Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

AI driven detection of soil nutrient deficiency and technogenic contamination: A Systematic Literature Review with emerging pathways for sustainable land use

JAYA Chakraborty

phdgrad.Jaya.Chakraborty@siu.edu.in

Symbiosis International University

Rajiv Chakraborty

Article

Keywords: Artificial Intelligence, Soil Health Monitoring, Digital Agriculture, Food Security, Machine Learning

Posted Date: November 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11410853/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

AI driven detection of soil nutrient deficiency and technogenic contamination: A Systematic Literature Review with emerging pathways for sustainable land use

1st Jaya Chakraborty (**Corresponding Author**)
Symbiosis Centre of Research & Innovation, Pune, Faculty of Management, Symbiosis International (Deemed University), Pune, India
phdgrad.Jaya.chakraborty@siu.edu.in (ORCID: 0009-0009-7419-5246)

2nd Rajiv Chakraborty (ORCID: 0009-0000-2070-0352)
R&D Product Development Manager, Metso Corporation (Perth) Scopus & Science Direct Affiliation, Vadodara, Gujrat, India
rajiv.chakraborty@metso.com

KEYWORDS: Artificial Intelligence, Soil Health Monitoring, Digital Agriculture, Food Security, Machine Learning

Abstract

Purpose: With millions of hectares of farmland in Vidarbha already affected by erosion, salinity and declining soil nutrition, the region faces a critical, worsening threat - technogenic contamination from electronic waste (e-waste) and other industrial waste adds further complexity. Nagpur is identified as one of India's top 10 e-waste generating cities. Artificial Intelligence (AI) offers a transformative potential to identify and isolate contaminant chemicals while assessing soil nutrition, yet adoption among rural farming communities remains constrained by a persistent digital and knowledge divide. This review systematically examines literature on key soil contaminants, AI-driven detection of hazardous chemicals, and recommended mitigation pathways toward sustainable agricultural land use.

Method: A systematic search across Scopus, Web of Science, IEEE Xplore, arXiv, Elsevier, and Google Scholar used terms spanning remote sensing, technology adoption, e-waste, soil contamination, digital agriculture and socio-cultural barriers. Of 169 records identified, screening against inclusion/ exclusion criteria focused on Indian rural contexts resulted in 124 studies for PRISMA- based thematic synthesis.

Research: Vision-based AI/ML in soil nutrient grading, contamination profiling, remote sensing and soil health advisory does show strong technical promise; however, adoption is severely constrained by traditional resistance, high initial investment, low contamination - risk awareness and gaps in digital literacy. Partnerships through Farmer Producer Organizations, government initiatives and localized voice-interface tools emerged as effective adoption enablers.

Conclusion: The review synthesizes literature-based recommendations and identifies systemic gaps – in policy enforcement, recycling infrastructure, as well as farmer-level digital literacy – that must be addressed to prevent further, compounding land degradation. The evidence points to decentralized, offline-capable AI tools deployed through trusted local intermediaries as the most consistently recommended pathway.

INTRODUCTION

The agricultural landscape of India shows an enormous diversity and is outlined by persistent contradiction. With over 138 million farm holdings and around 86% of them being marginal (Agricultural Census, 2015-16), this rural-driven economy generates around 18% of India's national GDP and gives employment to 40% of the workforce.

Uncontrolled dumping of electronic and industrial waste, with minimal recycling capacity or focus has led to further contamination of agricultural land and groundwater.

Surveys done by the National Bureau of Land and Soil Use Planning provide estimates that around 140 million hectares of land are degrading persistently due to various controlled or uncontrolled factors such as water and wind erosion, salinity, waterlogging, acidity, technogenic contamination and depleting soil nutrition (NBSS & LUP, 2018). Ground-level surveys of Nagpur reveal estimated 13,000 tonnes of solid waste generated each year (2016-2017), 37% of which comprise metals, glass and inert materials [Patil & Khan, 2020]. The application of spectral analytics and machine learning (ML) - including trained neural networks, gradient boosting techniques and self-organizing maps - to satellite-based soil imagery offers immense potential for monitoring localised soil health and contamination. The lack of public awareness and government- driven waste management initiatives, combined with uncontrolled open dumping, inadequate recycling capacity and the outpaced conversion of usable farmland to urban land, calls for immediate attention. This paper tries to address four key research questions as outlined below:

RQ1 – What are the most consistent technogenic chemical

contaminants associated with soil contamination, and their relative severity, as identified in the literature?

RQ2 – Which AI/ML methods identified in the literature have been successfully applied to detect, identify, and rank soil contamination as well as nutrient deficiency?

RQ3 – How effective are AI/ML techniques relative to conventional statistical methods as identified in the literature?

RQ4 – What are the future pathways for course correction applicable to the Vidarbha region, as recommended in the literature?

1.0 METHODOLOGY OF LITERATURE REVIEW

This research paper takes a four-step methodical approach to identify and analyze literature addressing the research themes:

a) Search relevant literature and case studies, published in English, addressing a combination of search terms - remote sensing, technology adoption, e-waste, soil contamination, digital agriculture and socio-cultural barriers
b) Screen literature covering e-waste contaminants and their relative ranking, AI/ML technologies successfully applied to detect, identify and rank soil contamination and nutrient deficiency, and literature recommending future mitigation pathways
c) Extract quantitative and qualitative evidence supporting the four themes and
d) Synthesize findings to reach conclusive recommendations and identify gaps requiring further attention.

This four-step approach follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Protocols 2015 (PRISMA) standard (Moher et al., 2015) using pre-specified criteria for the search, selection, and data extraction. The details are described in the following sections.

1.1 Search Strategy

The articles selected are mostly experimental, documentary, or based on real case studies that have been used for smart soil contamination and health measurement. A combination of search terms included digital agriculture, remote sensing, rural India, technology adoption, e-waste, soil contamination, artificial intelligence, machine learning, and socio-cultural barriers to adoption. Peer- reviewed studies and literature published in English were considered.

Studies identified in non-English, grey and duplicate literature, abstracts- only data, as well as studies with AI applications not related to agriculture or focused to South Asian/Indian farms were excluded.

The literature search was conducted by the lead author in July 2026, covering literature published between 2009 to 2026. The search encompassed records indexed in Web of Science and Scopus alongside major publisher databases (IEEE Xplore, Wiley, Springer, Elsevier), supplemented by arXiv and Google Scholar. The search keywords used were a concatenation of:

'E-waste AND Soil Contamination AND India' + "Technogenic Contamination AND Agricultural Land' + 'Digital Agriculture AND Rural India' + 'AI AND Soil AND India' + 'Technology Adoption AND Smallholder' + 'AI AND ML AND IoT AND NLP for Indian agriculture' + 'AI adoption barriers to Indian agronomy'

1.2 Selection of studies

A total of 169 records were identified and screened by the author, and reviewed by the Industry mentor for compliance with the inclusion criteria: (a) published in English, (b) focuses on use and adoption of AI/ML/IoT/NLP usage in South Asian/India agriculture, (c) uses empirical case studies with quantitative or qualitative primary data to answer RQ's and (d) removing duplicates, grey literature, unconfirmed doi as well as addresses any or all the four research themes. To check and validate for agreement, interrater reliability scores were calculated showing moderate-strong levels of agreement as per criteria (a) [% Agreement = 85, Cohen's Kappa k = 0.63, Z-score = 7.89, p-value < 0.001], moderate agreement (b) [% Agreement = 80, k = 0.56, Z-score = 6.6, p-value < 0.001] (c) [% Agreement = 87, k = 0.67, Z-score = 7.71, p-value < 0.001] and (d) [% Agreement = 85, k = 0.63, Z-score = 7, p-value < 0.001]. Disagreements were amicably discussed and aligned; studies which did not meet the criteria were subsequently removed. Cohen's Kappa calculation file can be shared. Figure 1 outlines the PRISMA flowchart used for study selection. The full list of selected studies, each with an individual numeric identifier and its mapped role in supporting the analysis, can be provided as Supplementary evidential file. Table 7 summarizes representative contaminant hotspot geographic locations identified across the included literature.

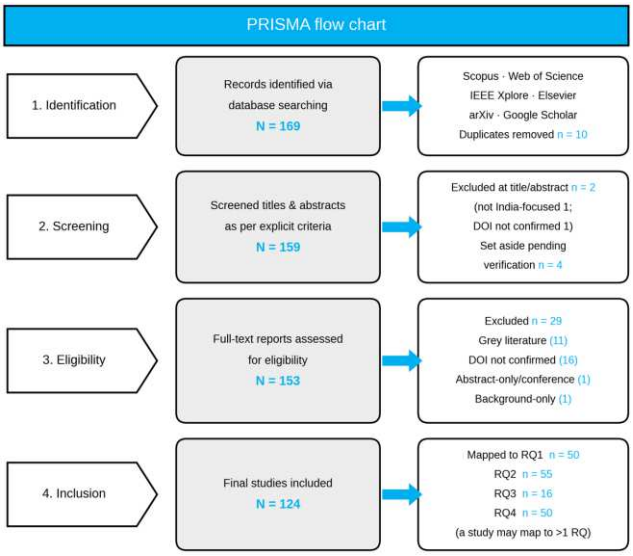


Figure 1*: *PRISMA flow chart for study selection

1.3 Data extraction

All selected articles were screened for publication year, publication journal, author details and citation count. Studies were then individually coded, with their abstracts, aims and data analyzed to group into following categories: (a) authorship, and country of origin (b) coverage of AI/IoT/ML/NLP studies and adoption in context to South Asian/Indian agronomy (c) barriers to AI adoption in context to South Asian/Indian agronomy (d) contaminant types, severity rankings, and AI/ML key performance metrics reported, wherever applicable; and (e) study design, coded as descriptive, experimental or co-relational.

1.4 Data synthesis

Extracted data were synthesized using a framework synthesis approach, structured around the four pre-defined research themes (RQ1-RQ4). Within each theme, findings from included studies were grouped and then compared to identify areas of convergence, divergence, and evidentiary gaps. RQ1 and RQ3 were addressed by synthesizing quantitative findings comprising contaminant severity rankings and AI/ML performance metrics, while RQ2 and RQ4 were addressed by synthesizing qualitative findings on adoption barriers and socio-cultural context. Recommendations and systemic gaps reported in this review were derived by cross-referencing the consistency and coverage of findings across all included studies within each theme, rather than any single isolated study.

2.0 Results

This section collates and presents the findings of the systematic review, structured around the four research questions that guide the study. Of 169 total records identified through database searching, 10 duplicates were removed, yielding 159 records for title/abstract screening, of which 2 were excluded, leaving 157 records eligible for full-text assessment. Of these, 4 records were set aside pending independent verification, leaving 153 articles for full-text assessment. Following full-text assessment, 124 studies met the inclusion criteria and form the evidential base for this synthesis. The included literature drawn predominantly from India, China, Southeast Asia as well as West Africa and European Union spans technogenic contaminant characterization, AI/ML based detection, government led soil health and e-waste management initiatives. Findings are presented as six parts: Study selection, study characteristics, technogenic contaminants and their relative severity, AI/ML detection and ranking methods, AI/ML effectiveness relative to conventional approaches, and recommended future pathways including government-initiative evidence.

2.1 Study Selection

Of 169 records identified through database searching across Scopus, Web of Science, arXiv, Elsevier, IEEE Xplore and Google Scholar, 10 duplicates were removed, resulting in 159 records for further title/abstract screening. 2 records were excluded at this stage (not India-focused (1); no confirmed DOI (1)), leaving 157 records. Of these, 4 records were set aside pending independent verification, leaving 153 full-text articles assessed for eligibility, of which 29 were excluded due to: grey literature (11), no confirmed DOI (16), abstract- only/conference (1), and background-only (1). This yielded a final pack of 124 studies included in the quantitative and qualitative synthesis (SLR extraction tool can be shared).

2.2 Study Characteristics

The 124 included studies span years 2009-2026, with an increase in count over the recent years: 40 % studies (50) were published in 2024-2026 alone, and 63 % (78) since 2021 – which shows consistency with AI/ML- based soil health and contamination research being a fast-accelerating domain rather than a mature, stable one, as shown in Table 1 below:

Publication Period	n	%
≤ 2015	8	6%
2016–2020	16	13%
2021–2023	28	23%
2024–2026	50	40%

Publication Period	n	%
Year not specified	22	18%

Table 1: Referenced publications timeline

Most of the evidential base as shown in Table 2, geographically is dominated by India (45 %, 56 studies) and China (14 %, 17 studies), with the balance distributed across Bangladesh, Ghana, Nigeria, Thailand, Vietnam while single-study representations are available from Indonesia, Sierra Leone, South Africa, Spain and the USA, plus global/multi-country reviews account for 11 more. Of the 56 India- based studies, only 7 % of the total corpus (9) are specific to Vidarbha, Nagpur or Akola – the regional focus of this review. This concentration gap of studies done in these regions is a key evidentiary basis for the novelty argument developed in Section 3.2.

Country / Region	n	%
India (total)	56	45%
— of which Vidarbha/Nagpur/Akola-specific	9	7%
China	17	14%
Not specified	18	15%
Global / multi-country (review)	11	9%
Nigeria	4	3%
Ghana	3	2%
Thailand, Vietnam, Bangladesh (2 each)	6	5%
South Africa, Sierra Leone, Indonesia, USA, Spain, and other single-country entries	9	7%

Table 2: Regional diversity of publications

By data type as Table 3 outlines, 53 % (66) studies report quantitative data, 46 % (57) are qualitative (mostly policy analyses and reviews), and 1 report mixed method. This data is further mapped against the four research questions - noting that studies frequently address more than one – 50 studies contribute to RQ1 (contaminant severity), 55 to RQ2 (AI/ML detection methods), 16 to RQ3 (comparative AI/ML effectiveness), and 50 to RQ4 (future pathways) respectively. The comparatively limited body of literature on RQ3 do reveal that benchmarking of AI/ML against conventional statistical methods is in a nascent stage.

Research Question	Studies mapped
RQ1 — Contaminants and severity	50
RQ2 — AI/ML detection methods	55
RQ3 — AI/ML effectiveness vs. conventional methods	16
RQ4 — Future pathways (incl. government initiatives)	50

Table 3: RQ based publication mapping

2.3 RQ1- Technogenic Contaminants and Severity Ranking

Across the 43 studies mapped to RQ1 in the extraction dataset, eight distinct heavy metals were consistently flagged out. Frequency of reporting and available severity evidence (food-safety exceedance, concentration extremes, and outcomes of human biomonitoring) were jointly used to derive the ranking table 4 below, since sole raw frequency data does not capture toxicological severity.

Chemical	Studies (of 43)	Study IDs
Cadmium (Cd)	11	S001, S003, S021, S028, S029, S030, S032, S033, S056/S057, S058, S059
Lead (Pb)	10	S001, S003, S021, S028, S029, S030, S032, S033, S056/S057, S058
Copper (Cu)	7	S003, S021, S029, S032, S033, S058, S059
Chromium (Cr)	4	S001, S021, S028, S032
Zinc (Zn)	4	S021, S033, S056/S057, S059
Arsenic (As)	2	S001, S029
Mercury (Hg)	2	S001, S029
Nickel (Ni)	2	S021, S029

Table 4: Contaminant and severity ranking

The top 5 contaminants ranked by severity in Table 5 are:

Rank	Chemical	Severity Basis
1	Cadmium (Cd)	Most-reported (11/43); primary bioavailable contaminant in Nagpur/Vidarbha dataset; food-safety exceedance in vegetables
2	Lead (Pb)	Second most-reported (10/43); only

Rank	Chemical	Severity Basis
		metal with direct pediatric health-outcome evidence (blood-Pb / thyroid hormone correlation)
3	Copper (Cu)	7/43 studies; co-occurs with Cd/Pb at extreme concentrations (up to 11,140 mg/kg); food-safety exceedance
4	Chromium (Cr)	4/43 studies but cross-regional (China, India independently); Cr (VI) carcinogenic risk
5	Zinc (Zn)	4/43 studies; primary industrial contaminant in strongest Vidarbha-specific evidence; food-safety exceedance

Table 5: Top 5 contaminants

Cadmium (Cd) and lead (Pb) were the two most consistently flagged and reported contaminants (11 and 10 out of 43 studies respectively), and each carries direct severity evidence beyond mere soil presence: CSIR- NEERI dataset (S057) identifies Cd as the primary bioavailable industrial contaminant in Nagpur/ Vidarbha and exceeded food- safety thresholds in vegetable-uptake studies (S059), while Pb was the linked to direct pediatric health outcomes- elevated blood-lead levels correlated with thyroid hormone alteration in 162 children in Guiyu, China (S030), reinforced by a body-burden review (S031). Zinc (Zn), reported in 4 studies, was notably one of the primary technogenic contaminants identified in the strongest Vidarbha- specific evidence (S057) and appeared in the vegetable food- safety exceedance data (S059), making it significant for the region despite lower global reporting frequency in this corpus.
Copper (Cu), while less frequently isolated as a standalone focus, co-occurred with Cd and Pb at extreme concentrations (up to 11,140 mg/kg at incineration sites, S033) and in the same food-safety exceedance study (S059). Chromium (Cr) appeared in only 4 of 43 studies but showed a consistent cross-regional signature (India and China independently) while its hexavalent form identified as a carcinogenic risk – a severity factor not captured by frequency alone.
Interestingly Arsenic (As) and Mercury (Hg), carry higher per-unit toxicological severity than the metals ranked above them and as such only 2 of 43 studies reported them, reflecting consistency of reporting across the included literature instead of an independent toxicological hazard assessment.

2.3.1 Soil impact mechanisms

Three mechanisms extracted from literature on how each contaminant affects the soil beyond mere concentration are: soil bioavailability, direct transfer to crops, and human exposure through cross- media. Table 6 below summarizes the findings:

Contaminant	Documented Soil Impact Mechanism	Evidence
Cadmium (Cd)	Highly bioavailable/mobile soil fraction (directly plant- and organism-accessible); direct soil-to-crop transfer at extreme concentrations (up to 11,140 mg/kg); measurable uptake into maize, tomato, cabbage	S056/S057, S033, S058, S059
Lead (Pb)	Persists in soil/sediment across seasons; cross-media transfer from soil into human blood via dust/soil-contact exposure, with downstream physiological effects	S028, S029, S030, S031
Copper (Cu)	Co-occurs with Cd/Pb at extreme concentrations near incineration/dismantling sites; transfers into vegetable tissue exceeding food-safety thresholds	S033, S058, S059
Chromium (Cr)	Consistently detected across independent processing stages (acid-leaching, dismantling, burning, abandoned sites) and across seasons — persistence is the dominant documented mechanism; no bioavailability/transfer data reported	S001, S003, S021, S028, S032
Zinc (Zn)	Primary bioavailable industrial/anthropogenic contaminant in soil (same mobile-fraction pathway as Cd); transfers into vegetables exceeding food-safety standards	S056/S057, S021, S033, S059

Table 6: Soil contamination impact

2.3.2 Geographic contaminant distribution evidence

There are two clusters identified by the primary evidence base for the top 5 contaminants: Northern/Central India (Moradabad and Nagpur/ Vidarbha) which is this review's regional focus and e-waste processing corridor of South China (Qingyuan, Guiyu and adjacent incineration sites). Tabulated in Table 7, this reflects the broader corpus-wide distribution of the countries as mentioned in Section 2.2, but with a sharpened geographical concentration

focused on these two countries obviously booming economic stature.

Location	Coordinates	Contaminants	Evidence
Moradabad, India	28.84°N, 78.77°E	Pb, Cd, Cr, Zn, Ni, Cu, Fe	S021
Nagpur, India (Vidarbha)	21.15°N, 79.09°E	Cd, Pb, Co, Zn	Nagpur, India (Vidarbha)
South China (incineration sites)	~23.1°N, 113.3°E	Cd, Cu, Pb, Zn	S033, S058, S059
Qingyuan, China	23.68°N, 113.06°E	Cd, Cu, Pb, Sb	S003
Guiyu, China	23.32°N, 116.35°E	Cd, Pb, Cu, Cr, As, Hg	S028, S029, S030, S031, S032

Table 7: Location versus contaminant mapping

2.4 RQ2- AI/ML Methods for Detection and Ranking

44 % (55 of 124) of the included studies apply AI/ML techniques or methods for the detection of soil contaminant as well as nutrient- deficiency. Table 8 summarizes these methods by grouping them into six methodological categories.

Method Cluster	n	Representative Techniques	Study IDs
Source apportionment (PMF/SOM/RF hybrids)	5	SOM + PMF + gradient boosting; RF + PMF + Monte Carlo; ML + receptor models	S006–S010
XRF-spectral quantification	7	Deep learning (DSPFormer), hierarchical DNN, PSO-CARS+BLS-Net, RF, LR/MARS	S043–S049
Remote sensing / hyperspectral nutrient & soil-health prediction	9	RF, SVM, ANN, DNN, quantile regression forest, XGBoost ensembles	S064–S068, S131, S136, S137, S150
IoT-integrated precision agriculture	9	Edge computing, reinforcement/transfer learning, graph-CRNN, IoT + UAV	S070–S072, S096–S098, S100, S101, S122
LLM/ NLP	9	Multilingual chatbots, farmer-advisory delivery (India-specific)	RAG + LLaMA, ASR benchmarking, multi-agent LLM	S102–S109, S127
Broad AI/ML/DL remediation & waste-management reviews	7	AI/ML/DL frameworks, geospatial/IoT integration, omics-AI	S011, S013–S016, S143, S148

Table 8: AI/ML detection methods

The XRF- spectral quantification category evidences the strongest quantitative performance: a Random Forest classifier reached 99.62 % accuracy for soil- type classification (S048), and a deep-learning spectral network (DSPFormer) achieved $R^2 = 0.95 – 0.97$ spanning five heavy metals (S043), though the unusually high value by Random Forest may warrant further scrutiny on the validation method utilized. In the nutrient/ remote- sensing category, a quantile regression forest applied to India's government Soil Health Card (SHC) data captured 28 – 65 % of nutrient zone variability (concordance 0.48 – 0.75, S131), while an XGBoost/ Random Forest ensemble classified soil health status with 85- 87 % accuracy depending on the type of soil (S136) – both directly co-relate to RQ2's nutrient-deficiency and detection scope, not just contamination.

A unique and most recent sub- category (9 studies across 2025-2026, pan India- focused) applies natural language processing (NLP) and large language models (LLM) to farmer- facing advisory delivery – multilingual voice-based chatbots, retrieval- augmented generation, and speech- recognition benchmarking across Hindi/Odia/Telugu (S102-S109, S127). Although these do not directly perform nutrient or contaminant detection themselves but represent the delivery layer through which the detected outputs, alarms and suggestions reach end users; the key unique aspect is their offline or low- connectivity operation which is directly relevant to the adoption- barrier evidence in Section 2.6.

2.5 RQ3- AI/ML Effectiveness vs. Conventional Statistical Methods

13% of the studies (16) report sufficient methodological or performance details elaborating comparative effectiveness of AI/ML techniques. These substantially overlap with XRF- spectral clusters and RQ2 source-apportionment evidenced by methodological specificity which forms the key basis for comparative assessment, outlined in Table 9.

Study ID	AI/ML Technique	Measure of reported Performance
S043	Deep learning (DSPFormer) + XRF	R^2 = 0.95–0.97 across 5 metals
S045	PSO-CARS + BLS-Net (Bayesian-optimized SVR)	Cr, Cd, Cu, Pb quantified
S046	Linear Regression, MARS	8 heavy metals via portable XRF
S047	Hierarchical deep neural network	59 soil samples, IAWEWT-GC preprocessing
S048	Random Forest	99.62% soil-type classification accuracy

Table 9: AI/ML performance mapping

Of the 16 RQ3- mapped studies, 5 report a concrete, detailed and quotable performance metric (S043, S045, S046, S047, S048); the remaining 11 define a statistical/ML hybrid method (for example, PMF in combination with gradient boosting or Random Forest) with no details about comparative performance. None of the other studies included explicitly present a head-to-head benchmark of an AI/ML technique against proven statistical methods (e.g. simple correlation analysis or PCA) applied to the same dataset. This is the clearest methodological gap in the overall study corpus relative to this review's own RQ3 and is elaborated further in section 3.4.

2.6 RQ4- Recommended Future Pathways

40% (50) of the total corpus contain explicit recommendations, barriers, or future -pathway statements. The four recurring clusters or themes abbreviated as TRAM are summarized and mapped with representative evidence in Table 10:

Cluster	n	Representative Evidence	Study IDs
Trust/ Adoption barriers	~15	Trust and language flagged as most critical (18-barrier study); COVID-19 ISM/MICMAC/SWARA analysis; 33-barrier UAV-specific taxonomy	S110, S112, S114, S125
Regulatory/ Government pathways	7	EPR proposed for India e-waste; MPCB regulatory framework; USDA/NIFA American AI Initiative funding; EU-aligned political-initiative call	S057, S143, S150, S155, S158
Adoption enabler for Localized/ offline AI	9	Multilingual, offline-capable advisory tools directly responding to trust/language barriers identified above	S102–S109
Methodological/ Technical pathways	3	AI-driven omics for phytoremediation; abandoned farmland as closest precedent for e-waste/farmland study design	S060, S148

Table 10: Recommended TRAM pathway

2.6.1 Trust/ adoption barriers:

The most granular evidence of barrier is defined by Tzachor's participatory- workshop study identifying 18 explicit AI- adoption barriers, which flagged trust and language as the most critical (S110) – a finding echoed structurally by the 9- study LLM/NLP advisory cluster in Section 2.4, nearly all of which are explicitly multi-lingual. Further taxonomies highlighting barriers include a 543- farmer MICMAC/ ISM/ SWARA analysis during COVID- 19 (S112), an m- TISM/ Delphi study of 9 implementation barriers (S114), and a 33- barrier, 6- category AHP/ Fuzzy Delphi analysis specific to adoption of UAV (S125).

2.6.2 Regulatory/ government enabled pathways:

Several studies point to not purely technical but policy- level solutions. The literature on India's e-waste converges on Extended Producer Responsibility (EPR) as a proposed structural fix given "weak enforcement; insufficient infrastructure" (S057), corroborated by Maharashtra Pollution Control Board's (MPCB) own regulatory framework (S155) and a national e-waste review citing a persistent informal recycling and limited treatment infrastructure (S158).

2.6.3 Adoption enabler for localized/ offline AI:

Internationally, the USDA/ NIFA S1090 program documents direct US federal investment in AI- driven agroecosystem monitoring under the American AI initiative (S143), while a Spanish mining-remediation case study explicitly advocates aligning AI/ GIS digital solutions to political initiatives, co- developed with stakeholders (S150) – both offering a government- initiative- as- pathway model with no current equivalent specific to Vidarbha.

2.6.4 Methodological/ Technical pathways:

AI- driven omics for optimizing phytoremediation via plant-microbe interaction prediction is proposed as a next- generation remediation approach (S148) and abandoned- farmland contamination is flagged as the closest existing precedent for a

dedicated e- waste/ farmland study design (S060) – directly informing the primary- research proposal in Section 5.1.

2.6.4 Study gap specific to Vidarbha:

Only 6% (3 of the 50 RQ4- mapped) studies are Vidarbha/ Nagpur – specific (S055, S057, S155), and none of the studies combine a government- initiative pathway with primary contaminant or nutrient data for the region- the central evidentiary gap this review is positioned to address.

3.0 Discussion

The focus of this section is to interpret the findings reported in Section 2- what they collectively mean, how they compare with prior work, and where exactly the evidential base falls short.

3.1 Synthesis of Key Findings

Read collectively, Sections 2.3 – 2.6 point to a consistent pattern: technical capability of AI/ ML outpaces both real- world deployment rigorous validation. The XRF- spectral and remote-sensing clusters (Section 2.4) report strong quantitative performance (R2 = 0.95 – 0.97, up to 99.62 % classification accuracy), yet only 13 % (16 of 124) studies engage with comparative effectiveness in the first place and none directly benchmark an AI/ ML method against a conventional statistical baseline on the same dataset (Section 2.5). Comparatively contaminant characterization (Section 2.3) is quite mature – 43 studies converge on a consistent five- metal severity profile (Cd, Cr, Cu, Pb, Zn) – but this maturity is geographically narrow, with concentration almost entirely in two countries (Section 2.2), and rarely paired with the AI/ ML methods documented in the same corpus. Meanwhile, the largest single theme by study count is ironically non- technical: regulatory/ government pathways and adoption barriers (Section 2.6, 50 studies) consistently flag language, trust, financial, and infrastructural constraints- not technical performance- as the binding constraint on real- world impact. Taken together, the corpus describes three largely separate conversations – contamination and contaminant study, AI/ ML techniques, and adoption/ policy – that rarely interact within a single study and never intersect specific to Vidarbha region.

3.2 The Vidarbha/Nagpur Case

Around 7 % (9 out of 124) of included studies are specific to Vidarbha, Nagpur, or Akola, and three of these directly tied to the case developed here. A field survey of around 380 scrap shops in Nagpur found at least 59 % of them engaged in informal e- waste dismantling to extract metals, alongside low public awareness of e-waste handling rules (S055). Independently, a CSIR- NEERI dataset identified cobalt, cadmium, zinc, and lead in the bioavailable soil fraction across Nagpur, highlighting industrial and technogenic activity – not yet linked explicitly to e- waste – identified as the primary source (S057). There is a regulatory framework dictated by Maharashtra Pollution Control Board (S155), yet a national e- waste review citing Nagpur as among India's top e- waste generating cities simultaneously highlights a persistently informal recycling sector and limited treatment infrastructure (S158) – indicating that the mere presence of regulation with no translation to enforcement does correlate with a consistent pattern with the government/ regulatory- pathway findings in Section 2.6.

This pattern – informal and unaudited dismantling activity, independently measured soil contamination, and a regulation-enforcement gap- mirrors the structure of better- studied e- waste hotspots in this corpus, particularly Guiyu, China (S028-S032) and the Agbogbloshie site in Ghana (S017-S019), both of which received substantially more dedicated research attention despite comparable or smaller informal-sector scale. This is largely attributed to the visible health impact on the population, identified as the aftermath of this toxicity. What this review is positioned to supply, and what Vidarbha lacks, is the connective evidence those sites already have: no study in this corpus utilized Nagpur's known informal dismantling clusters for direct soil sampling and measurement, and none tested whether the contamination leeches into adjacent agricultural land- despite Vidarbha being a major agricultural belt even though three studies done elsewhere in the corpus (S033, S058, S060) do reiterate that this exact farmland-transfer pathway is measurable where it has been studied.

3.3 Comparison with Prior Reviews

This review's closest a priori is a systematic review of e- waste-derived heavy metal contamination spanning 59 studies across 11 countries (S001), which established the same core contaminant set (As, Cd, Cr, Hg, Pb) this review independently converges on but predates the AI/ ML source- apportionment literature synthesized here and does not engage with detection methodology at all. Conversely, the AI/ML source-apportionment literature in this corpus (S006-S010) is methodologically sophisticated but was developed for general soil heavy-metal contamination- industrial, mining, agricultural- derived – and has not, in any study identified

here, been applied specifically to e-waste-derived contamination as a distinct source signature. This review's contribution is a deliberate amalgamation to present that neither prior body of work attempts: technogenic (e-waste and industrial) contaminant characterization, AI/ML detection methodology application, nutrient-deficiency detection, and government-initiated adoption pathways, synthesized together and grounded in a specific, evidenced regional case.

3.4 Limitations

The findings reported above are qualified by several limitations:

a) Geographic concentration: 59 % (73 of 124) of the included studies originate from just two countries (India, 56; China, 17), per Section 2.2; the resulting evidence base for contaminant severity (Section 2.3) and adoption barriers (Section 2.6) may not be used to generalize to e-waste-affected regions outside these two national contexts.

b) Sparsity of effectiveness benchmarking: Only 5 of 16 RQ3- mapped studies, as outlined in Section 2.5, report a quotable performance metric, and none directly compare AI/ML against a conventional statistical method on the same dataset - meaning the methodological question at the heart of RQ3 is answered only indirectly, through juxtaposition instead of any head-to-head evidence.

c) Incomplete study-design classification: study-design (descriptive/ correlational/ experimental) was explicitly stated only for 4 out of 124 included studies, limiting this review's ability to characterize the evidence base by a thorough methodological rigor.

d) Inconsistency in contaminant panels: The included studies report a range of 1 and 13 measured elements with no standardized panel, limiting direct cross-study comparability of severity rankings (Section 2.3) beyond the frequency-based approach used here.

e) Search currency: The search was conducted in July/2026; accordingly, any records published after this date, including any 2026 literature beyond the search cut-off are not captured in this synthesis.

4.0 Conclusion

This review set out to address a key gap at the intersection of three literatures that rarely seem to converge: technogenic soil contamination, AI/ML- based detection, and government backed adoption pathways, specifically as they apply to Vidarbha. Synthesizing 124 studies, it finds a consistent five-contaminant severity profile (cadmium, lead, copper, chromium, zinc; RQ1), a technically competent but under-benchmarked AI/ML detection landscape spanning source-apportionment, XRF-spectral quantification, remote sensing, and – notably – a fast-emerging cluster of multilingual, offline-capable advisory tools (RQ2-RQ3), and an adoption-barrier literature that converges overwhelmingly on trust, language, and infrastructure instead of a technical performance constraint (RQ4).

For Vidarbha specifically, the evidence establishes that the preconditions for contamination are already documented – informal e-waste dismantling activities, independently measured bioavailable soil contamination, and a regulation-enforcement gap - but connective, site-specific evidential link, and its extension into the region's agricultural land, does not yet exist. The most consistently supported pathway forward as collated from the reviewed literature suggest a combination of technologies: AI/ML detection methods coupled with government-backed institutional mechanisms (Extended Producer Responsibility, regulatory enforcement capacity) and delivered through a TRAM model – Trust building, Regulatory enforced, Adoption enablers for localized, offline AI usage and Methodologically driven pathways for AI/ML techniques. This same combination recurs, in different national contexts, across the government-initiative and adoption-barrier evidence synthesized in Section 2.6. Realizing this pathway for Vidarbha requires the primary research proposed in Section 5.1.

5.0 Future Research Directions

The following sections translate the identified gaps outlined in Sections 3.2-3.4 into a concrete research agenda.

5.1 Proposed Primary Research: Vidarbha/ Nagpur Sampling Study

This review proposes a two-part primary study directly informed by the evidential gaps identified above. First, soil sampling at and immediately around Nagpur's documented informal e-waste dismantling clusters (as per the scrap-shop distribution identified in S055), analyzed for the five-contaminant panel established in Section 2.3 (Cd, Cr, Cu, Pb, Zn) using an AI/ML detection method drawn from Section 2.4 - either the PMF/source-apportionment hybrid approach (S006-S010) to identify contribution from e-waste

dismantling specifically versus other industrial sources, or the XRF-spectral deep-learning approach (S043) given its strongest reported performance (R2 = 0.95- 0.97) in the corpus. Second, a comparative sampling arm on adjacent agricultural land, modeled methodologically on the crop-uptake and abandoned-farmland studies identified in Sections 2.3.1 and 3.2 (S033, S058, S060), to test whether the farmland-transfer pathway measured elsewhere is present in Vidarbha too. Together, these would supply the site-specific evidence that this review's synthesis highlights to be absent.

5.2 Framework/ Policy Recommendations

Three recommendations follow directly from the government initiative and adoption-barrier evidence pointed out in Section 2.6. First, strengthening enforcement capacity behind Maharashtra's existing regulatory framework (S155) rather than introducing new regulation, since the documented gap is enforcement, not the absence of policy (S158). Second, evaluating Extended Producer Responsibility (EPR) as a structural mechanism for the Vidarbha e-waste stream, consistent with its use as the proposed national-level solution in the broader India e-waste literature (S057). Third, prioritizing offline-enabled, multilingual advisory delivery - the design pattern common to the nine-study NLP/LLM cluster in Section 2.4 - as the technology layer most directly responsive to the trust-and-language barriers identified as most critical in the adoption literature (S110).

5.3 Broader Research Agenda

Beyond Vidarbha, two extensions follow from this review's scope. First, the same evidence gap - informal e-waste activity documented separately from soil contamination data, with no linking study – likely exists at other Indian e-waste generating clusters named in the national literature (S059) beyond Nagpur, and the sampling design proposed in Section 5.1 could be replicated across these sites. Second, the AI/ML detection framework developed through this line of research need not remain e-waste specific: the same source-apportionment and XRF-spectral methods reviewed in Section 2.4 are, in principle, transferable to other technogenic contamination sources – industrial effluent, mining waste - that this review's broader "technogenic contamination" framing was deliberately chosen to encapsulate.

DECLARATIONS

1st Author contribution	Writing – original draft, verification, publish manuscript (Corresponding author for all communications)
2nd Author contribution	Review of draft, technical inputs
Informed consent	The literature review was conducted based on available literatures from arXiv, IEEE, Scopus and other renowned literature databases. There were no human participants involved in the development.
Data Availability	The data used and presented in this review is available from various literature libraries
Conflict of interest	The author declares no conflicts of interest
Funding	No funding was available or used for this review

REFERENCES

[1] M. G. K. Houessionon, E.-M. D. Ouendo, C. Bouland, S. A. Takyi, N. M. Kedote, B. Fayomi, J. N. Fobil, and N. Basu, "Environmental heavy metal contamination from electronic waste (e-waste) recycling activities worldwide: A systematic review from 2005 to 2017," *Int. J. Environ. Res. Public Health*, vol. 18, no. 7, Art. no. 3517, Mar. 2021, doi: 10.3390/ijerph18073517.

[2] J. H. Li, H. B. Duan, and P. X. Shi, "Heavy metal contamination of surface soil in electronic waste dismantling area: Site investigation and source-apportionment analysis," *Waste Manag. Res.*, vol. 29, no. 7, pp. 727–738, 2011, doi: 10.1177/0734242X10397580.

[3] Y. Han, Z. Tang, J. Sun, X. Xing, M. Zhang, and J. Cheng, "Heavy metals in soil contaminated through e-waste processing activities in a recycling area: Implications for risk management," *Process Saf. Environ. Prot.*, vol. 125, pp. 189–196, May 2019, doi: 10.1016/j.psep.2019.03.020.

[4] J. T. Adu and F. I. Aneke, "Evaluation of heavy metal contamination in landfills from e-waste disposal and its potential as a pollution source for surface water bodies," *Results Eng.*, vol. 25, Art. no. 104431, Mar. 2025, doi: 10.1016/j.rineng.2025.104431.

[5] L. K. Bhardwaj, P. Rath, H. Jain, and M. Choudhury, "Exploring the effects of e-waste on soil, water quality and human health," *Discov. Civ. Eng.*, vol. 2, Art. no. 12, 2025, doi: 10.1007/s44290-025-00167-2.

[6] J. Zheng, P. Wang, H. Shi, C. Zhuang, Y. Deng, X. Yang, F. Huang, and R. Xiao, "Quantitative source apportionment and driver identification of soil heavy metals using advanced

machine learning techniques," *Sci. Total Environ.*, vol. 873, Art. no. 162371, May 2023, doi: 10.1016/j.scitotenv.2023.162371.

[7] J. Li, X. Li, X.-S. Tai, X.-Y. Tuo, F.-Y. Zhou, Y.-J. Rong, and F. Zang, "Machine learning-assisted source identification and probabilistic ecological-health risk assessment of heavy metal(loid)s in urban park soils," *Sci. Rep.*, vol. 15, Art. no. 17451, May 2025, doi: 10.1038/s41598-025-02307-1.

[8] Z. Bi, J. Sun, Y. Xie, Y. Gu, H. Zhang, B. Zheng, R. Ou, G. Liu, L. Li, X. Peng, X. Gao, and N. Wei, "Machine learning-driven source identification and ecological risk prediction of heavy metal pollution in cultivated soils," *J. Hazard. Mater.*, vol. 476, Art. no. 135109, Sep. 2024, doi: 10.1016/j.jhazmat.2024.135109.

[9] H. Zhang, A. Yin, X. Yang, M. Fan, S. Shao, J. Wu, P. Wu, M. Zhang, and C. Gao, "Use of machine-learning and receptor models for prediction and source apportionment of heavy metals in coastal reclaimed soils," *Ecol. Indic.*, vol. 122, Art. no. 107233, Mar. 2021, doi: 10.1016/j.ecolind.2020.107233.

[10] Y. Li, Y. Yu, S. Ding, W. Dai, R. Shi, G. Cui, and X. Li, "Application of machine learning in soil heavy metals pollution assessment in the southeastern Tibetan plateau," *Sci. Rep.*, vol. 15, Art. no. 13579, Apr. 2025, doi: 10.1038/s41598-025-97006-2.

[11] J. K. Janga, K. R. Reddy, and K. V. N. S. Raviteja, "Integrating artificial intelligence, machine learning, and deep learning approaches into remediation of contaminated sites: A review," *Chemosphere*, 2023.

[12] Y. Zhang, H. Chen, Y. Cao, X. Liang, H. Ji, K. Lin, and Y. Yang, "An interpretable machine learning framework for optimizing chemical oxidative remediation of organic pollutants in soils," *J. Environ. Chem. Eng.*, vol. 13, no. 5, Art. no. 118564, Oct. 2025, doi: 10.1016/j.jece.2025.118564.

[13] R. K. Mishra, R. Agarwal, and D. Mishra, "Integrated AI-driven assessment and sustainable remediation of contaminated soils: Innovations, challenges and future directions,". In: *Contaminated Soils – Remediation Technologies for Sustainable Environment*, S. Sarvajayakesavalu, M. A. Subbiah, and R. Khattak, Eds. IntechOpen, 2026, doi: 10.5772/intechopen.1015754.

[14] K. V. N. S. Raviteja and K. R. Reddy, "Application of artificial intelligence, machine learning, and deep learning in contaminated site remediation,". In: *Recent Developments in Energy and Environmental Engineering*, R. Al Khaddar, S. K. Singh, N. D. Kaushika, R. K. Tomar, and S. K. Jain, Eds. Singapore: Springer Nature, 2023, pp. 411–425, doi: 10.1007/978-981-99-1388-6_32.

[15] B. Fang, J. Yu, Z. Chen, A. I. Osman, M. Farghali, I. Ihara, E. H. Hamza, D. W. Rooney, and P. S. Yap, "Artificial intelligence for waste management in smart cities: A review," *Environ. Chem. Lett.*, vol. 21, no. 4, pp. 1959–1989, 2023, doi: 10.1007/s10311-023-01604-3.

[16] K. R. Reddy, J. K. Janga, and B. Nagaraja, "Artificial intelligence (machine learning) for predicting electrokinetic remediation performance: Initial study and challenges,". In: *Environmental Geotechnics and Pollution Control*, E. Koda, M. D. Vaverková, K. R. Reddy, and A. K. Agnihotri, Eds. Singapore: Springer, 2025, pp. 327–342, doi: 10.1007/978-981-96-1873-6_31.

[17] V. N. Kyere, K. Greve, and S. M. Atiemo, "Spatial assessment of soil contamination by heavy metals from informal electronic waste recycling in Agbogbloshie, Ghana," *Environ. Health Toxicol.*, vol. 31, Art. no. e2016006, 2016, doi: 10.5620/eht.e2016006.

[18] T. Itai, M. Otsuka, K. A. Asante, M. Muto, Y. Opoku-Ankomah, O. D. Ansa-Asare, and S. Tanabe, "Variation and distribution of metals and metalloids in soil/ash mixtures from Agbogbloshie e-waste recycling site in Accra, Ghana," *Sci. Total Environ.*, vol. 470–471, pp. 707–716, 2014, doi: 10.1016/j.scitotenv.2013.10.037.

[19] V. N. Kyere, K. Greve, S. M. Atiemo, D. Amoako, I. J. K. Aboh, and B. S. Cheabu, "Contamination and health risk assessment of exposure to heavy metals in soils from informal e-waste recycling site in Ghana," *Emerg. Sci. J.*, vol. 2, no. 6, pp. 428–438, 2018, doi: 10.28991/esj-2018-01162.

[20] W. K. Agbosu, "Environmental effects of uncontrolled dumping of discarded mobile telecommunication technology equipment in Accra, Ghana," *EQA Int. J. Environ. Qual.*, 2026, doi: 10.60923/issn.2281-4485/23749.

[21] A. Singh, S. P. Dwivedi, and A. Tripathi, "Study of the toxicity of metal contamination in soil samples collected from abandoned e-waste burning sites in Moradabad, India," *Nat. Environ. Pollut. Technol.*, vol. 17, no. 3, pp. 973–979, 2018.

[22] Sambyal, S. S., & Sohail, S. (2015, September 24). *The e-toxic trail*. Down to Earth; Centre for Science and Environment. https://cdn.cseindia.org/userfiles/E-toxic-trail.pdf

[23] Gangwar, C., Singh, A., Pal, R., Kumar, A., Sharma, S., & Tripathi, A. Environmental susceptibility: Soil contamination of heavy metals in the territory of e-waste recycling area. *International Journal of Plant and Environment*.

[24] R. M. Panwar and S. Ahmed, "Assessment of contamination of soil and groundwater due to e-waste handling," *Curr. Sci.*, vol. 114, no. 1, pp. 166–173, 2018, doi: 10.18520/cs/v114/i01/166-173.

[25] J. K. Pradhan and S. Kumar, "Informal e-waste recycling: environmental risk assessment of heavy metal contamination in Mandoli industrial area, Delhi, India," *Environ. Sci. Pollut. Res.*, 2014.

[26] M. Singh, P. S. Thind, and S. John, "Health risk assessment of the workers exposed to the heavy metals in e-waste recycling sites of Chandigarh and Ludhiana, Punjab, India," *Chemosphere*, vol. 203, pp. 426–433, 2018, doi:

10.1016/j.chemosphere.2018.03.138.

[27] A. Chauhan, R. Choudhari, A. Kumar, B. Singh, and A. Tripathi, "Effect of heavy metals caused by e-waste activities on soil samples, PM2.5, human fingernails, and scalp hair in Moradabad City, India," *J. Ecophysiol. Occup. Health*, vol. 21, no. 3, pp. 96–104, 2021, doi: 10.18311/jeoh/2021/24813.

[28] T. A. Yekeen, X. Xu, Y. Zhang, Y. Wu, S. Kim, T. Reponen, K. N. Dietrich, S.-M. Ho, A. Chen, and X. Huo, "Assessment of health risk of trace metal pollution in surface soil and road dust from e-waste recycling area in China," *Environ. Sci. Pollut. Res. Int.*, vol. 23, no. 17, pp. 17511–17524, 2016, doi: 10.1007/s11356-016-6896-6.

[29] Y. Guo, C. Huang, H. Zhang, and Q. Dong, "Heavy Metal Contamination from Electronic Waste Recycling at Guiyu, Southeastern China," *J. Environ. Qual.*, 2009.

[30] X. Xu, J. Liu, X. Zeng, F. Lu, A. Chen, and X. Huo, "Elevated serum polybrominated diphenyl ethers and alteration of thyroid hormones in children from Guiyu, China," *PLoS ONE*, vol. 9, no. 11, Art. no. e113699, 2014, doi: 10.1371/journal.pone.0113699.

[31] W. Huang, X. Shi, and K. Wu, "Human body burden of heavy metals and health consequences of Pb exposure in Guiyu, an e-waste recycling town in China," *Int. J. Environ. Res. Public Health*, vol. 18, no. 23, Art. no. 12428, Nov. 2021, doi: 10.3390/ijerph182312428.

[32] Q. Song and J. Li, "Environmental effects of heavy metals derived from the e-waste recycling activities in China: A systematic review," *Waste Manag.*, vol. 34, no. 12, pp. 2587–2594, 2014, doi: 10.1016/j.wasman.2014.08.012.

[33] C. Luo, C. Liu, Y. Wang, X. Liu, F. Li, G. Zhang, and X. Li, "Heavy Metal Contamination in Soils and Vegetables near an e-Waste Processing Site, South China," *J. Hazard. Mater.*, 2011.

[34] P. Pibul, S. Jawjit, and S. Yimthiang, "Soil heavy metal pollution from waste electrical and electronic equipment of repair and junk shops in southern Thailand and their ecological risk," *Heliyon*, vol. 9, Art. no. e20438, 2023, doi: 10.1016/j.heliyon. 2023.e20438.

[35] M. D. Adesokan, G. U. Adie, and O. Osibanjo, "Soil pollution by toxic metals near E-waste recycling operations in Ibadan, Nigeria," *J. Health Pollut.*, 2016.

[36] C. Moeckel, K. Breivik, T. H. Nøst, A. Sankoh, K. C. Jones, and A. Sweetman, "Soil pollution at a major West African E-waste recycling site: contamination pathways and implications for potential mitigation strategies," *Environ. Int.*, 2020.

[37] N. Uchida, H. Matsukami, M. Someya, N. M. Tue, L. H. Tuyen, P. H. Viet, S. Takahashi, S. Tanabe, and G. Suzuki, "Hazardous metals emissions from e-waste-processing sites in a village in northern Vietnam," *Emerging Contaminants*, 2018.

[38] B. Jiang, A. Adebayo, J. L. Jia, Y. Xing, S. Q. Deng, L. M. Guo, Y. T. Liang, and D. Y. Zhang, "Impacts of heavy metals and soil properties at a Nigerian e-waste site on soil microbial community," *J. Hazard. Mater.*, vol. 362, pp. 187–195, 2019, doi: 10.1016/j.jhazmat.2018.08.060.

[39] A. A. Adeyi and P. Oyeleke, "Heavy metals and polycyclic aromatic hydrocarbons in soil from e-waste dumpsites in Lagos and Ibadan, Nigeria," *J. Health Pollut.*, vol. 7, no. 15, pp. 71–84, 2017, doi: 10.5696/2156-9614-7.15.71.

[40] S. Damrongsiri, S. Vassanadumrongdee, and P. Tanwattana, "Heavy metal contamination characteristic of soil in WEEE dismantling community: a case study of Bangkok, Thailand," *Environ. Sci. Pollut. Res.*, 2016, doi: 10.1007/s11356-016-6897-5.

[41] T. Oguri, G. Suzuki, H. Matsukami, N. Uchida, N. M. Tue, L. H. Tuyen, P. H. Viet, S. Takahashi, S. Tanabe, and H. Takigami, "Exposure assessment of heavy metals in an e-waste processing area in northern Vietnam," *Sci. Total Environ.*, vol. 621, pp. 1115–1123, 2018, doi: 10.1016/j.scitotenv.2017.10.115.

[42] A. Bankole, A. Ogunkeyede, H. Ngo, L. Liang, H. Agboro, K. Isimekhai, E. Fadairo, G. Isangadighi, E. Isukuru, and C. Ogbodhu, "Ecological risks of heavy metals found in soils at informal e-waste processing sites in Nigeria," *Eur. J. Sci. Innov. Technol.*, 2024.

[43] Q. Zhang, F. Li, and W. Yang, "A deep spectral prediction network to quantitatively determine heavy metal elements in soil by X-ray fluorescence," *J. Anal. At. Spectrom.*, vol. 39, p. 478, 2024, doi: 10.1039/D3JA00392B.

[44] Ahmed A. AL-Tameemi, Fusheng Li, Zenan Xiao, Ghalib Raza; Advancements in machine learning, deep learning, and data fusion techniques for XRF spectrometry in heavy metal detection: a critical review. *J. Anal. At. Spectrom.* 2026; 41 (4): 1155–1180. https://doi.org/10.1039/d5ja00458f

[45] X. Lu, F. Li, W. Yang, P. Zhu, and S. Lyu, "Quantitative analysis of heavy metals in soil by X-ray fluorescence with improved variable selection strategy and bayesian optimized support vector regression," *Chemom. Intell. Lab. Syst.*, vol. 238, Art. no. 104842, 2023, doi: 10.1016/j.chemolab.2023.104842.

[46] F. Xia, T. Fan, Y. Chen, D. Ding, J. Wei, D. Jiang, and S. Deng, "Prediction of heavy metal concentrations in contaminated sites from portable X-ray fluorescence spectrometer data using machine learning," *Processes*, vol. 10, no. 3, Art. no. 536, 2022, doi: 10.3390/pr10030536.

[47] W. Yang, F. Li, S. Lyu, Q. Zhang, and Y. Zhao, "Quantitative analysis of heavy metals in soil via hierarchical deep neural networks with X-ray fluorescence spectroscopy," *J. Anal. At. Spectrom.*, vol. 38, p. 1830, 2023, doi: 10.1039/D3JA00120B.

[48] Y. Wang, T. Gan, N. Zhao, G. Yin, Z. Ye, R. Sheng, T. Li, T. Liang, R. Jia, L. Fang, X. Hu, and X. Li, "Identification study

of soil types based on feature factors of XRF spectrum combining with machine learning," *Spectrochim. Acta Part B At. Spectrosc.*, vol. 219, Art. no. 107001, Sep. 2024, doi: 10.1016/j.sab.2024.107001.

[49] Hu B, Chen S, Hu J, Xia F, Xu J, Li Y, Shi Z. "Application of portable XRF and VNIR sensors for rapid assessment of soil heavy metal pollution. PLoS One. 2017 Feb 24;12(2): e0172438. doi: 10.1371/journal.pone.0172438.

[50] M. S. Islam, M. B. Hossain, A. Matin, and M. S. I. Sarker, "Health risk assessment of humans exposed to soil and dust trace elements from e-waste sites in Bangladesh," *Environ. Geochem. Health*, vol. 41, no. 3, pp. 1041–1052, Jun. 2019, doi: 10.1007/s10653-018-0193-4.

[51] Zhao, L., Zhou, F., Wang, S., Yang, Y., Chen, H., Ma, X., & Liu, X. (2024). Bisphenol Chemicals in Surface Soil from E-Waste Dismantling Facilities and the Surrounding Areas: Spatial Distribution and Health Risk. *Toxics*, *12*(6), 379. doi: 10.1021/acs.est.0c03472.

[52] A. Parvez *et al.*, "Health consequences of exposure to e-waste: an updated systematic review," *Lancet Planet. Health*, vol. 5, no. 12, pp. e905–e920, Dec. 2021, doi: 10.1016/S2542-5196(21)00263-1.

[53] World Health Organization, "Electronic waste (e-waste)," WHO Fact Sheet, 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/electronic-waste-(e-waste

[54] Q. Bu, "Emerging pollutants in the environment: Occurrence, fate, risk assessment and degradation methods," *Int. J. Environ. Res. Public Health*, 2025.

[55] E. R. Raut, A. M. Sudame, and M. Shanti, "Scenario of E-waste in Nagpur city: A case study," in *Proc. Int. Conf. Recent Trends Sci. Technol.*, 2019.

[56] S. Singh *et al.*, "Occurrence, fractionation, and human health risk assessment of potentially toxic metals in urban soils of different land use types," *Water Air Soil Pollut.*, vol. 236, Art. no. 07817, 2025, doi: 10.1007/s11270-025-07817-2.

[57] N. Deshwal, "India's e-waste management: Analysis and opportunities for a sustainable future," M.S. thesis, Dept. Dev. Stud., 2025, doi: 10.13140/RG.2.2.27120.16647.

[58] L. Liu, L. Hu, J. Tang, Y. Li, Q. Zhang, and X. Chen, "Food Safety Assessment of Planting Patterns of Four Vegetable-Type Crops Grown in Soil Contaminated by Electronic Waste Activities," *J. Environ. Manage.*, 2012, doi: 10.1016/j.jenvman.2011.08.021

[59] X. Liu, S. Gu, S. Yang, J. Deng, and J. Xu, "Heavy Metals in Soil-Vegetable System around E-Waste Site and the Health Risk Assessment," *Sci. Total Environ.*, 2021, doi: 10.1016/j.scitotenv.2021.146438

[60] B. N. Lopez, Y. B. Man, Y. G. Zhao, J. S. Zheng, A. O. W. Leung, J. Yao, and M. H. Wong, "Major pollutants in soils of abandoned agricultural land contaminated by e-waste activities in Hong Kong," *Arch. Environ. Contam. Toxicol.*, vol. 61, no. 1, pp. 101–114, Jul. 2011, doi: 10.1007/s00244-010-9590-6.

[61] *Down To Earth*, "India's e-waste generation soars by 73% in five years, raising environmental concerns," 2024. [Online]. Available: https://www.downtoearth.org.in

[62] "Plastic waste management failures in Vidarbha: Fines, gaps, and administrative strain," *News Analysis*, 2025.

[63] "Factory Pollution, Illegal Dumping and Plastic Use: NMC Collects ₹70,000 in Fines," *The Live Nagpur*, 2025. [Online]. Available: https://thelivenagpur.com

[64] Barathkumar, S., Sellamuthu, K. M., Sathyabama, K., Malathi, P., Kumaraperumal, R., & Devagi, P. (2025). Advancements in Soil Quality Assessment: A Comprehensive Review of Machine Learning and AI-Driven Approaches for Nutrient Deficiency Analysis. *Communications in Soil Science and Plant Analysis*, *56*(2), 251–276. https://doi.org/10.1080/00103624.2024.2406484.

[65] F. Howari, "AI–Remote Sensing for Soil Variability Mapping and Precision Agrochemical Management: A Comprehensive Review of Methods, Limitations, and Climate-Smart Applications," *Agrochemicals*, vol. 5, no. 1, Art. no. 1, 2025, doi: 10.3390/agrochemicals5010001.

[66] Jain S, Sethia D, Tiwari KC. A critical systematic review on spectral-based soil nutrient prediction using machine learning. Environ Monit Assess. 2024 Jul 4;196(8):699. doi: 10.1007/s10661-024-12817-6. PMID: 38963427.

[67] Jain, S., & Sethia, D. (2023). A Review of Applications of Artificial Intelligence for Identifying Soil Nutrients. *Communications in Computer and Information Science*, 71–86. https://doi.org/10.1007/978-3-031-43605-5_6

[68] Gano, B., Ghimire, D., Diene, S. M., Srivastava, D., Cudjoe, D. K., & Shakoor, N. (2026). Remote Sensing and Machine Learning for Monitoring Soil Nitrogen Dynamics and Crop Nitrogen Status in Field Conditions. *Nitrogen*, *7*(3), 82. https://doi.org/10.3390/nitrogen7030082

[69] "How Plant Biosensors, IoT, and AI Are Advancing Precision Agriculture," *News-Medical*, 2026. [Online]. Available: https://www.news-medical.net

[70] Eze, V.H.U., Eze, E.C., Alaneme, G.U. *et al.* Integrating IoT sensors and machine learning for sustainable precision agroecology: enhancing crop resilience and resource efficiency through data-driven strategies, challenges, and future prospects. *Discov Agric* **3**, 83 (2025). https://doi.org/10.1007/s44279-025-00247-y

[71] Sudha, S.P., Loret, J.B.S. A review on machine learning-based precision agriculture techniques for crop farming monitoring with IOT. *Discov Environ* **4**, 10 (2026). https://doi.org/10.1007/s44274-025-00305-8

[72] Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies. *Sensors*, *25*(12), 3583. https://doi.org/10.3390/s25123583

[73] B. Bairwa, R. N. Katkar, and V. Bhende, "Influence of Sulphur, Zinc and Organic Inorganic Assorted Customized Fertilizer on Cotton," *International Journal of Current Microbiology and Applied Sciences, 9(8), 3053–3062*, 2020, 10.20546/ijcmas.2020.908.345.

[74] R. N. Katkar, S. R. Lakhe, S. S. Hadole, and P. A. Sarap, "Assessment of Spatial Variability of Major and Micro Nutrients in Soils of Akola District of Maharashtra," *PKV Research Journal, 43(1)*, 2019.

[75] Dr. Panjabrao Deshmukh Krishi Vidyapeeth, "AICRP on Micro and Secondary Nutrients and Pollutant Elements in Soils and Plants, Akola," Research Progress Report, Akola, Maharashtra, India.

[76] V. S. Patil, "Soil Fertility, Soil Quality and Soil Health in Maharashtra: A Review," *ResearchGate*, Preprint, 2025, doi: 10.13140/RG.2.2.14829.23521.

[77] A. K. Shukla *et al.*, "Deficiency of phyto-available sulphur, zinc, boron, iron, copper and manganese in soils of India," *Sci. Rep.*, vol. 11, Art. no. 19760, Oct. 2021, doi: 10.1038/s41598-021-99040-2.

[78] M. K. Ali *et al.*, "Challenges and strategies of resource poor farmers in adoption of innovative farming technologies: A comprehensive review," *Agric. Syst.*, vol. 227, Art. no. 104355, 2025, doi: 10.1016/j.agsy.2025.104355.

[79] S. Chaudhary, H. R. Meena, and J. Behera, "Adoption of Precision Agriculture Technologies in Northern India: A Push-Pull Framework Approach," *J. Exp. Agric. Int.*, vol. 47, no. 7, pp. 974–981, Aug. 2025, doi: 10.9734/jeai/2025/v47i73640.

[80] S. R. Kulkarni, "Precision-agriculture technology integration in a Maharashtra division," *LEX LOCALIS - Journal of Local Self-Government*, vol. 23, no. 1, pp. 88–102, 2025, doi: 10.4335/2025.12.04.

[81] X. Lei and D. Yang, "Digital tech adoption & farmer income (non-India-specific)," *PLOS ONE*, 2024, doi: 10.1371/journal.pone.0309675

[82] "Panel-data (2018–20) impact of digitalization on Indian farmer income," *Int. J. of Management, Humanities (IJMH)*, 2021, doi: 10.5281/zenodo.5502405.

[83] P. S. Shehrawat, B. Arulmanikandan, S. Singh, and Aditya, "Haryana field study on farmer awareness/adoption of digital agri-tech," *Int. J. of Economic Plants*, 2024, doi: 10.23910/2/2024.5694a.

[84] "Digital AgriStack/IDEA & NeGP-A e-governance digitization coverage," *Discover*, 2024, doi: 10.1007/s44279-024-00012-7.

[85] N. M. Trendov, S. Varas, and M. Zeng, "Case study on digital platforms connecting Indian smallholders to markets," *FAO Status Report*, 2019. [Online]. Available: openknowledge.fao.org

[86] A. R. Nair and A. Prakasan, "AI applications in soil health assessment (secondary citation, not independently retrieved)," *J. of Applied Science, Engineering, Tech. & Mgmt, 2(1), 35-39*, 2024.

[87] P. Novielli, M. Magarelli, D. Romano, L. de Trizio, P. Di Bitonto, A. Monaco, N. Amoroso, A. M. Stellacci, C. Zoani, R. Bellotti, and S. Tangaro, "Method reference on soil/water conservation (non-India; secondary citation)," *J. of Soil and Water Conservation, 35(4)*, 2024.

[88] P. Gayathri, D. Muthumanickam, S. Pazhanivelan, R. Kumaraperumal, P. Kannan, and P. C. Prabu, "Review of AI applications in soil health assessment," *Plant Science Today, 12(3), 1-14*, 2025, doi: 10.14719/pst.6669.

[89] "AI-powered data-driven soil health monitoring system," *IJRASET*, 2024. [Online]. Available: ijraset.com/research-paper/ai-in-soil-health-monitoring-a-data-driven-, doi: 10.22214/ijraset.2024.62102.

[90] M. N. Kathiravan, S. Bande, S. Tiwari, A. K. Koshariya, and D. Suganthi, "Soil analysis/classification via fast graph-CRNN for crop yield," *IEEE ICSSAS 2023 Proceedings, pp. 98-104*, 2023, doi: 10.1109/ICSSAS57918.2023.10331819.

[91] H. Mishra *et al.*, "Overview of AI/soil conservation incl. SOC estimation via Random Forest," *Journal of Scientific Agriculture*, 2024. [Online]. Available: updatepublishing.com/.../view/9661, doi: 10.21082/jp3.v40n1.2021.p21-30.

[92] Suprehatin, "Synthesis of 60+ studies on smallholder ag-tech adoption determinants," *Jurnal Penelitian dan Pengembangan Pertanian, 40(1), 21-30*, 2021, doi: 10.21082/jp3.v40n1.2021.p21-30.

[93] "UTAUT-based study of tech adoption determinants, small rural farmers," *Humanities and Social Sciences Communications*, vol. 11, 2024, doi: 10.1038/s41599-024-04163-2.

[94] D. Landmann, C. J. Lagerkvist, and V. Otter, "664-farmer survey (Bihar); TPB/SEM model of smartphone-adoption intention," *European Journal of Development Research, 33(6), 1435-1454*, 2021, doi: 10.1057/s41287-020-00284-x.

[95] World Bank research team, "Broad review of smallholder agri-tech adoption determinants/impacts," *World Bank Policy*

Research Working Paper, 2023, doi: 10.1596/1813-9450-10443.

[96] "Systematic review of IoT, big data & ML in precision agriculture incl. Indian model," Academia.edu Preprint, 2024. [Online]. Available: academia.edu/123634492.

[97] H. Mishra, "Review of AI/ML/IoT integration in precision agriculture," *Journal of Scientific Agriculture*, 2025. [Online]. Available: updatepublishing.com/.../view/9497, doi: 10.56557/josai/2025/v12i19497.

[98] "IoT + ML disease-prediction model, Kashmir apple orchards," *Ain Shams Engineering Journal*, vol. 13, no. 1, Art. no. 101582, 2022, doi: 10.1016/j.asej.2021.05.012.

[99] Patil, C. B., & Khan, A. (2020). Sustainable solid waste management: Case study of Nagpur, India. *International Journal of Engineering Research & Technology, 9*(11), 645–651. https://www.ijert.org/research/sustainable-solid-waste-management-case-study-of-nagpur-india-IJERTV9IS110278.pdf

[100] "IoT + UAV precision-agriculture review, C-DAC Patna field support," in *Springer Nature*, Springer, c. 2022, pp. 345–358, doi: 10.1007/978-981-19-4182-5_30.

[101] "AI/ML precision-agriculture review: disease detection, soil/yield prediction," *IJRASET*, vol. 12, 2024. [Online]. Available: ijraset.com/research-paper/ai-and-machine-learning-in-precision-agriculture, doi: 10.22214/ijraset.2024.61234.

[102] "Kisan Sathi — multilingual NLP/voice advisory assistant," *Int. J. Creative Res. Thoughts (IJCRT)*, 2025. [Online]. Available: ijcrt.org/papers/IJCRT25A4451.pdf

[103] "AgriSaathi — survey of LLMs for agricultural advisory," *Int. J. For Multidisciplinary Res. (IJFMR)*, vol. 7, 2025. [Online]. Available: ijfmr.com/papers/2025/6/60751.pdf

[104] Gates Foundation, GIZ, and CLEAR Global, "GenAI multilingual advisory pilot (AIEP), incl. Bihar smallholders," BMZ Digital Report, Dec. 2025. [Online]. Available: bmz-digital.global

[105] "Benchmarks ASR (Hindi/Telugu/Odia) for agri-advisory voice interfaces,", 2026, doi: 10.48550/arXiv.2602.03868.

[106] "GenAI bridging agronomic science & farm-level advisory, rice, India," *Front. Artif. Intell.*, vol. 9, Art. no. 1808028, 2026, doi: 10.3389/frai.2026.1808028.

[107] "Multilingual RAG + fine-tuned LLaMA for agri-advisory," *Int. J. Sci. Anal. Res. Technol. (IJSART)*, vol. 11, c. 2025. [Online]. Available: ijsart.com/.../IJSARTV11I4103140.pdf

[108] "Agri-SAGE — multi-agent LLM for India's Agro-Met Field Unit advisories,", 2026, 10.48550/arXiv.2607.00454.

[109] "AI/ML/NLP one-stop farmer platform (advisory, marketplace, weather)," *Int. J. Res. Tech. Innov. (IJRTI)*, vol. 10, no. 11, 2025. [Online]. Available: ijrti.org/papers/IJRTI2511038.pdf

[110] A. Tzachor, "Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry," *Int. J. of Innovation in the Digital Economy (IGI Global), 12(3)*, 2021, doi: 10.4018/IJIDE.2021070103.

[111] "fsQCA + TAM/justice-framework study of AI adoption, non-chemical-agriculture farmers," *Sustainability*, vol. 17, no. 19, Art. no. 8865, 2025, doi: 10.3390/su17198865.

[112] "Challenges Facing Artificial Intelligence Adoption during COVID-19 Pandemic: Agriculture and Agri-Food Supply Chain in India," *Sustainability*, vol. 15, no. 8, Art. no. 6377, 2023, doi: 10.3390/su15086377.

[113] "Generative AI in agriculture 4.0: Applications, challenges, and integration in the Indian context," *Engineering in Agriculture, Environment and Food*, 2025, doi: 10.1016/j.eaef.2025.100933.

[114] N. Hasteer, A. Mallik, D. Nigam, R. Sindhwani, and J. P. Belle, "Analysis of challenges to implement artificial intelligence technologies in agriculture sector," *Int. J. of System Assurance Engineering and Mgmt (Springer)*, 2024, doi: 10.1007/s13198-023-02164-z.

[115] World Economic Forum Research Team, "Roadmap for scaling AI in Indian agriculture; adoption-barrier mitigation," WEF Report, 2025. [Online]. Available: reports.weforum.org/docs/WEF_Future_Farming_in_India_2025.pdf

[116] "Synthesis section on digital-agriculture adoption barriers (cost, trust, complexity),", 2025, 10.48550/arXiv.2510.10360.

[117] "AgriStack/Digital Crop Survey data gaps as a structural AI-adoption barrier,", 2026, 10.48550/arXiv.2603.23289.

[118] S. Chatterjee, "AI strategy of India: policy framework, adoption challenges and actions for government," *Transforming Government: People, Process and Policy, 14(5), 757-775*, 2020, doi: 10.1108/TG-05-2019-0031.

[119] E. V. S. Prakasa Rao and K. V. Ramesh, "Digital Agriculture: Prospects and Challenges in India," *Souvenir, National Symposium on Digital Farming (CSIR-Fourth Paradigm Institute)*, 2023.

[120] R. Abiri, N. Rizan, S. K. Balasundram, A. B. Shahbazi, and H. Abdul-Hamid, "Broad digital-agriculture review (AI, IoT, robotics, blockchain); not India-specific," *Heliyon, 9(12), e22601*, 2023, doi: 10.1016/j.heliyon.2023.e22601.

[121] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: a comprehensive review," *IEEE Access, 9, 4843-4873*, 2021, doi: 10.1109/ACCESS.2020.3048415.

[122] M. R. Islam, K. Oliullah, M. M. Kabir, M. Alom, and M. F.

Mridha, "Machine learning enabled IoT system for soil nutrients monitoring and crop recommendation," *Journal of Agriculture and Food Research (Elsevier), 14, 100880*, 2023, doi: 10.1016/j.jafr.2023.100880.

[123] V. Patil and P. Chellattan Veettil, "Farmers' risk attitude, agricultural technology adoption and impacts in Eastern India," *Agriculture & Food Security, 13(1), 50*, 2024, doi: 10.1186/s40066-024-00497-x.

[124] H. M. Ali, S. Velayutham, K. S. Babu, F. T. Ayasrah, A. Smerat, S. Balasubramanian, A. Absamatov, and S. Sengan, "The Role of Mobile Technology Adoption in Developing Sustainable Agricultural Marketing Efficiency Among Smallholder Farmers," *Research on World Agricultural Economy, 7(2), 371-387*, 2026, doi: 10.36956/rwae.v7i2.2735.