



Agricultural Flood Damage Assessment: A Systematic Review of Methods, Coverage, and Integration Gaps

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Abstract. Agricultural flooding causes tens of billions of dollars in annual losses globally, yet the methods used to assess these losses systematically capture only a fraction of their true economic scope. This systematic review synthesizes 65 peer-reviewed studies published between 1984 and 2025 to evaluate how agricultural flood damage is measured, what damage categories are covered, and where critical methodological gaps persist. We find a structural asymmetry across the reviewed literature — all 65 reviewed studies address direct immediate damages — primarily crop yield loss estimated through depth-damage functions or remote sensing — while direct induced effects appear in only 8 studies, indirect damages in 9, and intangible damages in fewer than 5. This asymmetry has persisted for four decades, through a major remote sensing revolution, because the dominant methods are structurally incapable of measuring damage categories beyond direct immediate losses. We introduce a Methods-by-Damage-Category Matrix that maps eight assessment methods against five damage categories, making the coverage gap visible and providing a diagnostic framework for method selection. Three post-2013 damage frontiers — long-term land productivity degradation, supply chain finance disruption, and farmer mental health — are identified as emerging categories warranting dedicated methodological development. Existing agricultural flood damage estimates used in benefit–cost analyses and disaster compensation are systematically downward-biased; closing this bias requires integrating remote sensing-based physical detection with economic valuation methods capable of capturing the full damage taxonomy.

1 Introduction

1.1 Agricultural flood damage: scale, trend, and policy stakes

Flooding is the world’s most economically damaging natural hazard, responsible for approximately \$1.3 trillion in losses and 218,000 deaths across 168 countries between 1990 and 2022 (Liu et al., 2024). Agriculture bears a disproportionate share of these losses — the Food and Agriculture Organization of the United Nations (FAO) estimates that floods caused around \$30 billion in agricultural damage across Africa, Asia, the Caribbean, Eastern Europe, the Near East, Oceania, and South America between 2007 and 2024 alone, surpassing all other natural disaster types in those regions (FAO, 2023). The magnitude of flood damage to agriculture has grown over time — an earlier FAO estimate placed agricultural flood losses at approximately \$21 billion for 2008–2018 (FAO, 2021) — a trend expected to accelerate as climate change increases both flood frequency and the concentration of agricultural production in flood-prone lowlands (Brémond et al., 2013; Fornino et al., 2024).

The United States illustrates the scale of the problem in a high-income context. Inland flooding caused approximately \$203 billion in total economic damage between 1980 and 2024 (NOAA, 2025), with agriculture accounting for a substantial share in productive regions. In Iowa alone, where agricultural enterprises cover 85% of the state’s land area, floods cause an estimated \$230 million in annual crop production losses on average (Yildirim and Demir, 2019). Single large events can dwarf these averages — the Great Flood of 1993 across the Midwest caused approximately \$7.2 billion in agricultural damage and triggered \$1.2 billion in Federal Emergency Management Agency (FEMA) expenditures (Sarmiento and Miller, 2006). The June 2024 Upper Midwest Flood, affecting Minnesota, South Dakota, and Iowa, caused a further \$1.2 billion in damage, illustrating that large-scale agricultural flood events remain a recurring feature of the contemporary risk landscape (NOAA, 2025).

Accurate estimates of agricultural flood damage are not merely academic — they are the direct inputs to benefit–cost analyses that justify flood protection investments, to disaster compensation schemes that determine farm



recovery support, and to insurance pricing that shapes farmers' risk management decisions (Brémond et al., 2013). Yet existing studies employ highly heterogeneous methods and define the scope of damage inconsistently, producing estimates that are often not comparable across regions, events, or time periods (Redondo-Tilano et al., 2025). This methodological fragmentation is not a minor technical concern — when damage estimates omit categories of loss — as they routinely do — the resulting benefit–cost ratios systematically misrepresent the economic case for flood risk management in agricultural regions. The nature, extent, and consequences of this fragmentation are the subject of this review.

1.2 State of knowledge and critical gaps

A decade of methodological progress since Brémond et al.'s (2013) foundational review of agricultural flood damage assessment — most notably the proliferation of satellite remote sensing (RS) and machine learning (ML) approaches — has substantially expanded the toolkit available to researchers. Yet when the literature is evaluated against the full taxonomy of agricultural flood losses, three persistent gaps remain unresolved, and a fourth, more fundamental problem has emerged from the convergence of two parallel research approaches that have not yet been integrated.

Methodological fragmentation between physical detection and economic valuation. Two largely separate research approaches have developed in parallel without converging. The first, rooted in engineering economics, relies on depth-damage functions (DDF) derived from field surveys or expert elicitation to estimate crop yield losses and, more rarely, damage to farm assets (Brémond et al., 2013). The second, emerging primarily after 2010, leverages RS and Geographic Information Systems (GIS) to map inundated cropland at scale and proxy damage through vegetation indices such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) (Rahman and Di, 2020). Each approach has well-documented limitations — DDF lack transferability across geographies and crop systems, while RS techniques produce physical damage indicators — flood extent, NDVI anomaly, inundated acreage — that stop short of economic valuation. The critical unresolved gap is the bridge between these approaches. No established protocol exists for converting remotely-sensed physical damage signals into economically meaningful loss estimates suitable for benefit-cost analysis or insurance pricing. This review is, to our knowledge, the first to systematically characterize this integration gap across the full spectrum of agricultural flood damage categories.

Thematic concentration in a narrow damage category. Damage assessment across the reviewed literature is heavily concentrated in a single category — direct immediate crop yield loss — and within that, in a narrow set of annual crops, principally rice, corn, and wheat. This reflects data availability and methodological convenience rather than the actual distribution of agricultural flood losses. Post-event surveys consistently document that farm-scale disruption — livestock losses, damage to agricultural buildings and machinery, delayed field operations, and cascading working capital constraints — can match or exceed crop yield losses in absolute terms, particularly during winter floods when standing crops are minimal (Posthumus et al., 2009; Gaviglio et al., 2019). The consequence is systematic underestimation of total agricultural flood damage, with direct implications for the accuracy of benefit-cost ratios used to justify flood risk management investments.

Geographic concentration and limited transferability. The reviewed literature is geographically skewed toward East, South, and Southeast Asia — particularly China, Vietnam, Bangladesh, and the Philippines — and the United States, which together account for over 60% of reviewed studies. South America is entirely absent despite its large flood-exposed agricultural systems, and Sub-Saharan Africa is represented by fewer than three studies. This is not merely a bibliographic observation — damage functions calibrated for irrigated rice in the Mekong Delta do not transfer to rain-fed maize in West Africa or soybean production in the Brazilian Cerrado without substantial modification. The transferability problem is compounded by the fact that most studies do not explicitly report their data requirements, making it difficult for practitioners in data-scarce regions to assess which methods are feasible in their context.

Absence of an integrating framework. Taken together, these gaps reflect a structural problem — the existing literature treats damage categories, assessment methods, and geographic contexts as independent domains — when flood risk management decisions require integrated estimates that span all three. A flood risk manager evaluating a levee setback program, an insurer pricing agricultural flood coverage, or a development agency allocating post-disaster recovery funds cannot use an estimate that covers only crop yield loss in rice, derived from a depth-damage curve calibrated in Japan and applied to a watershed in Myanmar. What the field lacks is an explicit mapping of



which methods are capable of capturing which damage categories, under what data conditions, and in which geographic contexts.

This study addresses these gaps through a systematic literature review of methods used to assess the economic damages of floods to agriculture, covering peer-reviewed journal articles published between 1984 and 2025 following Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines. Three contributions distinguish this review from its predecessors. First, whereas Brémond et al. (2013) reviewed economic damage methods prior to the remote sensing revolution and Rahman and Di (2020) reviewed RS methods without engaging economic valuation, this review explicitly bridges both traditions and maps their integration gap. Second, we introduce a Methods-by-Damage-Category Matrix (MDCM) — a novel analytical instrument that evaluates coverage, applicability, and data requirements of each method class across the full agricultural flood damage taxonomy. Third, we extend the geographic and methodological scope beyond previous reviews to include indirect, induced, and intangible damage categories and to assess the suitability of methods for data-scarce and lower-income agricultural contexts. The remainder of the paper is structured as follows: Section 2 presents the conceptual framework for agricultural flood damage classification; Section 3 describes the systematic review protocol; Section 4 presents results organized by damage category; Section 5 synthesizes findings and identifies priorities for future research; and Section 6 concludes.

2 Conceptualization of agricultural flood damages

2.1 The foundational taxonomy: three axes of damage classification

This section begins from the three-axis taxonomy introduced by Brémond et al. (2013) and then identifies three extensions warranted by post-2013 developments. Each axis reflects a genuine conceptual distinction with direct methodological consequences, but each also contains contested boundaries that the literature has not always treated consistently.

Tangible versus intangible damage. Tangible damages are those that can, in principle, be assigned a monetary value through market prices or their proxies — crop yield losses valued at farm-gate prices, repair costs for damaged buildings and machinery, and veterinary costs for affected livestock are canonical examples. Intangible damages, by contrast, resist monetary valuation — the psychological burden on farming households, the erosion of community cohesion in rural areas, and the loss of non-market ecosystem services provided by agricultural floodplains do not have observable prices.

Direct versus indirect damage. The spatial axis distinguishes damages occurring within the flooded area (direct) from those arising outside it as a consequence of the flood (indirect). Direct agricultural damages include crop yield losses, livestock losses, and damage to farm infrastructure on flooded land. Indirect damages include supply chain disruptions experienced by input suppliers, food processors, and retailers who depend on flooded farms, as well as economy-wide multiplier effects transmitted through the agricultural sector's linkages with the broader economy (Nga et al., 2018; Hallegatte, 2008).

Immediate versus induced damage. The temporal axis separates damages occurring during or immediately after the flood event (immediate) from those that emerge over subsequent weeks, seasons, or years as the consequences of the initial shock propagate through the farm system (induced). Immediate damages — standing crop losses, livestock fatalities, building and machinery damage — are directly observable and relatively straightforward to estimate. Induced damages — reduced productivity from soil compaction and contamination, additional production costs incurred to compensate for damaged inputs, disrupted crop rotations, and long-term land abandonment — require longitudinal observation and are far more difficult to attribute causally to a specific flood event (Bhowmik et al., 2021; Posthumus et al., 2009).

Taken together, these three axes generate a taxonomy of eight damage cells ($2 \text{ spatial} \times 2 \text{ temporal} \times 2 \text{ tangibility}$ levels) illustrated in Table 1. Brémond et al. (2013) documented that even at the time of their review, the literature covered only two of these eight cells with any regularity — direct-immediate-tangible damages dominated, and all other combinations were sparsely represented. As the coverage row in Table 1 makes plain, this asymmetry has not fundamentally changed in the decade since.



150 2.2 Extensions to the taxonomy: three post-2013 damage frontiers

The foundational taxonomy captures the conceptual structure of agricultural flood damage as understood in 2013. Three categories of damage have emerged with sufficient clarity in the post-2013 literature to warrant explicit recognition as extensions to that framework. None fits neatly into the existing eight-cell structure, and each requires methods that the depth-damage function tradition does not provide.

155 **Long-term land productivity and repeated-flood degradation.** The foundational taxonomy treats induced damage primarily as a within-season phenomenon — delayed operations, additional costs, reduced yields in the year of the event or immediately following. What has become increasingly clear from panel data studies and agronomic research is that agricultural land subjected to repeated flooding undergoes cumulative degradation that operates on timescales of years to decades, not seasons. Soil compaction from floodwater weight and post-flood machinery traffic reduces hydraulic conductivity and root penetration depth across multiple growing seasons (Blöschl et al., 2019). Sediment deposition from overbank flooding can alter soil texture and pH across affected parcels. In coastal and low-lying agricultural zones, salinization from marine and estuarine flood intrusion can render land unproductive for years. These processes are not captured by any DDF calibrated on a single event, yet they represent some of the most economically significant consequences of living in a flood-prone agricultural landscape. Quasi-experimental methods using satellite-derived yield data and flood occurrence records have begun to address this gap (Yildirim and Demir, 2022; Antolini et al., 2020), but the category remains underrepresented in the economic assessment literature.

Supply chain finance and working capital disruption. The indirect damage category in the foundational taxonomy focuses primarily on physical supply chain disruption — interrupted input delivery, halted processing operations, transportation network damage. A distinct but related category has emerged in the post-2013 literature that might be called supply chain finance disruption — the impairment of the credit, insurance, and working capital flows that enable agricultural production to continue through and after a flood event. Farms operating with thin margins and high input costs are particularly vulnerable to disruptions in their access to seasonal credit and input supply arrangements; a flood that destroys a portion of expected yield can trigger cascading defaults that affect not only the directly flooded farm but its suppliers and creditors (FAO, 2023). This category sits at the intersection of direct induced damage (the farm's own financial position) and indirect damage (creditors and suppliers outside the flooded area) and has no established assessment method in the reviewed literature. It is, however, increasingly recognized in disaster risk finance literature as a critical driver of recovery timelines.

180 **Farmer mental health and household wellbeing.** Agricultural flood damage literature has historically treated the farm as a production unit rather than a household, focusing on output losses and asset damage while leaving the human consequences largely outside the assessment frame. A growing body of research in agricultural sociology and disaster psychology documents that flooding has substantial and lasting effects on farmer mental health — elevated rates of depression, anxiety, and post-traumatic stress among flood-affected farming households, with consequences for farm decision-making, investment, and succession planning. These effects constitute real economic losses — impaired decision-making reduces the efficiency of farm adaptation responses, mental health treatment has direct costs, and in severe cases, farm abandonment and out-migration represent permanent losses of agricultural human capital in flood-prone regions. The category is intangible — no market price attaches to a farmer's psychological distress — but stated preference methods, wellbeing indices, and health-adjusted economic valuation approaches exist and have been applied in adjacent literatures. Their near-total absence from agricultural flood damage assessment is a gap this review documents explicitly.

Table 1: Extended taxonomy of agricultural flood damages.

Damage Dimension	Direct–Immediate (during/just after flood)	Direct–Induced (later, same system)	Indirect (outside flooded area)	Post-2013 Extensions (new/underrepresented)
TANGIBLE (quantifiable in market terms)	▪ Crop yield loss ▪ Livestock fatalities & production loss	▪ Multi-season yield loss (soil compaction, contamination) ▪ Loss of added value from	▪ Supply chain disruption ▪ Input supply interruption ▪ Market access & transport loss	▪ Long-term land productivity ▪ Repeated-flood soil degradation ▪ Salinization (coastal, river backwater)



Damage Dimension	Direct–Immediate (during/just after flood)	Direct–Induced (later, same system)	Indirect (outside flooded area)	Post-2013 Extensions (new/underrepresented)
	- Damage to farm buildings & machinery - Stored inputs & products - Soil erosion & debris deposits - Damage to perennial plant material	- orchard/vineyard, replanting lag - Additional production costs (inputs, labor, phytosanitary) - Delayed field operations cascade - Livestock herd rebuilding costs	- Processing & storage sector losses - Price effects in regional markets - Economy-wide multiplier effects (via IO or CGE models)	- Supply chain finance disruption - Working capital constraints - Credit access post-disaster - Food security spillovers - Regional price & availability effects
INTANGIBLE (difficult to monetize)	- Psychological stress & trauma - Anxiety during flood event - Community cohesion disruption - Loss of cultural/heritage land use	- Chronic stress & uncertainty - Anticipatory anxiety (repeat risk) - Loss of farming identity & purpose - Decision paralysis on investment	- Environmental & ecosystem - Biodiversity loss in floodplains - Habitat & wetland degradation - Non-market ecosystem services	- Farmer mental health - Depression, anxiety, burnout - Measured via wellbeing surveys - Community & social capital - Erosion of local knowledge networks - Out-migration of farm labor
Literature coverage (this review)	 65 / 65 studies (100%)	 8 / 65 studies (12%)	 9 / 65 studies (14%)	< 5 studies (8%) each category (emerging research frontier)
	Well-covered in literature	Partially covered	Rarely covered	Post-2013 frontier categories

2.3 Uncertainty and risk in agricultural flood damage assessment

195 All agricultural flood damage estimates are uncertain, but the sources, magnitudes, and treatment of that uncertainty vary substantially across methods and damage categories. Recognizing this is important not only for interpreting the results, but for understanding why different methods produce non-comparable estimates even when applied to ostensibly similar flood events.

200 Risk and uncertainty are related but distinct concepts in the flood assessment literature. Risk is conventionally defined as the product of flood probability and associated damage — a quantity that can in principle be calculated if both the probability distribution of flood events and the damage function are known (Merz et al., 2010; Apel et al., 2008). Uncertainty, by contrast, refers to imperfect knowledge about either of these components. The two concepts operate across different dimensions in agricultural flood damage assessment and conflating them leads to assessment frameworks that quantify the wrong thing.

205 **Hydrological and climatological uncertainty.** Flood frequency distributions are estimated from historical records that are rarely long enough to reliably characterize the tails of the distribution — precisely the high-damage, low-probability events that dominate expected annual damage calculations (Milly et al., 2008; Blöschl et al., 2019). Non-stationarity under climate change compounds this problem — a depth-damage function calibrated on floods from 1980 to 2010 applied to a 2050 flood regime in the same watershed may produce systematically biased estimates because the underlying flood distribution has shifted. Very few of the studies reviewed here acknowledge this source of uncertainty explicitly, and fewer still incorporate it into their damage estimates.

Data and transferability uncertainty. The majority of depth-damage functions in the reviewed literature were constructed from historical post-event data specific to a particular region, crop system, and flood regime. When these functions are applied to different contexts — as practitioners frequently must do in data-scarce settings —



the resulting estimates carry transferability uncertainty that is rarely quantified. Van Zyl and Groenewald (1984) identified this problem four decades ago, and it remains unresolved — no systematic protocol exists for adjusting agricultural flood damage functions across agronomic contexts, and no standardized reporting of the uncertainty introduced by such transfers.

Economic valuation uncertainty. Even when physical damage is estimated with reasonable confidence, converting it to monetary values introduces additional uncertainty through crop price volatility, market disruption effects on prices (a large flood that destroys regional supply may raise prices, partially offsetting farm-level losses in aggregate while concentrating them at the individual farm), and the choice of valuation method for non-market damages (Hallegatte, 2008). Input-output and CGE models introduce further uncertainty through their structural assumptions about sectoral linkages and market clearing mechanisms.

Model and method uncertainty. Different methods applied to the same event routinely produce substantially different estimates. This method-induced uncertainty is the most tractable of the four sources — it can be reduced through model intercomparison, sensitivity analysis, and ensemble approaches — but is rarely reported in primary studies. Of the 65 studies reviewed here, fewer than 15 report any form of sensitivity or uncertainty analysis on their damage estimates, and fewer than 5 use ensemble or intercomparison approaches.

3 Systematic review methods

3.1 Review protocol and search strategy

Before conducting the systematic review, we examined the literature to confirm that no prior systematic review had addressed agricultural flood economic damage assessment as its primary focus. The only study identified that specifically evaluated economic methods for agricultural flood damage was Brémond et al. (2013), which predates the remote sensing revolution in damage assessment. No subsequent systematic review on this topic was found, confirming the rationale for the present study.

This review is scoped to studies that develop, apply, compare, or critically evaluate methods for assessing the economic damage of floods to the agricultural sector. Studies are included if their central contribution is methodological — that is, if they advance knowledge of how agricultural flood damage is measured or valued — regardless of whether they also address policy. Studies focused solely on flood hazard mapping, flood susceptibility modelling, morphometric analysis, or hydrological simulation without an economic damage assessment component are excluded, even if they involve agricultural land. The review follows PRISMA (2020) guidelines of Page et al. (2021) throughout. The following Boolean search string was applied across all six databases:

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("flood" OR "flooding") AND ("agriculture" OR "agricultural" OR "crop"  
OR "farm" OR "rural") AND ("damage" OR "damages" OR "loss" OR "losses")  
AND ("economic" OR "economy")
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The literature search was conducted across six bibliographic databases: Web of Science, Scopus, ScienceDirect, EconLit, JSTOR, and Agricola, in one session on 16 October 2025. The search covered all publication years without a lower year limit — the earliest study retrieved that met inclusion criteria was van Zyl and Groenewald (1984), which establishes the effective lower bound of the review period as 1984.

3.2 Screening, review, and assessment

The search returned a total of 4,896 records. Studies were restricted to peer-reviewed journal articles, including early access publications. Book chapters, reports, and books were excluded. The search was limited to English-language publications. This restriction is acknowledged as a limitation — relevant methodological contributions published in other languages may have been missed. Health sciences and biological sciences subject categories were excluded from database filters where available, as these returned large volumes of irrelevant results.

Retrieved records were imported into Mendeley for initial deduplication, which identified and removed 791 duplicate records, leaving 4,105 unique records. These were then uploaded to Rayyan, an AI-assisted systematic review platform (Ouzzani et al., 2016; Valizadeh et al., 2022), which identified a further 97 duplicates, reducing the pool to 4,008 records. Document type classification in Rayyan identified 3,881 journal articles, 81 book



chapters, 32 reports, and 13 books. Consistent with the inclusion criteria, only the 3,881 journal article records were retained for keyword screening.

265 Rayyan’s AI-assisted screening feature was used as a prioritization tool rather than as an automated decision-maker. Following document type filtering, a two-stage keyword screen was applied within Rayyan. In Stage 1, the keyword pair “flood” AND “agriculture” was applied to titles and abstracts, reducing records from 3,881 to 254. In Stage 2, the additional keyword “economic” was applied to the same fields, reducing records further to 84. These 84 records were retrieved in full text and assessed for eligibility. All inclusion and exclusion decisions were
270 made by human reviewers — no record was excluded solely on the basis of the AI ranking. Where the AI ranking suggested high relevance, but human review indicated exclusion, the reason for exclusion was recorded. Where two reviewers disagreed on inclusion, the conflict was resolved by team consensus discussion. The Rayyan session log is available from the corresponding author on request.

275 The 84 full-text articles were assessed against the inclusion criteria. Each article was classified into one of three categories based on its primary contribution: (1) methods-oriented — the central contribution is a new or evaluated method for measuring agricultural flood damage; (2) policy-oriented — the central contribution is a policy recommendation or program evaluation without a novel methodological element; or (3) both methods and policy — the study makes a methodological contribution and draws policy conclusions. Studies in category (2) were excluded as outside the scope of this review. Studies in categories (1) and (3) were retained.

280 This classification yielded 39 methods-oriented studies, 19 policy-oriented studies (excluded), and 26 studies spanning both methods and policy (retained), for a final corpus of 65 studies included in the qualitative synthesis. Inter-rater agreement on the three-category classification was assessed prior to consensus discussion; disagreements occurred on 11 of the 84 records (13%), all of which were resolved through discussion without requiring a third reviewer arbitration. The full PRISMA flow for the review is presented in Figure 1. The complete
285 list of included studies with their bibliographic details and damage category classifications is provided in the Supplementary material A.

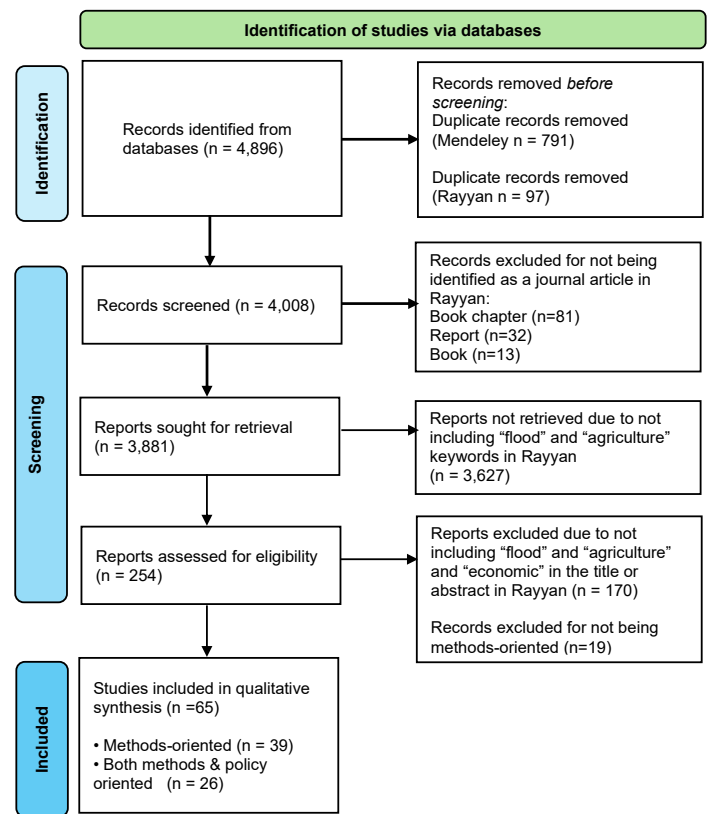


Figure 1: PRISMA flow diagram for the systematic review of agricultural flood economic damage assessment methods.

4 Results

4.1 Overview

The 65 studies reviewed span four decades, from early economic assessments of agricultural flood damage in the 1980s to recent applications of remote sensing, machine learning, and CGE modeling. Three broad patterns emerge from the literature.

First, publication activity increased substantially after 2018, with 2025 recording the highest number of studies in the dataset. This growth coincides with the widespread availability of Sentinel satellite imagery and cloud-based processing platforms, which have facilitated large-scale remote sensing applications for agricultural flood damage assessment.

Second, the literature is geographically concentrated. China (n = 10), Vietnam (n = 8), and the United States (n = 7) account for 38% of all studies, while East, South, and Southeast Asia together contribute more than 60% of the reviewed research. In contrast, Sub-Saharan Africa is represented by only three studies and no studies were identified from South America, highlighting important regional gaps in the evidence base.

Third, and most importantly, the review reveals a strong imbalance in damage-category coverage. All 65 studies assess direct immediate damages, whereas only 8 examine direct induced damages, 9 consider indirect damages, and fewer than 5 address intangible damages. No studies were identified for the indirect-induced damage category. This pattern indicates that agricultural flood damage assessment remains overwhelmingly focused on direct and immediately observable losses, with limited attention to broader economic and social impacts.



310 4.2 Direct immediate damage

Direct immediate damage — physical losses occurring at the flooded location during or immediately after the event — is covered by all 65 reviewed studies, making it by far the best-documented category. However, even within this category, coverage is uneven — annual crop yield loss dominates, while livestock, farm buildings, machinery, and perennial crops receive limited and methodologically immature treatment.

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4.2.1 Crop yield loss: depth-damage functions and their evolution

The depth-damage function (DDF) is the foundational method for direct immediate crop damage assessment and has been used in some form since the earliest reviewed study (van Zyl and Groenewald, 1984). In its simplest form, a DDF maps flood depth to a damage rate (proportion of yield lost), which is then multiplied by the monetary value of expected yield to produce an economic loss estimate. The method's appeal is its parsimony: it requires only flood extent and depth data — both derivable from hydraulic models or RS — plus local crop price and yield statistics.

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Studies across the review period have progressively refined the DDF by adding parameters. Seasonality — the crop growth stage at the time of flooding — emerged as a critical modifier in early studies (Chau et al., 2015; van Zyl and Groenewald, 1984) and has been incorporated in most subsequent work. Win et al. (2020) developed depth-duration-damage curves for rice in Myanmar's Bago floodplain using farmer interviews, finding that damage at a given depth varies substantially across the vegetative, reproductive, and maturity stages. Lamichhane et al. (2025) extended this with a probabilistic approach linking flood probability distributions to phenological stage exposure, enabling expected annual damage calculations that account for the joint probability of flood timing and crop stage. Lucaora et al. (2025) integrated distributed hydrodynamic modelling with crop phenology in a coastal Italian basin, demonstrating that spatially explicit flood depth combined with crop-stage calendars substantially improves damage estimates over spatially uniform DDFs.

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RS has transformed the scalability of DDF-based assessment. Where early studies required field surveys to establish flood depths, Cian et al. (2018) demonstrated that high-resolution SAR combined with LiDAR-derived DEMs can estimate flood depth at sub-meter resolution over large areas. Chang et al. (2023) operationalized inundation extent forecasting using REOF analysis over the lower Mekong, linking forecast extents directly to agricultural damage estimates. Do and Do (2025) applied deep learning to Sentinel-1A data to estimate rice biomass loss in Hanoi, representing the leading edge of the RS-ML integration for direct crop damage. Kumar et al. (2023) demonstrated cloud-based machine learning using Google Earth Engine for flood impact assessment on agricultural land across India. Li and Zhang (2021) applied a Grey BP Neural Network to multi-hazard agricultural disaster data in China, one of the few studies explicitly treating uncertainty in the damage prediction.

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Despite this methodological progress, the DDF approach has four persistent limitations that no reviewed study has fully resolved. First, transferability — DDFs calibrated in one region perform poorly in others because crop physiology, soil type, flood water quality, and farming practices all affect damage rates. George et al. (2022) documented this directly, finding substantial divergence between official damage assessments and survey-based estimates at farm level in India, attributable partly to the use of generic national damage coefficients. Syldon et al. (2024) found similar transferability problems when applying existing DDFs to Bhutanese mountain agriculture. Second, monetization — most RS-based studies convert physical damage estimates to monetary values using a single average crop price, ignoring spatial and temporal price variation and the price-increasing effect of large supply disruptions — a structural bias identified by Hallegatte (2008) that no reviewed study explicitly addresses. Third, crop coverage — rice dominates, with corn and wheat as secondary subjects. Bahar et al. (2024) studied T. Aman rice in Bangladesh's Jamuna floodplain and Giang and Vy (2021) analyzed rice in Vietnam under climate change scenarios — both contributing to the rice-heavy literature. Djanibekov et al. (2024) provide a partial exception, examining multiple crop types in the Awanui catchment of New Zealand under climate change, but multi-crop studies remain rare. Fourth, uncertainty reporting — fewer than 15 of the 65 reviewed studies report any form of sensitivity or uncertainty analysis on their damage estimates, despite the substantial parameter uncertainty inherent in DDF applications.

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4.2.2 Livestock damage: absence of a standard framework

Livestock damage is acknowledged as potentially significant but is methodologically underdeveloped relative to crop damage. Posthumus et al. (2009), studying the 2007 UK summer floods through farm surveys across the West Midlands, Oxfordshire, and Yorkshire, documented livestock losses including fatalities, reduced production, emergency feeding and relocation costs, and veterinary expenses. They found that at farm scale, livestock-related losses were substantial and in some cases exceeded crop losses, particularly on specialist livestock farms where no standing crops were present. Gaviglio et al. (2019) proposed a systematic method specifically for dairy farms, identifying death, injury, disease, miscarriage, malnutrition, and stress as the key damage variables, and noting that quantifying reduced milk quality and quantity requires longitudinal data collection beyond the immediate post-flood period. No reviewed study has applied a standardized livestock damage function analogous to a depth-damage curve for crops. The absence of such a framework means that livestock damage is either omitted entirely, estimated through ad hoc survey methods, or — as Gaviglio et al. (2019) note — approximated using residential building depth-damage curves adapted to agricultural buildings, which is methodologically indefensible.

4.2.3 Farm buildings, machinery, and perennial crops

Farm building and machinery damage is addressed in even fewer studies and with less methodological rigor. Shrestha et al. (2016), studying the 2011 Philippine floods, conducted household surveys and used regression modelling to develop depth-damage curves for one-story, two-story, and stilt houses with their contents, multiplying damage rates by surveyed asset values. This is the most methodologically complete treatment of agricultural building damage in the reviewed literature, but it covers residential farm buildings rather than commercial agricultural structures (storage sheds, processing facilities, machinery housing). Perennial crop damage — vineyards, orchards, permanent pasture — requires a fundamentally different framework from annual crop DDFs because the economic loss extends for multiple seasons until the productive stand is re-established. Vozinaki et al. (2015), studying olive and fruit tree damage from a Greek flash flood through farmer surveys, assigned damage factors based on flood depth, velocity, and timing relative to harvest, but did not capture the multi-year income loss stream from orchard replanting — a gap the authors acknowledge explicitly.

4.3 Direct induced damage

Direct induced damages — losses arising at the flooded location over weeks, seasons, or years after the flood event — are covered by only 8 of 65 reviewed studies. This persistent under-representation is not primarily a data problem, though data scarcity is real; it is partly a definitional problem (the temporal boundary between immediate and induced damage is contested and inconsistently applied) and partly a methodological one (the dominant RS and DDF approaches cannot observe damage that manifests months after inundation).

4.3.1 Soil degradation and multi-season productivity loss

Posthumus et al. (2009) provide the most detailed farm-scale account of direct induced damage in the reviewed literature. Their UK survey documented soil compaction from floodwater weight and machinery operating on saturated ground, reduction in earthworm populations reducing soil structural quality, delays in establishing crops for the following season, and induced livestock feeding and relocation costs persisting weeks after flood recession. Farmers reported yield penalties extending two to three growing seasons beyond the flood event. Lukianas et al. (2006), using field observations from Lithuanian summer polders, documented overloading of soil with potassium and phosphorus from flood sediment, with expected long-term effects on soil chemistry and crop response. Van Zyl and Groenewald (1984), in the earliest reviewed study, identified re-establishment costs, time lost during re-establishment, and soil cleaning costs as distinct induced damage components that most subsequent studies have failed to account for separately. Nga et al. (2018) identified similar categories in Vietnam — reseeding costs, soil remediation, and production losses during the re-establishment period — and noted that these induced costs are typically excluded from official post-disaster damage assessments, leading to systematic underestimation of total flood impact on agriculture.



4.3.2 Quasi-experimental methods: the best available approach for induced damage

Xiao (2011) represents the methodologically most rigorous treatment of direct induced damage in the reviewed literature. Using county-level farm income data from the US Midwest and a quasi-experimental pairwise matching design — matching flooded counties to comparable non-flooded control counties on pre-flood observables — the study estimated that the 1993 Midwest flood caused permanent farm income reductions of \$3.5–\$4.1 million for some affected counties, with effects detectable over a multi-year window. The matching approach is the most defensible available method for estimating induced damage because it provides a counterfactual — what farm income would have been in the absence of flooding — that neither DDFs nor IO models can supply. The approach requires longitudinal administrative data on farm income at sub-regional scale, which limits its application to data-rich settings. Antolini et al. (2020) applied a related approach to evaluate flood risk reduction from agricultural best management practices in the US, using spatial regression to identify the income effects of repeated flood exposure.

4.3.3 Input-Output models and sectoral induced effects

Haque and Jahan (2015), using a multi-sector regional IO model for Bangladesh, found that agriculture was the sector most severely affected by induced losses from the 2007 flood, with an induced output reduction of 0.19% of total national output, and that the agricultural sector recovered more slowly than industry and construction — which benefited from post-disaster reconstruction spending. Khalid and Ali (2019) found similar agricultural recovery lags in Pakistan using IO analysis of the 2010 floods. Sun et al. (2025), using IO tables for the Yangtze River basin, documented that the most severe induced losses extended across manufacturing, agriculture, forestry, and transportation sectors. These IO-based analyses capture economy-wide induced effects more comprehensively than farm surveys, but they treat agriculture as a single homogeneous sector and cannot distinguish within-agriculture damage patterns across crop types, farm scales, or production systems.

Bhowmik et al. (2021) and Sun et al. (2025) both capture direct induced damages explicitly within their broader multi-category analyses. Bhowmik et al.'s household survey approach in Bangladesh identified soil quality degradation, altered crop rotation, and loss of perennial plantings as the primary induced damage channels, while Sun et al.'s IO approach captured the sectoral propagation of initial agricultural damage through the broader economy.

4.4 Indirect damage

Indirect damages — economic losses arising outside the flooded area as a consequence of agricultural flood impacts — are addressed by 9 of 65 reviewed studies. Two distinct methodological traditions handle this category: household surveys that document business interruption and livelihood disruption experienced by individual actors connected to the flood-affected agricultural system, and macroeconomic models (IO and CGE) that estimate economy-wide transmission of agricultural flood shocks through sectoral linkages.

4.4.1 Business interruption and livelihood disruption: survey-based evidence

Nga et al. (2018) provide the most complete multi-method treatment of indirect agricultural flood damage in the reviewed literature. For floods in 2007 and 2013 in central Vietnam, they conducted household surveys and used contingent valuation to estimate both tangible and intangible indirect damages. Their key quantitative finding — that indirect business interruption costs (\$13.8 million) exceeded direct crop damage (\$8.7 million) for a 100-year flood event in the study area — is the single most important result in the reviewed literature for demonstrating that direct-damage-only estimates systematically undercount total agricultural flood losses. Nga et al. (2018) attribute indirect costs to lost sales opportunities during flood periods, disruption of marketing relationships, and ripple effects on traders, processors, and input suppliers who depend on the affected farms.

Islam et al. (2022), studying the Mayurakshi River Basin of India, documented a distinct form of indirect damage — labor migration induced by repeated flooding, as rural households unable to maintain agricultural income relocated to urban areas. The study quantified remittance flows generated by this migration and traced their sectoral effects using an economic multiplier, finding that the construction sector benefited while agriculture lost human



capital — a finding with long-term implications for agricultural productivity that conventional damage assessments completely miss. Dutta et al. (2006) and Gaviglio et al. (2019) identified traffic disruption and infrastructure damage as indirect agricultural costs, though without quantification.

460 **4.4.2 Economy-wide indirect effects: IO and CGE models**

The IO and CGE literature captures indirect agricultural flood damage at regional and national scale. Mirza (2002) estimated that when indirect effects — agricultural employment losses and sectoral multipliers — were included in the assessment of the 1998 Bangladesh flood, total damage rose to approximately 3% of GDP, substantially above direct damage estimates alone. Khalid and Ali (2019, 2020) used IO analysis and multi-criteria decision making across Pakistan's infrastructure sectors, finding that agricultural supply chain linkages transmitted flood shocks broadly across the economy, with longer recovery times for agriculture than for services or transport.

He et al. (2025) represent the most methodologically advanced treatment of indirect agricultural flood damage in the reviewed literature. Using a multi-regional CGE model (TERM) with 2017 IO data across 42 sectors and 31 Chinese provinces, they demonstrated that proximity and economic connectivity amplified indirect losses — regions adjacent to the Yangtze River flood zone experienced larger GDP declines than more distant regions due to upstream-downstream production linkages and increased factor costs. Critically, they also found that some regions outside the flood zone experienced economic gains — through labour reallocation from flooded areas and increased demand for substitute goods — illustrating that indirect effects can have both positive and negative components that IO models, which lack market-clearing mechanisms, cannot capture. Sun et al. (2025), using IO tables for the same basin, found that manufacturing, agriculture, forestry, animal husbandry, and transportation were the sectors experiencing the largest indirect losses, confirming the economy-wide reach of agricultural flood shocks.

Johnson et al. (2023, 2025) examined indirect agricultural flood damage through the lens of inland waterway infrastructure disruption, using economic interdependence, agent-based, and Bayesian models to evaluate how port and waterway flooding propagates through agricultural supply chains in the US Midwest. Yaseen et al. (2020) applied dynamic inoperability IO modelling to estimate economic losses across interdependent infrastructure sectors during flooding in Pakistan.

4.5 Intangible damage

485 Intangible damages — those that resist monetary valuation through market prices — are the least represented category in the reviewed literature, addressed substantively by fewer than 5 of the 65 studies. Two distinct types appear — psychological and social wellbeing effects on farming households, and environmental damage to non-market ecosystem services. Both are acknowledged across the literature as significant, but the absence of established quantification methods and the data demands of the available approaches have kept them at the margins of agricultural flood damage assessment.

Bhowmik et al. (2021), using household surveys in Bangladesh, documented a range of intangible induced damages following flood events: psychological stress and emotional wellbeing impairment, health burden from disaster-associated diseases, disruption of social and ceremonial activities, temporary migration, and permanent occupational change among farming households. These effects were identified qualitatively through structured survey instruments but were not monetized. The study argues that intangible damages have significant long-term implications for public policy because they affect household decision-making on investment, crop choice, and farm succession — consequences that propagate through the agricultural system for years after the flood event.

Nga et al. (2018) provide the only example in the reviewed literature of a monetized intangible damage estimate for agricultural flood impacts, using the Contingent Valuation Method (CVM) to value soil and water remediation costs in central Vietnam. Their estimate of \$1.8 million in intangible soil and water remediation costs against \$8.7 million in direct crop damage — representing approximately 21% of direct damage — illustrates that intangible costs, even narrowly defined, are not negligible. CVM elicits willingness-to-pay or willingness-to-accept compensation from affected households and is the standard non-market valuation method in environmental economics, but its application to agricultural flood contexts is extremely rare in the reviewed literature.



505 Djanibekov et al. (2024), studying flood impacts in New Zealand under climate change, acknowledged environmental and ecological dimensions of flood damage to agricultural landscapes but stopped short of valuing them. Islam, M.M. (2024), in a review of wetland agriculture economics, identified ecosystem service losses from flood-altered wetland agriculture as a significant but unquantified damage category.

510 The subsection-by-subsection analysis above reveals a consistent pattern across damage categories — the dominant methods in the field are structurally matched to direct immediate tangible damage and increasingly mismatched as one moves toward induced, indirect and intangible categories. Table 2 below formalizes this pattern as a method-category fit matrix based on the 65 reviewed studies, providing an empirical foundation for the Methods-by-Damage-Category Matrix presented in Section 5 (Table 2).

515 **5 Synthesis, gaps, and implications for future research**

The 65 studies reviewed span four decades of methodological development and represent a substantial expansion of the knowledge base since Brémond et al.'s (2013) landmark review. Yet when the literature is assessed against the full taxonomy of agricultural flood damages — direct and indirect, immediate and induced, tangible and intangible — three structural patterns emerge that constrain the usefulness of existing estimates for economic decision-making.

5.1 The damage coverage asymmetry

520 All 65 reviewed studies address direct immediate damages, but only 8 include direct induced effects and fewer than 10 incorporate any form of indirect damage. This is not a recent trend — the same asymmetry was documented by Brémond et al. (2013) and by van Zyl and Groenewald as early as 1984. The persistence of this gap across four decades and a major remote sensing revolution suggests the cause is structural, not merely a function of data availability.

530 Three structural causes can be identified. First, the dominant method — the DDF applied to RS-derived flood extent — is structurally incapable of capturing farm-scale disruption costs, livestock losses or indirect supply chain effects. The method's strength (scalability, low data requirements) is purchased at the cost of thematic coverage. Second, the institutional incentives of rapid post-disaster assessment — the need to report damage quickly for disaster compensation and emergency response — reward methods that are fast rather than comprehensive. Third, the data infrastructure required for induced and indirect damage assessment — longitudinal farm-level income data, regional input-output tables, household panel surveys — exists in few countries and is rarely compiled for flood-affected agricultural regions specifically.

535 The consequence is systematic underestimation. Posthumus et al. (2009) documented that farm-scale induced costs — soil compaction, delayed planting, livestock relocation and feeding — were substantial and persisted for one to two seasons after the 2007 UK floods. Nga et al. (2018) found indirect business interruption costs in Vietnam exceeded direct crop damage for a 100-year flood event. If benefit-cost analyses of flood risk management investments are built on estimates that capture only the direct immediate crop damage component, the resulting benefit estimates are systematically downward-biased, potentially causing under-investment in flood protection for agricultural areas.

5.2 The physical-to-economic integration gap

545 The most technically significant finding of this review is the unresolved gap between the physical detection tradition and the economic valuation tradition. Table 2 (the Methods-by-Damage-Category Matrix) maps this gap explicitly — RS methods — including vegetation index approaches, SAR-based inundation mapping, and machine learning classifiers — perform well in the “direct immediate crop yield loss” column but are absent or marginal across all other damage categories. Conversely, methods capable of capturing induced, indirect, and intangible damages — household surveys, quasi-experimental panel methods, input-output models, CGE models, and non-market valuation techniques — do not appear in the remote sensing literature at all.

This bifurcation has a practical consequence that has not been previously identified in the literature — RS-based damage estimates, which are increasingly used as primary inputs to disaster compensation and insurance decision-



555 making systematically undercount agricultural flood losses because they measure only the physical signal of
inundation and vegetation response. The monetization step — converting NDVI anomaly or inundated hectares
into an economic loss figure — is typically performed using a single average crop price and a generic yield loss
ratio, without accounting for crop-stage variability, market price changes induced by the disaster, or the full range
of farm-scale costs. As Rahman and Di (2020) acknowledged, this monetization step is the weak link in the chain,
yet it has received almost no methodological attention.

560 A productive direction for future research is the development of hybrid assessment frameworks that sequence RS-
based physical damage detection with economic valuation steps calibrated from farm surveys or quasi-
experimental data. Antolini et al. (2020) and Yildirim and Demir (2022) represent early steps in this direction for
the US context, but neither generalizes the approach or explicitly bridges the two traditions methodologically.

565 5.3 Geographic coverage and transferability

The geographic distribution of reviewed studies reveals a concentration that mirrors the distribution of satellite
data infrastructure and research capacity rather than the distribution of agricultural flood risk. China (10 studies),
Vietnam (8), and the United States (7) together account for roughly 38% of the reviewed literature. South America
is entirely absent despite the Pampas, Amazon basin, and Bolivian lowlands representing major flood-exposed
570 agricultural systems. Sub-Saharan Africa, home to some of the world's most flood-vulnerable smallholder farming
systems, contributes fewer than three studies.

This skew has two implications. First, the damage functions and assessment methods developed in the reviewed
literature are not globally applicable. Depth-damage curves for irrigated rice in the Mekong Delta do not transfer
to rain-fed sorghum systems in the Sahel; vegetation index anomaly thresholds calibrated for Midwest corn-
soybean rotations do not apply to intercropped systems in Sub-Saharan Africa. Second, the income-level context
575 shapes which methods are feasible: the farm-survey and quasi-experimental approaches that best capture the full
damage taxonomy require data infrastructure that is rarely available in lower-income agricultural systems. The
field has not yet developed a coherent framework for matching method choice to data availability context — a gap
that limits the practical utility of this literature for the majority of flood-vulnerable farming populations globally.

580 Future research should prioritize: (a) application of existing methods to South American and African agricultural
flood contexts; (b) development of low-data methods — including rapid rural appraisal techniques and remotely-
sensed proxies for non-crop damage — suitable for data-scarce environments; and (c) explicit reporting of data
requirements and transferability conditions in methods papers, to enable practitioners to assess method feasibility
in their context.

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5.4 Priority directions for future research

Based on the synthesis above, four priority directions emerge:

Develop hybrid physical-economic assessment frameworks. The most pressing methodological need is a
validated protocol for translating RS-derived physical damage indicators into economically complete loss
590 estimates. This requires explicit linkage between the flood detection step (extent, depth, duration from SAR/optical
RS) and economic valuation steps that incorporate crop-stage-specific depth-damage functions, farm-scale
induced cost modules, and uncertainty quantification. Pilot frameworks should be developed and validated against
farm-survey benchmarks in at least two contrasting agricultural systems.

Expand the damage taxonomy in empirical studies. Future studies should be designed to capture at minimum
595 two damage categories beyond direct immediate crop yield loss. Livestock damage, farm infrastructure, and direct
induced costs (multi-season productivity losses) are the most feasible extensions given existing data collection
methods. Standardized survey instruments for post-flood farm damage assessment, analogous to those developed
by the Flood Hazard Research Centre in the UK, should be developed and tested in Asian and African contexts
where current coverage is weakest.

600 **Address the monetization gap in remote sensing approaches.** Studies using RS methods to estimate damage
should be required by journals and funding agencies to include an explicit and justified monetization step that goes
beyond multiplying inundated area by average crop price. At minimum, this step should account for crop-type



heterogeneity, phenological stage at flood occurrence, and local market price data. Where possible, RS-based physical estimates should be validated against independently collected economic loss data.

- 605 **Invest in longitudinal data infrastructure for induced and indirect damage.** The persistent absence of induced and indirect damage assessment from the literature is fundamentally a data problem. Regional input-output tables for agricultural-flood-affected economies, and longitudinal farm income panels designed to track recovery trajectories over multiple seasons, are prerequisites for filling the largest remaining gaps in the damage taxonomy. Investment in this data infrastructure, coordinated across national statistical agencies and international agricultural research organizations, would enable a generation of research that the current literature cannot produce.
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Table 2: Methods-by-damage-category matrix for agricultural flood economic assessment.

Assessment Method	Direct Immediate		Direct Induced		Indirect Damages		Intangible / Long-term	
Method	Crop Yield Loss	Livestock & Farm Assets	Soil Degradation & Long-term Productivity	Farm-Scale Activity Disruption	Supply Chain & Market Disruption	Economy-wide Sectoral Effects	Psychological & Social Wellbeing	Environmental & Ecosystem Damage
Remote Sensing & GIS								
Depth-Damage Function (RS-derived flood extent + depth)	●●● Primary method ~40 studies	●○○ Rare; no standard function	—	—	—	—	—	—
Vegetation Index Approach (NDVI, EVI, VCI time-series)	●●● Well-established; crop condition proxy	—	●●○ Soil recovery monitoring; limited	—	—	—	—	—
SAR-Based Inundation Mapping (Sentinel-1, RADARSAT)	●●○ Growing rapidly; cloud-free advantage	—	—	—	—	—	—	—
Machine Learning / Deep Learning (RF, CNN, ANN on RS data)	●●○ Emerging; few studies 2020–2025	—	●○○ Experimental only	—	—	—	—	—
Hydro-Economic Models								
Depth-Damage Curves (flood depth × loss rate)	●●● Core workhorse; most studies globally	●●○ Adapted from residential curves	—	—	—	—	—	—
Hydro-Economic Integrated Models (HEC-FDA, HAZUS-MH Ag)	●●○ US-focused; limited global transfer	—	—	—	—	—	—	—
Crop Simulation Models (DSSAT, ORYZA, AquaCrop)	●●○ Biophysical yield; needs economic step	—	●●○ Multi-season yield gaps; data intensive	—	—	—	—	—
Economic Assessment Methods								
Gross/Net Margin Analysis (market price × yield loss)	●●● Standard monetization step after	—	—	—	—	—	—	—



Assessment Method	Direct Immediate		Direct Induced		Indirect Damages		Intangible / Long-term		
Method	Crop Loss	Yield	Livestock & Farm Assets	Soil Degradation & Long-term Productivity	Farm-Scale Activity Disruption	Supply Chain & Market Disruption	Economy-wide Sectoral Effects	Psychological & Social Wellbeing	Environmental & Ecosystem Damage
	RS/depth-damage								
Household Farm Survey / (primary data collection)	●●○ Gold standard; costly and slow		●●● Primary method for livestock & assets	●●○ Long-term income recovery tracking	●●● Only method capturing farm disruption costs	—	—	●●● Only method for wellbeing & stress	●●○ Farmer-reported environmental loss
Quasi-Experimental Methods (DiD, Matching, Panel regression)	●●○ Causal inference; county-level data needed		—	●●● Best method for long-term yield effects	●●○ Farm income panels; limited studies	—	—	—	—
Input-Output (IO) Models	—		—	—	—	●●● Supply chain disruption standard	●●○ Sector-level impacts; static limitations	—	—
Computable General Equilibrium (CGE / Multi-regional CGE)	—		—	—	—	●●○ Dynamic spillovers; data-intensive	●●● Economy-wide gold standard	—	—
Non-Market Valuation (CVM, Hedonic, WTP/WTB)	—		—	—	—	—	—	●●○ Willingness to pay for risk reduction	●●● Only rigorous method for ecosystem/env. loss

Note: Damage categories follow the classification of Brémond et al. (2013) extended with an intangible/long-term column. Method coverage ratings are based on frequency and centrality of use across the 65 reviewed studies (1984–2025). ‘Primary’ (●●●) = method used as the central approach in ≥5 studies for that damage category and well-validated. ‘Secondary’ (●●○) = method used in 2–4 studies or used primarily for adjacent categories. ‘Emerging’ (●○) = fewer than 2 studies, experimental application only. ‘—’ = method not encountered in reviewed literature for that damage category.

6 Conclusion

This systematic review of 65 peer-reviewed studies published between 1984 and 2025 establishes that agricultural flood damage assessment is methodologically bifurcated and structurally incomplete. The RS and DDF tradition — the de facto standard in the field — achieves scalability and speed at the cost of damage-category coverage, producing estimates of direct immediate crop yield loss that are increasingly precise but increasingly unrepresentative of total agricultural flood damage. A smaller tradition of farm surveys, quasi-experimental panel methods, input-output models, and computable general equilibrium approaches captures the induced, indirect, and intangible damage categories that the RS-DDF stream cannot reach, but at data and resource costs that limit its deployment. These two traditions have developed in parallel for four decades without converging, and the integration gap between them is the central unresolved problem in the field.



630 This review makes three contributions to that problem. First, we introduce a Methods-by-Damage-Category Matrix
that systematically maps eight assessment methods against five damage categories, providing an empirical
characterization of where the field has coverage and where it does not — a diagnostic instrument that did not
previously exist for agricultural flood damage. Second, we identify and justify three post-2013 damage frontiers
635 — long-term land productivity degradation from repeated flooding, supply chain finance and working capital
disruption, and farmer mental health and household wellbeing — that have emerged with sufficient empirical
clarity to warrant dedicated methodological development but have not been incorporated into any previous review
framework. Third, we characterize the physical-to-economic translation step — converting remotely-sensed flood
extent and vegetation anomaly into a defensible monetary loss estimate — as the weakest link in the assessment
chain, absent a validated protocol and systematically introducing bias of unknown direction and magnitude into
640 estimates used for flood risk management decisions.

The practical implication is direct — benefit-cost analyses of flood risk management investments in agricultural
regions that rely on existing damage estimates are working with inputs that are systematically downward-biased,
because those estimates capture at most the direct immediate tangible component of agricultural flood loss. The
magnitude of the resulting underestimation varies by flood type, season, agricultural system, and regional
645 economy, and cannot be bounded from existing evidence. Policymakers, insurers, and development agencies using
existing damage estimates to allocate flood risk management resources should treat those estimates as lower
bounds, not central values.

The most consequential single advance the field could make is the development and validation of a hybrid
assessment protocol that sequences RS-based physical damage detection with an economic valuation step
650 calibrated from farm surveys or quasi-experimental data, covers at minimum three damage categories beyond
direct immediate crop yield loss, and explicitly reports uncertainty bounds on its monetary estimates. Such a
protocol would not require abandoning the scalability advantages of RS methods; it would require connecting them
to the economic infrastructure needed to convert physical signals into complete and defensible loss figures. Until
that protocol exists, the gap between what agricultural flood damage assessment produces and what flood risk
655 management decisions require will remain one of the most consequential unresolved problems in applied disaster
economics.

Data availability

This study is a systematic review of published literature. No new primary data were generated. The list of included
660 studies and PRISMA screening records are provided in the Supplementary material A. The Rayyan session log is
available from the corresponding author on request.

Author contributions

SMJ: conceptualization, supervision, methodology, formal analysis, visualisation, writing. **HG**: conceptualisation,
665 methodology, writing, and **RM**: writing.
SMJ prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.
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