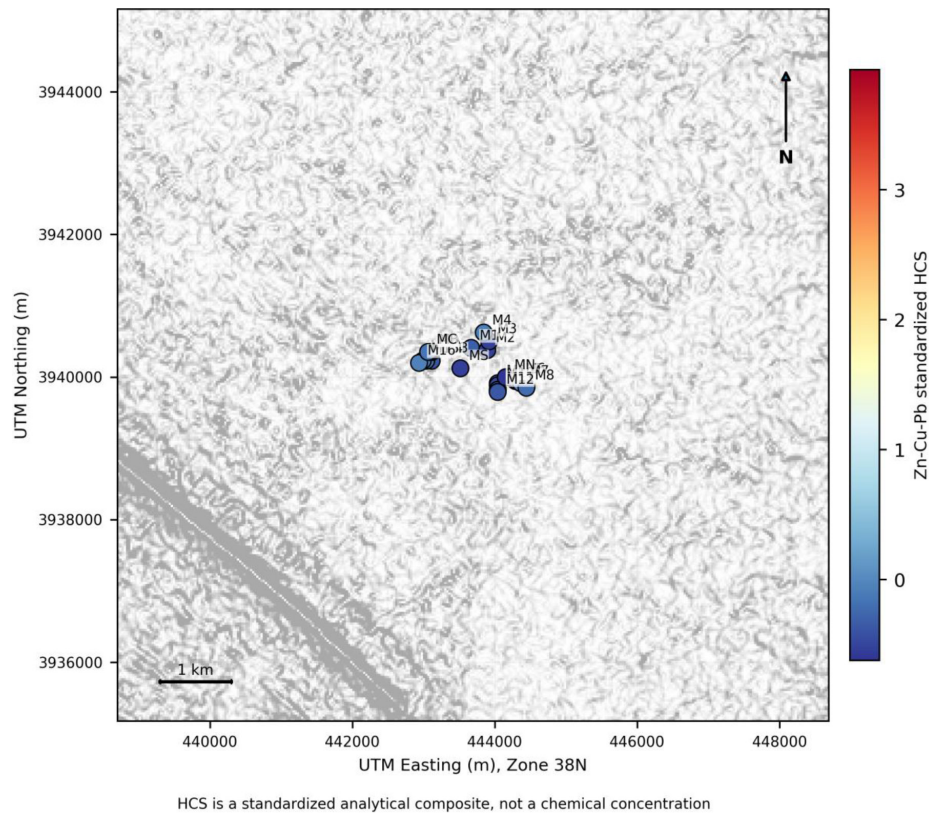


Figure 3. Spatial pattern of the standardized Zn-Cu-Pb hotspot composite (HCS) at the 21 archived sampling locations

was relatively close to some modeled drainage networks, HCS–drainage relationships were weak and threshold-sensitive. HCS was more strongly related to slope ($\rho \approx 0.519$, $p \approx 0.0158$), but this association did not remain significant after multiple-testing adjustment. The terrain agreement and topographic context are illustrated in Figure 4; the slope surface and modeled flow pathways are shown in Figures 5 and 6, respectively.

Multi-temporal surface change

The median NDVI was 0.127 in 2017, 0.120 in 2021 and 0.112 in 2025. A similar trend was observed in SAVI (0.107, 0.098, 0.092). The median NDBI increased from 0.039 in 2017 to 0.060 in 2021 and was around 0.059 in 2025. NDWI became slightly less negative over the same period. These patterns indicate measurable

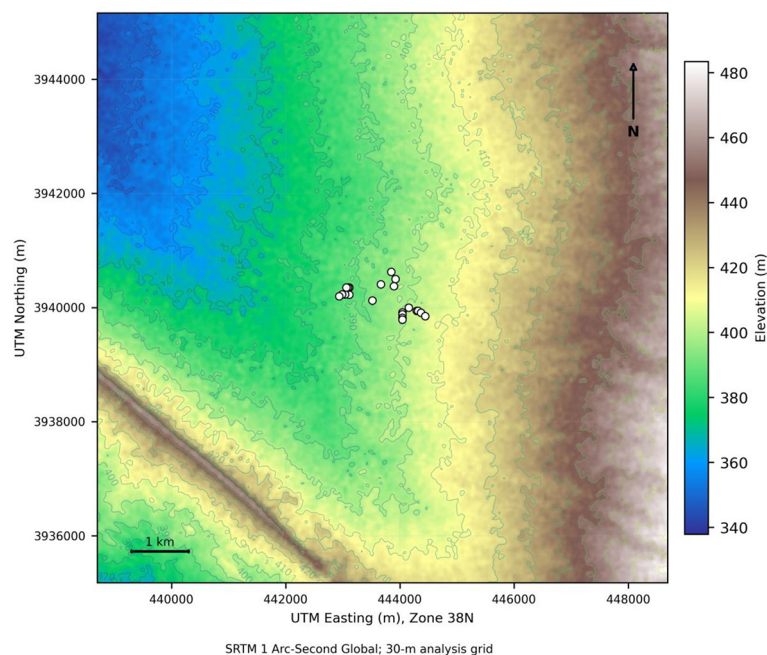


Figure 4. SRTM-derived digital elevation model (DEM), contour overlay, and archived sampling locations

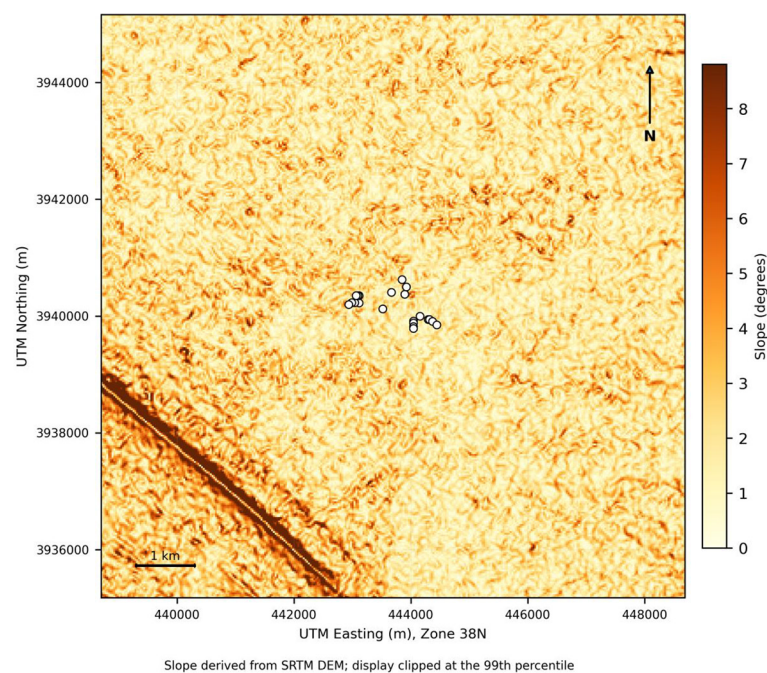
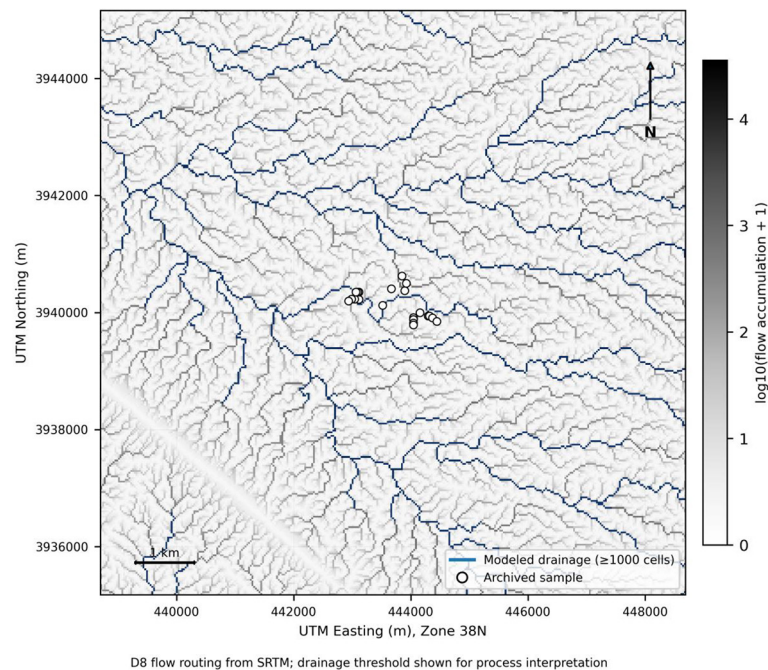


Figure 5. SRTM-derived slope surface across the 333 × 333-cell, 30-m analysis grid (9.99 × 9.99 km; 99.8001 km²)



D8 flow routing from SRTM; drainage threshold shown for process interpretation

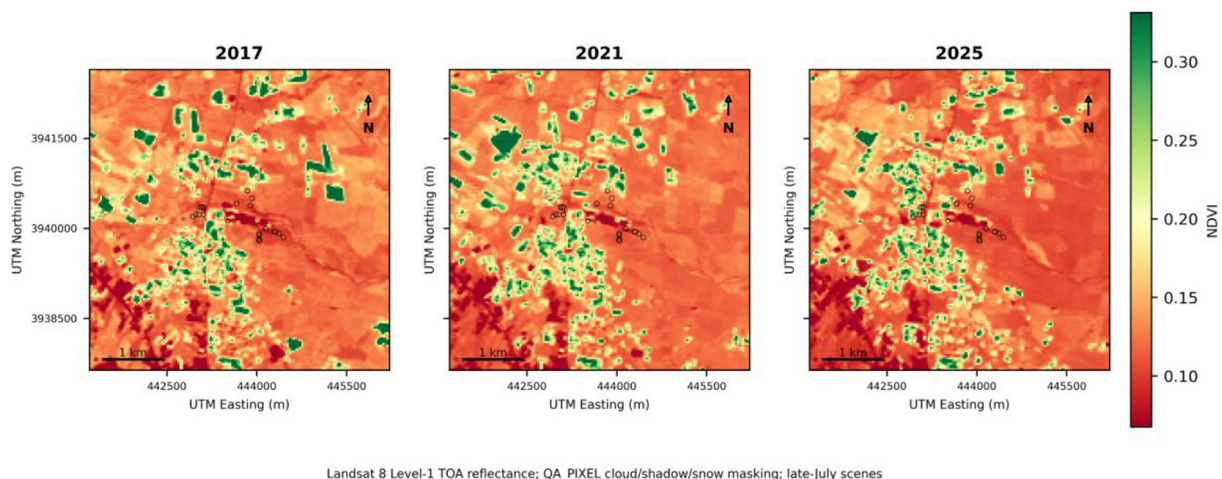
Figure 6. Modeled flow accumulation and major drainage pathways in relation to the archived sampling network

long-term modification of surface conditions, without establishing a chemical cause. The multi-temporal NDVI surfaces are shown in Figure 7, while the long-term NDVI and SAVI changes are shown in Figure 8.

The strongest HCS–remote-sensing relationships involved long-term vegetation-related change. ΔSAVI for 2017–2025 showed $\rho \approx 0.592$ ($p \approx 0.0047$), while ΔNDVI showed $\rho \approx 0.567$ ($p \approx 0.0073$). After Benjamini–Hochberg adjustment, both had $q \approx 0.059$. The relationships were therefore retained as strong exploratory evidence but were not interpreted as causal or independently significant under a strict adjusted 0.05 criterion.

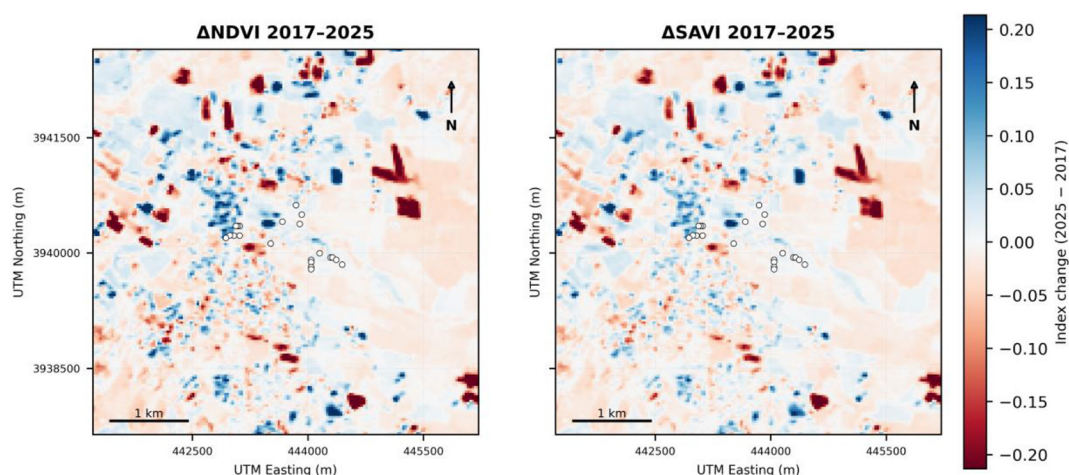
Direct predictive modelling

The refinery-center-distance model produced LOOCV $R^2 = -0.0387$ and RMSE = 0.9768, with an observed-versus-predicted Spearman $\rho = 0.656$ ($p = 0.00125$). The four-predictor integrated environmental model performed more poorly, with LOOCV $R^2 = -0.2391$ and RMSE = 1.0669; its observed-versus-predicted Spearman ρ was 0.190 ($p = 0.410$). Thus, neither model provided defensible out-of-sample prediction of HCS magnitude, and the negative cross-validated R^2 values motivated the shift from concentration forecasting to process-based susceptibility



Landsat 8 Level-1 TOA reflectance; QA_PIXEL cloud/shadow/snow masking; late-July scenes

Figure 7. Multi-temporal NDVI surfaces for 2017, 2021, and 2025 using a common cartographic scale



Positive and negative changes are displayed symmetrically around zero; indices are contextual, not metal concentrations

Figure 8. Long-term surface change between 2017 and 2025 expressed as Δ NDVI and Δ SAVI HCS and remotely sensed change

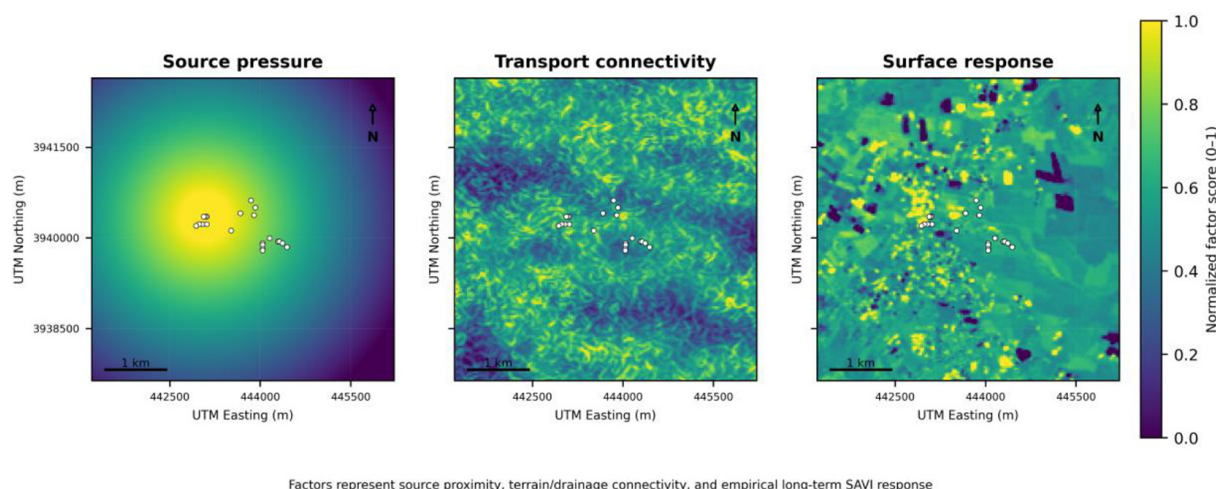
assessment. A complete rerun using the documented four predictors and fold-wise standardization reproduced the archived integrated-model statistics to numerical precision (recalculated $R^2 = -0.2391313728$ and $RMSE = 1.0669011232$), confirming that the reported values and interpretation are unchanged.

PESI and scenario sensitivity

The balanced PESI showed a moderate association with HCS ($\rho \approx 0.486$, $p \approx 0.026$), the connectivity-dominant scenario produced $\rho \approx 0.503$ ($p \approx 0.020$), and the consensus score produced $\rho \approx 0.468$ ($p \approx 0.033$). These associations are reported solely as internal spatial-consistency diagnostics. Because the documented MA–MB–MC waste-valley

sector contributes to the definition of the source-pressure component, the PESI–HCS comparison is not statistically independent and is therefore not interpreted as model validation, independent confirmation, or evidence of predictive capability. The component factor surfaces are presented in Figure 9, and the consensus PESI with scenario sensitivity is shown in Figure 10. Recalculation of the PESI factors using the documented P2–P98 normalization thresholds reproduced the archived consensus raster to numerical precision, so the scenario associations, mapped susceptibility pattern, and priority-area results remain unchanged.

The final monitoring-priority raster contained 9.698 Tier 1 cells and 3.280 Tier 2 cells at 30-m resolution. Tier 1 therefore covered 8.7282 km² (8.746% of the 99.8001 km² analysis grid), while



Factors represent source proximity, terrain/drainage connectivity, and empirical long-term SAVI response

Figure 9. Process-based PESI factor surfaces: source pressure, transport connectivity, and remotely sensed surface response

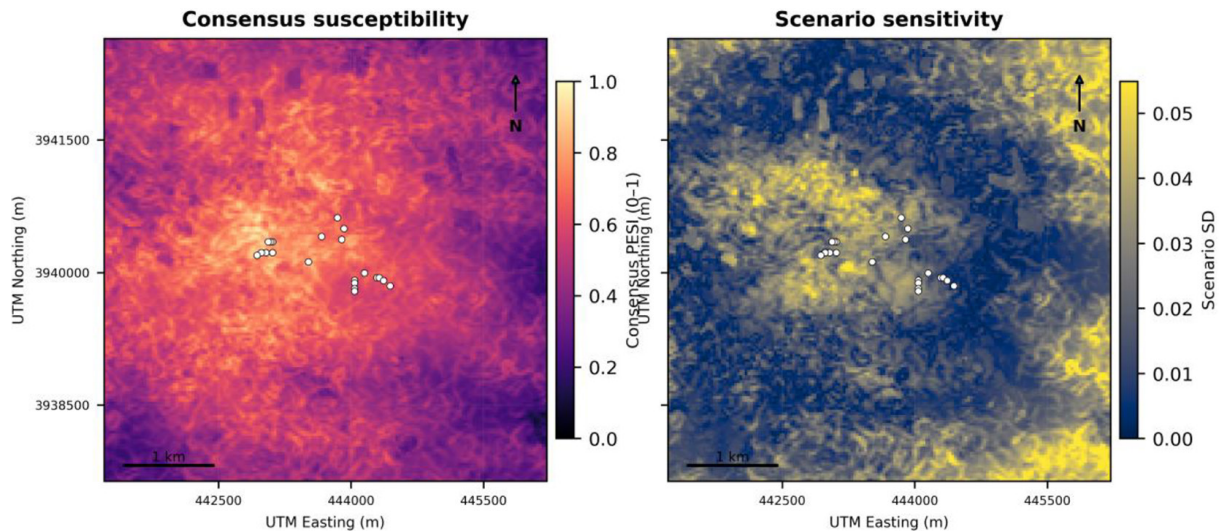


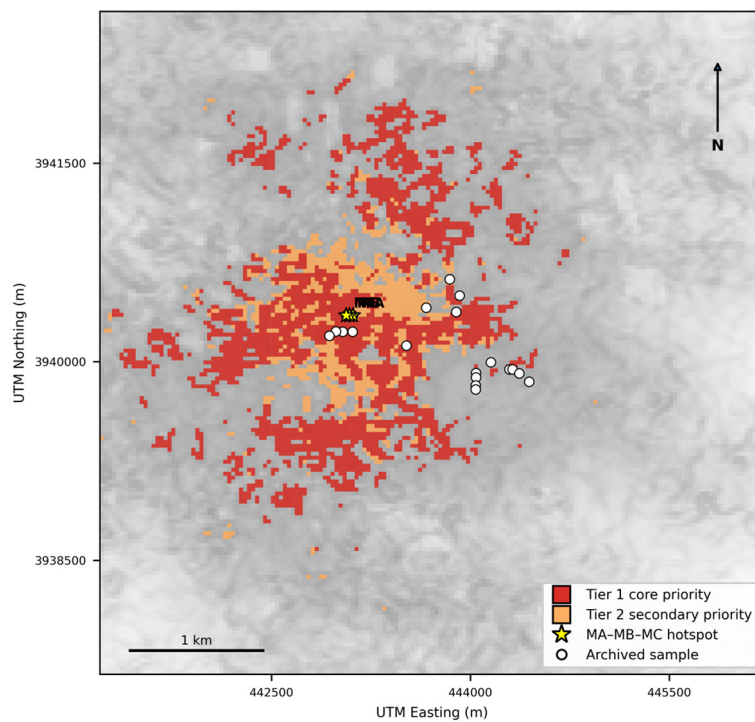
Figure 10. Consensus PESI surface and spatial sensitivity to alternative weighting scenarios
Final monitoring-priority zones

Tier 2 covered 2.9520 km² (2.958%). Together, the two priority classes occupied 11.6802 km² (11.704%). Raster coding used value 2 for Tier 1 core priority and value 1 for Tier 2 secondary priority. MA, MB, and MC were located within the Tier 1 class. These areas are monitoring priorities, not forecasts of future metal concentration or proof of contaminant transport (Figure 11).

DISCUSSION

Localized source structure rather than a simple refinery-distance gradient

The contamination pattern is inconsistent with a simple monotonic decline away from the refinery. The strongest Zn-Cu-Pb signal is



Tier 1 = 8.7282 km² (8.746%); Tier 2 = 2.9520 km² (2.958%); combined = 11.6802 km² (11.704% of 99.8001 km²)

Figure 11. Final susceptibility-based monitoring-priority zones. Tier 1 core priority covers 8.7282 km² (8.746%), Tier 2 secondary priority covers 2.9520 km² (2.958%), and the combined priority area is 11.6802 km² (11.704% of the 99.8001 km² analysis grid)

concentrated in the northwestern waste-valley sector, particularly at MB and MA, whereas other directions show different metal-specific behavior. This favors a localized waste-handling or deposition interpretation over a single radial refinery-distance gradient. Similar studies of industrial sites indicate that production zones, material storage zones, hydrogeological conditions and soil properties can interact to generate sharply differentiated heavy-metal risk zones (Lin et al., 2024). Likewise, site-scale source-sink analysis indicates that historical hotspots may function as secondary or potential sources where runoff connectivity permits redistribution (Wang et al., 2024b). Integrated work around industrial parks has also shown that GIS hotspot patterns become more informative when combined with independent source-apportionment evidence such as PMF and isotopic fingerprinting (Shao et al., 2024). Because such tracers are unavailable for KAT, the present interpretation of the northwestern hotspot is kept at the level of a spatially plausible source association rather than formal source attribution.

Terrain as a redistribution control, not proof of transport

The lower topographic position of the MA–MB–MC sector and its proximity to selected modeled drainage pathways provide a plausible physical setting for secondary redistribution. However, drainage-distance relationships were not statistically stable across extraction thresholds. The results therefore support terrain and surface-flow connectivity as potential transport controls, while direct waste deposition remains the more strongly supported explanation for the hotspot itself.

Meaning of the Landsat signal

The decreasing trend of vegetation indices and increasing trend of NDBI indicate the change in the surface environment during 2017–2025, but these changes cannot be attributed to heavy metals alone, as similar multispectral responses are generated by agricultural management, exposed soil, industrial disturbance, moisture variability and other land cover processes. This cautious interpretation is important because even hyperspectral heavy-metal studies report substantial uncertainty and strong dependence on indirect soil/vegetation relationships (Wang et al., 2024a). The Landsat component is therefore used as

contextual evidence of environmental response, not as a concentration proxy. A recent Iraqi GIS study of heavy metals in soils east and west of the Tigris River in Baghdad likewise demonstrates the growing use of spatial analysis for soil-metal assessment in Iraq (Musa et al., 2025); however, that study used IDW-based spatial assessment and therefore serves as regional context rather than methodological validation of the KAT susceptibility framework.

Why susceptibility is more defensible than concentration forecasting

The negative LOOCV R^2 values provide an important methodological boundary. With 21 observations and a strongly localized hotspot, a precise future concentration surface would convey more certainty than the data support. Reframing the problem as susceptibility preserves the useful spatial information while explicitly separating observed contamination from modeled future potential.

Interpretation and management value of PESI

PESI is best understood as a spatial hypothesis generator and monitoring-priority tool. Its contribution is not a new regulatory contamination index, but a transparent method for combining an observed contamination anchor with process variables that may influence persistence or redistribution. The process-based perspective is a complement to the recently formulated source-pathway-receptor based approaches for long-term industrial risk assessment (Su et al., 2025), and extensive reviews on the combination of GIS, modeling and site characteristics for heavy-metal risk analysis (Wang et al., 2022). The moderate rank agreement between HCS and several PESI scenarios demonstrates internal coherence, while scenario sensitivity mapping reveals where classification depends on weighting assumptions. Because the same dataset informed variable screening and exploratory agreement testing, this should not be presented as external validation. The practical value of the framework is to design a stronger next field campaign: sampling should extend from MA-MB-MC through Tier 1, cross the Tier 1-Tier 2 boundary, and include lower-susceptibility controls. A 30-year source-pathway-receptor assessment of nonferrous-metal industrial sites similarly identified surface runoff as a major

pathway affecting spatiotemporal risk, supporting the inclusion of terrain/connectivity information in industrial-site prioritization while also illustrating that full risk assessment requires receptor information beyond the scope of the present study (Su et al., 2025). From a management perspective, susceptibility mapping should be coupled with practical measures that limit contaminant transfer to water where relevant. Zahorodniuk et al. (2019) demonstrated that modified cellulose-palygorskite filtering materials can combine filtration and sorption functions, including removal of heavy-metal ions from water. Although such treatment technology was not tested at KAT, it illustrates the broader need to link monitoring priorities with appropriate water-protection or remediation measures where field verification identifies an active pathway.

Comparison with recent industrial-site contamination frameworks

The KAT framework can be interpreted by referring to recent studies of industrial sites. Lin et al. (2024) combined receptor modeling and GeoDetector to demonstrate that production areas, material-storage areas, hydrogeological conditions and soil properties together can delineate primary, high-risk and potential heavy-metal pollution areas. Wang et al. (2024b) extended this process logic by explicitly considering source–sink relationships and surface-runoff pathways at site scale, distinguishing direct waste sources from historical pollution hotspots. A related source–sink assessment in a non-ferrous industrial agglomeration also demonstrated strong spatial heterogeneity and the value of multi-source geospatial evidence for linking sources with receiving areas (He et al., 2024). These studies support the process-based structure adopted here, but the KAT analysis is deliberately more conservative: Landsat indices are treated as contextual surface-response evidence, the archived 21-point dataset is not used to claim a remotely sensed

concentration inversion, and susceptibility is reported separately from observed contamination. This distinction is important because the present dataset cannot support the type of high-sample-density source apportionment, hyperspectral inversion, or receptor modeling used in those studies. In addition, GIS-based PCA and PMF work around a smelting site demonstrated that surface runoff and atmospheric deposition may act as distinct transport routes for different metals (Anaman et al., 2022). This is directly relevant to the KAT interpretation: the terrain-derived drainage component represents only one plausible transport mechanism, while the absence of wind-field and deposition data prevents the present study from resolving atmospheric transport. The framework therefore identifies where surface redistribution is plausible without excluding other pathways. This conservative interpretation is also consistent with recent industrial-soil risk assessments that emphasize integrated pollution and risk evidence rather than unsupported extrapolation (Xu et al., 2024).

Strengths, limitations, and scope of inference

Table 4 summarizes the evidence-to-inference boundaries adopted in the study. The principal strength of this study is methodological restraint: archived soil chemistry, terrain-process variables, and multi-temporal Landsat observations were treated as distinct evidence streams and were integrated only at the susceptibility stage. Seasonally matched Landsat 8 scenes, a common projected grid, QA masking, DEM cross-checking, multiple-testing control, predictor-redundancy screening, leave-one-out cross-validation, and alternative PESI weighting scenarios were used to reduce avoidable analytical overinterpretation. Nevertheless, four limitations define the scope of inference. First, the chemical baseline comprises only 21 archived surface-soil samples from a single 2021 campaign reported by Al-Taey (2022). This sample network is spatially informative for exploratory hotspot and susceptibility

Table 4. Evidence-to-inference boundaries used to avoid overinterpretation

Evidence	Supported inference	Not claimed
2021 soil chemistry	Observed spatial metal pattern and HCS hotspot	Future metal concentration
SRTM slope/drainage	Potential surface-flow connectivity	Confirmed contaminant transport
2017–2025 Landsat indices	Land-surface/environmental response	Direct spectral measurement of metals
PESI consensus	Relative susceptibility / monitoring priority	Regulatory risk class
PESI–HCS rank agreement	Exploratory internal coherence	Independent model validation

analysis, but it is insufficient for high-confidence concentration prediction, detailed source apportionment, or fine-scale geostatistical generalization. Second, no independent post-2021 chemical campaign was available for external validation. The observed PESI-HCS rank agreement therefore represents internal exploratory coherence rather than independent model validation; repeat sampling should explicitly test Tier 1, Tier 2, and lower-susceptibility locations. Third, the strongest remote-sensing associations with HCS (including 2017–2025 SAVI and NDVI changes) had nominal *p*-values below 0.01 but Benjamini-Hochberg adjusted *q*-values of approximately 0.059. They are consequently retained only as exploratory temporal evidence and are not interpreted as statistically confirmed spectral signatures of metal contamination. Fourth, PESI does not incorporate receptor exposure, groundwater vulnerability, food-chain transfer, or human-health risk. This omission is intentional: the framework is designed as a spatial susceptibility and monitoring-priority tool, not as a comprehensive source-pathway-receptor or regulatory risk assessment. Accordingly, PESI classes should guide where additional field verification is most valuable, rather than being interpreted as future metal concentrations or health-risk categories. The presence of Pb in the archived soil dataset also has potential human-health significance, but the present study did not measure occupational exposure, blood Pb, biomarkers, or clinical outcomes and therefore cannot estimate human health risk. In an occupational study of lead-exposed workers, Karlova et al. (2017) reported a positive relationship between blood lead and serum homocysteine and discussed hyperhomocysteinemia as a marker relevant to cardiovascular pathology. This evidence supports treating verified Pb exposure as a reason for appropriate exposure assessment, while it should not be interpreted as evidence that workers or residents around KAT experienced the same exposure or health effects.

Recommended independent validation design

A follow-up field campaign should use stratified sampling over Tier 1, Tier 2 and low-susceptibility areas, keeping some of the original 2021 locations for comparison of temporal change. Adaptive or information-based sampling studies at heavy-metal sites show that the best additional

samples are in the vicinity of uncertain pollution boundaries, rather than randomly, or evenly spaced (Man et al., 2023). Validation should evaluate whether the new measurements of Zn–Cu–Pb show ordered differences across the susceptibility classes, whether the MA–MB–MC anomaly persists, and whether the observed change is consistent with the mapped drainage and surface-response gradients. Independent validation should be reported separately from model development, ideally with spatially blocked evaluation where sample density allows.

CONCLUSIONS

The KAT refinery environment is characterized by a localized northwestern Zn–Cu–Pb hotspot rather than a simple refinery-centered contamination gradient. Terrain analysis and multi-temporal Landsat observations provided complementary evidence on the environmental setting of the archived 2021 contamination pattern, while leave-one-out cross-validation showed that direct quantitative forecasting of HCS magnitude was not supported. The analysis was therefore expressed as a redistribution-susceptibility problem. The PESI integrates source pressure, terrain/connectivity, and long-term surface response under three alternative weighting scenarios. The consensus PESI showed moderate internal rank agreement with HCS ($\rho \approx 0.468$, $p \approx 0.033$), interpreted as internal spatial consistency rather than independent validation. The final priority analysis identified 8.7282 km² (8.746%) as Tier 1 core priority and 2.9520 km² (2.958%) as Tier 2 secondary priority, together representing 11.6802 km² (11.704%) of the 99.8001 km² analysis grid; MA–MB–MC occurred within Tier 1. These results establish a spatially explicit susceptibility and monitoring-priority framework in which archived soil chemistry, modeled terrain connectivity, and multi-temporal land-surface response are kept as distinct evidence streams and integrated without treating spectral indices as direct measurements of heavy-metal concentration.

Acknowledgements

The authors acknowledge the archived primary dataset reported by Al-Taey (2022), which provided the 2021 KAT soil-chemistry baseline used in this secondary spatial analysis.

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