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 evaluating flood damage models for crops, and applies it to rice. 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 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. We present the most comprehensive review of flood damage models for rice 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-X

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). 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),

35 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

40 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

45 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

50 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 Learning methods and Bayesian inferencing 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

55 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

60 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 Machine Learning), 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 scarcity of agricultural damage survey data in many countries. Only 31 countries submitted hazard-

65   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

70   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),

75   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

80   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).

85   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.,

90   2024). However, most damage models for crops rely on national loss databases or expert knowledge without a transferability assessment (Brémond et al., 2022).

1.3 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 conceptualize and implement a four-step methodological

95   framework for advancing flood damage models in the agricultural sector. The framework supports flood damage modeling for crops that integrates machine learning approaches in the model development and validates models across regions.

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 (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 validation.

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 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 framework CROP DAMage modeling (CROPDAM-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-X framework (Fig. 1) outlines the steps for developing and validating damage models for the agricultural sector.
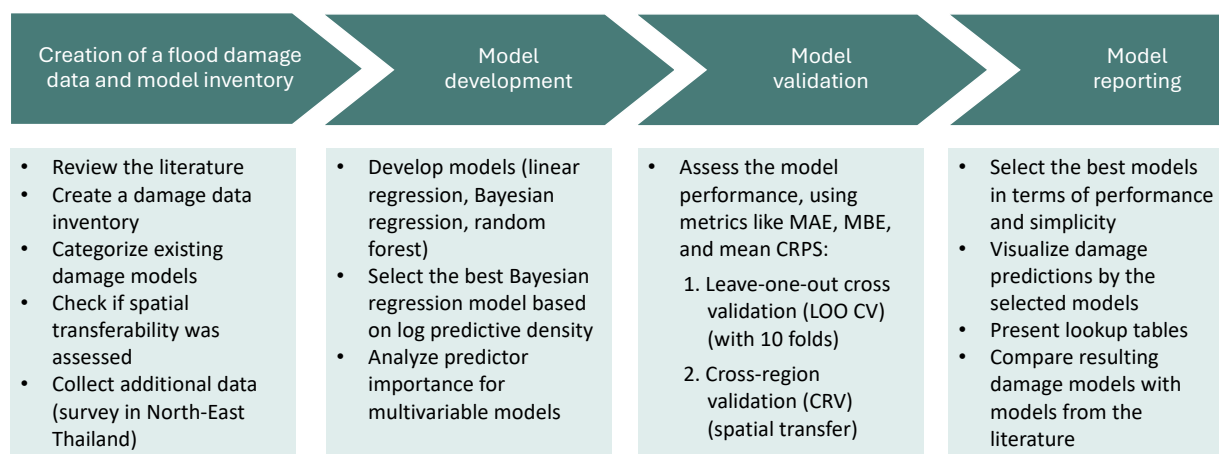
Fig. 1: Methodological framework CROPDAM-X for damage model development and validation for the agricultural sector through machine learning & model transferability assessments

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 S5). 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 period	Flood events covered	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

135   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

140   size for a 95% confidence level (see Fig. S1 and Tables S1-S2 for details on the data collection).

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).

145   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 (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

150   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

155   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

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 regression, Bayesian regression, and Random Forest models – to

160   estimate direct physical flood damage to crops, with rice as an example crop. Each model type is presented in Table 3 and explained in the Supplementary Information.

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

165 the same dataset to allow direct comparison.

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]	$relative\ yield\ loss\ (\%) = \alpha + \beta\sqrt{wd} + \varepsilon$ 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. $relative\ yield\ loss\ (\%) = 0$ if wd < h_{min}. $relative\ yield\ loss\ (\%) = 1$ if wd > $h_{saturation}$.	New
	Univariable Bayesian regression [probabilistic stage-damage function]	See Supplementary Information	New
water depth, duration, growth stage	Ramp function	$relative\ yield\ loss\ (\%) = (wd - h_{min}) * (a + b * D_{flood})$ 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
	Multivariable Bayesian regression	See Supplementary Information	New
	Random Forest	See Supplementary Information	New

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2.3 Model validation

We evaluated model performance using 10-fold cross-validation (CV), applying leave-one-out (LOO) CV (Fig. S3), to assess predictive accuracy and cross-region validation (CRV) to test model transferability across locations. Leave-nothing-out (LNO) models were trained on the full dataset for future application. Table 4 summarizes the calibration and validation strategies for

175 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 are provided in the Supplementary Information.

180 We also assessed predictor importance for the multivariable models. For the Bayesian Regression Model, predictor relevance

was derived from posterior coefficient distributions (see Suppl. Information, Section 2.2).

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) CV, Leave-nothing-out (LNO) (creation of models trained with all the data
185 **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 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 CV	Model evaluation
Localized models for Thailand	fit with the Thailand data excluding the training data for CV	Thailand	LOO 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 2 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.
190 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).
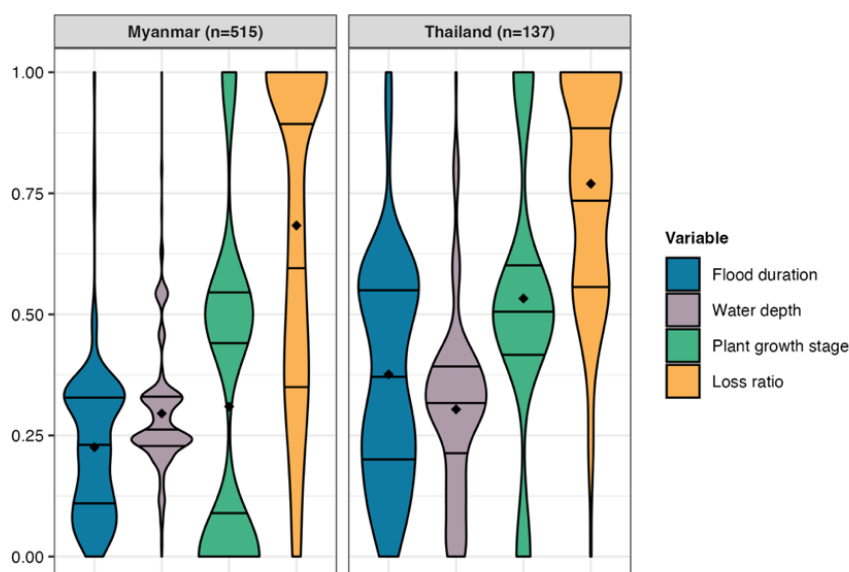
Fig. 2: Kernel density estimations of the variable distributions for the Myanmar and Thailand datasets, with lines representing the quartiles and the dots showing the mean. Continuous variables were scaled to the range [0;1] and integers were assigned to each growth stage [(1) "vegetative stage", (2) "reproductive stage", (3) "maturity stage"].

3.2 Model performance

3.2.1 Performance of the generalized models

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 summarizes the results.

Among the generalized models, RF achieved the best performance:

- 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, 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%).

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.
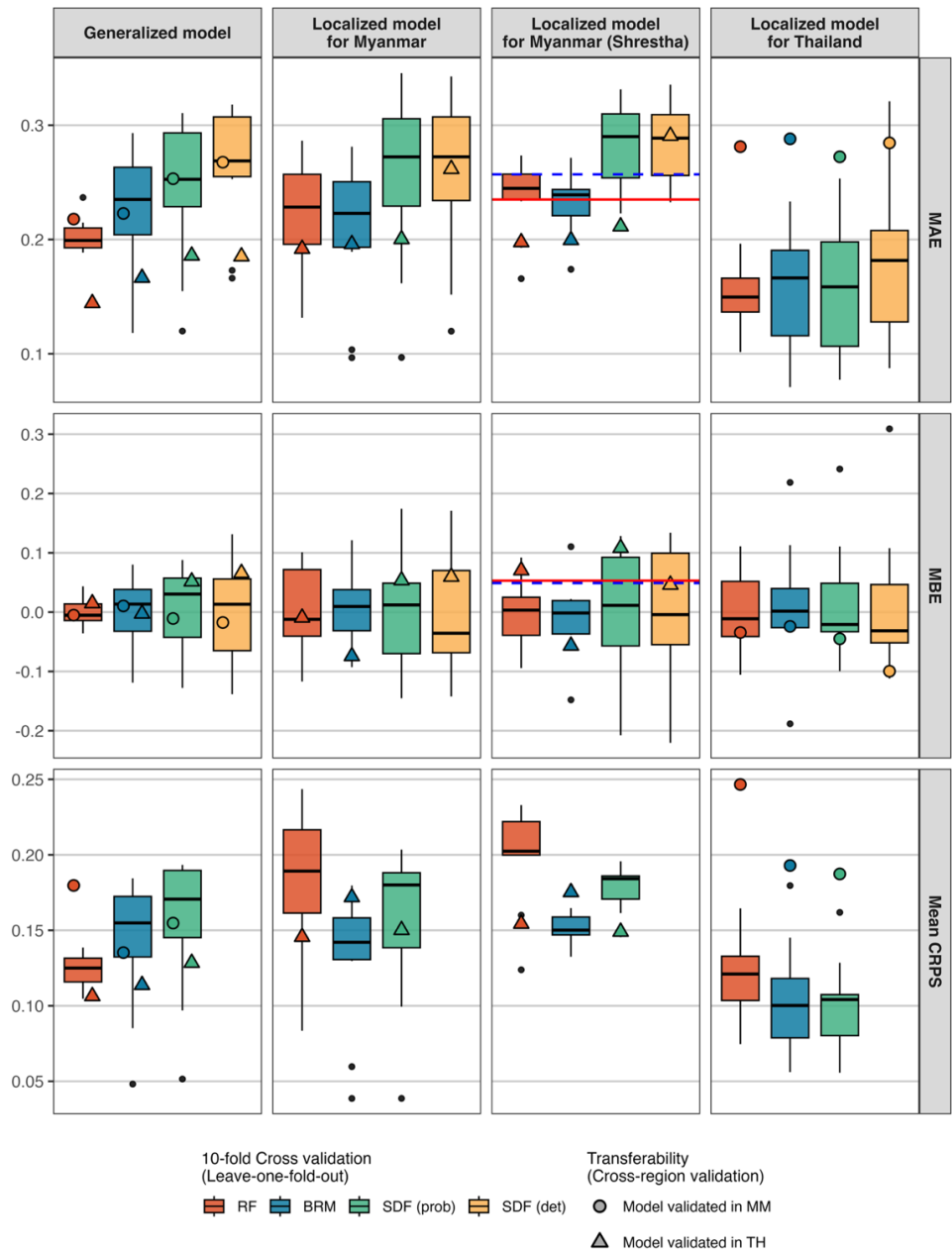
Fig. 3: Results of performance evaluation and transferability assessment. Results are shown for three performance metrics (rows) and four calibration setups (generalized, localized for Myanmar and Thailand, and localized with data by Shrestha et al.) (columns). Colors indicate the model types (RF, BRM, probabilistic and deterministic SDF). Boxplots show the 10-fold cross-validation results. The thick line is 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. Shapes indicate the performance of transferred models (CRV). Red solid lines mark the performance of the benchmark ramp functions in Myanmar and 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. 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. 4). 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
255   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
260   Thailand dataset, which overrepresents high-damage events, may also affect predictor importance.
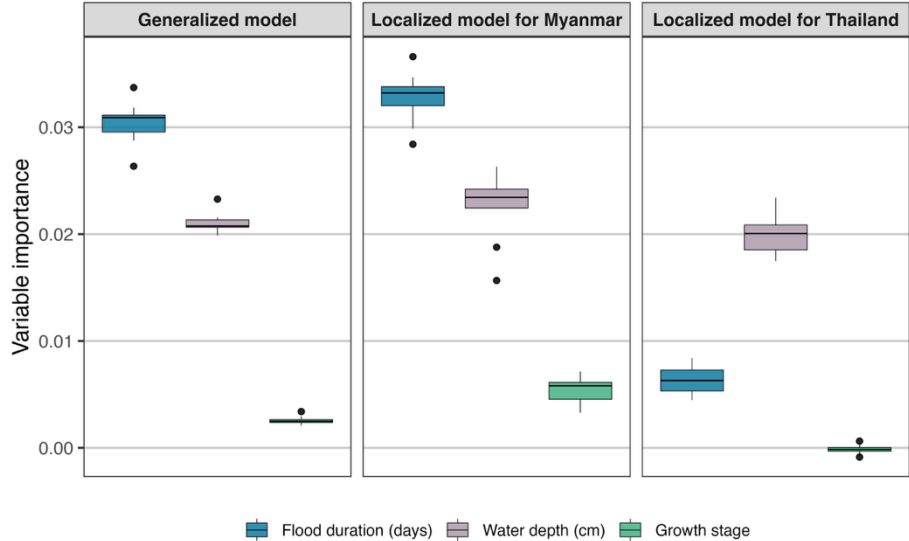
**Fig. 4: Violin plots indicating the kernel density estimations of the variable distributions for the two locations, with lines representing
the quartiles and the dots showing the mean. Variables were scaled to the range [0;1].**

3.4 Transferability of flood damage models

265   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-CV) and localized models (cross-region validation) in
Thailand and Myanmar. Figure 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:

270   • Local models perform best; 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.

275   • 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**

280 **percent**age **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**

285 **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. 3 and Table S7).

Model transferability suffers when training data is skewed and does not comprehensively represent local damage

290 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. S7) – regardless of the model type. Focusing on major flood events, the survey data collected in Thailand was 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 Myanmar but also for predicting yield loss from small floods in Thailand.

295 The direction of the bias should be considered in spatial transfers; it differs depending on model type and flood characteristics (Fig. 3 and Fig. S7). 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. 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

300 Myanmar show the reverse trend; they overpredict losses under these conditions (Fig. S7). 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 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

305 resulting in smaller losses, all generalized models tend to overpredict the loss (Fig. S7).

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

310 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.

315 We also include a review of existing flood damage models for rice, expanding on the compilation by Shrestha et al. (2021) by incorporating both peer-reviewed and grey literature. The models are categorized by predictor variables, region of application, and modeling approach. This inventory – selected models of which are shown in Fig. 6a – provides context for the development of more flexible, multivariable, and probabilistic approaches presented in this study.

3.5.1 Inventory of existing flood damage models for rice

320 We created an inventory of flood damage models for rice, comprising 20 models from 12 countries. Figure 5 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). Less than half of the models incorporate growth stage as a predictor. Two-thirds

325 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). No model offers probabilistic outputs or formal uncertainty analysis. This highlights the need for more data-driven, multivariable, and transferable models.

Fig. 6a 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. A

330 summary of the models in the inventory is provided in Table S5. 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). Lookup tables for the generalized models developed in this study are presented in the inventory and Tables S8-S11. The generalized and localized models are available for use in flood damage assessments in rice-cultivating regions (see Data Availability Statement).

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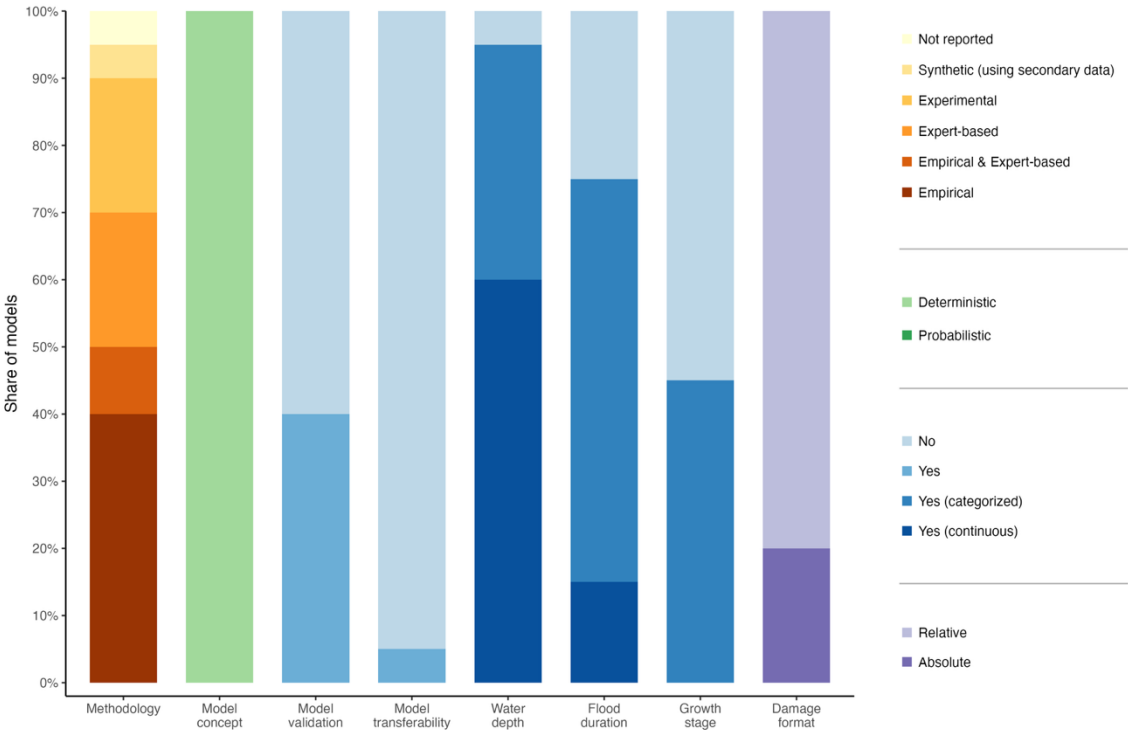
Fig. 5: Characteristics of flood damage models for rice in the inventory. The Figure shows model characteristics, including the methodology to build the model, the model concept (deterministic or probabilistic), and whether model validation and model transferability assessment were reported in the publication. 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
340 **model variations with the same variables for one country, the model was counted once.**

3.5.2 Stage-damage functions (SDF-det and SDF-prob)

Figures 6b and 6c 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

345 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 Bayesian Regression Model (BRM)

Figure 6d 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 ($25^{th} – 75^{th}$ 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 Random Forest model (RF)

Figure 6e 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.

385 **3.5.5 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.
390 - 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.
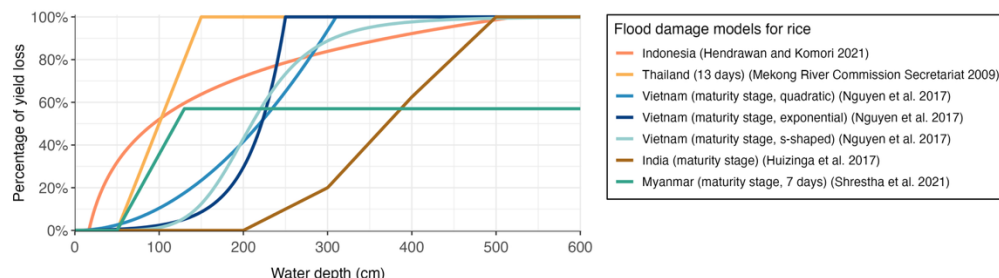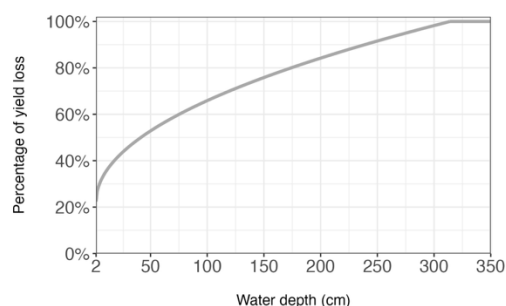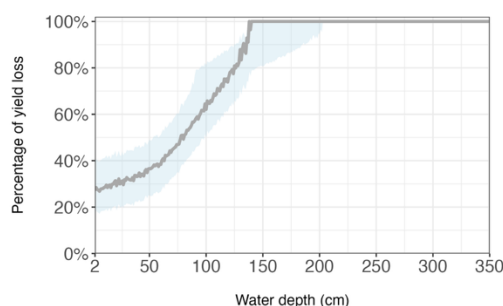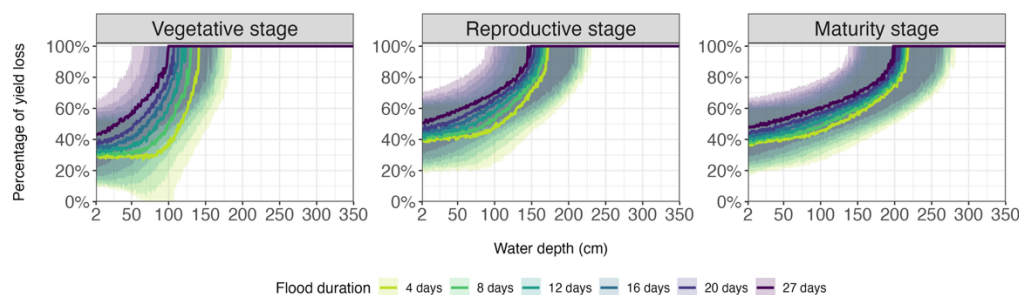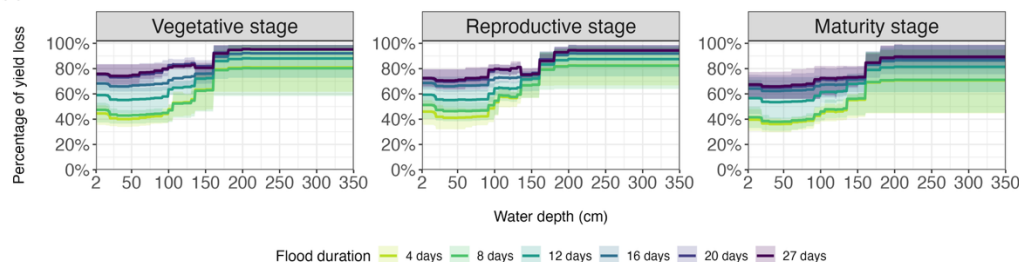
Fig. 6: Flood damage models for rice. The Figure presents predictions by selected models from the literature (panel a, see Table S5) and from the generalized models developed in this study, including the deterministic and probabilistic SDF (panels b-c) and two probabilistic, multivariable models: Bayesian 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).

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 existing flood damage models for rice remain limited in flexibility, generalizability, and probabilistic prediction capability. We introduced the CROPDAM-X framework for developing and validating flood damage models for crops. In this study, we applied the framework to build and evaluate a suite of flood damage models for rice. We provide several models – specifically, higher-performing Random Forest and Bayesian Regression Models for data-rich contexts and simpler, deterministic and probabilistic stage-damage functions for data-scarce contexts. 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 the generalized RF model performs best, with an MAE of 20%, an MBE of 0.1%, and a CRPS of 12%, followed by the generalized multivariate BRM. The results indicate that each model provides unique strengths depending on the use case: Exceling 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 (as shown by 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 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 datasets to include more variables and a broader spectrum of flood characteristics is essential to cover important damage processes, which could improve performance, transferability, and answer open questions regarding the variable importance in the RF models. Future research could apply CROPDAM-X to other crops and regions. 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-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 models 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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