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Review article

Can Machine Learning See Maladaptation? A Systematic Evidence Map of AI in Global South Agricultural Adaptation to Climate Change

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Abstract

Climate change threatens agriculture and rural livelihoods across the Global South, and machine learning (ML) is increasingly deployed to support climate adaptation. Nevertheless, the literature has not systematically mapped whether ML reaches beyond upstream hazard prediction into the downstream stages where adaptation outcomes and maladaptation become visible. This article develops a PRISMA-guided systematic evidence map of AI/ML in Global South agricultural adaptation. A Scopus search using a four-block Boolean string (ML/AI, climate hazard, adaptation/livelihood, and agrarian population) returned 310 records. Records were screened through three eligibility layers (topical relevance, climate-adaptation relevance, and Global South relevance) and were coded according to the deepest stage of the adaptation cycle reached. At the current evidence-mapping stage, 241 records were retained. The studies are dominated by publications from 2024-2026 and are concentrated in India, China, Pakistan, and Ethiopia. ML is heavily concentrated upstream: hazard prediction and monitoring (151 studies; 62.7%) and adaptation decision-making (82 studies; 34.0%). Downstream stages are almost empty: only 6 studies (2.5%) address vulnerability assessment, 2 studies (0.8%) evaluate adaptation outcomes, and none (0.0%) evaluate maladaptation. Within this mapped corpus, machine learning cannot yet see maladaptation: it predicts hazards but remains largely disconnected from the livelihood consequences of adaptation responses. Future research should shift ML from predictive accuracy toward causal, longitudinal, and justice-sensitive evaluation of adaptation outcomes.

Keywords: machine learning; artificial intelligence; climate change adaptation; maladaptation; rural livelihoods; Global South; systematic evidence map.

1. Introduction

Climate change represents a structural pressure that increasingly defines agriculture and rural livelihoods across the Global South. Evidence spanning several decades demonstrates that rising temperatures, shifting precipitation patterns, and the increasing frequency and intensity of droughts and floods significantly reduce agricultural productivity, with projections indicating a continued deterioration through the mid-century (Fischer *et al.,* 2005; Wiebe *et al.,* 2015; Moore *et al.,* 2017). This burden is unevenly distributed: low-income agrarian regions bear the brunt of the impact on food security, particularly in West Africa and the Horn of Africa (Sultan & Gaetani, 2016; Alemu & Mengistu, 2019; Onyutha, 2019). This threat is felt most acutely by smallholder farmers and pastoralists who rely on climate-sensitive resources and whose adaptive capacities are already constrained (Jakariya *et al.,* 2020; Derbile *et al.,* 2022; Das, 2026). Data-driven projections suggest that maximum temperatures and drought stress will continue to rise in many low-income agrarian regions, exacerbating already high levels of vulnerability (Shah, 2025). In arid regions such as the Sahel rangelands and North African oases, land degradation and desertification are further narrowing the basis for pastoral and agropastoral livelihoods (Lo *et al.,* 2022; Moumane *et al.,* 2026).

In response, climate change adaptation has become a central agenda item for policy and research, ranging from local farmers' strategies and the adoption of climate-smart agricultural technologies to transformative adaptation at the system level (Alam *et al.,* 2017; Khatri-Chhetri *et al.,* 2017; Panda, 2018). Conceptually, adaptation can be understood as a phased cycle: climate hazard and risk assessment, vulnerability assessment, adaptation decision-making, strategy implementation, and evaluation of livelihood outcomes. Ideally, every stage of this cycle should be supported by sufficient evidence to ensure that adaptation genuinely reduces vulnerability rather than merely shifting it. Studies have also shown that shifting temperatures and rainfall patterns have already altered productivity, accounting for fluctuations and yield losses in many crops globally (Xie, *et al.,* 2025; Hultgren *et al.,* 2025). As a result, adaptation strategies, such as developing climate-resilient crop varieties and adopting agroforestry or crop rotation practices, are continuously promoted to mitigate the impacts of climate change on food security (Charoenratana & Kharel, 2024).

Over the past decade, artificial intelligence (AI) and machine learning (ML) have emerged as promising tools to support this cycle. Their capacity to process high-dimensional data from satellite imagery, sensors, and historical records makes them exceptionally robust, particularly for prediction. ML is now widely utilized to monitor and predict droughts (Naresh, 2026; Shahfahad, 2024; Kundu *et al.,* 2024), forecast rainfall and precipitation (Garai, 2024; Jumadi *et al.,* 2025; Sutanto *et al.,* 2025; Jumadi *et al.,* 2026; Nafea *et al.,* 2026), project crop yields under climate stress (Samrin, 2026; Xie *et al.,* 2025), map soil salinity and agroforestry land through remote sensing (Nguyen *et al.,* 2025; Uthappa *et al.,* 2025; Mehedi *et al.,* 2024), and support village-level water governance (Singh, 2026; Zhang, 2026). Studies in related domains, such as urban flood prediction, show a similar shift from physical process-based models toward ML-based approaches (Putra *et al.,* 2024; Anik *et al.,* 2025). This momentum is reflected in a recent surge of publications, with the majority of studies appearing between 2024–2026. This trend also aligns with literature on digital agriculture and decision-support systems, which demonstrates an accelerated use of AI, sensors, and recommendation systems in agriculture; however, most remain oriented toward technical optimization and accuracy (Talaviya *et al.,* 2020; Zhai *et al.,* 2020; Parra-López *et al.,* 2024).

However, this is precisely where a systematically unmapped problem lies. The strength of ML is sharply concentrated on one side of the adaptation cycle: hazard prediction. Conversely, the other side—the evaluation of livelihood outcomes and maladaptive consequences—remains virtually untouched. ML can predict when a drought will occur, but it rarely assesses whether the chosen adaptation strategies actually improve livelihoods or instead generate unintended harm. Studies touching upon farmer adaptation decision-making remain limited (Mkondiwa, 2025; Dudu, 2026; Ramalebo, 2026), and those addressing distortions in the adaptation process—for instance, how misinformation and information asymmetry skew adaptation decisions among smallholder farmers—are still very scarce (Ullah *et al.,* 2026). The concept of maladaptation—adaptation that, instead of reducing vulnerability, shifts, magnifies, or creates new vulnerability—is practically absent from the ML literature; even studies that touch on the resilience of water systems stop at strengthening predictive capacity, without linking it to maladaptive outcomes (Zhang, 2026).

This asymmetry is significant because it has direct implications for adaptation justice and effectiveness. When ML only "sees" hazards but remains "blind" to the socio-economic consequences of adaptation responses, there is a risk that technological investment reinforces the technocratic side of adaptation while ignoring fundamental questions: adaptation for whom, and at what cost? ML-based vulnerability assessments are indeed developing (Begum *et al.,* 2026; Jakariya *et al.,* 2020), but they generally stop at mapping biophysical exposure and have yet to link this to livelihood outcomes or maladaptation pathways systematically. In other words, the ability of ML to "see" maladaptation—to anticipate, detect, or evaluate it—remains an almost empty territory.

Although ML literature for climate-smart agriculture is growing rapidly, the existing knowledge base remains fragmented into four clusters that rarely communicate directly. First, research in AI and digital agriculture primarily evaluates technical performance in yield prediction, irrigation optimization, remote sensing, and decision-support systems (Talaviya *et al.,* 2020; Zhai *et al.,* 2020; Parra-López *et al.,* 2024). Second, literature on climate-smart and climate-resilient agriculture discusses adaptation practices, food security, and sustainability, but does not systematically examine how algorithmic systems shift evidence priorities across the adaptation cycle (Sahoo *et al.,* 2025; Pervez *et al.,* 2026). Third, literature on climate services demonstrates that data-driven information can shape agrarian decisions, yet evaluation of livelihood outcomes and maladaptation risks remains limited (Bunn *et al.,* 2019; Gioli & Bettini, 2026). Fourth, studies on maladaptation and adaptation justice have developed robust conceptual critiques but remain insufficiently connected to the ML literature. Consequently, there is no systematic evidence map showing whether the growth of ML in agricultural adaptation is actually moving beyond prediction toward the evaluation stages where adaptation success, distributional impacts, and maladaptation are determined.

This gap is more than just a bibliographic deficiency. It signals an epistemic problem: ML makes certain aspects of adaptation highly visible—namely hazards, biophysical patterns, and predictive signals—while slower, relational, and political aspects such as livelihood impacts, inter-group trade-offs, and maladaptive lock-ins remain obscured. Thus, the key question is not just how accurately ML predicts climate risk, but whether ML can evaluate the consequences of the adaptation responses it helps to inform.

Building on this gap, this study is positioned as a global systematic evidence map regarding the application of ML and AI in climate adaptation for agriculture in the Global South. Rather than evaluating the model's technical performance, this study maps where ML is present and where it disappears across the adaptation cycle and empirically tests the question posed in the title: can machine learning "see" maladaptation? Specifically, this study is directed to answer the following research questions:

1. At which stages in the climate adaptation cycle (hazard prediction, vulnerability assessment, decision-making, implementation monitoring, outcome evaluation, and maladaptation evaluation) is ML applied in Global South agriculture?
2. Which ML techniques, data sources, and climate hazards dominate, and for which regions and livelihood systems?
3. To what extent does ML literature touch upon the evaluation of adaptation outcomes, livelihoods, distribution of benefits/risks, and maladaptation?
4. Where are the structural gaps in the evidence base, and what research agenda should be prioritized so that ML not only predicts hazards but also evaluates adaptation consequences?

This study offers three contributions. Conceptually, this article reframes ML in agricultural adaptation not as a neutral technological tool, but as an epistemic infrastructure that makes certain parts of adaptation visible while leaving others invisible. Methodologically, this article develops a coding framework that places each study at the deepest stage of the adaptation cycle it has reached and distinguishes among hazard prediction, vulnerability assessment, decision support, implementation monitoring, outcome evaluation, and maladaptation evaluation. Empirically, this article demonstrates that the ML-adaptation evidence base is concentrated on upstream prediction and is extremely weak with respect to livelihood outcomes and adaptation justice. Thus, this study shifts the agenda from the question of "how accurately does ML predict climate risk" to the question of "can ML evaluate the consequences of the adaptation it helps shape?"

2. Methods

2.1. Review Design: PRISMA-Guided Systematic Evidence Map

This study employs a PRISMA-guided systematic evidence map, incorporating a narrative synthesis to delineate the distribution of empirical evidence: specifically, identifying where machine learning (ML) is integrated into the climate adaptation cycle, pinpointing areas of evidence scarcity, and determining where evaluation of maladaptation is absent. Reporting adheres to the PRISMA guidelines (Page *et al.,* 2021), while research questions and eligibility criteria were formulated utilizing a PICoS framework modified specifically for the ML-adaptation domain. The review protocol was established prior to data extraction and encompassed the search strategy, eligibility criteria, screening process, coding framework, quality appraisal, and sensitivity analysis.

2.2 Data Sources and Search Strategy

The primary search was conducted via the Scopus database, selected for its comprehensive coverage of peer-reviewed literature across the disciplines of agriculture, environmental science, geography, remote sensing, and computer science. The search string was constructed using four conceptual blocks linked by the AND operator: (i) ML/AI, (ii) climate hazards or stressors, (iii) adaptation/livelihoods/food security, and (iv) agrarian populations. An exclusion block was utilized to omit research concerning genomics, plant breeding, pure plant physiology, disease/pest/weed detection, and generic image classification, as these topics lack a direct nexus with climate adaptation. Consequently, the findings should be interpreted as a conservative evidence map of ML studies that explicitly bridge agriculture, climate hazards, adaptation, and agrarian livelihoods.

```
TITLE-ABS-KEY (
  ( "machine learning" OR "deep learning" OR "artificial intelligence"
    OR "neural network*" OR "random forest" OR "support vector machine*"
    OR "gradient boosting" OR "ensemble learning" OR "data-driven model*"
    OR LSTM OR "convolutional neural" )
) AND TITLE-ABS-KEY (
  ( "climate change" OR "climate variability" OR drought OR flood*
    OR "rainfall variability" OR "extreme weather" OR "heat stress"
    OR "climate risk*" OR "climate hazard*" )
) AND TITLE-ABS-KEY (
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 ( adaptation OR adaptive OR maladaptation OR maladaptive
   OR "coping strateg*" OR "adaptation strateg*" OR "adaptation decision*"
   OR "adaptive capacity" OR "food secur*" OR livelihood* )
) AND TITLE-ABS-KEY (
 ( smallholder* OR farmer* OR pastoral* OR agropastoral* OR peasant*
   OR "rural communit*" OR "rural household*" OR agrarian
   OR "farm household*" OR "rural livelihood*" )
)
AND NOT TITLE-ABS-KEY (
 ( genom* OR genotyp* OR phenotyp* OR "gene expression" OR transcriptom*
   OR proteom* OR "molecular marker*" OR "plant breeding" OR cultivar*
   OR "abiotic stress toleran*" OR photosynth* OR germplasm
   OR "disease detection" OR "pest detection" OR "leaf disease"
   OR "weed detection" OR "image classification" )
)
AND ( LIMIT-TO ( LANGUAGE , "English" ) )
AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "re" ) )
AND PUBYEAR > 2010
```

2.3. Eligibility Criteria and Screening Layers

Study eligibility was assessed through three screening layers: topical relevance, climate-adaptation relevance, and Global South relevance. This layered approach mitigates the risk of conflating general precision agriculture studies with climate adaptation studies that are genuinely relevant to livelihoods. The core corpus was restricted to peer-reviewed empirical articles in English published after 2010. Review articles, editorials, commentaries, and studies lacking empirical data were not coded as primary evidence but were utilized for background synthesis and snowballing.

2.4. Study Selection Process and Coding Reliability

The study selection process and the number of records at each stage are summarized in Figure 1. All records were managed using reference management software (Ouzzani *et al.,* 2016), and deduplication was performed based on DOI, title, and fuzzy title matching. Subsequently, all records passing title-abstract screening were evaluated via full-text screening, with exclusion reasons explicitly recorded: not Global South, not ML/AI, not climate adaptation context, not agriculture/rural livelihoods, precision agriculture without an adaptation dimension, review/non-empirical, or insufficient information.

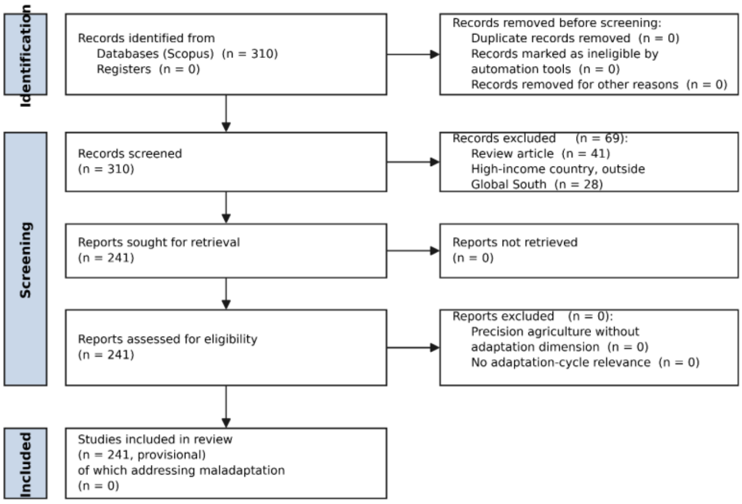

Figure 1. PRISMA workflow for literature selection.

2.5. Data Extraction and Adaptation Cycle Coding Framework

Data were extracted using a standardized form covering bibliometric attributes, geographic location, livelihood systems, climate hazards, data sources, ML techniques, unit of analysis, evaluated outcomes, and the deepest stage of the adaptation cycle reached. The primary categorization used the principle of the "deepest stage reached," in which each study was placed at the deepest stage genuinely analyzed, rather than merely mentioned. Supplementary multi-label coding was applied to ML techniques, hazard types, data sources, and outcome indicators.

To map the linkages between agrarian livelihood systems and the climate hazards examined, the entire 310-record corpus was multi-label coded across two axes: nine livelihood systems and seven hazard categories. A tree diagram was utilized as an analytical classification framework to code ML application throughout the climate adaptation cycle. Each study was classified based on the deepest stage reached, ranging from upstream functions (hazard prediction, vulnerability assessment, and decision-making) to downstream functions (implementation monitoring, outcome evaluation, and maladaptation evaluation). This framework enables the review to distinguish between studies that merely predict climate stressors or support adaptation choices from those that genuinely assess whether adaptation is implemented, improves livelihood outcomes, or generates unintended maladaptive consequences.

2.6. Coding Maladaptation Visibility

Maladaptation was coded not merely as an explicit term, but as a level of visibility regarding the negative consequences of adaptation. This framework distinguishes between studies that do not mention maladaptation, studies that only provide a conceptual mention of trade-offs, studies that provide proxies for potential maladaptation, and studies that genuinely evaluate maladaptation empirically. This approach is necessary because maladaptation often emerges as a delayed, relational, and distributional process rather than as a stable, single label.

2.7. Methodological Quality Appraisal

An ML-adaptation quality appraisal framework was designed to be applied at the full-text stage, assessing ten domains: adaptation relevance, population relevance, hazard specification, data transparency, ground-truth quality, validation design, interpretability, livelihood linkage, justice sensitivity, and maladaptation visibility. Each domain is scored on a scale of 0–3: 0 = absent, 1 = weak/implicit, 2 = adequate, 3 = strong. Scores are not utilized to mechanically exclude studies but serve as a basis for sensitivity analysis and interpretation of the strength of evidence.

2.8. Synthesis Strategy and Sensitivity Analysis

Synthesis was conducted narratively and based on evidence mapping. Planned primary outputs include: (i) a heatmap of adaptation cycle stage x region x climate hazard; (ii) a matrix of ML technique x adaptation stage; (iii) a matrix of data source x adaptation stage; (iv) a "downstream visibility index" ranging from 0 to 5, where 0 = hazard only and 5 = maladaptation evaluation; and (v) a summary of geographic, methodological, and outcome gaps. To test the robustness of conclusions, sensitivity analysis will be performed during the full review by repeating primary results after excluding review articles, ambiguous precision-agriculture studies, studies lacking full-text verification, global studies without an explicit focus on the Global South, and studies with low quality scores.

As an additional bibliometric diagnostic, impact per country is calculated using the citations per paper (CPP) indicator—total Scopus citations for a country divided by the number of papers mapped to that country. Study countries were identified from titles, abstracts, and keywords, rather than author affiliation addresses, to ensure the map better represents empirical study locations. Global records, multi-country records without specific locations, or those not geographically identifiable were excluded from the country map. The CPP indicator is used to interpret relative bibliometric influence, not as a direct measure of substantive quality or adaptation effectiveness.

Table 1. PICoS framework and eligibility criteria.

PICoS Component	Inclusion Criteria	Exclusion Criteria
Population	Agriculture, smallholder farmers, pastoralists, agropastoralists, farm households, rural communities, and agrarian livelihood systems in the Global South.	High-income country contexts as primary focus; non-agrarian populations; laboratory studies without livelihood context.
Interest	Application of ML/AI at any stage of the climate adaptation cycle: hazard prediction, vulnerability, decision-making, implementation, outcome, or maladaptation.	Studies without ML/AI; pure smart/precision agriculture without climate-adaptation relevance; pest/disease/weed detection without climate stress context.
Context	Climate hazards or stressors in agrarian systems: drought, flood, rainfall variability, heat, salinity, water scarcity, food security risk.	Non-climate hazards: genetics, plant physiology, breeding, or pure plant biology experiments.
Study design	Peer-reviewed empirical articles, in English, published after 2010.	Reviews, editorials, commentaries, proceedings without empirical data; used only for state-of-the-art and snowballing.

Table 2. Three screening layers to distinguish ML-adaptation from general precision agriculture.

Screening Layer	Operational Question	Decision
Topical relevance	Is ML/AI applied to agriculture, farmers, pastoral/agropastoral, rural livelihood, food security, or water/agricultural risk?	Include if yes; exclude if agricultural technology is unrelated to agrarian populations/systems.
Climate-adaptation relevance	Is the study related to climate change, climate variability, drought, flood, heat, rainfall, salinity, water scarcity, or livelihood risk?	Exclude if only smart farming/standard production optimization without adaptation dimension.
Global South relevance	Is it focused on LMIC/Global South countries, or global studies with explicit analysis of the Global South?	Exclude if the focus is primarily on high-income countries or if the location cannot be determined.

Table 3. Coding framework for the deepest stage of the adaptation cycle.

Code	Adaptation Cycle Stage	Operational Definition	Practical Inclusion Criteria
S0	Not adaptation-relevant / excluded	ML for agriculture but without a clear link to climate adaptation or livelihood risk.	General smart farming, greenhouse automation, pest/weed/leaf disease detection, genomics/breeding.
S1	Hazard prediction & monitoring	ML predicting or monitoring biophysical hazards/stressors.	Drought, rainfall, heat, flood, salinity, crop stress, yield loss as climate risk proxies.
S2	Vulnerability, exposure & impact assessment	ML assessing who/where is vulnerable, exposed, or impacted.	Vulnerability index, risk hotspot, crop-failure risk, food-security risk, household exposure.
S3	Adaptation decision & planning	ML supporting adaptation choices or predicting decisions/adoption.	DSS, climate advisory, crop choice, irrigation planning, insurance, adoption/participation prediction.
S4	Implementation monitoring	ML monitoring actual implementation of adaptation strategies.	Adoption/implementation tracking, agroforestry uptake, irrigation implementation, land-use adaptation.
S5	Adaptation outcome evaluation	Studies evaluating adaptation outcomes on livelihood/welfare/resilience.	Income, food security, water security, yield stability, reduced loss, adaptive capacity after intervention.
S6	Maladaptation evaluation	Studies examining negative consequences, trade-offs, harm, lock-in, or vulnerability transfer.	Inequality, resource depletion, risk displacement, exclusion, debt, loss of autonomy, delayed harm.

Table 4. Maladaptation visibility score.

Score	Label	Definition
0	No maladaptation visibility	Does not mention or measure maladaptive consequences.
1	Conceptual mention	Mentions maladaptation, trade-offs, harm, or unintended consequences but does not measure them.
2	Proxy-based visibility	Measures indicators that could suggest maladaptation but does not explicitly draw a conclusion.
3	Empirical maladaptation evaluation	Explicitly tests and interprets evidence of maladaptation.

Table 5. Operational indicators of maladaptation for full-text coding.

Indicator	Operational Definition	Example Proxy
Vulnerability transfer	Adaptation by one group increases risk for another group.	Water conflict, downstream water loss, risk displacement, unequal access.
Social exclusion	The benefits of adaptation reach only those with capital or large landholdings.	Gender gap, landholding bias, digital divide, exclusion from advisory/insurance.
Resource depletion	Short-term benefits degrade supporting resources for adaptation.	Groundwater depletion, soil degradation, salinity increase, biodiversity loss.
Economic lock-in	An adaptation strategy creates cost/technology/input dependencies.	Debt, high irrigation costs, dependence on proprietary DSS, subsidy lock-in.
Exposure intensification	Adaptation response encourages expansion into higher-risk areas.	Cropland expansion into flood- and drought-prone areas.
Temporal rebound	Short-term benefits turn into long-term losses.	Short-term yield gain but long-term vulnerability increase.
Loss of local autonomy	Predictive systems replace local knowledge without co-production.	Top-down advisory, reduced farmer agency, distrust in climate services.
Ecological/emissions trade-off	Adaptation increases environmental externalities.	Diesel pumping, energy-intensive irrigation, fertilizer intensification.
Food-security trade-off	Commodity production increases but household diet diversity/nutrition decreases.	Cash-crop substitution, monocropping, reduced subsistence food.
Maladaptive information pathway	Information, misinformation, or asymmetry leads to poor adaptation decisions.	False advisories, unequal access to climate information, distorted adoption.

Table 6. ML-adaptation quality appraisal framework.

Appraisal Domain	Assessment Question
Adaptation relevance	Does the study truly relate to climate adaptation, rather than just production optimization?
Population relevance	Are the agrarian, rural, or livelihood populations clearly explained?
Climate-hazard specification	Is the climate hazard/stressor explicitly defined?
Data transparency	Are data sources, period, resolution, and variables explained?
Ground-truth quality	Are labels, field observations, or outcome validation adequate?
Validation design	Is the model tested with temporal/spatial splits, external validation, or valid validation design?
Interpretability	Does the study explain drivers, feature importance, uncertainty, or explainability?
Livelihood linkage	Are there indicators for income, food security, yield stability, water access, adaptive capacity, or welfare?
Equity/justice sensitivity	Does the study differentiate impacts by gender, class, landholding, location, or access inequality?
Maladaptation visibility	Does the study detect trade-offs, harm, lock-in, displacement, or vulnerability transfer?

3. Results

3.1. General Characteristics and Keyword Landscape

The corpus is dominated by very recent publications: 70 studies were published in 2025 and 53 in 2026, whereas only 14 studies existed prior to 2020. This surge confirms that the application of ML to agricultural climate adaptation in the Global South has exploded in the last two years, making this mapping synthesis particularly timely (Figure 2).

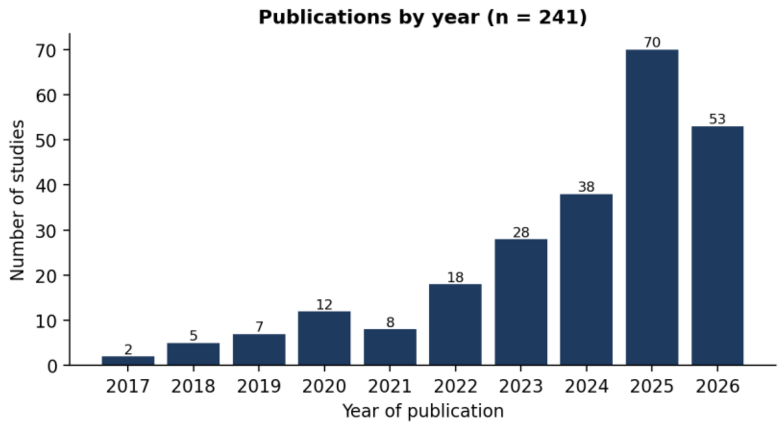

Figure 2. Distribution of the 241 included studies by year of publication.

The keyword landscape of the corpus (Figure 3) reinforces the field's orientation. The most prominent terms center on prediction and technique (machine learning, climate change, food security, remote sensing, crop yield, forecasting, drought, and random forest), while terms marking the downstream side of the adaptation cycle, such as "livelihood" and "adaptation strategies," appear significantly smaller. The term "maladaptation" is virtually absent. This keyword map visually confirms the field's shift in attention toward predictive capacity rather than outcome evaluation.

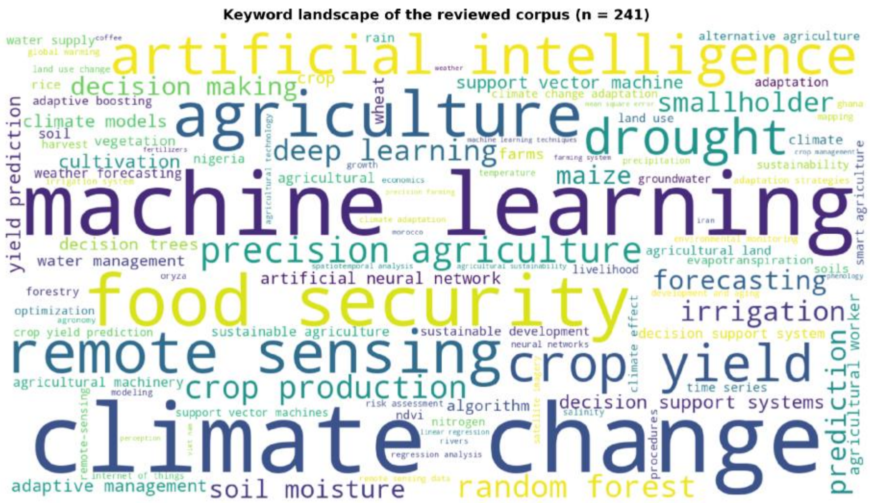

Figure 3. Keyword landscape of the reviewed corpus. Prediction- and technique-oriented terms dominate; outcome- and maladaptation-related terms are marginal or absent.

3.2. Geographic Distribution

Geographically, evidence is concentrated in a limited number of countries: India (37 studies), China (25), Pakistan (12), and Ethiopia (12) are prominent, followed by Bangladesh, South Africa, Nigeria, and Ghana (Figure 4). Regionally, Africa (65 studies) and South Asia (58 studies) dominate, while Latin America (4 studies) and small island nations are virtually unrepresented Figure 5; 72 studies are global in scope or do not specify a location. This disparity mirrors patterns well established in the climate vulnerability literature (Jakariya *et al.,* 2020; Das, 2026) and simultaneously identifies geographic gaps that necessitate prioritization.

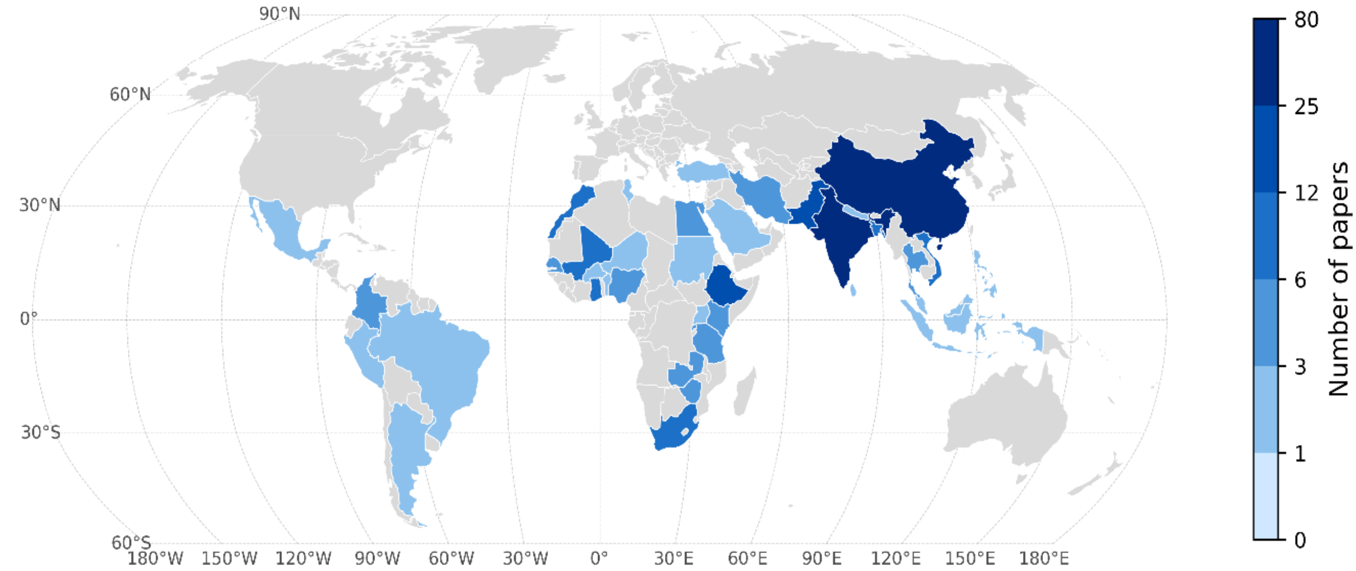

Figure 4. Geographic distribution of the included studies across the Global South (country-level study counts).

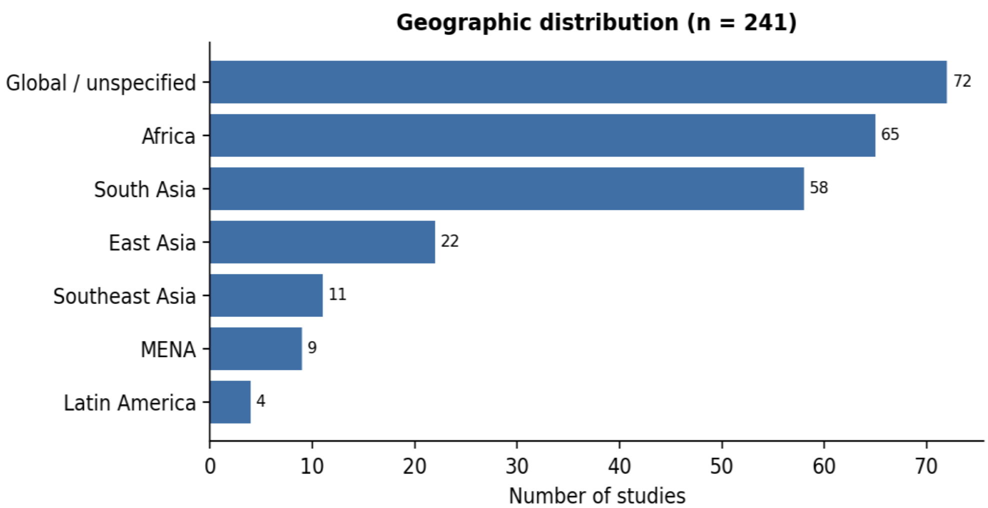

Figure 5. Regional aggregation of the included studies.

Beyond the absolute number of studies, geographic distribution was also analyzed for bibliometric impact using the Citations per Paper (CPP) indicator. This mapping is critical because publication volume does not necessarily align with the intensity of scientific influence; a country may produce numerous papers with low average citations, whereas countries with smaller publication outputs may generate higher impact per paper.

The CPP map reveals a pattern distinct from the absolute volume map. India remains a primary hub by volume (36 articles in the mapped subset). However, its CPP is relatively moderate (11.5), suggesting that quantitative dominance does not automatically translate to the highest citation intensity per paper. China shows a similar pattern: high volume (24 articles) but a lower CPP (6.3), indicating a broader yet less concentrated influence than in smaller corpora. Conversely, Vietnam stands out with the highest CPP among countries with at least five papers (36.4), followed by Bangladesh (22.8), Ghana (21.3), Ethiopia (17.7), and South Africa (12.8). This pattern indicates that studies that are more contextual and concentrated on specific regions can attain relatively strong bibliometric influence despite lower absolute volumes. Consequently, geographic inequality in the ML-adaptation literature is not merely a question of where studies are produced, but which countries serve as the primary references in shaping the scientific agenda.

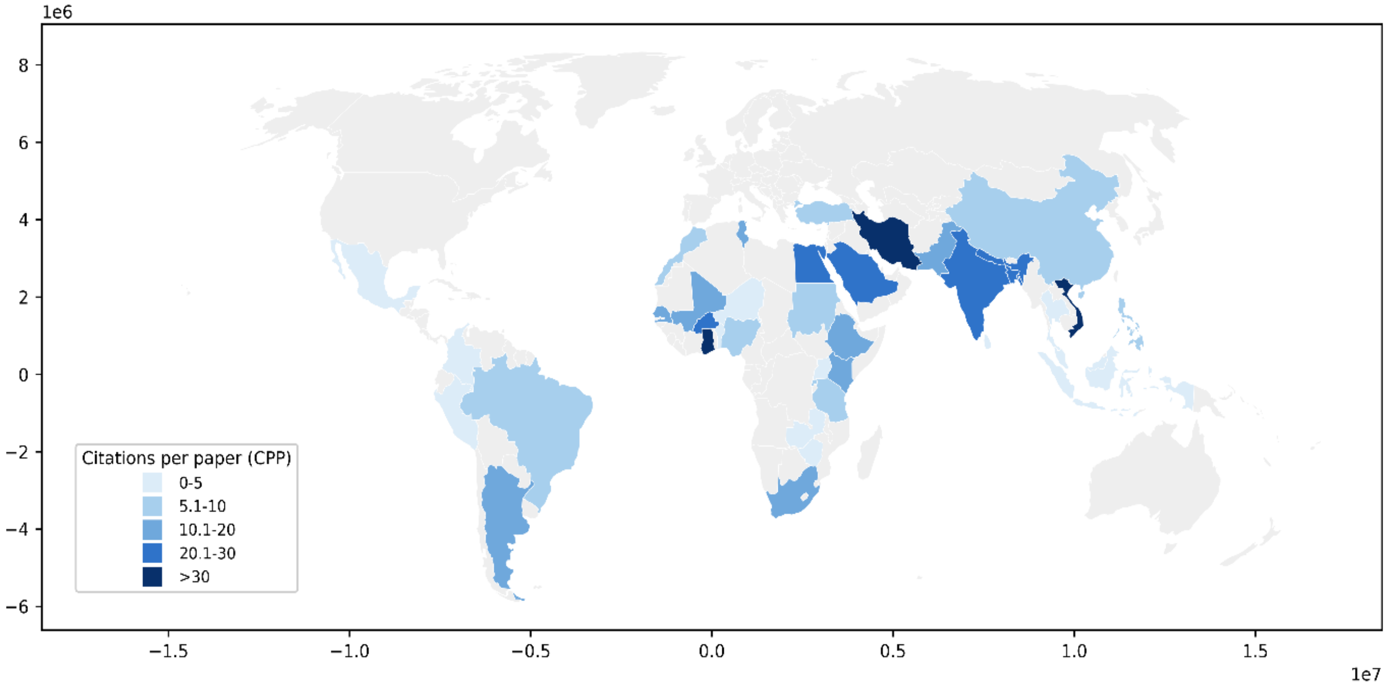

Figure 6. Country-level citation impact across the Scopus article corpus. Color indicates citations per paper (CPP), and graticules show geographic coordinates; global or unspecified records are excluded from the country map.

3.3. ML Techniques and Climate Hazards

The most frequently employed techniques are random forest (96 studies), followed by regression and other ML models (85), deep learning/neural networks (73), boosting/ensemble methods (67), and support vector machines (30) (Figure 7). Regarding climate hazards, the majority of studies are framed within the context of general climate change (192), followed by rainfall variability (76), heat/temperature (70), water and salinity (66), drought (60), and flood (16) (Figure 8). The dominance of drought and water-related hazards over flood is consistent with the focus on rainfed agriculture in arid regions.

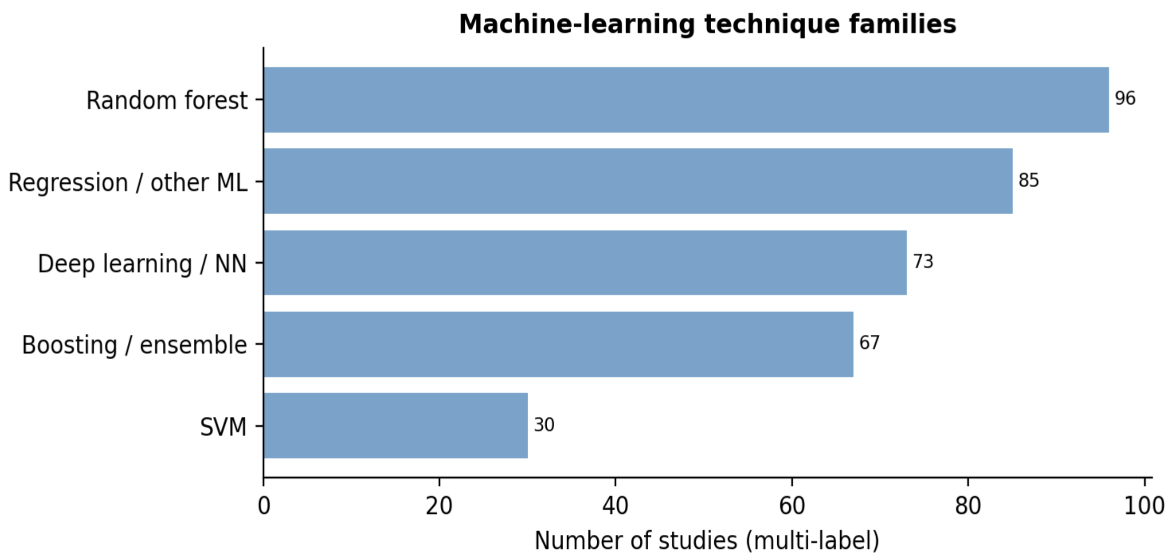

Figure 7. Machine-learning technique families across the corpus (multi-label).

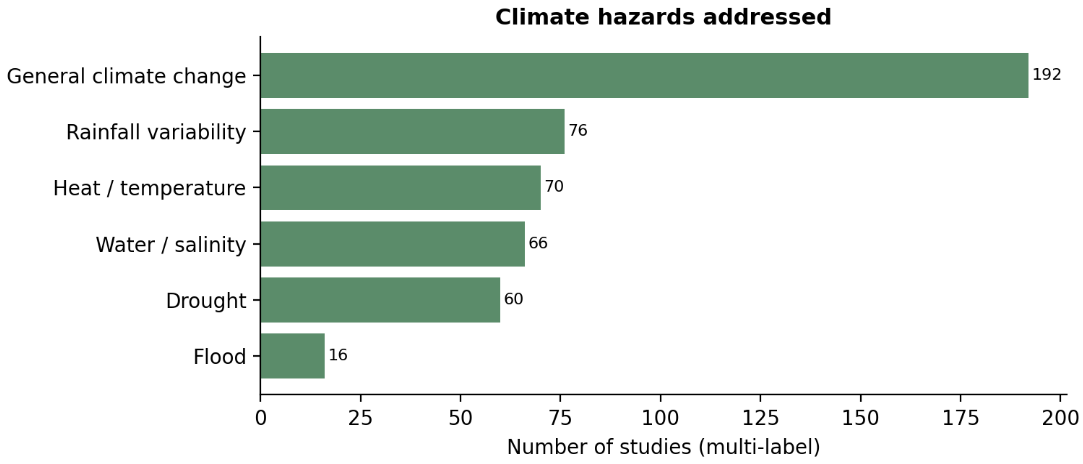

Figure 8. Climate hazards addressed across the corpus (multi-label).

3.4. Livelihood–Climate Hazard Matrix

As explained in Subsection 2.5, the livelihood–hazard matrix was coded for the entire corpus and is presented in Figures 9 and 10. Since a single study may address multiple livelihood systems and multiple hazards (257 of 310 studies addressed multiple livelihood systems, and 117 addressed multiple hazards), the matrix contains 1,129 study–hazard links rather than a count of individual studies (Figure 9). The distribution is heavily concentrated in two rows: smallholder crop farming (440 links) and food-security/household livelihood (321 links), which together account for approximately two-thirds of all links. Conversely, the systems most exposed to adaptation trade-offs—coastal/delta farming (35), agroforestry/tree-crop systems (20), mixed rural livelihoods (43), and pastoral/agropastoral systems (47) are sparsely represented.

Regarding hazards, one column dominates the landscape: "general climate change / multiple hazards" accounts for 588 of 1,129 links (52.1%), followed by drought (193; 17.1%) and water scarcity (134; 11.9%), while flood (46; 4.1%) and particularly salinity/sea-level stress (18; 1.6%) remain nearly empty. In other words, more than half of the links do not pair a specific livelihood with a specific climate stressor, but rather with a generalized framing of climate change.

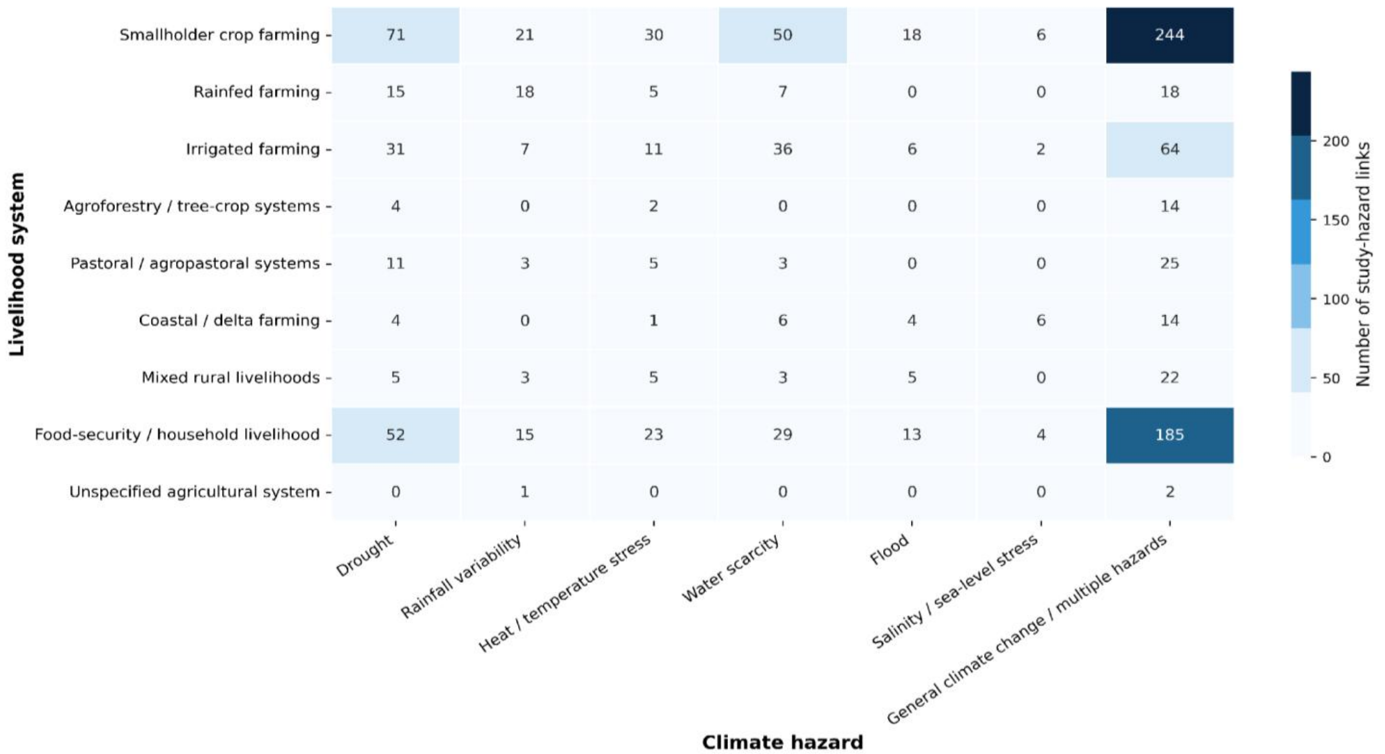

Figure 9. Livelihood–hazard evidence matrix (study–hazard link counts) across the full 310-record corpus; cells are multi-label. Evidence concentrates in the smallholder crop farming and food-security/household livelihood rows and in the "general climate change / multiple hazards" column.

Row-wise normalization (Figure 10) sharpens the pattern of specialization for each livelihood system. Although the absolute volume is small, coastal/delta farming is the only system proportionally linked to both salinity/sea-level stress (17.1% of its links) and water scarcity (17.1%); rainfed farming is most inclined toward rainfall variability (28.6%) and drought (23.8%); irrigated farming toward water scarcity (22.9%); and pastoral/agropastoral systems toward drought (23.4%). However, in almost every row, the "general climate change / multiple hazards" category accounts for the largest share (approximately 40% to 70%, except for rainfed farming at 28.6%), indicating that even when specific livelihoods are identified, hazards are often treated in aggregate.

This pattern reinforces the study's main argument from a different perspective. First, the dominance of the "general climate change / multiple hazards" column indicates a lack of granularity: the literature tends to frame hazards in aggregate rather than linking specific stressors to specific livelihood systems, even though it is precisely at this coupling that adaptation trade-offs and potential maladaptation become evaluable. Second, the two hazards most closely linked to irreversible consequences and vulnerability displacement—salinity/sea-level stress (1.6%) and flood (4.1%)—are the least investigated, meaning that maladaptation pathways typical of coastal and deltaic regions, such as salinity intrusion and land loss, are almost entirely unmapped. Third, livelihood systems where adaptation trade-offs are likely to be sharpest (coastal/delta, pastoral/agropastoral, agroforestry, and mixed livelihoods) are the least well represented. At the same time, evidence accumulates for systems that are relatively easy to measure (smallholder crop farming and household food security indicators). Thus, the livelihood–hazard matrix not only completes the map of "who is studied against what" but also signals that the blind spots in the corpus coincide with the loci where maladaptation is most likely to occur.

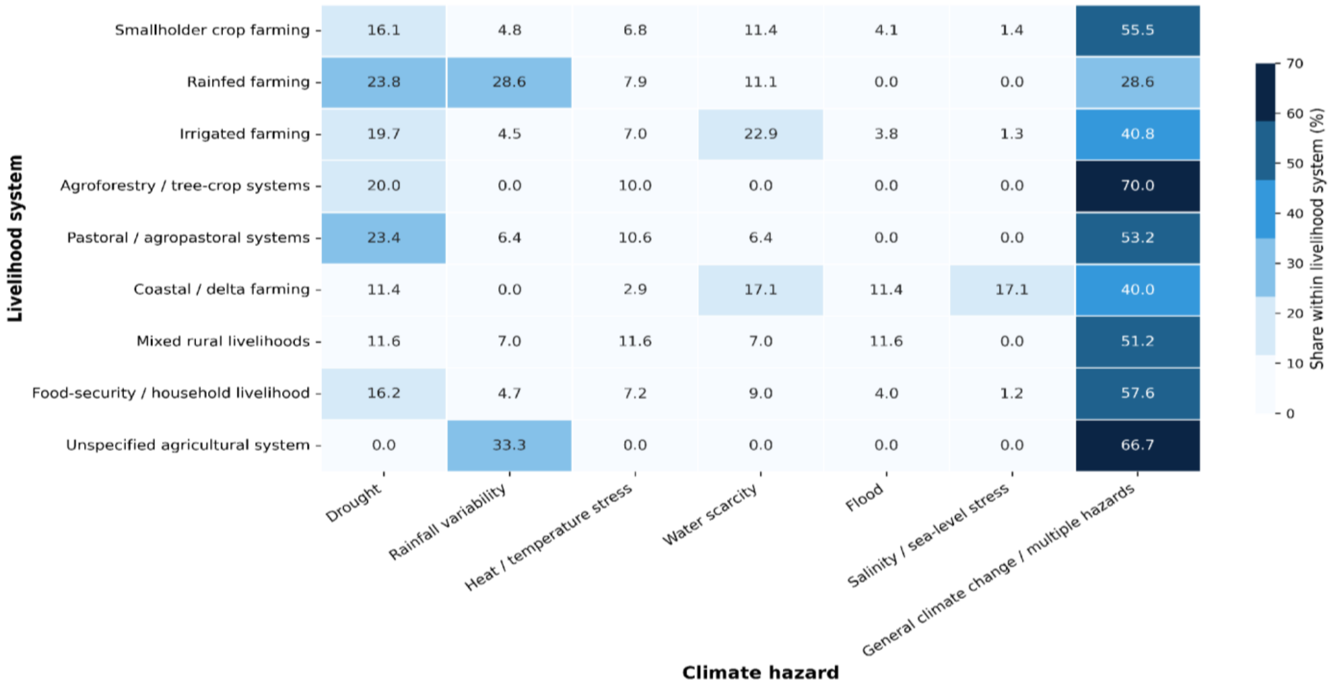

Figure 10. Livelihood–hazard evidence matrix, row-normalized (%). Each cell shows the share of a livelihood system's study–hazard links attributable to a given hazard. The "general climate change / multiple hazards" category absorbs the largest share in almost every row.

Figure 11 maps the intersections between themes within the corpus, rather than merely their frequency. As the coding is multi-label, thematic overlap serves as the most informative indicator of how the field constructs its object of study. Within the climate-hazard theme (panel a), the strongest intersection occurs between drought, water scarcity, and the general climate change frame: drought and water scarcity co-occur in 28 studies. In comparison, drought and the general frame appear in 45 studies.

Conversely, salinity/sea-level stress (6 studies) and flood (21 studies) lie at the periphery of the network and barely intersect with other themes. A similar pattern is repeated in the livelihood theme (panel b): smallholder crop farming and food-security/household livelihood form a very dense core with 196 shared studies, while coastal/delta farming, agroforestry, pastoral, and mixed rural livelihoods attach only thinly to this core. Panel (d) confirms this at the level of crosscoupling: of the twelve strongest livelihood–hazard couplings, almost all center on smallholder farmers, food security, and irrigation paired with drought, water scarcity, or heat stress. Panel (c) demonstrates the structural consequence in the knowledge map. The co-occurrence weight between the technique–hazard prediction cluster and the adaptation–food–decision cluster is 1,360, which exceeds the internal weights of either cluster (1,089 and 1,038). This implies that these two groups have practically merged into a single upstream core, while the yield-forecasting cluster is much looser (internal weight 91). Analytically, thematic overlap functions as a centripetal force: it draws research attention to the predictive center while leaving coastal, salinity, agroforestry, and pastoral themes in the rare periphery. It is precisely in this periphery that adaptation trade-offs are most pronounced, thereby reinforcing the finding that the corpus's blind spots coincide with the loci where maladaptation is most likely to occur.

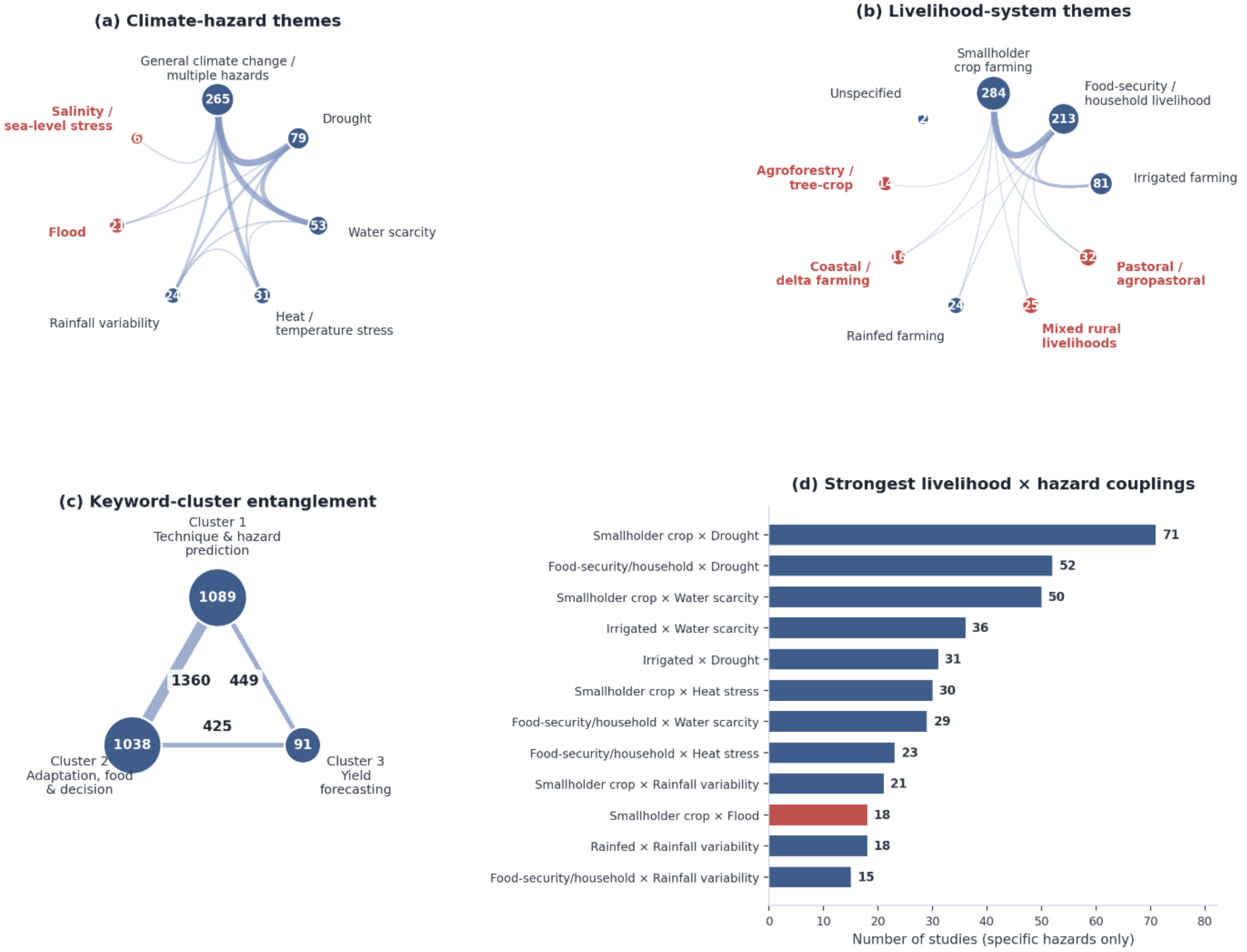

Figure 11. Overlapping themes in the ML–adaptation evidence base. (a) Climate-hazard themes and (b) livelihood-system themes: node size denotes the number of studies addressing a theme and ribbon width denotes the number of studies addressing both themes. (c) Entanglement among the three detected keyword clusters: node values are within-cluster co-occurrence weights and link values are across-cluster weights. (d) The twelve strongest livelihood-hazard couplings for specific hazards. Coding is multi-label across the full 310-record corpus.

3.5. The Position of ML in the Adaptation Cycle

The tree diagram in Figure 12 illustrates that the application of machine learning (ML) within the climate adaptation cycle is not confined to hazard prediction; conceptually, it can also be extended to evaluating adaptation consequences. The six themes presented—hazard prediction, vulnerability assessment, decision-making, implementation monitoring, outcome evaluation, and maladaptation evaluation—demonstrate a shift from upstream functions, which are primarily predictive and technical, to downstream functions, which are evaluative and normative. Analytically, this diagram asserts that the capacity of ML to predict drought, flooding, rainfall variability, or vulnerability hotspots is insufficient to substantiate adaptation success, as adaptation effectiveness can only be appraised when implementation, livelihood outcomes, food security, resilience, and potential adverse impacts—such as vulnerability transfer, social exclusion, resource depletion, and technological lock-in—are explicitly evaluated. Consequently, this diagram reinforces the article's central thesis: that the ML-adaptation literature remains robust at stages amenable to measurement and modeling, yet underdeveloped at downstream stages that ultimately determine whether adaptation genuinely reduces vulnerability or degrades into maladaptation.

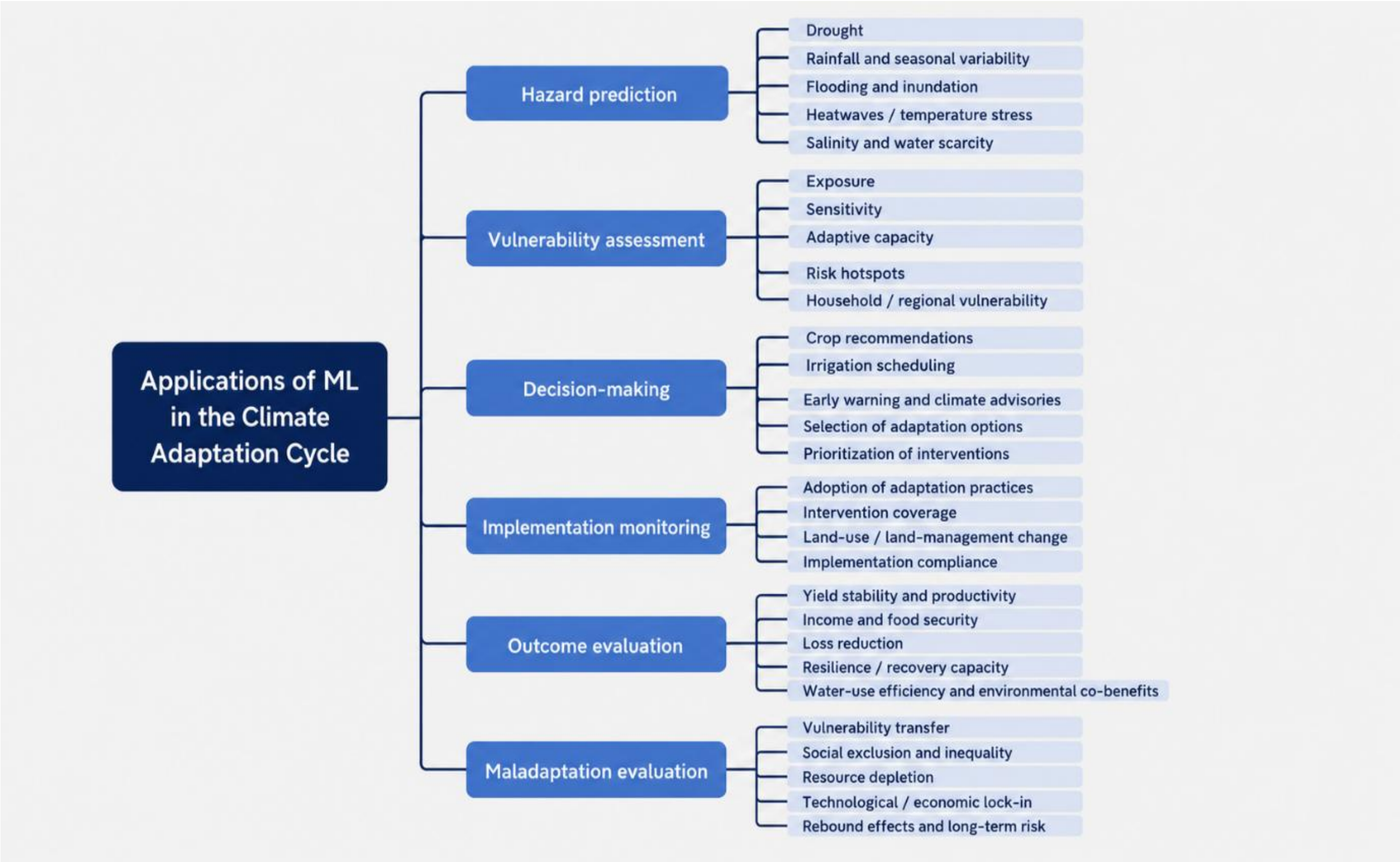

Figure 12. Conceptual tree diagram of machine-learning applications across the climate adaptation cycle and maladaptation evaluation.

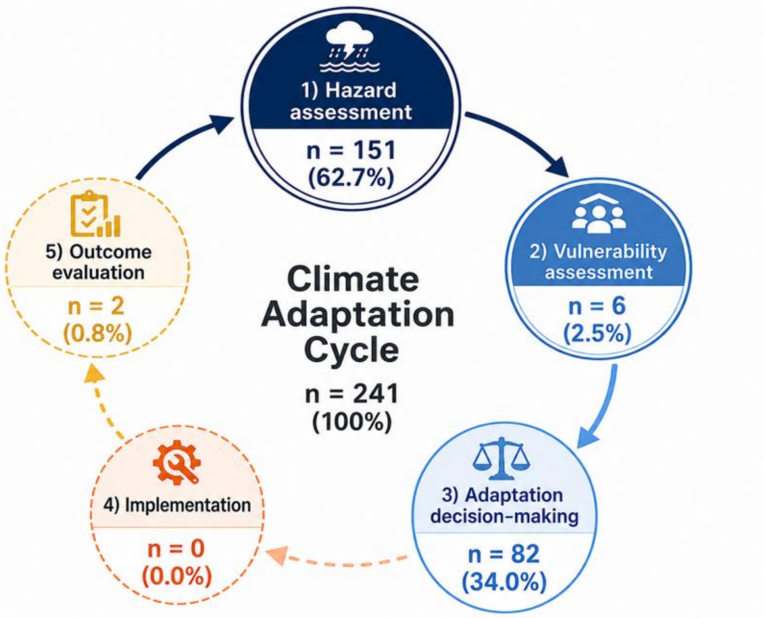

Figure 13. Climate adaptation cycle and the number of studies coded at the deepest stage reached. Upstream stages dominate the evidence base, while implementation and outcome evaluation are nearly absent.

To address the first research question, each study was coded mutually exclusively based on the deepest stage of the adaptation cycle attained: hazard assessment, vulnerability assessment, adaptation decision-making, implementation monitoring, outcome evaluation, and maladaptation evaluation. The results reveal a sharp disparity Figure 13. Of the 241 studies, 151 (62.7%) terminate at hazard assessment/prediction; 6 (2.5%) reach vulnerability assessment; 82 (34.0%) are situated in adaptation decision-making and planning; no studies (0.0%) evaluate implementation; only 2 (0.8%) evaluate adaptation outcomes; and no studies (0.0%) evaluate maladaptation. Thus, upstream cycle stages (hazard assessment, vulnerability, and decision-making) account for 239 studies (99.2%), while downstream stages (implementation monitoring, outcome evaluation, and maladaptation evaluation) account for only 2 studies (0.8%).

4. Discussion

The cycle diagram in Figure 13 transforms quantitative findings into a conceptual diagnosis: the current ML-adaptation literature does not move through the adaptation cycle as a whole. It concentrates upstream—generating predictions, risk mapping, and decision information—but rarely follows the chain of evidence toward implementation and outcomes. This pattern is critical because adaptation success is not determined by prediction accuracy alone, but by whether information alters action, whether that action is executed, and whether it reduces vulnerability without creating new harm. In other words, the collapse of evidence from 99.2% at the upstream stage to 0.8% at the downstream stage is not merely a bibliometric description, but a symptom of deeper conceptual, epistemological, and political problems.

4.1. Can Machine Learning "See" Maladaptation? The Problem of Operationalization

Evidence answers the title question directly: at present, ML cannot "see" maladaptation. However, beneath that 0% figure lies a problem more fundamental than mere scarcity, namely the intrinsic difficulty of operationalizing maladaptation as an object that machines can learn. Recent conceptual literature asserts that maladaptation is not a binary category easily labeled, but a process that is contextual, delayed, and relational: an adaptation action is only revealed as maladaptive when it displaces vulnerability to another group, locks in a detrimental development trajectory, or erodes future adaptive capacity (Rouzaneh *et al.,* 2024). This definition—which is constantly being "redefined"—implies that the maladaptation label depends on value frameworks, timescales, and who is harmed —dimensions not captured by the supervised learning paradigm, which demands stable and measurable labels.

Here, the corpus findings gain theoretical significance. Studies linking resilience, vulnerability, and adaptation indicate that adaptation outcomes can only be assessed longitudinally relative to livelihood trajectories (Hung, 2024), while concrete cases reveal how interventions that appear adaptive can become maladaptive when the time horizon is extended (Scott *et al.,* 2024). ML, which excels in mapping static patterns from abundant data, is not structurally designed to capture such counterintuitive dynamics. Most illuminating are studies on climate services: archetype analyses show that even data-driven information systems can produce maladaptation when they reduce adaptation decisions to predictive outputs without accounting for social context (Biella *et al.,* 2024). These findings extend the argument: it is not only climate services that are at risk, but the entire wave of ML applications we mapped, as 99.2% of them terminate before the very stage that determines whether adaptation succeeds or backslides into harm. In other words, ML's inability to "see" maladaptation is not an oversight that can be corrected with more studies, but rather a fundamental incompatibility between the relational-temporal nature of maladaptation and the predictive paradigm that dominates this field.

4.2. Prediction–Evaluation Asymmetry as an Epistemic Bias of AI

The prediction–evaluation asymmetry shown in Figure 13 reflects a broader critique of AI epistemology: the tendency to optimize what is easily measured rather than what is most important. Hazard prediction is a supervised learning problem well-suited to abundant, standardized, and relatively clearly labeled satellite imagery and climate data. Conversely, evaluating implementation, livelihood outcomes, and maladaptation demands longitudinal socio-economic data, causal tracing, and normative judgments about who benefits and who bears the costs. Therefore, the roughly 120:1 ratio between upstream evidence (239 studies) and downstream evidence (2 studies) is not just a numerical disparity but an indicator that the ML research culture is more comfortable producing predictions than verifying the consequences of adaptation.

The implication is that claims that ML "supports adaptation" must be read with caution. A model can predict drought, map harvest risks, or recommend irrigation. However, without evidence of implementation and outcomes, such studies cannot demonstrate that adaptation genuinely occurs, or that vulnerability is reduced. The vacuum at the implementation stage (n = 0) is significant: it severs the attribution chain linking the information the model produces to changes on the ground. The vacuum in outcome evaluation (n = 2) weakens claims of social benefit, because adaptation success must ultimately be measured through yield stability, income, food security, water security, or household adaptive capacity, not merely by the model's prediction accuracy.

Critical AI literature supports and deepens this reading. Studies on AI for sustainable development warn that data-driven technologies tend to pursue efficiency and measurable accuracy while ignoring dimensions of justice and context that are harder to quantify (Bachmann *et al.,* 2022; Wilson *et al.,* 2022). Calls for "human-centered" AI arise precisely because systems optimized for technical metrics often fail to serve deeper social goals (Mhlanga, 2022). In the agricultural domain, surveys of AI, digital agriculture, and decision-support systems show a similar pattern: technology is discussed primarily as an instrument for optimization, recommendation, and efficiency improvement, not as a tool for evaluating socio-ecological consequences (Talaviya *et al.,* 2020; Zhai *et al.,* 2020; Parra-López *et al.,* 2024). Even discourse on AI sustainability itself is largely focused on computational footprints and energy efficiency (Verdecchia *et al.,* 2023; Richie, 2022), rather than on the distributive consequences of its application. Our findings provide systematic, corpus-scale evidence for critiques that have hitherto been largely theoretical: the ML-adaptation field not only has the potential for epistemic bias but measurably allocates most of its attention to the upstream of prediction and abandons the evaluation side.

4.3. Implications for Adaptation Justice and Governance

The evaluation blind spot is not merely a methodological issue; it has direct implications for adaptation justice. When ML guides "when and where hazards arrive" without assessing "who benefits or suffers from the response," the technology risks reinforcing the technocratic side of adaptation while closing off distributive and procedural questions. Adaptation justice literature shows that interventions appearing technically neutral can produce displacement and dispossession: nature-based solutions, for example, can trigger resource grabbing if justice is not integrated from the outset (Anguelovski *et al.,* 2023), and access to ecosystem services is often systematically inequitable (Nazmul Haque et al., 2024). These mechanisms—transferring vulnerability from one group to another—constitute the essence of maladaptation, and this is precisely what remains invisible to all studies in our corpus, as none of the 241 studies reached the maladaptation evaluation stage.

This disparity operates across scales. Studies of adaptation funding reveal multi-scalar inequities, in which resources flow to interventions that are easy to measure and report rather than to those most needed by vulnerable communities (Venner *et al.,* 2024). When ML systems prioritize "measurable" hazard prediction, there is a real risk that the same allocation logic is reproduced algorithmically. Conversely, transformative adaptation literature emphasizes the importance of building community capacity and local agency (Ziervogel *et al.,* 2022), as well as recognizing societal resistance as a legitimate form of adaptation (Mills-Novoa *et al.,* 2025), dimensions that are inherently difficult to reduce to model features. Empirical examples from coastal Bangladesh, where salinity erodes household food security, confirm that livelihood outcomes ultimately determine adaptation success (Lam *et al.,* 2022)—exactly the metric absent from the corpus. Our findings thus challenge the solutionist narrative that ML automatically strengthens resilience: without the capacity to evaluate outcomes, such claims (Zhang, 2026) remain largely untested and potentially mask inequality rather than reducing it.

The livelihood–hazard matrix (Figures 9–10) systematically strengthens this concern: coastal/delta systems and salinity hazards—the exact context of the aforementioned Bangladesh case—are among the least studied in the corpus, meaning the maladaptation pathways most damaging to livelihoods are the least "visible" to the ML literature. Bibliometric impact dimensions deepen the reading of geographic justice. The CPP map shows that centers of volume and centers of influence do not always coincide: India and China dominate in terms of the number of papers, but citation intensity per paper is higher in smaller countries such as Vietnam, Bangladesh, Ghana, and Ethiopia. Analytically, this suggests two points. First, the Global South ML-adaptation agenda is not solely driven by countries with the largest publication volumes; studies that provide strong empirical context, use rare datasets, or make clear methodological contributions can be relatively more influential. Second, CPP should not be read as an indicator of adaptation success, as citations are influenced by publication age, journal reputation, open access, and the size of the research community. However, the misalignment between volume and

CPP reinforces this study's key message: ML-adaptation evidence is not only spatially unequal but also unequal in how it forms knowledge authority and research priorities.

4.4 Toward a Machine Learning That Can See Maladaptation: Knowledge Gaps and Research Agenda

Beyond the aggregate distribution in Figure 13, the knowledge structure of the field can be read directly from the corpus keyword bibliometrics. Three complementary visualizations—the co-occurrence network Figure 14, temporal evolution overlay Figure 15, and concentration density map Figure 16 triangulate the location of the actual knowledge gap, thereby guiding the most urgent future research directions. The most striking finding is straightforward: of the 55 keyword nodes in this map, not a single node signifies maladaptation, livelihood, outcome, welfare, equity/justice, gender, vulnerability, or evaluation. The vocabulary of the downstream adaptation cycle is literally absent from the field's semantic map, a qualitative confirmation of the evidence collapse shown quantitatively in Figure 13.

The co-occurrence network Figure 14 is organized into three tightly interconnected clusters, all of which are situated upstream: (i) the technique–hazard prediction core (ML, random forest, remote sensing, support vector machine, artificial neural network, drought, soil moisture); (ii) the adaptation–food–decision cluster (climate change, food security, AI, precision agriculture, irrigation, decision making, adaptive management, smallholder farmers, decision support systems); and (iii) the yield-forecasting cluster (crop yield, forecasting, yield prediction, deep learning, wheat). The strongest links, namely climate change–ML (weight 60), climate change–food security (49), climate change–crops (39), and ML–food security (34), all reside within the nexus of prediction and food supply. Crucially, there are no nodes for maladaptation, livelihood, outcome, welfare, income, equity, gender, or evaluation. Thus, the knowledge gap is not merely quantitative (few studies), but semantic-structural: the field does not even have a lexicon for naming downstream outcomes. Future research directions should introduce and standardize a downstream lexicon (livelihood outcome, vulnerability transfer, adaptation outcome, distributional effect) so that outcomes and maladaptation become categories that can be named, coded, and eventually learned by machines.

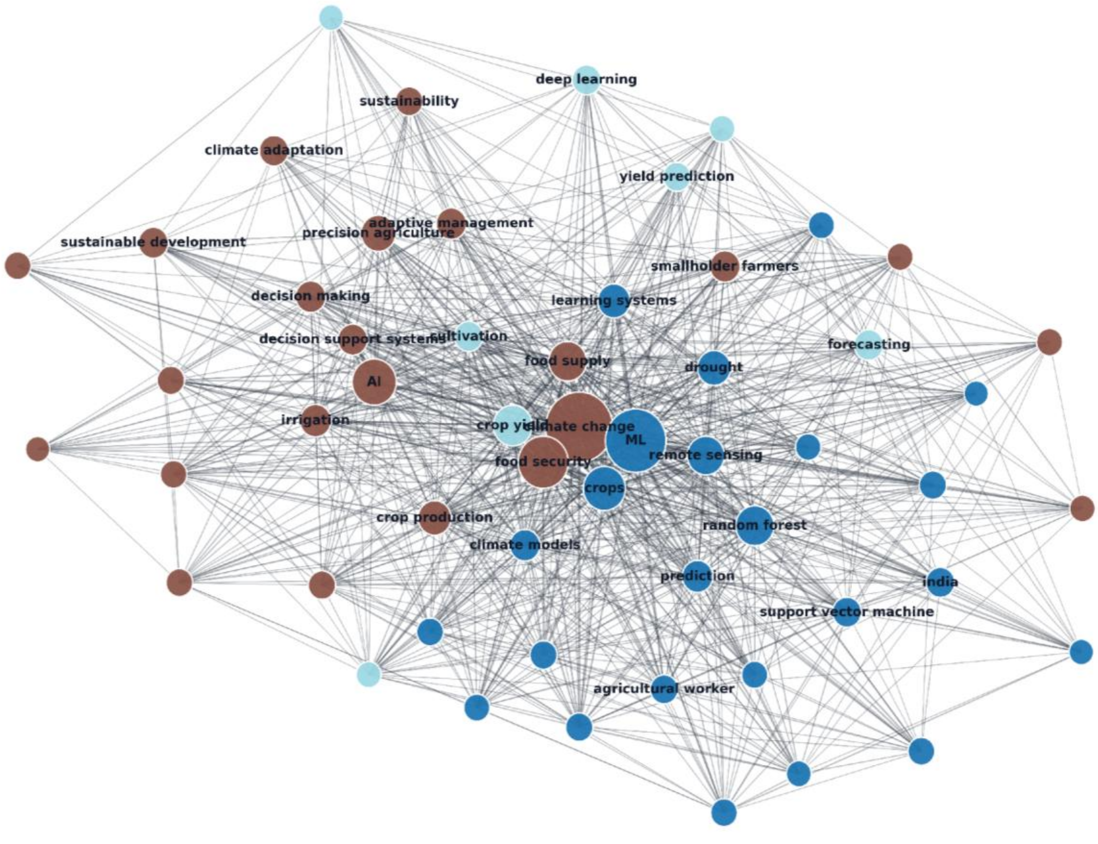

Figure 14. Network visualization of keyword co-occurrence. Node size denotes term frequency, edge thickness denotes co-occurrence strength, and color denotes the detected topic cluster.

Figure 15 shows the topic evolution overlay. The overlay colors nodes based on the average publication year, thereby highlighting the field's leading edge. The most current front (2025–2026) is dominated by agricultural machinery (avg. 2025.6), smart agriculture (2025.4), sustainable agriculture (2025.3), learning systems (2025.1), and deep learning (2024.7), all of which remain technique- and production-oriented. This means that even the newest wave reproduces the upstream orientation; the field is not self-correcting toward outcome evaluation. The only faint social turn is the appearance of "smallholder farmers" (2024.8) and "climate adaptation" (2024.1) in the more recent range, but these are not accompanied by any outcome or maladaptation vocabulary. Analytically, the prediction–evaluation gap is widening, not narrowing: more sophisticated models (deep learning, learning systems) deepen predictive capacity without extending to downstream consequences. Future research directions should intentionally steer the growing frontier, particularly the deep learning and learning systems wave, toward causal and outcome-based longitudinal tasks, for instance, through funding calls and datasets that incentivize outcome evaluation rather than merely predictive accuracy.

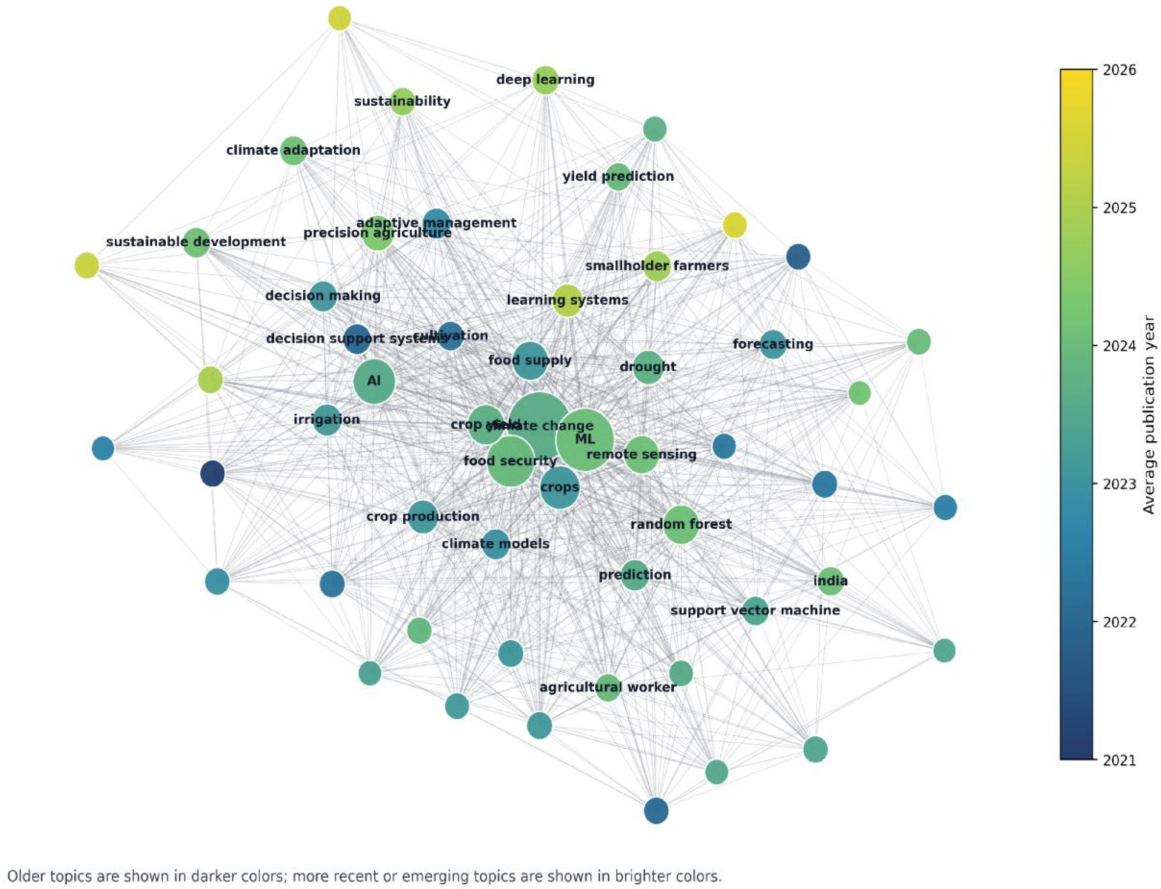

Figure 15. Overlay visualization of topic evolution. Nodes are colored by average publication year (darker = older, brighter = more recent).

The density map Figure 16 displays a single hotspot centered on climate change–ML–crops–food security–remote sensing—the nodes with the highest frequency and degree (climate change: 146; ML: 118; food security: 77). The field's intellectual gravity is locked into the prediction–technique–hazard nexus, while social, evaluative, and place-specific vocabulary are in the cold periphery or absent entirely. This concentration confirms that what is monopolized upstream is not only the number of studies but also research attention. Future research directions should shift analytical attention from the dense predictive core toward the sparse periphery, where questions of livelihood, justice, and maladaptation must be built—a redistribution of research attention that complements the geographic coverage redistribution discussed in Sub-section 4.3.

These three visual readings unify a single diagnosis: the knowledge gap in ML-adaptation literature is structural (downstream vocabulary is absent), temporal (even the latest frontier remains upstream), and attentional (intellectual gravity is locked into prediction). Proceeding from this diagnosis, we formulate six research directions to shift ML from the upstream of prediction to the downstream of evaluation.

First, methodologically, the field needs to adopt causal and counterfactual inference frameworks, rather than mere predictive correlation, to ask whether an adaptation strategy genuinely improves livelihoods or, conversely, causes harm. Second, data integration needs to be strengthened: blending remote sensing with longitudinal socio-economic data, farmer knowledge, and local knowledge can bridge the gap between biophysical prediction and livelihood evaluation (Iticha & Husen, 2019; Alvarez *et al.,* 2026). Studies combining artificial and collective intelligence for irrigation and drought adaptation also suggest potential for more deliberative hybrid designs (Polo-Murcia *et al.,* 2026). Third, data infrastructure is a prerequisite: without FAIR, longitudinal data linked to well-being indicators, outcomes, and maladaptation will remain difficult for machines to learn (Hu *et al.,* 2023). Fourth, the scope of outcomes must be expanded to food-security crises, diet, and livelihood consequences, not just yield or hazard signals (Busker *et al.,* 2024; Khan *et al.,* 2025).

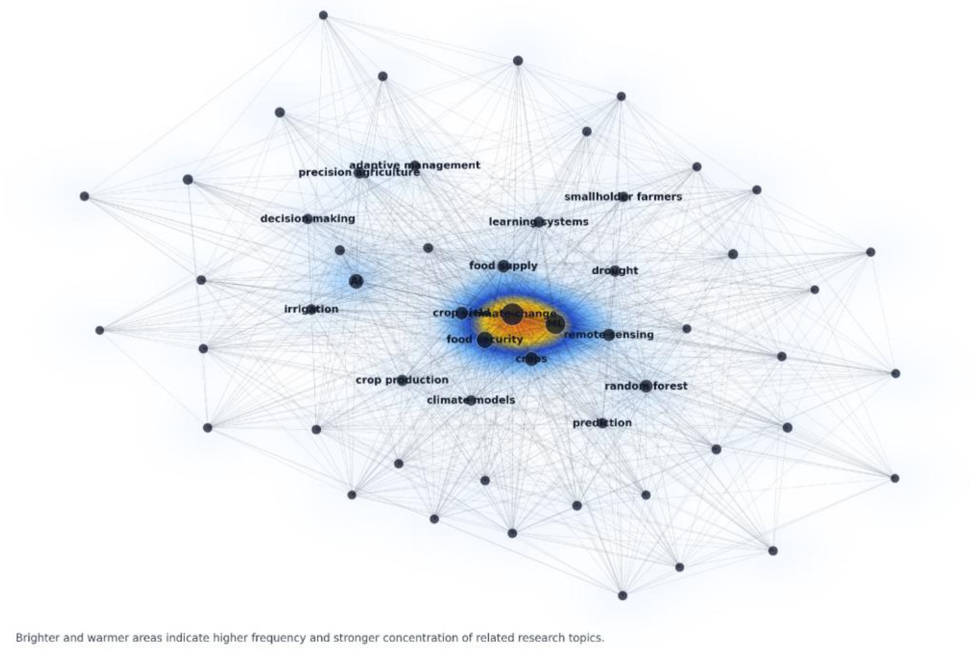

Figure 16. Density visualization of keyword concentration. Brighter and warmer areas indicate higher frequency and stronger concentration of related terms. A single dominant hotspot forms around the climate change-ML-crops-food security-remote sensing nexus, showing that research attention, not only study counts, is monopolized by the upstream predictive core.

Fifth, transparency and governance. Because adaptation decisions concern the equitable allocation of resources, ML systems at the downstream stage require greater interpretability and accountability than purely predictive models. The development of explainable AI (Yenkikar *et al.,* 2025) and principles for AI governance (Sousa-Pinto *et al.,* 2025) provide a foundation. However, they need to be adapted specifically for the context of just adaptation. Sixth, empirical coverage must be expanded to include underrepresented regions: Latin America, small island nations, agroforestry landscapes, and dryland livelihoods, where trade-offs are often sharpest (Kmoch *et al.,* 2024; Imbach *et al.,* 2017). Reviews of adaptation implementation in response to extreme heat show that the evidence base for implementation and evaluation lags behind that for prediction (Turek-Hankins *et al.,* 2021). Making maladaptation "visible" to machines, therefore, is not merely a technical challenge, but a socio-technical project that simultaneously demands new data, methods, and governance.

5. Conclusion

This study conducts a systematic evidence map of machine learning applications in climate change adaptation for agriculture in the Global South, mapping 241 studies across six stages of the adaptation cycle: hazard assessment, vulnerability assessment, decision-making, implementation monitoring, outcome evaluation, and maladaptation evaluation. The core findings are firm and consistent: ML application is highly concentrated in upstream stages, particularly hazard assessment/prediction (151 studies; 62.7%) and adaptation decision-making (82 studies; 34.0%), while downstream stages are nearly empty. The implementation stage has no coded studies (0.0%), outcome evaluation appears in only 2 studies (0.8%), and maladaptation evaluation is nil (0.0%), implying that there is still a lack of studies applying machine learning to maladaptation evaluation. Thus, 99.2% of the evidence resides in upstream stages, while only 0.8% reaches the downstream stages. The keyword landscape and geographic distribution reinforce this pattern: the field is dominated by prediction and technique vocabulary, centered in a handful of countries such as India, China, Pakistan, and Ethiopia, and under-reaches Latin America and small island nations.

The results indicate that ML can predict the hazards that trigger adaptation needs but is nearly blind to the consequences of adaptation responses themselves, including the possibility that adaptation might displace or magnify vulnerability. This structural blind spot is significant because it lies precisely at the cycle stage most decisive for adaptation justice and effectiveness. Consequently, the future research agenda must direct ML capacity from the upstream of prediction toward the downstream of evaluation: developing livelihood outcome indicators that machines can learn, blending remote sensing with longitudinal socio-economic data, building causal frameworks to tag maladaptive adaptations, and expanding coverage to underrepresented regions.

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Author Contributions

Conceptualization: Musiyam, M., Amin, C., Fikriyah, V. N., Rohman, A., Nugroho, M. T., & Jumadi J; **methodology**: Musiyam, M., Amin, C.; **investigation**: Musiyam, M., Fikriyah, V. N., Jumadi J; **writing—original draft preparation**: Musiyam, M., Rohman, A., Nugroho, M. T., & Jumadi J; **writing—review and editing**: Musiyam, M., Amin, C., Fikriyah, V. N., Rohman, A., Nugroho, M. T., & Jumadi J; **visualization**: Musiyam, M., Jumadi J. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

Generative AI Declaration

During the preparation of this work the author(s) used Claude.ai and ChatGPT to generate python visualization code and language editing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data availability

Data and visualization scripts are available at:

https://colab.research.google.com/drive/1SyYU1NJSRi6du3hxquVH0upNR2JrtXMQ?usp=sharing

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