

Response to Anonymous Referee #1

We thank the reviewer for a careful and constructive reading of the manuscript. We address each of the five comments in turn below. For each comment we provide:

- Original reviewer's comment in black font,
- Authors' responses to review comments are in blue font, and
- Where needed, new manuscript text material is in green font to be inserted (with the indication of the insertion point by a line number).

Comment 1

Add the database you searched for the literature and the selection criteria.

We thank the reviewer for this comment. The six databases searched — Web of Science, Scopus, ScienceDirect, EconLit, JSTOR, and Agricola — as well as the Boolean search string and the two-stage screening workflow (title/abstract screening followed by full-text review) are already described in Sections 3.1–3.2 and illustrated in the PRISMA flow diagram (Fig. 1). We direct the reviewer to lines 230–250 where this information is presented.

We acknowledge, however, that the inclusion and exclusion criteria — while present in prose at lines 230–250 — are not presented in a tabular form that makes them explicit and auditable. Therefore, we propose adding a Table 1 (below) to the subsection 3.1 “Review protocol and search strategy”, presenting the seven eligibility dimensions across three columns. Simultaneously we remove some text at lines 237–243 that the table makes redundant.

Table 1. Inclusion and exclusion criteria applied in the systematic literature search (to be inserted at the end of subsection 3.1).

Dimension	Include	Exclude
Publication type	Peer-reviewed journal articles	Books, reports, grey literature, conference abstracts
Language	English	Non-English publications
Time period	1984–2025	Publications before 1984
Hazard type	Riverine or pluvial floods	Droughts, hail, frost, or combined hazards where flood damage is not disaggregated
Sector	Agriculture (crops, livestock, farm assets, supply chains)	Urban flood damage, fisheries-only, forestry-only studies
Damage scope	Any economic damage category (direct or indirect)	Physical impact only (e.g., flood extent mapped) with no economic estimate
Geographic scope	Any country or region	Studies limited to household non-agricultural income

Comment 2

All existing assessment methods were just briefly introduced about their research target, method, and outcomes. The details of these assessment methods/models should be included and compared, such as procedure, suitability, and expected outcomes.

We agree that Section 4's subsection-by-subsection narrative, while grounded in the reviewed literature, does not provide the structured, side-by-side method comparison that practitioners need when selecting an approach for their context. The section describes each method's research targets and principal findings but does not present procedure steps, suitability conditions, and expected outputs in a directly comparable format.

To address this, we propose adding Table to a new Supplementary material B (below). Table presents all eleven method classes reviewed in Section 4 across seven dimensions: (1) step-by-step procedure, (2) suitability (context, data environment, and use case), (3) expected output, (4) damage quantification approach (directly responding to Comment 3), (5) required parameters, and (6) key studies from this review that applied the method. This structure directly addresses the reviewer's request for procedure, suitability, and expected outcomes in a comparable format, while also responding to Comment 3 on quantification and parameters.

The table is placed in the Supplement material rather than the body to avoid exceeding the journal word limit. A cross-reference sentence is added to the main text after line 618 (the Table note), directing readers to it (below):

A detailed comparison of all eleven method classes — covering step-by-step procedure, suitability, expected outputs, damage quantification approach, and required parameters — is provided in Supplementary material B, with representative studies from this review identified for each method.

Comment 3

How to quantify different kinds of damages and what are the required parameters for economic models?

This is a substantive methodological question that lies at the heart of what a practitioner review should answer. Our response addresses it through Table (Supplementary material B, proposed in response to Comment 2), which includes two columns dedicated to this question: "Damage quantification approach" and "Required parameters."

The quantification approach column specifies, for each of the eleven methods, the mathematical or procedural steps through which physical damage signals are converted to monetary loss estimates — including the standard formula or model structure used in the reviewed studies. The required parameters column lists the specific inputs each method demands (flood depth raster, crop calendars, IO tables, SAM, survey instruments, etc.), drawn directly from the 65 reviewed studies. This means that a reader who wants to know, for instance, what parameters a CGE model needs to quantify economy-wide agricultural flood damage, or what inputs a quasi-experimental DiD design requires, can find this information directly in Table in Supplementary material B.

Comment 4

1-2 case studies would help readers to understand the proposed MDCM method.

We appreciate the spirit of this suggestion, demonstrating how the MDCM guides method selection in a concrete context would strengthen its practical value. However, we respectfully note three constraints that prevent us from adding full illustrative case studies.

- First, the NHESS review article guidelines call for synthesis and critical evaluation of existing evidence rather than primary application exercises. Adding one or two case studies — which would require selecting a flood event, assembling data, running a method, and interpreting results — would constitute new empirical work beyond the scope of a systematic review.
- Second, Section 4 of the current manuscript already applies the MDCM row by row across all eleven method classes (lines 316–504), explicitly noting for each method which damage categories it covers, what data it requires, and where it has been applied geographically. This constitutes a structured, evidence-grounded demonstration of the matrix framework applied to the reviewed literature.
- Third, the manuscript is at the journal word limit. Adding even a condensed case study would require removing substantive content elsewhere.

As a targeted compromise, we propose adding the following practitioner scenario paragraph to Section 5.2 (after line 563) that narrates how a flood risk manager would navigate the MDCM to select a method — without constituting a full empirical case study:

To illustrate how the MDCM guides method selection in practice, consider a flood risk manager designing a levee setback program in a rain-fed corn region of West Africa with limited administrative data. Table 2 shows that depth-damage function methods — the dominant approach in data-rich countries — require field surveys and crop calendars unlikely to be available. The matrix instead directs the manager towards vegetation index methods (NDVI deviation from Sentinel-2 imagery), which require only freely available satellite data and have demonstrated applicability in smallholder systems. It simultaneously flags that this method produces a physical damage proxy rather than a monetary estimate and points to the quasi-experimental DiD approach as the minimal feasible path to an economic valuation if a modest panel dataset can be assembled.

Comment 5

The conclusions should be simplified and itemized.

We fully agree. The current conclusion is written as continuous prose and does not adequately surface the specific, numbered findings of the review. We propose replacing Conclusion section entirely with the revised, itemized conclusion below. The new conclusion is structured in four parts: (1) a one-paragraph synthesis of core findings, (2) three numbered methodological research priorities, (3) three numbered thematic/geographic priorities, and (4) a closing paragraph on the MDCM's policy utility:

6. Conclusion

This systematic review synthesized 65 peer-reviewed studies published between 1984 and 2025 on the economic assessment of agricultural flood damage. Using the Methods-by-Damage-Category Matrix (MDCM) as an organizing framework, we find that the field is characterized by substantial methodological, thematic, and geographic fragmentation, limiting the comprehensiveness, transferability, and comparability of estimates across studies.

The MDCM reveals three structural imbalances. First, 74% of reviewed studies assess only direct, immediate crop yield losses, whereas direct induced damages are addressed in just 12% and intangible damages in fewer than 8%. Second, 58% of studies employ remote-sensing or depth–damage function approaches, while economy-wide and quasi-experimental methods together account for fewer than 14%. Third, 63% of studies originate from five countries—China, Vietnam, Bangladesh, the Philippines, and the United States. Sub-Saharan Africa is represented by only two studies, while South America is entirely absent.

These findings point to three methodological research priorities. First, physical-to-economic integration. Further research is needed to develop and validate robust methods for translating remotely sensed indicators, such as inundated area and vegetation anomalies, and flood-depth estimates into monetary loss estimates suitable for benefit–cost analysis. This integration represents a critical methodological challenge for connecting physical flood impacts with economic decision-making. Second, broader damage coverage. Future assessments should more systematically account for post-flood soil degradation, farm-asset and working-capital disruption, and farmers’ psychological well-being, each of which has received limited attention in the reviewed literature. Household panel surveys and quasi-experimental designs offer promising approaches for quantifying these less-studied impacts. Third, improved transferability documentation. Methodological studies should systematically report data requirements, contextual assumptions, and known limitations to help practitioners assess whether existing methods can be applied in data-scarce settings. Supplementary material B provides a starting point for such standardization.

Three additional priorities concern the thematic and geographic scope of research. First, expand geographic coverage to Sub-Saharan Africa and South America. Damage functions developed for irrigated agricultural systems in monsoon Asia may not adequately represent the production systems, climatic conditions, and farming practices of rain-fed smallholder agriculture in these regions. Context-specific empirical studies and comparative meta-analyses are therefore needed. Second, strengthen evidence on livestock and farm-asset damage. Fewer than ten reviewed studies address these categories, despite evidence from some flood contexts that their economic consequences can be substantial relative to crop losses. Standardized farm-asset and livestock survey instruments could facilitate more consistent measurement and comparison. Third, quantify supply-chain and economy-wide effects. Input–output (IO) and computable general equilibrium (CGE) models offer established frameworks for tracing indirect losses through agricultural supply chains, yet their application to agricultural flood damage remains limited. Linking these models with remotely sensed estimates of direct damage offers a promising pathway towards more integrated assessments.

The MDCM developed in this review provides a practical framework for identifying the damage categories covered by an assessment, evaluating methodological options given available data, and recognizing where estimated losses may be incomplete. By making these gaps explicit, the framework can help flood risk managers, insurers, and development agencies assess the strengths and limitations of existing estimates. Addressing the priorities identified here—particularly the integration of physical and economic assessments and the underrepresentation of induced, intangible, and economy-wide damages—would strengthen the evidence base for agricultural flood risk management and improve the information available for benefit–cost analyses of flood mitigation investments.

Supplementary material B.

Structured comparison of assessment methods for agricultural flood damage — procedure, suitability, outputs, quantification approach, required parameters, and key studies

Method	Step-by-step procedure	Suitability	Expected output	Damage quantification approach	Required parameters	Key studies in review
A. Remote-sensing / geospatial methods						
Depth-Damage Function + Remote Sensing (DDF+RS)	(1) Map flood extent and depth from SAR/optical imagery or hydraulic model. (2) Overlay with crop layer (LULC or cadastral map). (3) Apply crop-specific DDF: damage rate = $f(\text{depth, crop stage})$. (4) Multiply by expected yield $\times$ market price per inundated area.	Large-scale rapid assessment; data-rich contexts with existing DDFs; post-event insurance or disaster compensation.	Monetary crop yield loss (USD/ha or total USD); maps of loss intensity.	Direct crop yield loss: $\text{Loss} = \sum(\text{area}_i \times \text{yield}_i \times \text{price}_i \times \text{DDF}(\text{depth}_i, \text{stage}_i))$. Livestock/farm assets: rarely applied; some studies adapt residential DDFs (methodologically contested).	Flood depth raster; crop-stage calendar; crop-specific DDF table; expected yield (t/ha); farmgate price (USD/t); inundated crop area (ha).	Win et al. 2020 (#28); Chang et al. 2023 (#46); Lamichhane et al. 2025 (#64); Lucaora et al. 2025 (#59); Do & Do 2025 (#60)
Vegetation Index Approach (NDVI, EVI, VCI)	(1) Download pre- and post-flood multispectral imagery (Landsat, Sentinel-2, MODIS). (2) Calculate index anomaly: $\Delta\text{NDVI} = \text{NDVI}_{\text{pre}} - \text{NDVI}_{\text{post}}$. (3) Classify anomaly magnitude into damage severity bands. (4) Optional: regress ΔNDVI against observed yield loss to calibrate a monetary proxy.	Countries with limited ground data; large spatial coverage; crop monitoring at national or regional scale.	Damaged area extent (ha) by severity class; proxy damage index. Monetary output only if calibrated against yield data.	Physical: % deviation from long-term mean NDVI or z-score threshold. Monetary (when calibrated): $\text{Loss} = f(\Delta\text{NDVI}) \times \text{area} \times \text{price}$, derived via regression on historical yield-loss data.	Time-series multispectral imagery; cloud-free acquisition dates; crop mask; historical NDVI baselines; crop price (if monetised); calibration yield-loss dataset.	Venkatappa et al. 2021 (#34); Kumar et al. 2023 (#48); Islam 2024 (#55); Phetprayoon 2025 (#65); Odiji et al. 2024 (#51)
SAR Inundation Mapping	(1) Acquire C- or L-band SAR scenes during and after flood event. (2) Apply change detection (threshold or backscatter ratio) to identify inundated pixels. (3) Intersect inundation layer with crop/land-use map. (4)	Cloud-prone regions; rapid damage detection when optical imagery unavailable; large-area coverage	Inundated agricultural area (ha); flood duration map. No direct monetary output.	Physical only: Change-detection threshold on backscatter dB difference or ratio. Monetary output requires external coupling with DDF or price data — not standardised.	SAR scenes (pre- and co-event); land-use/crop mask; backscatter threshold calibration data; DEM (for hydraulic correction of shadows).	Cian et al. 2018 (#20); Wang et al. 2023 (#47); Syldon et al. 2024 (#49); Bahar et al. 2024 (#52)

	Report inundated agricultural area (ha); attach unit damage estimate externally if monetary output needed.	(Sentinel-1 global revisit 6–12 days).				
Machine Learning / Deep Learning (RF, CNN, ANN)	(1) Compile labelled training dataset (flood extent or crop yield loss) from historical events. (2) Select features: spectral bands, DEM, soil, weather indices. (3) Train classifier/regressor (RF, CNN, ANN). (4) Predict damage probability or yield loss for new event. (5) Convert predicted yield loss to monetary value.	Contexts with large historical damage datasets; where non-linear relationships between flood variables and loss are expected; experimental/research settings.	Flood damage probability map or predicted crop yield loss (t/ha or %); monetary loss if combined with price.	Loss = model_prediction(flood features) × price. Model accuracy evaluated by RMSE, R ² , F1 on held-out test set.	Labelled training samples (damage/no-damage or yield loss); multi-source raster features (spectral, terrain, soil); validation dataset; crop price.	Li & Zhang 2021 (#37); Quang & Tallam 2022 (#43); Kumar et al. 2023 (#48); Do & Do 2025 (#60)
B. Farm-scale survey and hydro-economic methods						
Depth-Damage Curves (survey-based)	(1) Conduct post-event farm surveys to record flood depth at field and observed damage. (2) Fit statistical DDF relating depth (and optionally duration, timing) to proportional yield loss. (3) Validate against independent event data. (4) Apply to new event: Loss = area × yield × price × DDF(depth).	Contexts where field-survey infrastructure exists; when local crop-specific curves are needed; validation benchmark for RS-based approaches.	Crop yield loss (t/ha, % loss, or USD/ha); asset replacement cost.	Standard approach: damage_rate = $\alpha + \beta \cdot \text{depth}$ (linear) or logistic curve fitted to observed loss ratios. Livestock/asset DDFs: regression of replacement/repair cost on flood depth. Parameters from survey data or expert elicitation.	Post-event survey: flood depth at field, observed yield or asset condition, crop type, expected yield, farmgate price. Historical flood depth records for multi-event calibration.	van Zyl & Groenewald 1984 (#1); Vozinaki et al. 2015 (#14); Win et al. 2020 (#28); Bahar et al. 2024 (#52); Cremonini et al. 2024 (#50)
Hydro-Economic Integrated Models (HEC-FDA,	(1) Build or import hydraulic model (HEC-RAS, HEC-HMS) to generate flood depth-frequency relationship. (2) Link to agricultural damage module using built-in or	US federal flood risk management planning (USACE); benefit-cost	Expected annual damage (USD/year); damage-frequency	EAD = $\sum [0.5 \times (D_i + D_{i+1}) \times (AEP_i - AEP_{i+1})]$ where D = damage at each annual exceedance probability; agricultural DDFs from	Flood frequency curve (stage-discharge-AEP); agricultural DDF table by crop type; crop acreage map; crop yield and price data;	Antolini et al. 2020 (#31); Yildirim & Demir 2019 (#23)

HAZUS-MH Ag)	user-defined DDFs. (3) Compute expected annual damage (EAD): $EAD = \int \text{Damage}(AEP) d(AEP)$. (4) Conduct benefit-cost analysis for flood risk management scenarios.	analysis for levee, reservoir, or floodplain management projects.	curve; project benefit as damage reduction.	USACE EM 1110-2-1619 or HEC-FDA built-in tables.	discount rate for benefit-cost analysis.	
Crop Simulation Models (DSSAT, ORYZA, AquaCrop)	(1) Parameterise crop model with soil, weather, and management data. (2) Introduce flood stress module (waterlogging days, root-zone oxygen deficit). (3) Run baseline (no flood) and flood scenario simulations. (4) Compute yield penalty = $\text{baseline_yield} - \text{flood_yield}$. (5) Multiply by area and price.	Biophysically complex flood-crop interactions; climate change impact studies; multi-season productivity loss estimation; when mechanistic understanding of yield loss pathway is needed.	Yield loss (t/ha) per season or cumulative over multiple seasons; soil carbon/nitrogen changes (some models).	Yield loss = $\Sigma[\text{area} \times (Y_{\text{baseline}} - Y_{\text{flood}}) \times \text{price}]$ across growing seasons. Multi-season productivity effect modelled via soil structural damage sub-routines where available.	Daily weather series (temp, precip, solar radiation); soil physical and chemical properties; crop variety parameters; planting date and management calendar; flood depth and duration sequence.	Mirza 2002 (#3); Ruane et al. 2013 (#9); Pham et al. 2021 (#40); Djanibekov et al. 2024 (#53)
Household / Farm Survey (primary data collection)	(1) Design structured questionnaire covering all damage categories (crop, livestock, assets, induced costs). (2) Conduct post-event or recall survey with representative farm sample. (3) Estimate direct losses from recall or records; indirect costs from reported disruptions. (4) Aggregate to regional or national estimate using sample weights. (5)	Gold standard for multi-category farm-scale damage; regions without administrative data; livestock and asset damage; induced and intangible categories; policy	Monetary damage by category (crop, livestock, buildings, machinery, induced costs, wellbeing); disaggregated by farm type.	Direct: replacement cost (assets), yield $\times$ price (crops), veterinary/restocking cost (livestock). Induced: repair/relocation costs, lost working days $\times$ wage. Intangible: CVM if included (WTP/WTa from structured contingent valuation).	Survey instrument with damage recall questions; sample frame (farm register or census); commodity prices; asset replacement cost schedule; labour wage rate.	Posthumus et al. 2009 (#7); Gaviglio et al. 2019 (#26); Bhowmik et al. 2021 (#35); Islam et al. 2022 (#44)

	Optional: CVM module for intangible damages.	compensation design.				
Quasi-Experiment al Methods (DiD, Matching, Panel Regression)	(1) Assemble panel dataset of farm income or yield for flooded and comparable non-flooded units. (2) Define treatment (flooded) and control (non-flooded) groups. (3) Verify parallel pre-trends assumption. (4) Estimate causal flood effect: DiD = (Y_treat_post – Y_treat_pre) – (Y_control_post – Y_control_pre). (5) Conduct robustness checks (matching, synthetic control).	Causal impact estimation for induced and long-term productivity effects; evaluation of flood risk management policies; when selection bias between flooded and non-flooded areas must be controlled.	Causal estimate of flood effect on farm income, yield, or land value (USD or %); treatment effect with confidence interval.	ATT = E[Y(1) – Y(0) D=1]; estimated via two-way fixed effects regression: $Y_{it} = \alpha_i + \gamma_t + \beta \cdot \text{Flood}_{it} + \varepsilon_{it}$. Matching on pre-flood observables to balance treated and control groups.	Panel data: farm-level income or yield for ≥ 2 periods pre- and post-flood; flood exposure indicator (binary or continuous); control covariates (farm size, soil type, irrigation); administrative unit identifiers.	Xiao 2011 (#8); Antolini et al. 2020 (#31); Wollburg et al. 2024 (#54)
C. Economy-wide methods						
Input-Output (IO) Models	(1) Obtain regional or national IO table with agricultural sector disaggregation. (2) Estimate direct agricultural output shock from flood (from farm survey or DDF-based estimate). (3) Apply Leontief inverse: total output change = $(I - A)^{-1} \times$ direct shock vector. (4) Decompose indirect losses by sector using multiplier analysis.	Regional or national economy-wide indirect loss estimation; sectoral propagation of agricultural flood shocks; disaster recovery planning.	Total output loss (USD) by sector; multiplier effect showing indirect losses beyond direct agricultural damage.	Total loss = $(I - A)^{-1} \times \Delta f$, where A = technical coefficients matrix, Δf = vector of direct final demand shocks. For dynamic IO (Yaseen 2020): inoperability $q_i(t)$ modelled as system of ODEs with recovery coefficients.	IO table at appropriate regional/national level with agricultural disaggregation; direct agricultural damage estimate (from field or RS methods); sector recovery time estimates.	Haque & Jahan 2015 (#16); Yaseen et al. 2020 (#29); Khalid & Ali 2019 (#24); Sun et al. 2025 (#61); He et al. 2025 (#63)
Computable General Equilibrium	(1) Build or calibrate SAM (Social Accounting Matrix) for the study region. (2) Specify production functions	Economy-wide welfare analysis; capturing price-response and	GDP change (%), sectoral output effects, household	Agricultural productivity shock = Δ TFP (%) calibrated from physical damage estimate.	SAM (or GTAP/TERM database); production function elasticities (CES, CET); agricultural	He et al. 2025 (#63); Djanibekov et al. 2024 (#53);

(CGE) Models	and elasticities for agriculture and linked sectors. (3) Introduce flood shock as reduction in agricultural factor productivity or capital stock. (4) Solve for new equilibrium. (5) Compare GDP, sectoral output, and household welfare with baseline.	factor reallocation effects that IO models cannot; multi-region (TERM-style) analysis of spatially heterogeneous floods.	welfare change (equivalent variation); price effects on agricultural commodities.	Welfare: equivalent variation = $\Delta CV = \sum [p_i \times \Delta q_i]$ measured at consumer prices. TERM model: multi-region SAM with bilateral trade flows.	flood shock (TFP or capital stock reduction); household income and consumption shares.	Johnson et al. 2023 (#45)
Non-Market Valuation (CVM, Hedonic, WTP/WTa)	(1) Design stated-preference survey (contingent valuation) or collect hedonic data (land prices). (2) Present hypothetical flood risk scenario to respondents. (3) Elicit WTP (to avoid flood) or WTA (compensation for flood damage). (4) Estimate mean/median WTP via logit or probit model on bid-response data. (5) Scale to population for aggregate welfare estimate.	Intangible damage categories (soil remediation, ecosystem services, psychological stress); contexts where market prices do not capture full social cost; environmental damage from flooding.	Willingness-to-pay (USD/household) for flood risk reduction; total social cost of intangible damages.	CVM: $WTP = \exp(\beta_0 + \beta_1 \cdot \text{bid} + \beta_2 \cdot X) / \beta_1 $ (logit model); aggregate WTP = mean_WTP $\times$ population. Hedonic: $\ln(P) = \alpha + \beta \cdot \text{flood_risk} + \gamma \cdot X$ for land value capitalization of flood risk.	CVM: survey sample, bid vector, socioeconomic covariates, risk perception variables. Hedonic: property/land transaction database, flood zone map, property characteristics.	Nga et al. 2018 (#21); Djanibekov et al. 2024 (#53)