Flood damage functions for rice: Synthesizing evidence and building data-driven models

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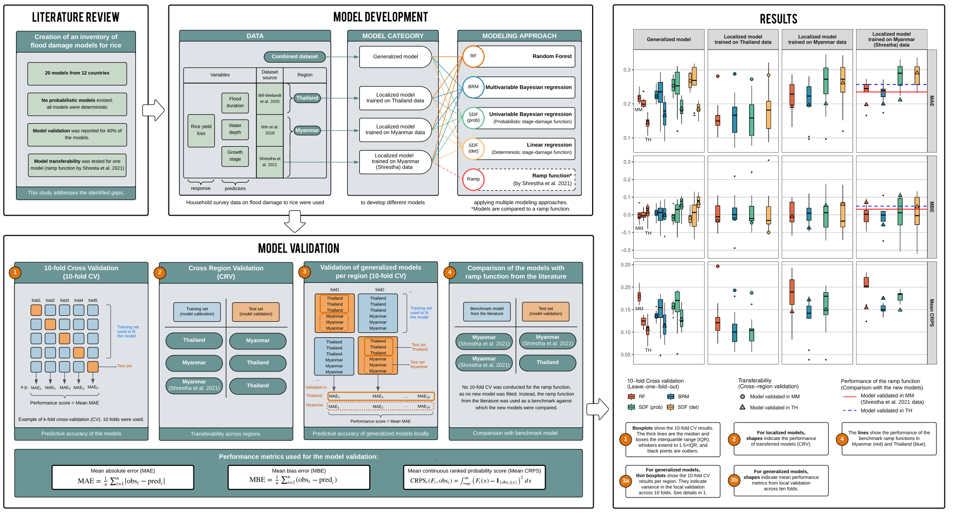
Floods are a major cause of agricultural losses, yet flood damage models for crops are scarce, often lack validation, uncertainty estimates, and assessments of their performance in new regions. This study ~~introduces CROPDAM-X, a framework for developing and~~ evaluates~~ing~~ and compares flood damage model~~s~~ling approaches for ~~crops, and applies it to~~ rice crops. We compile and review 20 damage models from 12 countries, identifying key gaps and limitations. Using empirical survey data from Thailand and Myanmar, we develop a suite of empirical models, including deterministic and probabilistic stage-damage functions, Bayesian regression, and Random Forest, based on key flood characteristics like water depth, duration, and plant growth stage. We assess predictive performance through cross-validation and test how well models trained in one region perform when applied to another. Our results show that model performance depends on complexity and context: Random Forest achieves the highest accuracy, while simpler models offer ease of use in data-scarce settings. The results also demonstrate the potential errors introduced by transferring models spatially, highlighting the need for diverse training data or local calibration. In summary, ~~W~~we present the most comprehensive review of flood damage models for rice crops to date and provide practical guidance on model selection and expected errors when transferring models across regions.

Keywords: Crops, Agriculture, Transferability, Machine learning, Bayesian regression, Random Forest, ~~CROPDAM~~Crop-Loss-X

Graphical abstract:



1 Introduction

1.1 Flood damage models for the agricultural sector

Extreme events have caused estimated losses of USD 3.8 trillion in the agricultural sector over the past three decades (1991-2021) (FAO 2023). This is equivalent to an average annual loss of about USD 123 billion or 5% of the global agricultural GDP (FAO 2023). Agricultural losses affect the livelihoods of people globally – in 2019, about half of the population worldwide (3.83 billion people) lived in households with agrifood system-based livelihoods (Davis et al., 2023). In 2023, 29% of the global population faced moderate or severe food insecurity, meaning they did not have regular access to adequate food, while 9.1% of the global population faced hunger (FAO 2024). Stress to agricultural production is caused by abiotic (non-living environmental) factors – such as flooding, drought, and extreme temperatures – and biotic factors such as pests, diseases, and invasive species. Among these, flooding is especially damaging, as it affects not only crops but also agricultural assets.

Crop models are used to predict or explain yield under varying conditions. There are three state-of-the-art approaches to assess the impact of extreme climatic events on yield: field experiments, process-based models (relying on biophysical processes), and statistical and empirical models (like regression models and machine-learning algorithms) (Hu et al., 2024). Crop models can integrate biological, physiological, ecological, physical, and economic components (Pasquel et al., 2022). While progress has been made in modeling yield reductions from droughts and heat, few process-based crop models account for the effects of excessive rainfall (Kim et al., 2024). These models often overestimate yields under wet conditions, because they consider the plants' water requirements but disregard submergence-related damage (Li et al., 2019; Liu et al., 2022). Integrating flood damage models into crop models has the potential to improve yield estimations under wet conditions.

Quantifying flood damage is imperative for effective flood risk management and transfer solutions in the agricultural sector. Flood damage models, often represented by vulnerability curves estimate asset damage due to submergence based on hazard intensity variables (e.g., flood duration and water depth). The choice of the flood damage model can have significant effects on impact estimates (Apel et al., 2009; De Moel et al., 2012; Jongman et al., 2012). Flood damage in rural areas is often underestimated or overlooked, largely due to their lower exposures and associated losses in comparison to urban settings (Förster et al., 2008). However, this neglect can have serious consequences as flooding in agricultural regions poses a significant threat to global food security.

Key drivers of yield loss due to flooding include flood duration, seasonality, and velocity (Brémond et al., 2013). Yield loss is influenced by both inundation characteristics (water depth, flood duration, flow velocity, water contamination, and sediment load) and plant characteristics (crop type, growth stage, plant height, minimum damageable flood depth, and tolerable flood duration) (Förster et al., 2008; Nguyen et al., 2021; Shrestha et al., 2021). Although yield loss results from complex, nonlinear interactions between multiple variables, few machine learning algorithms exist for crop damage modeling (Monteleone et al., 2023b). Machine l~~L~~earning methods and Bayesian inference~~ing~~ have been found suitable for estimating the size of agricultural areas damaged by flooding and flood-induced yield loss based on remote sensing data (Nhangumbe et al., 2023; Tapia-Silva et al., 2011), complemented by meteorological data (Lazin et al., 2021).

Despite these advancements, the prediction of flood losses from crop models is associated with high uncertainty. For instance, state-of-the-art crop models were found to underestimate losses by up to 7-fold (Monteleone et al., 2023a). The high variability in damage processes calls for probabilistic models, which are capable of accounting for uncertainty in model parameters, structure, and damage process, to inform flood risk management decisions (Sairam et al., 2020). In contrast to deterministic models, which predict a single loss estimate, probabilistic models quantify uncertainty in the damage predictions by providing the likelihood of the whole spectrum of loss values.

Despite the high prevalence of data-driven (including m~~M~~achine l~~L~~earning), probabilistic modeling approaches for the built-up sector (Dottori et al., 2016; Schröter et al., 2014; Wagenaar et al., 2018), they do not exist for the agriculture sector. This can be attributed to the scarcity of agricultural damage survey data in many countries. Only 31 countries submitted hazard-disaggregated agricultural losses to the Sendai Framework Monitor, from 2015 to 2021 (FAO 2023, p.19), which highlights a lack of data for developing damage models for crops. In the absence of local yield damage data, risk modelers rely on generalized models or localized models trained on data from other regions (transferred models). They are confronted with the question of which flood damage model is the most suited for their case. A popular choice of models is from practice-oriented literature including the HAZUS Flood Model, Multi-Coloured Model (MCM), and the damage curves from the Joint Research Centre (JRC). The HAZUS Flood Model estimates yield loss from river flooding based on flood duration and time of the year (FEMA 2020). The MCM presents yield reductions and the financial gain (or loss) resulting from cultivating one more (or less) hectare of land for crops in England and Wales, under different drainage conditions (Penning-Rowsell, 2013; Penning-Rowsell et al., 2005). The JRC report provides continental stage-damage functions (SDFs) – also known as depth-damage curves – for crops in Asia and Europe as well as five country-specific SDFs for agriculture (including three SDFs for rice), created based on models and maximum damage values from the literature. The JRC report found limited damage models available for the agriculture and infrastructure/roads sectors (Huizinga et al., 2017).

1.2 Spatial transferability of flood damage models

The choice of transferred damage models introduces biases in risk assessment. For instance, a case study in Thailand reported an 8-fold increase in estimated losses when applying the damage models from the Philippines in comparison to the ones from Myanmar (Budhathoki et al., 2024; applying models by Shrestha et al., 2021, 2016). In addition, most crop damage models consider the time of the year to incorporate seasonality in damage estimation. However, the usage of "time of the year" as a proxy for growth stage hinders the transfer of the model to a region with different climatic conditions and crop planting cycles as this approach inherently ties the model's processes to a specific region, reducing its applicability elsewhere (Brémond et al., 2013).

Assessing transferability across regions helps risk modelers balance the cost of collecting localized, detailed damage data against the benefits of adopting more pragmatic, cost-effective damage modeling approaches. While transferability is a key requirement in process-based model development, transferability assessments remain limited (Brémond et al., 2022). Agricultural studies have assessed the transferability of linear flood damage models for wheat (Scorzini et al., 2021), piecewise linear (ramp) functions for rice (Shrestha et al., 2021), and crop yield prediction models (Priyatikanto et al., 2023; Stiller et al., 2024). However, most damage models for crops rely on national loss databases or expert knowledge without a transferability assessment (Brémond et al., 2022).

~~3.5.~~1.3 Inventory of existing flood damage models for rice

Commented [#Author1]: As suggested by one reviewer, we moved the text in this section from the results (3.5 and 3.5.1) to the introduction.

We created an inventory of flood damage models for rice, comprising 20 models from 12 countries. Figure ~~5~~1 presents a structured overview of flood damage models for rice in the inventory (categories adapted from Gerl et al. (2016)). Half of the models are based on empirical data, 20% rely on experimental data with potted rice, and another 20% are based on expert knowledge. Model validation was reported for 40% of all models, and model transferability was only tested for a single model, the ramp functions by Shrestha et al. (2021). This study addresses these gaps by conducting model validation and transferability assessments. Less than half of the models incorporate the plant's growth stage as a predictor. Two-thirds of the models incorporate flood duration as a predictor, primarily as a categorized variable (60% of all models) and rarely as a continuous variable (15% of all models). The models developed in this study use flood duration as a continuous input variable. No model offers probabilistic outputs or formal uncertainty analysis. This highlights the need for more data-driven, multivariable, and transferable models. Most flood damage models for rice define the response variable in relative terms. In line with the existing literature, the models developed in this paper predict relative yield loss. A summary of the models in the inventory is provided in Table S~~5~~1. The models are categorized by ~~predictor variables,~~ region of application, and modeling approach (methodology and model concept), model validation, and model transferability as well as predictor variables and damage format (see Fig. 1 and Table S1). The inventory of flood damage models, including an overview of the model characteristics, the damage datasets, and lookup tables, is publicly available (Bill-Weilandt et al., 2025).

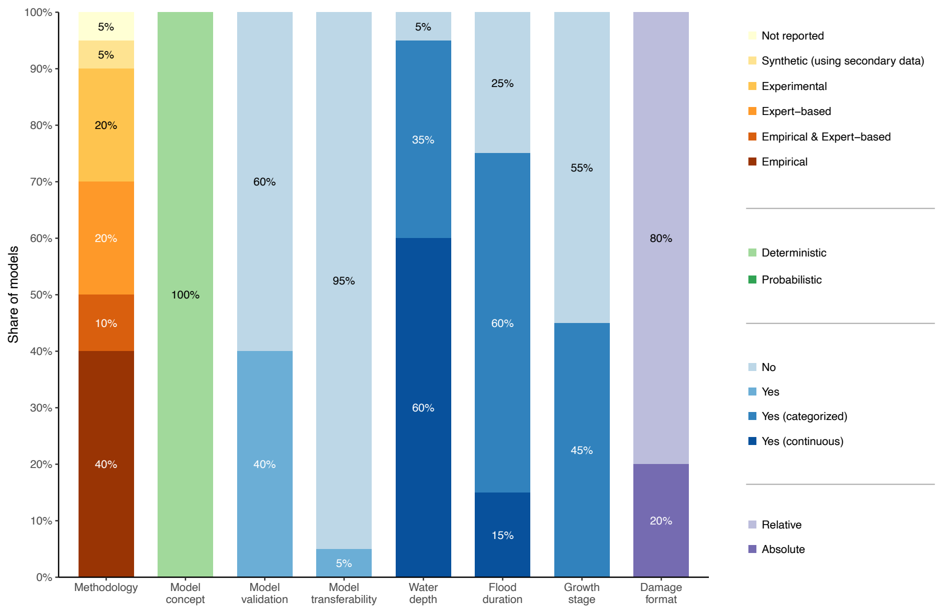


Fig. 1: Characteristics of flood damage models for rice in the inventory. The ~~F~~figure shows model characteristics, including the methodology to build the model, the model concept (deterministic or probabilistic), and whether model validation and model transferability assessment were reported in the publication. The four columns on the right indicate the inclusion and format of three commonly used predictors (water depth, duration, and growth stage) and the damage format. When a publication presented multiple model variations with the same variables for one country, the model was counted once.

1.4~~3~~ Research contributions and scope

The objective of this study is ~~twofold: 1. We create an inventory of state-of-the art flood damage models for the agriculture sector from scientific and practice-oriented literature; 2. We~~to conceptualize and implement a four-step methodological framework for advancing flood damage models for rice, which is also applicable to other crops~~in the agricultural sector~~. The framework supports flood damage modeling for crops that integrates machine learning approaches in ~~the model~~model development and validates models across regions. The methodology aims to advance flood damage models for rice crop losses. In this context, ~~Ttwo major challenges exist: first,~~here is a lack of models that quantify prediction uncertainties~~y estimation~~

and ~~second,~~evaluate the possibility of transferability across regions~~–challenges~~. Empirical data (reported from farm owners) provide real-world observations of hazard, exposure, and damage for calibrating and validating flood damage models. Machine-~~l~~Learning models use empirical data to learn complex, multi-level relationships between flood characteristics and resulting losses, often outperforming traditional stage-damage functions. Combining empirical data with machine learning-based probabilistic models has enabled transferable and reliable flood damage predictions (Rözer et al., 2019; Sairam et al., 2020).

In line with the key recommendations for the development of damage models for crops ~~of a systematic review~~ (Monteleone et al., 2023b), the methodological framework developed in this study (1) uses field observations (collected through household surveys), disaggregated by growth stage~~, which~~ (2) enables the selection of easily measurable predictors instead of crop model-derived predictors, (3) involves detailed reporting of the damage models and their parameters, and (4) validation of the damage models, including cross-region transferability~~validation~~. ~~Compared to an existing methodological framework for developing process-based flood damage models that rely on expert judgement (Brémond et al., 2022), the methodological framework presented in this study uses a purely data-driven approach.~~

The methodological framework is implemented to model flood damages to rice in two countries – Thailand and Myanmar – since rice is the primary staple crop for a large share of the global population. Grown and consumed predominantly in Asia, which accounted for almost half (45%) of the agricultural losses from natural hazards from 2015 to 2021 (FAO 2023, p.26, estimate based on FAO and EM-DAT data), rice crops are at high risk due to disasters. Moreover, a few flood damage models for rice exist, allowing us to compare the performance of models based on different approaches.

Figure ~~1~~2 presents the methodological framework, which includes (1) the creation of a flood damage data and model inventory for rice, (2) the development of machine learning and statistical flood damage model for rice, and (3) model validation (out of sample 10-fold validation and cross-region validation), and (4) model reporting. We call the crop loss modeling framework ~~CROP DAMage modeling (CROPDAM~~Crop-Loss-X~~)~~, where "X" stands for next-generation modeling approaches – such as machine learning and probabilistic methods – and cross-regional learning.

In this study, flooding refers to excessive water accumulation in a field that causes unintended submergence of plants – when part or all of the shoot (the aboveground portion) is underwater (Kim et al., 2024). Since paddy fields are routinely submerged during parts of the growth cycle, this definition differs from that of the Intergovernmental Panel on Climate Change (2022), which describes flooding as water overflowing natural boundaries or accumulating in normally dry areas. The study focuses on the vulnerability of rice plants to submergence. We disregard other causes of water-related yield loss like waterlogging (when the soil becomes overly saturated with water), lodging (when heavy rain or strong winds displace the shoots), pests and diseases (Kim et al., 2024), saltwater intrusion, and water pollution.

2 Methodology

The ~~CROPDAM~~Crop-Loss-X framework (Fig. 2~~1~~) outlines the steps for developing and validating damage models for ~~the agricultural sector~~crops.

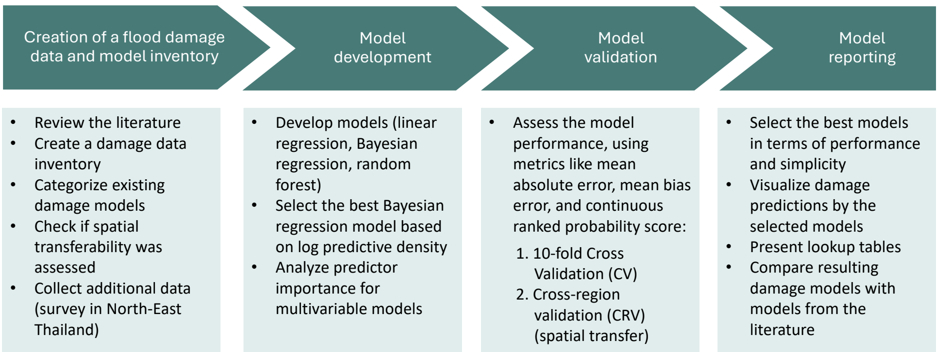


Fig. 2: Methodological framework ~~CROPDAM~~Crop-Loss-X for damage model development and validation for the agricultural sector through machine learning & model transferability assessments

2.1 Data for the model development

As a preparatory step before model development, we gathered flood damage data for rice from scientific and grey literature. In the next step, we extended the review to non-academic publications and compiled a table of existing flood damage models for rice (Table S1~~5~~). To develop new flood damage models for rice, we combined the three datasets presented in Table 1.

Table 1: Flood damage datasets for rice used for the model development, including the variables relative yield loss, water depth, flood duration, and growth stage

Country	Basin	~~Data collection~~Household survey period	Flood events covered by the survey questionnaire	Damage cases	Number of rice farming households surveyed	Reference
Thailand	Lower Songkhram River Basin	March 11 – 28, 2023	Major flood events from 2013-2023	c=137	n=491 rice farming households out of 584 surveyed households	(Bill-Weilandt et al., 2025)
Myanmar	Bago River Basin (Bago, Thanatpin, and Kawa townships)	October 22 - November 3, 2019	in August 2011, July 2018 (and dam breach in August), and August 2019	c=429	n=174 with income from rice out of 340 surveyed households	(Shrestha et al., 2021)
Myanmar	Bago River Basin (Bago township)	June - July 2016 and May 2017	June-July 2016 and May 2017	c=86	n=78 with income from rice out of 254 surveyed households	(Win et al., 2018)

We used survey-based flood damage data published by Shrestha et al. (2021), including four key variables: relative yield loss, water depth, flood duration, and growth stage. This dataset was complemented with additional data from the same basin in

Myanmar (Win et al., 2018). These were the only publicly available datasets that included all four variables and were suitable for developing predictive models.

In addition to the secondary datasets, we conducted a household survey among farmers in Northeast Thailand to collect flood damage data concerning rice. The survey data collected in Thailand are comparable to those from Myanmar. We interviewed 584 households (20% of the 2,904 total) in the Lower Songkhram River Basin in March 2023, exceeding the minimum sample size for a 95% confidence level (see a map in Fig. S1 and Tables S~~1~~2-S3~~2~~ for details on the data collection). The methodology of the household survey conducted from March 11-28, 2023, is described in detail in the Supplementary Information (1.2). The data used for the model development is publicly available (Bill-Weilandt et al., 2025).

In the Lower Songkhram River Basin in Northeast Thailand, over 80% of households earn income from rice farming. Located in the Mekong Delta near the Lao PDR border, the area often experiences flood-related rice yield losses. On May 15, 2020, it was designated Thailand's 15th Ramsar site for its rich biodiversity and vital ecosystem services. The site includes wetlands, the nearly 100 km long Lower Songkhram River, floodplains, and marshlands, surrounded by paddy fields (Ramsar, 2019).

In the Bago River Basin in Southern Myanmar, ~~40,00 ha of~~ paddy fields account for about half of the sown area. The 331 km long Bago River is used for hydropower generation, irrigation, and fishing (Win et al., 2018). ~~(Shrestha et al., 2021; Win et al., 2018).~~ Hosting over 20,000 migratory waterbirds, the Moeyungyi Wetland Wildlife Sanctuary, located west of the Bago River Basin, between the Waw Township and the Bago Township, was declared a Ramsar site in 2004 (Ramsar Site Information Service, 2004). Win et al. (2018) interviewed 254 households, and Shrestha et al. (2021) interviewed 340 households in the downstream area of the Bago River Basin. The downstream part of the basin is flat (with an elevation below 10 m) in contrast to the hilly upstream parts (with an elevation of 50-750m) (Shrestha et al., 2021).

2.2 Model development

Each of the three selected dataset contains three predictor variables (flood duration, water depth at the flood location, and plant growth stage) and a response variable (relative yield loss), describing the share of yield lost from 0 (no yield loss) to 1 (total yield loss, Table 2). The considered phenological traits (duration of each plant growth stage and the plant height at each plant growth stage) are similar in the datasets used to develop the models (see Fig. S2).

Table 2: Overview of predictor and response variables used for flood damage model fitting. The variables describe flood events reported in the household surveys conducted in Thailand and Myanmar described in Table 1. The ranges indicate the minimum and maximum values reported in the household surveys.

Model components	Variable	Scale: range (of values in the combined data~~-~~set), unit (if applicable)
Predictors (n=3)	Flood duration	continuous: 1 – 100 days
	Water depth	continuous: 2 – 500 cm
	Growth stage	ordinal: (1) "vegetative stage", (2) "reproductive stage", (3) "maturity stage"
Response (n=1)	Relative yield loss (or loss ratio)	continuous: 0 – 1

In this study, we develop data-driven models – namely linear regression, Bayesian regression, and Random Forest models – to estimate direct physical flood damage to crops, with rice as an example crop. Each modeling approach ~~type~~ is presented in ~~Table 3 and explained~~ in detail in Section 2 of the Supplementary Information, and formulas are provided in Table 3.

Linear regression: In line with similar studies (Merz et al., 2013; Schoppa et al., 2020; Schröter et al., 2014; Wagenaar et al., 2017), the linear regression uses the square root of water depth, which is commonly used as a reference damage model for assessing the value of additional model complexity. The root function has two coefficients α and β. We defined these coefficients by fitting them to the data such that we minimize the error on the training data using the ordinary least-squares method. The formula we used is: $relative\ yield\ loss = \alpha + \beta\sqrt{water\ depth} + \varepsilon$ (Wagenaar et al., 2017).

Bayesian regression: Bayesian regression is used to model relative damage using a zero-and-one–inflated beta distribution whose parameters are estimated within a probabilistic framework. Instead of predicting only a single mean value, the Bayesian approach models all distributional parameters including the zero- and one-inflation, position, and precision of the beta distribution as functions of covariates. This multi-parameter formulation allows the regression to capture both the probability of extreme outcomes and the continuous variation in losses simultaneously.

Random Forest:~~-~~ Random Forest was selected because it has performed well in past flood-loss studies (e.g., Merz et al., 2013; Wagenaar et al., 2017) and is suitable for representing non-linear multivariable relationships using relatively small datasets. A Random Forest is a supervised learning algorithm based on an ensemble of regression trees. A regression tree is a set of rules to predict an output value (e.g. damage) based on a set of inputs (e.g. water depth and growth stage). These regression trees can be generated from historical data on input - output combinations using the method of (Breiman, 2001). Each tree in the Random Forest is based on a subset of historical data, which is resampled for each tree. The individual trees each predict one output value and, as such, the method provides a probabilistic distribution of damage prediction. More details on Random Forests can be found in the Supplementary Information (2.1).

For each model type, we developed one generalized model using the combined dataset and one localized model for each region (Myanmar or Thailand). To evaluate model performance against the current standard in the literature, we included the most recently published ramp functions based on empirical data from Myanmar (Shrestha et al., 2021), and retrained our models on the same dataset to allow direct comparison. Figure 3 provides an overview of the developed models and validation steps.

Table 3: Overview of flood damage model types evaluated in this study, with relative yield loss ranging from 0 to 100%. For each new model type, we developed a generalized model trained on the combined data and two localized models (one per region). For comparison with the ramp function, we also trained the localized Myanmar models with a smaller dataset, limited to the Shrestha et al. 2021 data.

Predictors	Modeling approach	Equation	Origin of model
water depth	Linear regression [deterministic stage-damage function (SDF (det))]	$relative\ yield\ loss\ (\%) = \alpha + \beta\sqrt{water\ depth} + \varepsilon$ if wd > h_{min}, where relative yield loss is the observed yield loss ratio in percent, α is the intercept, β is the regression coefficient, ~~wd is the water depth,~~ ε is the error, and h_{min} is the minimum damageable flood depth. h_{min} = 2cm. $h_{saturation}$ = 314 cm. $relative\ yield\ loss\ (\%) = 0$ if water depth < h_{min}. $relative\ yield\ loss\ (\%) = 1$ if water depth > $h_{saturation}$.	New. See Supplementary Information, Section 2.3.1, for details.

	Univariable Bayesian regression [probabilistic stage-damage function (SDF (prob))]	Bayesian regression models approximate relative yield loss, using a zero-one-inflated-beta distribution and a logit link transformation function. The mathematical function of the damage model is: $y_i \sim ZOIB(\mu_i, \phi_i, zoi_i, coi_i)$, where $y_i \in [0,1]$, relative yield loss for observation i (e.g., one rice field) is modeled as a share that can take on the values 0 (no loss) and 1 (complete loss) or values in between (partial loss); μ (mu) is the mean of the beta distribution, ϕ (phi) is the precision of the beta component, zoi_i is the probability that the relative yield loss is either 0 or 1, and coi_i is the conditional probability that $y_i = 1$ given $y_i \in \{0,1\}$. The probability density function is (Ospina and Ferrari, 2010): $f(y_i) = \begin{cases} zoi_i \cdot (1 - coi_i), & if\ y_i = 0 \\ zoi_i \cdot coi_i, & if\ y_i = 1 \\ (1 - zoi_i) \cdot Beta(y_i; \mu_i, \phi_i), & if\ 0 < y_i < 1. \end{cases}$ h_{min} = 2cm. $h_{saturation}$ = 140 cm. ~~See Supplementary Information~~	New. See Supplementary Information, Section 2.3.2, for details.
water depth, duration, growth stage	Ramp function	$relative\ yield\ loss\ (\%) = (water\ depth - h_{min}) * (a + b * D_{flood})$ where ~~wd is water depth,~~ h_{min} is the minimum damageable flood depth, D_{flood} is the flood duration in days, and a and b are constant parameters that depend on the growth stage. The following conditions apply: If $wd > SLCS$, then $wd = water\ depth\ at\ SLCS$, where SLCS is the starting level of complete submergence of the plant. Predicted relative yield loss values are constrained to the range 0–100%.	Shrestha et al. 2021. See Supplementary Information, Section 2.4, for details.
	Multivariable Bayesian regression (BRM)	Bayesian data analysis is used to generate multivariable regression models to predict relative yield loss, with a zero-one-inflated-beta distribution and a logit link function. The mathematical derivation of the damage model is: $y_i \sim ZOIB(\mu_i, \phi_i, zoi_i, coi_i)$, where the variables are defined as described above (see univariable Bayesian regression). In addition to water depth, other loss influencing variables - duration and growth stage are included as predictors. All the variables are used as predictors for the mean of the beta distribution (mu) and zero-or-one inflation probability (zoi). Based on model performance, the predictors of the precision parameter (phi) and conditional one-inflation probability (coi) were limited to water depth and duration. ~~See Supplementary Information~~	New. See Supplementary Information, Section 2.2, for details.
	Random Forest (RF)	A Random Forest is an ensemble of regression trees. Each tree is trained on a random subset of the training data, and the tree repeatedly splits this data based on simple rules (e.g., water depth<50cm) to minimize the variation within each branch, ultimately forming a simple rule-based model. In our project, we used an ensemble of one thousand trees and allowed the trees to grow deep, relying on a large number of trees to avoid overfitting. The quantile regression forest model (Meinshausen, 2006) provides probabilistic outputs, as each tree in the Random Forest provides one output. ~~See Supplementary Information~~	New. See Supplementary Information, Section 2.1, for details.

2.3 Model validation

We evaluated model performance ~~using~~ following the four model validation steps shown in Fig. 3. First, we conducted 10-fold cross-validation (CV)~~,~~ ~~applying leave-one-out (LOO) CV~~ (Fig. S3)~~,~~ to assess predictive accuracy. For the 10-fold CV, we randomly split the observed rice yield loss data into ten folds of roughly the same size. Each fold served as a validation set for a model that was fitted with the remaining observations in the training set (James et al., 2013). Second, ~~and cross-region validation (CRV) two~~ tested model transferability across locations, also referred to as cross-region validation (CRV), by training the models on damage data from region A and validating them on data from region B. Third, we tested the performance of the generalized models in each region as part of the 10-fold CV. In this step, we used all observations per left-out fold from one region for the validation and calculated mean performance metrics across the 10 folds. Fourth, the models trained on the Shrestha et al. data from Myanmar were compared with the ramp functions by Shrestha et al. (2021). After the validation, l~~L~~eave-nothing-out (LNO) models were trained on the full dataset for future application. Table 4 summarizes the calibration and validation strategies for each model type.

Performance was assessed using three established metrics: mean absolute error (MAE), mean bias error (MBE), and continuous ranked probability score (CRPS). These allow for comparison across deterministic and probabilistic models and align with prior flood damage modeling studies (e.g., Schoppa et al., 2020; Gneiting and Katzfuss, 2014). Full definitions and formulas of the performance metrics are provided in the Supplementary Information (Section 3). By examining how performance metrics vary across folds in the 10-fold CV, we gained insights into the stability and robustness of the models. Low variability (tightly clustered errors) indicates model stability, while high variability (widely spread errors) indicates model instability, meaning that the model is not generalizing well.

We also assessed predictor importance for the multivariable models, based on the unconditional computation of the importance using the R function partykit::varimp(). For the Bayesian Regression Model, predictor relevance was derived from posterior coefficient distributions (see Supplementary~~.~~ Information, Section 2.2).

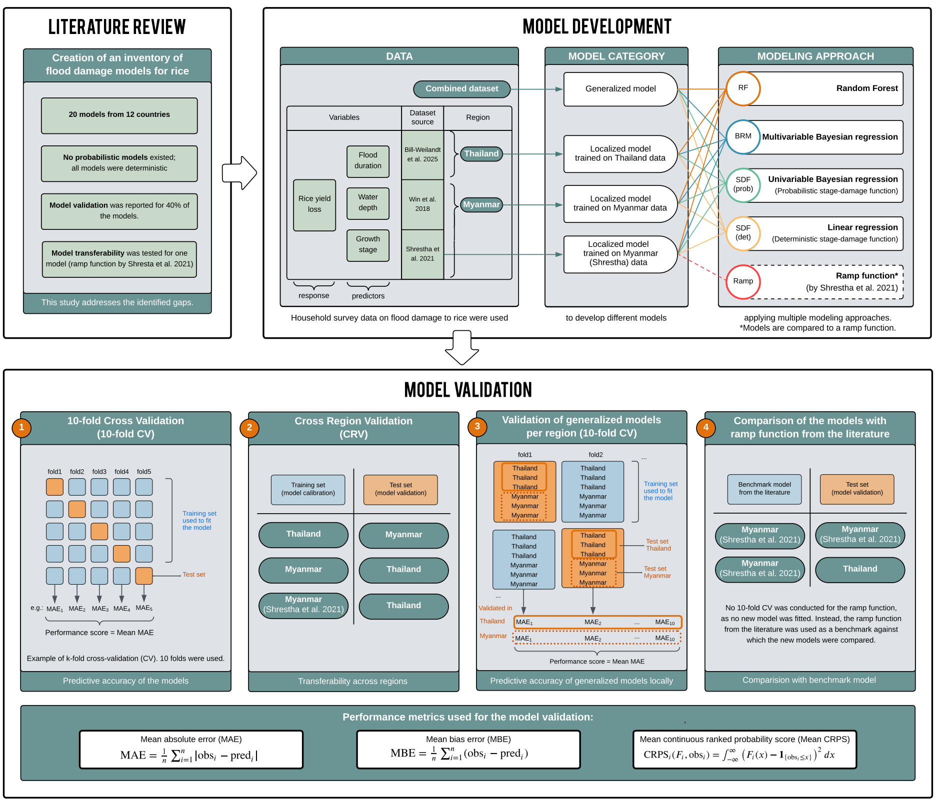


Fig. 3: Visualization of the model development and validation steps. The figure highlights key findings from the literature review that informed the methodological framework. Household survey data were used to develop different models; for each model category, four modeling approaches (boxes with solid lines) were applied. In addition, results were compared against the benchmark

ramp function for Myanmar created by Shrestha et al. 2021 (box with dashed line). Three model validation steps were defined. In each step, the same three performance metrics were used.

Table 4: Overview of performance evaluation approaches. The Table presents the model category (either generalized or localized model), the data used to fit the model (calibration), and the data used to assess the performance (validation). It further describes the approach used, including ~~Leave-one (fold)-out (LOO)~~10-fold CV, Leave-nothing-out (LNO) (creation of models trained with all the data for use in future risk assessments), and cross-region validation (CRV). Finally, the use case of each model type is mentioned.

Model category	Calibration	Validation	Approach	Use case
Generalized models	fit with all the data excluding the training data for CV	Myanmar & Thailand	~~LOO~~ 10-fold CV	Model evaluation
Generalized models*	fit with all the data	~~Myanmar & Thailand~~	LNO	For future use
Localized models for Myanmar	fit with the Myanmar data excluding the training data for CV	Myanmar	~~LOO~~ 10-fold CV	Model evaluation
Localized models for Thailand	fit with the Thailand data excluding the training data for CV	Thailand	~~LOO~~ 10-fold CV	Model evaluation
Localized models for Myanmar*	fit with all the Myanmar data	Thailand	CRV	Spatial transferability assessment and for future use
Localized models for Thailand*	fit with all the Thailand data	Myanmar	CRV	Spatial transferability assessment and for future use

3 Results and discussion

3.1 Summary statistics of the damage data used for the model development

Figure 42 presents the kernel density estimations of the variable distributions for the datasets from Myanmar (n=515) and Thailand (n=137). In the Myanmar dataset, flood duration and water depth are more concentrated than in the Thailand dataset. In Myanmar, yield loss occurred primarily in the vegetative stage (255 cases), followed by the reproductive stage (88) and the maturity stage (29). In Thailand, yield loss primarily occurred in the reproductive stage (88 cases), followed by the maturity stage (29) and the vegetative stage (20). The kernel density estimations were computed using the default Gaussian kernel in the R stats::density() function to produce the violin plot visualization.

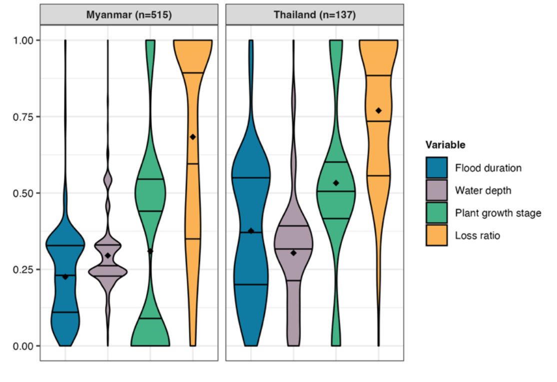


Fig. 4: Kernel density estimations of the variable distributions for the Myanmar and Thailand datasets, with lines representing the quartiles and the dots showing the mean. Continuous variables were scaled to the range [0;1] and integers were assigned to each growth stage [(1) "vegetative stage", (2) "reproductive stage", (3) "maturity stage"].

3.2 Model performance

For each metric, this study examined model performance based on two criteria: firstly, based on local data (using testing data from the same region, where the training data originated from) in a 10-fold CV (boxplots in Fig. 5), and, secondly, in a CRV (shapes in the localized model columns of Fig. 5; Section 3.4). The performance of generalized models in a specific region was assessed by separately calculating the performance for the observations per region in the left-out folds of the 10-fold CV (shapes and thin boxplots in the left column of Fig. 5). A detailed summary of the model performance assessment is provided in Table S6. This subsection presents the performance of the generalized models based on the first criterion (3.2.1) and compares their performance with the ramp functions (3.2.2).

3.2.1 Performance of the generalized models in a 10-fold cross-validation

We evaluated four model types: deterministic Stage-Damage Function (SDF), probabilistic SDF, Bayesian Regression Model (BRM), and Random Forest (RF) model, using generalized (cross-regional) training data. Model performance was assessed using Mean Absolute Error (MAE), Mean Bias Error (MBE), and Continuous Ranked Probability Score (CRPS). Figure ~~3~~5 summarizes the results. Fig. S7 in the Supplementary Information presents a comparison of predicted and observed relative yield loss for randomly sampled farms.

Among the generalized models, RF achieved the best performance in a 10-fold CV conducted with a joint dataset combining observations from Myanmar and Thailand:

- MAE: RF had the lowest error (20.3%), followed by BRM (22.3%), probabilistic SDF (24.4%), and deterministic SDF (26.3%).
- MBE: All models showed low bias, with RF (0.1%) ~~performing best~~having the lowest bias, followed by BRM (0.2%), deterministic SDF (0.4%), and the probabilistic SDF (0.5%).
- CRPS: RF also achieved the lowest CRPS (12.4%), indicating stronger probabilistic prediction performance than the BRM (14.2%) and the probabilistic SDF (15.4%).

In the 10-fold CV for generalized models, ~~M~~model complexity improved performance consistently: multivariable models (RF and BRM) outperformed the simpler univariable SDFs. Moreover, model complexity reduced the range of the MBE observed in the CV. These gains in accuracy suggest that incorporating multiple flood characteristics – more precisely, water depth, duration, and growth stage – enhances prediction quality.

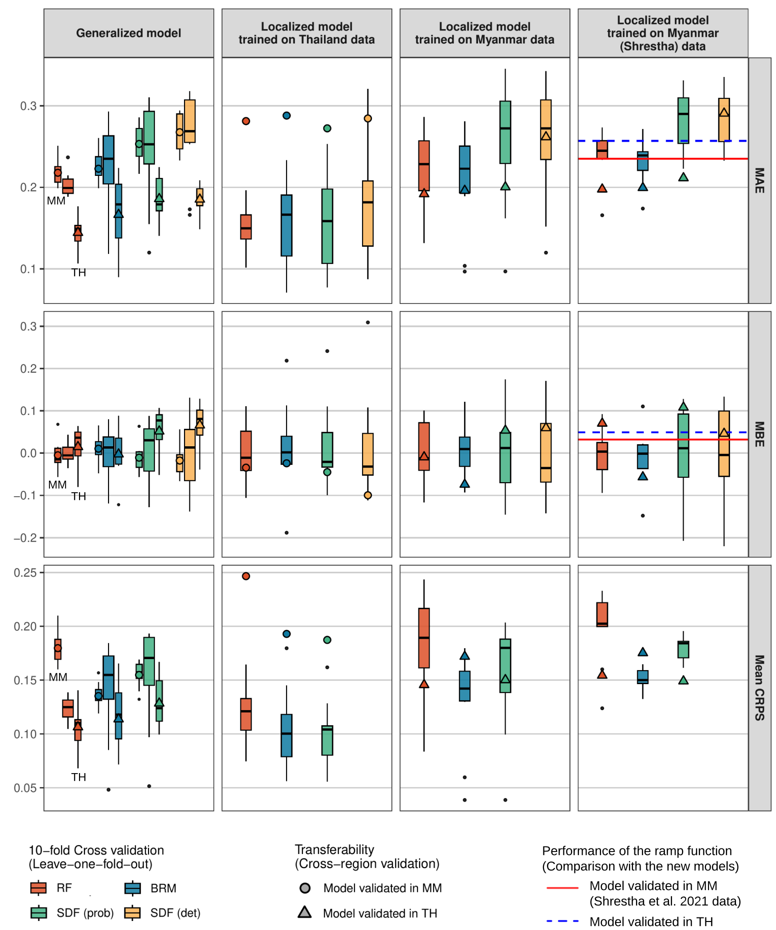


Fig. 5: Results of performance evaluation and transferability assessment. Results are shown for three performance metrics (rows) and four calibration setups (generalized, localized ~~for~~ trained on ~~Myanmar~~ Thailand data and ~~Thailand~~Myanmar data, and localized ~~with~~trained on Myanmar data by Shrestha et al. 2021) (columns). Colors indicate the model types (RF, BRM, probabilistic SDF, and deterministic SDF). Boxplots show the 10-fold cross-validation results. The thick lines ~~is~~ show the median; boxes represent the interquartile range (IQR); whiskers extend to 1.5×IQR; and black points are outliers. Each box summarizes variability across 10 folds. For localized models, ~~S~~shapes indicate the performance of transferred models (CRV). For generalized models, shapes indicate mean performance metrics from local validation across ten folds, and the thin boxplots summarize variability in the local validation

across the 10 folds. ~~Red solid~~The lines mark the mean performance of the benchmark ramp function~~s~~ in Myanmar (solid red line) and in Thailand (dashed blue lines)~~ mark their performance in Thailand~~.

3.2.2 Comparison of the new models with the ramp functions from the literature

To benchmark model performance, we compared the new models against the ramp functions from Shrestha et al. (2021), which were developed for rice in Myanmar. When tested on the full dataset (Myanmar + Thailand), the ramp functions yielded an MAE of 23.3% and an MBE of 5.3%.

Compared to this baseline:

- RF and BRM reduced the MAE by 6% and 4%, respectively.
- All new models showed significantly lower bias, with bias reductions ranging from 4.8 (RF) to 3.5 (deterministic SDF) percentage points compared to the ramp functions.
- The deterministic and probabilistic SDF had a slightly higher MAE (+3.5 and +2 percentage points, respectively), indicating limitations when excluding duration and growth stage.

To enable a more direct comparison with the ramp functions, we also trained all models using only the Shrestha et al. (2021) dataset. The findings from comparing the ramp functions with the mean performance metrics obtained from a 10-fold CV are summarized below and presented in detail in the Supplementary Information (Table S7). In this restricted setting:

- The MAE for RF and BRM converged with that of the ramp functions (around 23%).
- Both SDFs performed worse (MAE = 28.4%).
- All new models exhibited lower bias (MBE of 0.0–1.0%) than the ramp functions (MBE = 3.2%).

This confirms that while point prediction accuracy can be similar, the new models – especially RF and BRM – offer improved calibration and flexibility, particularly for regional or large-scale applications where reducing systematic bias is critical for accurate loss estimation.

3.3 Predictor importance in the Random Forest

We assessed predictor importance in the generalized and localized RF models to understand which variables most strongly influence predicted relative yield loss (Fig. 64). Importance values reflect the overall contribution of each predictor (water depth, flood duration, and growth stage) to model performance (Hothorn and Zeileis, 2023). Additionally, we also assessed the BRM coefficients (Fig. S6).

In the generalized RF model and the localized model for Myanmar, flood duration emerged as the most important predictor, followed by water depth. Growth stage contributed the least. In contrast, the localized RF model for Thailand ranked water depth highest, with flood duration playing a secondary role. Growth stage showed almost no importance in the Thailand model. These differences likely reflect regional and dataset-specific factors. The Myanmar dataset includes flood events across a wider range of growth stages and more variability in flood timing, which may explain the greater role of duration. In Thailand, floods tended to occur during a narrower window in the reproductive stage, reducing the influence of the growth stage as a predictor.

In addition, Thailand's landscape includes greater elevation differences, and the dataset captures a wider range of water depths, likely increasing the relative importance of water depth in that model.

Despite these insights, some expected relationships (shorter floods and lower water depths leading to less severe losses) were not consistently observed. This may be due to the limited number of predictor variables collected. Other relevant factors – such as rice variety, water turbidity, pest or disease pressure, plant health, and floodwater rise rate – were not included in the surveys but could influence outcomes. The growth stage variable disregards variability in the plants' vulnerability to flooding within a growth stage – further investigation would be needed to confirm if this can explain the low importance of growth stage in the model trained on the Myanmar dataset (which shows variability in growth stages). The skewed nature of the Thailand dataset, which overrepresents high-damage events, may also affect predictor importance.

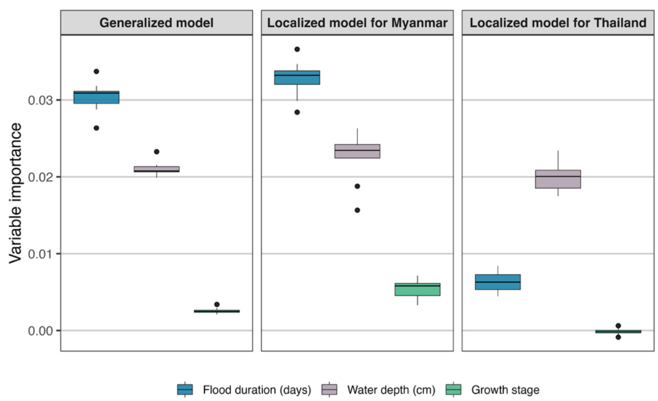


Fig. 6: ~~Violin~~ Box plots indicating the predictor importance for the generalized and localized RF models. Each boxplot shows the median (thick horizontal line), the interquartile range (IQR), the most extreme values within 1.5xIQR (whiskers), and outliers (black points). ~~kernel density estimations of the variable distributions for the two locations, with lines representing the quartiles and the dots showing the mean. Variables were scaled to the range [0;1].~~

3.4 Transferability of flood damage models

Understanding the performance of flood damage models under transfer is essential for practical risk assessment in data-scarce contexts. We assessed the performance of generalized models (~~LOO~~ 10-fold CV) and localized models (cross-region validation) in Thailand and Myanmar. Figure 5~~3~~ shows the performance of transferred models (points for validation in Myanmar and triangles for validation in Thailand). Tables S6 and S7 report the performance metrics under transfer. The results provide four key findings, which are further described below:

- Local models perform ~~best~~better than transferred models; transfer reduces accuracy, especially with skewed training data.

- Complex models (RF, BRM) generally transfer better than simple ones (including the baseline ramp functions from the literature), but they still lose performance without representative damage data.
- The direction of bias matters: overprediction may lead to high insurance costs; underprediction may leave risks underestimated.
- Generalized models can work across regions if trained on diverse data that captures relevant damage processes.

Local models outperform transferred models. In Myanmar, the worst-performing localized model for Myanmar (SDF-det) outperforms the best-performing transferred localized model for Thailand (SDF-prob). The same holds for Thailand, where the simplest localized model (SDF-det) outperforms the best complex transferred model trained in Myanmar (RF). The MAEs of the worst-performing Myanmar-trained model and the best-performing TH-trained model differ by 11.4 percentage points, which can lead to considerable differences in the loss estimates. This highlights the importance of assessing model performance and transferability.

Complex models (RF, BRM) generally transfer better than simple ones, but they still lose performance in the absence of representative damage data. The deterministic SDF loses the most predictive accuracy when transferred. The deterministic SDFs are unable to capture complex, nonlinear interactions, which makes them less applicable to new contexts with different conditions from the data they are trained on. To enable a direct comparison of the new models with the ramp functions, we also tested the transferability of the new models trained only on the Shrestha et al. (2021) dataset. In this restricted setting, all new models except for the deterministic SDF outperformed the Shrestha et al. ramp functions in terms of MAE (Fig. 5~~3~~ and Table S7).

Model transferability suffers when training data is skewed and does not comprehensively represent local damage characteristics. The models trained on Thailand data show poor transferability to Myanmar, with MAEs of 27-29% and over 50% for low-loss events (Fig. S~~7~~8) – regardless of the model type. Focusing on major flood events, the survey data collected in Thailand w~~as~~ere skewed toward extreme events, which resulted in a lack of low-loss cases. Even the best ML algorithm cannot perform well without data that captures relevant local damage processes. Broader data coverage would improve performance in transfer settings ~~like~~ such as in Myanmar, ~~but also~~as well as for predicting yield loss from small floods in Thailand.

The direction of the bias should be considered in spatial transfers; it differs depending on model type and flood characteristics (Fig. ~~3~~5 and Fig. S~~7~~8). In the present study, the localized Myanmar BRM tends to overestimate yield losses in Thailand, while the simple Myanmar models (SDF-det and SDF-prob) tend to underestimate yield losses – the RF has a low bias (Fig. 5~~3~~). All models tend to overpredict losses concerning low-impact events. Models trained in Myanmar and validated in Thailand tend to underpredict losses from short floods and shallow water depth. In contrast, models trained in Thailand and validated in Myanmar show the reverse trend; they overpredict losses under these conditions (Fig. S~~7~~8). Overprediction may lead to high insurance costs, while underprediction may lead to insufficient allocation of disaster response resources.

Generalized models perform well across regions if trained on sufficient data. They outperformed transferred models on all three performance metrics (MAE, MBE, Mean CRPS). The spread of the MAEs of the generalized BRM across ten folds is smaller in the model validation in Myanmar than in Thailand, indicating less stable results in Thailand (thin boxplots in the “generalized models” column in Fig. 5). The generalized models perform better in Thailand than in Myanmar, likely because the Thailand dataset contains fewer low-loss cases for which the model predictions are less accurate. For floods resulting in smaller losses, all generalized models tend to overpredict the loss (Fig. S~~7~~8).

Limitations in the spatial transfer analysis were the difference in sample size of the datasets for each region and a small number of regions considered (n=2). The transferred models show a considerable error, which could result from uncertainty in the historical data, a limited total sample size (n=652), a skewed Thailand dataset (towards high losses), and the lack of variables that capture potentially critical damage processes in the model.

3.5 Reporting of flood damage models for rice

~~To support practical application of our damage models in agricultural flood risk assessments, we present the outputs (Fig. 6b-e) and lookup tables (Tables S8-S11) for the generalized models: the deterministic and probabilistic stage-damage functions (SDF-det and SDF-prob), the Bayesian Regression Model (BRM), and the Random Forest (RF) model. Lookup tables for the models developed in this study are provided in the Supplementary Information.~~

We ~~also include a review of existing~~created an inventory of flood damage models for rice, based on both peer-reviewed and grey literature, expanding ~~on~~ the compilation by Shrestha et al. (2021)~~ by incorporating both peer-reviewed and grey literature~~. This inventory ~~—selected models of which are shown in Fig. 6a—~~provided~~s~~ context for the development of more flexible, multivariable, and probabilistic approaches presented in this study, and it highlighted~~s~~ the lack of transferability assessments. Figure 7a presents a selection of damage models from the inventory. The majority are deterministic stage-damage functions that relate percentage yield loss to water depth using simplified threshold or ramp functions, often for different duration classes. To support the practical application of our damage models in agricultural flood risk assessments, we present the outputs (Fig. 7b-e) and lookup tables (Tables S8-S11) for the generalized models: the deterministic and probabilistic stage-damage functions (SDF-det and SDF-prob), the Bayesian Regression Model (BRM), and the Random Forest (RF) model. Lookup tables for the generalized models developed in this study are presented in the inventory and Tables S8-S11. ~~The g~~Generalized and localized models are ~~available~~ provided for use in flood damage assessments in rice-cultivating regions (see Data Availability Statement).

3.5.~~2~~1 Stage-damage functions (SDF-det and SDF-prob)

Figures ~~6~~7b and ~~6~~7c show predictions from the deterministic and probabilistic versions of the stage-damage function (SDF). Both models are univariable and rely on water depth as the sole predictor. The SDFs predict a smooth, gradual increase in relative yield loss with increasing water depth. The deterministic SDF shows a steeper increase of relative yield loss at lower water depth and reaches complete loss at 3.15 m. In contrast, the probabilistic SDF shows a steeper increase at higher water depths, predicting complete loss at 1.40 m (median), while reaching complete loss at 2.03 m is also plausible based on the 25th percentile.

While less accurate (higher MAE and MBE) and flexible than multivariable models, the SDFs are simple to apply and useful in data-scarce contexts. Lookup tables for the SDFs are provided in Tables S8 and S9.

3.5.~~3~~2 Bayesian Regression Model (BRM)

Figure ~~6~~7d shows predictions from the BRM, a multivariable, probabilistic model using water depth and flood duration as predictors, disaggregated by growth stage. The model estimates encompass not only expected median yield loss (line) but also the uncertainty around predictions (25th – 75th percentile ribbon).

The BRM indicates that young rice plants are more vulnerable to flooding than more mature ones. As plants grow taller and reach advanced growth stages, yield loss increases more gradually with increasing water depth, and complete loss occurs at greater water depth.

- Vegetative stage: Complete loss occurs at relatively shallow water depths – a four-day flood at 1.4 m depth or a 27-day flood at 1.0 m.
- Reproductive stage: Higher tolerance is observed, with complete loss reached after a four-day flood at 1.72 m or a 27-day flood at 1.49 m.
- Maturity stage: This is the most resilient stage, where complete loss occurs only at water depths exceeding 2 m - after a four-day flood at 2.18 m or a 27-day flood at 2.00 m.

These findings highlight the combined influence of water depth, duration, and growth stage on yield loss, and indicate that even short-duration floods can lead to total yield loss in the vegetative stage. Reasons for the low loss in the maturity stage include the plant height and the possibility of early harvest to mitigate yield losses. By providing a distribution of possible predictions, probabilistic models like the BRM make uncertainty in the loss estimates visible and capture unlikely extreme events. Lookup tables for the BRM are provided in Table S10.

3.5.~~4~~3 Random Forest model (RF)

Figure ~~6~~7e shows predictions from the RF model, a non-parametric ensemble method that captures complex nonlinear relationships and interactions between predictors.

- The RF predicts stepwise increases of the relative yield loss with rising water depth, shown by flat segments followed by sharp increases of the damage curve, reflecting the tree-based model structure; it partitions the predictor space into discrete regions rather than fitting continuous functions.
- Across all growth stages, yield loss tends to plateau at a similar water depth (~2 m). In contrast to the BRM (where all curves plateau at complete loss), the RF curves for shorter flood durations plateau at lower relative yield loss.
- The maximum relative yield loss increases with longer durations and decreases with advanced growth stages; it is the highest in the vegetative stage (95 %), followed by the reproductive stage (94 %), and lowest in the maturity stage (88 %).

- The maximum relative yield loss slightly increases with growth stage, and slightly decreases with later growth stages, indicating that more mature plants are more resilient.
- Greater variability in the predictions is observed at water depths above 2 m, as indicated by the wider interquartile range.

While the RF model achieved the highest predictive accuracy overall (lowest MAE), it is more difficult to interpret and communicate than SDF and BRM models. Lookup tables for the RF model are provided in Table S11.

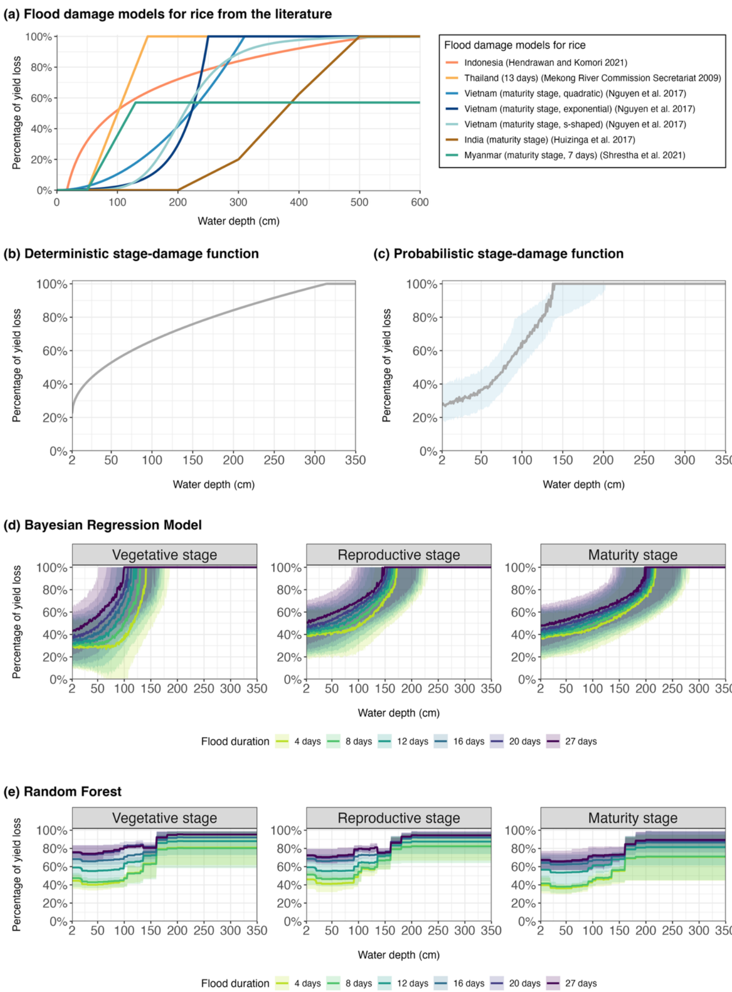


Fig. 7: Flood damage models for rice. The ~~F~~figure presents predictions by selected models from the literature (panel a, see Table S5) and from the generalized models developed in this study, including the deterministic and probabilistic SDF (panels b-c) and two probabilistic, multivariable models: Bayesian Regression Model (panel d) and Random Forest (panel e). Solid lines represent the median prediction of the BRM and the mean prediction from the ensemble of trees in the RF; shaded ribbons show the interquartile range (25th to 75th percentile).

3.5.~~4~~5 Summary and practical application

Each model provides distinct advantages depending on the intended application:

- SDF-det and SDF-prob are simple, interpretable, and suitable for settings with limited data.
- BRM offers transparency, probabilistic outputs, and robust performance, making it appropriate for informed policy planning.
- RF provides high predictive accuracy and captures complex nonlinear effects, best suited for data-rich applications.

The accompanying lookup tables enable rapid, non-technical application of these models for insurance pricing, disaster risk assessment, and climate adaptation planning. Users may select a model based on available inputs, intended use, and the required level of interpretability.

4 Conclusion

~~Flooding is a leading cause of agricultural loss in rice-growing regions globally, and climate change is expected to increase both the frequency and severity of flood events. Yet~~ Eexisting flood damage models for rice remain limited in flexibility, generalizability, and probabilistic prediction capability. This study presented an inventory comprising 20 flood damage models for rice from 12 countries, which highlighted limitations of current flood damage models for rice. We introduced the ~~CROPDAM~~Crop-Loss-X framework for developing and validating flood damage models for crops, which was applied to rice in this study. We ~~In this study, we applied the framework to~~ built~~d~~ and evaluated a suite of flood damage models for rice~~. We provide several models~~, ~~- specifically, higher-performing~~including Random Forest and Bayesian Regression Models ~~for data-rich contexts and~~ as well as simpler, deterministic and probabilistic stage-damage functions for data-scarce contexts. For each of these modeling approaches, we fit generalized models (trained on data from multiple regions) and localized models (trained on data from one region) and test their spatial transferability. The models are made available for future applications. ~~The models can be integrated into tools such as AGRIDE-c to assess the economic impacts on farmers under various risk reduction strategies (Molinari et al., 2019).~~

Our findings highlight that, among the generalized models, the Random Forest (RF) model performs best~~, with an MAE of 20%, an MBE of 0.1%, and a CRPS of 12%~~, followed by the ~~generalized~~ multivariate Bayesian Regression Model (BRM). The results indicate that each model provides unique strengths depending on the use case: Excelling in predictive power and modeling complex nonlinear relationships, RF models are best suited to data-rich applications. BRM are easier to interpret than RF models, tend to provide stronger probabilistic outputs on smaller datasets than RF and stage-damage functions (as shown by the mean CRPS in the localized model validation), ~~and solid performance,~~ making them appropriate for evidence-based flood risk management policymaking. The simple stage-damage functions with water depth as the only predictor are easy to interpret and ideal for contexts where data availability is limited.

This study also provides a systematic investigation of transferability of rice damage models across regions. We find limited transferability of localized models across regions, especially when data ~~is~~ are skewed. RF models show the most consistent performance, making them the most reliable for cross-regional applications, especially when aiming for a low bias in large-scale assessments. In contrast, BRM and deterministic SDF exhibit higher bias and error, highlighting the challenges of transferring them. The direction of bias matters: Overprediction may lead to over-preparedness, and underprediction may leave risks underestimated.

Expanding the datasets to include more variables and a broader spectrum of flood characteristics (from in-situ measurements or flood models) would provide insights into additional ~~is essential to cover important~~ damage processes. This~~, which~~ could improve performance, as well as transferability~~,~~ and ~~answer~~address open questions regarding the variable importance in the RF models. Future studies could investigate whether model ensembles, e.g. Bayesian model averaging (Huang and Merwade, 2023), yield higher performance scores than single flood damage models for rice. ~~Future research could~~ While we apply ~~CROPDAM~~Crop-Loss-X to rice, it could be applied to other crops and regions in the future. A global inventory of available flood damage data categorized by crop and country would be necessary to scale up crop-specific, multi-variable models developed and validated using the ~~CROPDAM~~Crop-Loss-X framework.

Author contributions

ABW: Conceptualization, data curation, formal analysis (lead), writing – original draft preparation, funding acquisition

NS: Methodology, formal analysis (supporting), writing - reviewing & editing

DW: Methodology, writing – review & editing

KRS: Methodology

HK: Writing – reviewing & editing, supervision

PH: Writing – review & editing

DL: Conceptualization, writing – review & editing, supervision, funding acquisition

All authors read and approved the final manuscript.

Data availability

The inventory of flood damage models and data for rice is published (Bill-Weilandt et al., 2025). The inventory file includes lookup tables for models from the literature and models developed in this paper. The ~~best performing~~generalized models and localized models for Thailand and Myanmar built in this paper are available on GitHub https://github.com/ntu-dasl-sg/flood_damage_models_rice. We used the varimp() function from the partykit package in R to measure variable importance (Hothorn and Zeileis, 2023).

Competing interests

Some authors are members of the editorial board of the journal Natural Hazards and Earth System Sciences.

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