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FARMER KNOWLEDGE AND VALIDATION IN DIGITAL SOIL MAPPING: A SYSTEMATIC REVIEW (2013–2025) WITH EMPHASIS ON SUB-SAHARAN AFRICA AND COMPARATIVE REGIONS

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ABSTRACT

Land suitability assessment plays a central role in agricultural planning, sustainable land management, and climate adaptation. Recent decades have witnessed rapid methodological advancement driven by Geographic Information Systems (GIS), Digital Soil Mapping (DSM), and Machine Learning (ML). However, the extent to which these technological developments incorporate farmer knowledge remains unclear. This study conducts a systematic review of 60 peer-reviewed land suitability and DSM studies published between 2013 and 2025, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Studies were analysed across three dimensions: methodological approach, validation strategy, and degree of farmer knowledge integration. Results indicate that 81.67% of studies excluded farmer participation entirely, while only 6.67% implemented structured participatory validation. The lowest levels of engagement were observed in ML/DSM studies, despite their methodological sophistication. Validation practices were dominated by statistical and biophysical approaches, with limited attention to socio-ecological relevance. These findings reveal a structural imbalance in contemporary land suitability research: predictive accuracy has advanced faster than contextual validation. The paper proposes a hybrid validation framework integrating predictive modelling, independent field verification, structured farmer participation, and uncertainty communication. Incorporating experiential knowledge alongside computational methods is argued to be essential for producing land suitability assessments that are scientifically robust, socially credible, and operationally adoptable.

Keywords: Land suitability assessment; digital soil mapping; machine learning; farmer knowledge; participatory validation; co-production

INTRODUCTION

Land suitability assessment is a critical scientific framework for matching land characteristics to agricultural production needs and remains central to sustainable land-use planning and food security strategies worldwide. Since the establishment of the Food and Agriculture Organisation's (FAO) framework for land evaluation in the 1970s, the assessment of suitability has undergone a major methodological change, evolving from field-based evaluations to more advanced analytical approaches (FAO, 1976).

Geographic Information Systems (GIS), remote sensing, and multi-criteria decision-making (MCDM) have been incorporated to better understand spatial variability. More recently, Digital Soil Mapping (DSM) and Machine Learning (ML) approaches have improved predictive accuracy and scalability (Jankowski, 1995; Das et al., 2018). However, the extent to which improved predictive performance translates into practical agricultural applications remains unclear, limiting their use in practice because many studies, such as Dinga et al. (2019), focus on statistical accuracy metrics like cross-validation and ROC-AUC rather than real-world usability and farmer adoption (Llewellyn & Brown, 2020).

Agricultural systems are increasingly recognized as socio-ecological systems in which farmers possess important local knowledge (Hualpa et al., 2025; O'Connor et al., 2021), yet their direct involvement is rarely systematically integrated into suitability assessment workflows. To fill this gap, a global systematic review of land suitability studies published from 2013 to 2025 was carried out based on three criteria: methodological approaches, validation strategies, and farmer participation (i.e., the extent to which local knowledge is incorporated in their methods), to highlight implications for agricultural decision-making by region.

The study is important because excluding farmers' knowledge may limit the practical applicability and adoption of land suitability assessments, particularly in smallholder agricultural systems. Understanding this gap is essential for improving the relevance and usability of soil and land evaluation models.

MATERIALS AND METHODS

Review Design

This study employed a systematic literature review guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparent identification and selection of studies. Relevant studies were sourced from Scopus, Web of Science, Google Scholar, and Elicit (with verification in indexed databases), and 60 peer-reviewed articles published between 2013 and 2025 were selected based on predefined inclusion criteria. Each study was analysed using a structured coding framework covering methodological approach, validation strategy, and farmer knowledge integration, with descriptive statistics and cross-tabulation used to identify key patterns and relationships.

Information Sources and Search Strategy

To ensure comprehensive and systematic coverage of peer-reviewed research, literature searches were conducted across major academic databases, including Scopus, Web of Science Core Collection, Google Scholar, and Elicit, the latter serving as an AI-assisted discovery tool. All records identified through Elicit were independently verified in indexed databases prior to inclusion to maintain data integrity. Given the extensive global body of literature, clearly defined inclusion criteria were applied to ensure methodological rigor and reproducibility. The review was limited to English-language studies published between 2013 and 2025, capturing a period of rapid advancement in digital soil mapping and machine learning applications in soil-related research. Although global in scope, the study adopts a criteria-based selection approach rather than exhaustive coverage, with particular emphasis on Sub-Saharan Africa and comparative regions.

Boolean search queries were developed and refined through pilot searches to balance sensitivity (maximizing relevant results) and specificity (minimizing irrelevant results), thereby reducing omission bias. The search strategy combined three thematic concept groups:

1. Land suitability terminology: "land suitability", "land evaluation", "crop suitability"
2. Validation and accuracy assessment concepts: "validation", "accuracy assessment", "model evaluation"
3. Methodological and participatory terms: GIS, remote sensing, digital soil mapping, machine learning, participation, farmer knowledge

Regional patterns were subsequently examined to identify variations in methodological approaches and levels of farmer participation across different geographical contexts.

Coding and Analytical Framework

A structured coding framework has been developed to enable comparative analysis across the studies. Each article has been categorized into two analytical dimensions: farmer knowledge integration and validation strategy.

Farmer Knowledge Integration (FK)

- **FK0:** No farmer involvement reported
- **FK1:** Indirect expert representation or proxy knowledge
- **FK2:** Consultative interaction with farmers
- **FK3:** Structured participatory validation or knowledge co-production

Validation Strategy (V)

- **V1:** Statistical or model-based validation only
- **V2:** Independent field-based validation
- **V3:** Participatory or stakeholder-based validation

The coding relied solely on the explicitly reported methodological descriptions to limit interpretation. The operational definitions have been iteratively refined during the preliminary coding exercise to improve the clarity of the categories. A subset of studies was reassessed for internal consistency, and inconsistencies were resolved by refining the rules, thereby minimizing classification bias.

RESULTS AND DISCUSSION

Temporal Trends in Land Suitability Research

The final dataset showed a distinct methodological shift over time, with 60 studies published between 2013 and 2025. Land suitability evaluations were primarily based on parametric evaluation techniques and multi-criteria decision-making, supported by GIS, prior to 2018. Data-driven modeling began to grow significantly in 2019. During the 2019–2025 period, 68 percent of studies used machine learning (ML) and digital soil mapping (DSM) techniques, as shown in Table 1.

Table 1: Summary of Reviewed Land Suitability Studies

S/N	Author(s) & Year	Study Area	Crop(s)	Methodology	FK	V	Key Limitation
1	Maddahi et al. (2017).	Amol District, Iran	Rice	GIS-FMCDM, FAO framework, FAHP	0	1	Extensive expert input, subjective weight assignments
2	Dongare et al. (2019)	Tirora Tehsil, Maharashtra, India	Rice	Remote sensing, soil profile analysis, AGROMA GIS model	0	1	Limited soil classification accuracy
3	Kabir et al. (2024)	Sarankhola Upazila, Bangladesh	Rice	Secondary soil data, GIS-based weighted overlay	0	1	Reliance on secondary data
4	Dalle et al. (2021)	Peatlands	Rice	Web-based system, FAO guidelines, 22 land parameters	0	1	Focus on peatlands only
5	Deka et al. (2021)	Ghiladhari watershed, Assam, India	Rice	Soil classification, sample analysis, productivity index	0	2	Limited spatial modeling
6	Agbeshie & Adjei (2019)	Nkrankwanta Lowland, Dormaa West District, Ghana	Rice	Soil pits, nutrient analysis, and the FAO Land Quality Index	0	1	Focuses only on rainfed rice; no GIS-based analysis
7	Kumar & Patel (2020)	Bhal Region, Gujarat, India	Rice	GIS-based analysis, AHP & MCE methods, soil & topographic data	0	2	Needs field validation; ignores long-term soil

							fertility changes
8	Ibrahim et al. (2019).	Kubanni Floodplain, Zaria, Nigeria	Rice	Soil survey (100m × 100m grid), lab analysis, parametric & qualitative methods	0	2	Requires significant soil amendments; lacks remote sensing techniques
9	Suntoro et al. (2020)	Magetan District, Indonesia	Rice, Corn, Soybean	Soil sampling, land unit classification, and lab analysis	0	2	Does not incorporate socio-economic factors; mainly soil-based analysis
10	Baroudy et al. (2020).	Nile Delta, Egypt	Rice	Remote sensing (Sentinel-2, NDVI), soil sampling, lab testing, parametric & qualitative evaluation	0	1	Needs validation in other agroecological zones; lacks socio-economic factors
11	Ojara et al. (2017)	Uganda	Upland Rice	Soil and climate analysis, GIS-based weighted overlay, MaxEnt model	0	2	Limited ground-truthing
12	Gyekye et al. (2021)	Ghana	Rice	Grid-based field survey, soil sampling, laboratory analysis	0	2	Small study area, lacks climate integration
13	Suheri et al. (2018)	Indonesia	Upland Rice	GIS-based soil mapping, field sampling, and lab analysis	0	2	Requires long-term monitoring of improvement strategies
14	Bharteey et al. (2022).	India (Assam)	Rice	Satellite imagery, soil sampling, lab analysis, productivity index assessment	0	2	Productivity improvement measures have not been tested
15	Sharma & Sharma (2013)	India (Punjab)	Rice	Soil profile evaluation, physicochemical analysis, parametric approach	0	1	Climate and hydrological factors were not considered
16	Obasi et al. (2021).	Ohaozara, Nigeria	Rice	Soil sampling, profile analysis, laboratory testing, parametric & non-parametric suitability assessment	0	2	Limited study area, no long-term soil improvement trials
17	Osinuga et al. (2020).	Alabata, Southwest Nigeria	Rice	Soil survey, characterization, classification (USDA taxonomy), suitability assessment	0	2	Low macronutrient levels, organic matter deficiency, and limited CEC
18	Ovai (2019)	Abi, Cross River State, Nigeria	Rice	Soil profile analysis, parametric and non-parametric suitability evaluation	0	2	Soil fertility constraints and poor texture for rice production
19	Manasseh & Sharifai (2014)	Watari Irrigation Project, Kano State, Nigeria	Rice	FAO 1985 land evaluation framework, soil mapping, profile sampling, augering, and suitability assessment	0	1	Constraints in soil physical properties and nutrient availability
20	Babalola et al. (2023).	Derived Savanna, Southwestern Nigeria	Rice	Soil profile analysis, laboratory testing, field experiment, randomized complete block design, rice yield assessment, t-test analysis	1	2	Soil fertility limitations, marginal actual suitability, site-specific assessment
21	Ukabiala (2022)	River Niger Floodplains, Kogi East, Nigeria	Multiple	Free survey technique, field soil description, soil sampling, laboratory analysis of physical and chemical properties	1	2	Soil fertility limitations for crops other than rice
22	Obasi et al. (2023).	Northern Ebonyi, Southeastern Nigeria	Rice	Soil sampling from upland, lowland, and irrigated rice farming areas, 9 profile pits analyzed	0	2	Wetness, poor fertility, and toxicity issues affect suitability
23	Tobore et al.	Ogun River	Rice	Remote sensing (NDVI,	0	1	Limitations in

	(2022).	Basin, Nigeria		NDWI, LST), TOPSIS multi-criteria analysis, Ca-Markov model			remote sensing accuracy, lack of field validation
24	Osawe et al. (2017).	Five agroecological zones in Nigeria	Rice	Survey of 149 rice farmers, crop budget analysis, double-log production function model	3	3	Does not focus on specific regions, limited sample size per zone
25	Saleh et al. (2019).	Northern Guinea Savanna, Kaduna State, Nigeria	Rice	Field trials in two locations (Barangwaje and Dutsen Abba), and a stochastic frontier model to analyze efficiency	3	3	The study is limited to two locations and has no long-term sustainability
26	Abdulmumini et al. (2021)	Jigawa State, Nigeria	Rice	Survey of 203 respondents, descriptive statistics	3	3	Financial constraints and a limited geographical scope may contribute to low adoption rates.
27	Umar & Haruna (2019)	Hadejia Valley, Jigawa State, Nigeria	Rice	Survey of 353 respondents, t-test, and FGT Index	3	3	Limited to one irrigation project, with no long-term impact assessment
28	Ibrahim (2023)	Challawa-Karaye Mini Irrigation Scheme, Kano State, Nigeria	Rice	GIS-based AHP model with Sentinel-2 LULC classification; soil classified via pedon approach	0	2	Limited to one irrigation scheme; soil constraints require amendments
29	Ojha et al. (2024).	Chitwan, Nepal	Maize	DSM, ML, 452 soil samples	0	2	Limited to maize-growing areas; DSM needs refinement
30	Piikki et al. (2020)	Global (Review)	Multiple	Systematic review of DSM validation approaches	0	1	Inconsistent validation methods; lack of transparency in reporting
31	Bargaoui et al. (2019)	Brittany, France	Multiple	DSMART to downscale legacy soil map; validated with independent samples	0	2	Accuracy varied across soil properties; more data needed
32	Mello et al. (2021)	Brazil	Multiple	Random forest model with existing soil maps and environmental variables	1	2	The model underestimated certain soil types
33	Cherlinka et al. (2019).	Chernivtsi, Ukraine	Multiple	5m DEM, morphometric predictors, 11 ML models	0	2	Requires high-resolution DEM; results vary by region
34	Rodrigues et al. (2019).	Semiarid Brazil	Fruit crops	Kriging and deterministic mapping; validated with 119 grid points and 40 independent samples	0	2	The study focused only on soil texture
35	Buenemann et al. (2023)	Namibia	Multiple	Compared soil maps with National Soil Survey field data	0	2	Maps are unreliable for policy decisions; limited to Namibia
36	Alsalmi & Suliman (2021)	Shekh Saad, Iraq	Multiple	Collected soil samples at 100-500m intervals; GIS-Kriging and IDW	0	2	IDW may not always be the best method across regions
37	Coelho et al. (2021).	Brazil	Multiple	Systematic review of DSM studies (2006–2019)	0	1	Limited to selected studies
38	Maynard et al. (2023)	Ghana	Multiple	Compared 4 web-based soil maps to 6,514 field soil profiles	0	2	Soil maps had low accuracy; they were reliant on the LandPKS dataset
39	Rossiter	Global	Multiple	DSM 250m–30m resolution,	0	1	Accuracy uncertain

	(2022)			uncertainty measures			in areas with sparse data
40	Liu et al. (2022).	USA, Wisconsin	Multiple	Simulated errors in conventional soil maps; tested training sample selection & data mining models	0	2	Focused on specific terrain type; results may not generalize
41	Sun et al. (2022)	China, Guangdong Province	Multiple	Tested 6 modeling methods on 1,861 soil samples	0	2	Accuracy varied depending on sample randomness and modeling choice
42	Sari et al. (2021).	Indonesia, Tropical Forests	Land cover	Automated vs visual interpretation; stratified random sampling; confusion matrix	0	2	The automated method is less accurate; the visual interpretation is subjective.
43	Han et al. (2022)	Australia	Multiple	DSM products validated using 394 soil observations from 14 farms	0	2	Focused on clay and SOC; findings may not apply to other soil properties
44	Lozbenev et al. (2022)	Russia, Southern Cis-Ural Region	Multiple	DSM vs conventional soil mapping	0	2	DSM struggled with fluvial soils; the accuracy is terrain-dependent
45	Muhammad et al. (2022).	Nigeria, Karaye-Challawa Irrigation Scheme, Kano State	Multiple	Supervised classification in ArcGIS 10.8 with Landsat-8 OLI; validated with 119 accuracy points	0	2	Study limited to one irrigation scheme; accuracy may vary
46	Singh et al. (2025)	Hisar, Haryana, India	Wheat, Paddy, Maize, Sugarcane, Vegetables, Oilseeds, Horticulture	Soil pedon analysis; morphological & physico-chemical characterization; land capability & irrigability classification; crop-wise suitability	0	1	No farmer knowledge; no independent field/yield validation
47	Abdelrahman et al. (2022).	General agricultural area	Annual & perennial crops	Soil-indicator approach; AHP; FAO criteria; GIS/geomatics	0	1	Model-based validation only; no field verification
48	Mandal et al. (2020).	Sagar Island, India	Sunflower, Chilli, Potato, Mustard	Grid soil sampling; PCA-weighting; FAO land limitation; IDW interpolation; GIS	0	1	No farmer input; limited generalizability (coastal soils)
49	Awoonor et al. (2023).	Nkoranza North & South, Ghana	Maize	Soil sampling from smallholder farms; climate & physico-chemical analysis; suitability indices	1	2	No structured participatory framework; limited spatial coverage
50	Ismaili et al. (2023).	Arid & semi-arid regions	Multiple crops	Soil & phenological parameters; ML models (RF, XgbTree, ANN, KNN, SVM); ROC-AUC	0	1	No farmer knowledge; limited ground-truth validation
51	Swafo & Dlamini (2022)	Makuleke Farm, SSA	Banana	Transect walks; auger sampling; soil classification; land capability & suitability mapping	2	2	Small study area (12 ha); limited scalability
52	Rashed (2021)	Moshtohor, Egypt	Multiple crops	GIS & remote sensing; soil fertility and suitability indices	0	1	Limited farmer integration; weak field validation

53	Sadiq et al. (2025)	Nigeria	Tomato	FAO Land Evaluation Framework; AHP; soil morphological & physico-chemical analysis	0	1	Single crop focus; no farmer-based validation
54	Jalhoum et al. (2024)	Nile Delta, Egypt	Quercus robur, Pinus silvestris	GIS; PCA; AHC clustering; parametric suitability assessment	0	1	Salinity constraints; no participatory validation
55	Feudis et al. (2020).	Ravenna, Italy	Multiple crops	GIS; remote sensing; pedologic & topographic analysis; land capability & suitability mapping	0	1	Coastal salt intrusion limits transferability; no farmer input
56	Mihoub et al. (2021).	Southern Algeria	Wheat	Expert-based MDS; PCA; scoring functions; soil quality index; parametric mapping	0	2	Expert-driven framework; limited crop scope
57	Moshago et al. (2022).	Gurage Zone, Ethiopia	Maize, Teff, Wheat	Soil classification; FAO maximum limitation method; slope-based pedon analysis	1	2	Small sample size (4 pedons); no highly suitable (S1) class
58	Baroudy et al. (2020).	Nile Delta, Egypt	Rice	Remote sensing; soil quality indicators; parametric & qualitative methods; NDVI & yield comparison	0	2	Limited farmer knowledge; mostly model comparison validation
59	Mostafiz et al. (2021).	Not specified	Multiple crops	Satellite-derived soil–vegetation indices; fuzzy MCDM; GIS; ground-truth yield validation	1	2	Partial expert input; accuracy dependent on RS indices
60	Bilas et al. (2022).	Belgium, Hungary, China	Maize	Land Suitability Analysis (LSA); AHP; Soil-Improving Cropping Systems (SICS) scenarios	0	1	Scenario-based; no participatory integration

In contrast to methodological expansion, farmer participation showed minimal temporal variation. Throughout the study period, participatory integration remained consistently low, with no observable increase associated with the adoption of advanced modelling techniques.

Methodological Approaches

Four principal methodological categories were identified across the reviewed studies, as presented in Figure 1.

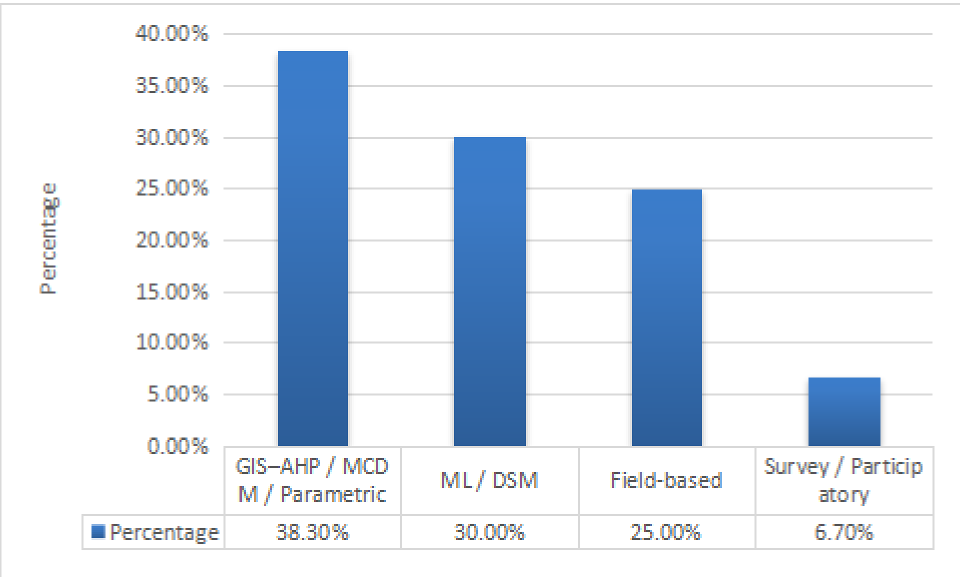

Figure 1: Methodological Approaches

ML/DSM applications were predominantly implemented in regions characterized by extensive environmental datasets and established digital infrastructure. In contrast, GIS-AHP/MCDM approaches were more frequently applied in developing agricultural contexts, where modelling frameworks relied on expert-derived weighting schemes and locally available data sources.

3.3 Validation Practices

Three main validation strategies have been observed. The most common approach, found in 58.33 percent of the studies, was independent field validation. 33.33 percent of the studies included statistical or model-based validation methods, including cross-validation and precision metrics. Participation verification involving stakeholder involvement was relatively rare, occurring in only 8.33 percent of the reviewed articles.

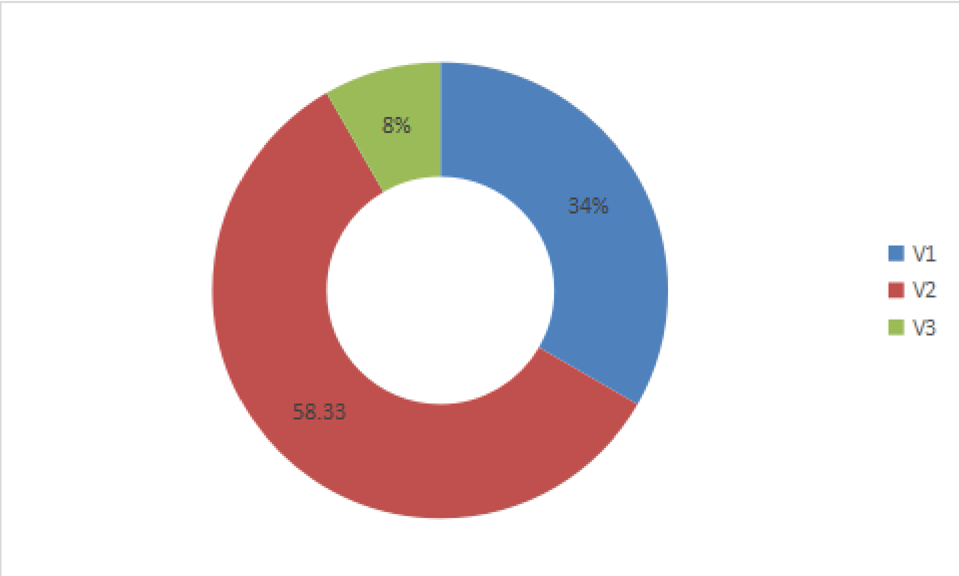

Figure 2: Validation Strategies

The distribution indicates a strong emphasis on technical verification methods relative to stakeholder-based evaluation procedures.

Farmer Knowledge Integration

Farmer knowledge integration was limited across the dataset. Classification according to the Farmer Knowledge (FK) framework is shown in Figure 3.

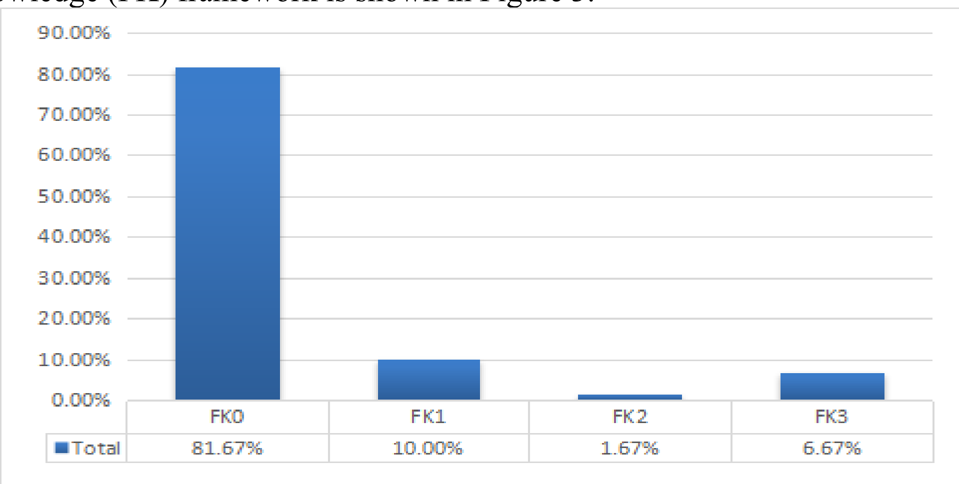

Figure 3: Distribution of farmer knowledge integration levels

The distribution of farmer knowledge integration levels is presented in Figure 2. The majority of studies (81.67%, n = 49) reported no farmer involvement (FK0), while only 6.67% (n = 4) implemented structured participatory validation (FK3). Indirect expert representation (FK1) accounted for 10% (n = 6), whereas consultative interaction with farmers (FK2) was extremely rare (1.67%, n = 1). This highlights a strong dominance of non-participatory approaches in land suitability research.

Relationships Between Methodological Approach and Participation

The cross-tabulation of participation levels by methodological category indicated that the ML/DSM-based studies had the lowest farmer participation (81.67% FK0). Participatory validation (V3) was most common in studies in which farmer participation was already part of the evaluation process. Generally, higher analytical complexity was associated with lower levels of reported stakeholder participation in suitability assessment workflows across methodological groups.

Regional Patterns

Regional analysis showed a high degree of geographical disparity in methodological and participatory approaches. Only 8.33% (n = 5) of the 60 studies included in this review had moderate-to-high levels of farmer participation (FK2 and FK3). All participatory studies (100%) were conducted in Sub-Saharan Africa, with four studies from Nigeria and one from the broader region.

In contrast, European studies employed non-participatory designs (FK0) and data-intensive methods such as machine learning (ML) and digital soil mapping (DSM). There was little to no evidence of farmer participation, suggesting a stark difference between agro-ecosystems characterized by smallholder farming and high-tech modelling approaches in developed areas.

Technological Advancement and Participatory Deficit

The findings show that while machine learning and digital soil mapping have sophisticated predictive capabilities, there is a gap between technical advancement and participatory integration. However, the lack of farmer knowledge incorporated into these systems may limit their practical application (Tsikada, 2025), demonstrating that while technological progress is important, it does not ensure efficient agricultural decision-making (Singhal et al., 2025).

Limits of Statistical Validation

Although statistical and model validations like cross-validation, ROC-AUC, and Kappa statistics are common practice, they do little to tell a farmer if a decision-making context is possible for management, whereas field validation, which can be more biophysical in nature, often only validates soil or environment rather than usefulness or socio-economic relevance (von Diest et al., 2020; Nduka, 2020). These findings are consistent with previous evaluations showing that technically accurate maps may not inform practical decisions when farmer perspectives are excluded (Maynard et al., 2023). So, relying on quantitative metrics alone risks producing outputs that are scientifically sound but operationally inconsistent.

Epistemic Value of Farmer Knowledge

Farmer knowledge is a longitudinal, site-specific layer of knowledge that can complement short-term sampling and remote-sensing data and provide empirical insights that algorithmic models lack (Awoonor et al., 2023; Obasi et al., 2023). Including experience in validation processes increases model interpretability, builds trust with stakeholders, and improves opportunities for co-production, in line with knowledge co-production principles (Rossiter, 2022; Piikki et al., 2020). Importantly, this integration does not replace scientific modelling, but it provides a critical epistemic check on the assumptions underlying the computation of the results.

Regional Inequalities

While the models used in Europe, China, and Australia are more methodologically diverse and sophisticated, participation in land suitability studies is disproportionately concentrated in Sub-Saharan Africa (Sun et al., 2022; Coelho et al., 2021), an area that may reflect institutional priorities, the availability of data, and disciplinary guidelines, rather than inherent methodological superiority. However, in such a research environment where there is plenty of data, the need to involve stakeholders may appear less important, but farmer decision-making remains an inherent part of land use outcomes regardless of what type or amount of information exists (Maynard & Maynard, 2019; Buenemann et al., 2023); hence, participation should be considered a methodological necessity for social relevance rather than contextual choice.

Toward Hybrid Validation Frameworks

Hybrid validation frameworks combining predictive modeling (such as DSMs/ML approaches), independent field verification, structured farmer evaluation (e.g., through workshops, scoring exercises, or participatory mapping), and explicit uncertainty communication (to convey model limitations transparently) may bridge the gap between technological innovation and participatory integration for future land suitability studies.

These integrated approaches combine computational accuracy with socio-ecological applicability, ensuring that the assessment of land suitability is both scientifically sound and operationally meaningful. This Recommendation builds on prior literature promoting soil assessments in co-production (Piikki et al., 2020; Rossiter et al., 2022; Awoonor et al., 2023) and offers a concrete way forward to enhance acceptance, credibility, and resilience across diverse agricultural environments.

CONCLUSION

This systematic review shows that the same progress has not kept pace with advances in digital soil mapping and machine learning in participatory validation. Three-quarters of the reviewed studies excluded farmers' knowledge, and structured participation remained rare. The dominance of statistical validation highlights the growing gap between prediction accuracy and practical application.

This discrepancy means rethinking validation as not merely a technical but also a social procedure. The use of these models for assessing the quality or suitability of land may be enhanced by combining computational modelling with experience; incorporating farmer knowledge into methodological standards will further enable such frameworks to be both scientifically rigorous and practically viable.

These results are significant because smallholder farming is widespread throughout Sub-Saharan Africa, where integration of farmers could be constrained, cutting-edge modeling methods can ignore variability at regional scales or experiential data in high information areas like Europe and Australia; a more place-based approach that combines technological systems with local knowledge may prove to enhance agricultural decision-making globally.

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