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

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S1 Inventory of flood damage model for rice and data

S1.1 Flood damage models for rice in the literature

Table S1 presents an inventory of the identified flood damage models.

Table S1: Overview of flood damage models and data in the literature. The table presents details on the country, methodology, variables, rice variety, equation, model validation and model transferability assessment.

Reference	Country	Methodology	Response variable	Water depth	Duration	Growth stage	Others	Rice variety	Equation	Model validation	Transferability assessment	Model type
Hussain (1995)	Bangladesh	Expert-based	Yield reduction (in %)	Indirectly, as percentage of plant submerged (3 classes)	Yes (4 values)	Yes (6 classes)	Turbidity	BR3, B11, and B14	Equation was not reported, but lookup tables for three plant submergence classes were provided.	No	No (but lookup tables for Japan, Korea, and IR-30 rice are shown)	Deterministic
Intarathaiwong and Vudhivanich (1996)	Thailand	Experimental	Yield reduction (in %)	Yes (5 values)	Yes (4 values)	No (1 value: 45 days after planting)	No	RD 23	Ramp functions for different flood durations; equation was not reported.	No	No (but lookup tables for Japan, Korea, and the Philippines are shown)	Deterministic
Dutta et al. (2003)	Japan	Empirical	Damage (in %)	Yes (3 classes)	Yes (8 values)	No	No	Not reported	Polynomial: $AD(i,j) = \sum_{k=1}^{n} [D_m(i,j,k) CRP_a(i,j,k) mn(k)]$ and $D_m = CP_k Y_k DC_k(i,j)$, where k = crop type k at any grid (i, j), AD = the total agricultural damage to crops, D_m = damage to crop per unit area (damage as a share of normal gross returns), CRP_a = total area of cultivation of crop type k, mn = loss factor for crop type k depending on the time period in a year, CP_k = estimated cost p. unit weight of crop; Y_k = normal year yield per unit area, and DC_k = stage-damage function for crop type k (p. 29-30).	No	No	Deterministic
Kotera and Nawata (2007)	Vietnam	Experimental	Yield loss (percentage of unsubmerged plant yield)	Indirectly, as percentage of plant submerged (2 classes)	Yes (3 values)	Yes (6 classes)	Relative threshold depth for yield loss for the plant height (RTD) per growth stage; starting date of water inflow (10 values)	CR203	Weibull function: $YL = 1 - \exp\{-\rho * DSUB^x\}$, where YL (%) = relative yield loss compared to non-submerged plants, ρ = sensitivity to yield loss given by a specific growth stage and depth of submergence, DSUB (days) = duration of effective submergence for yield loss, and x = a constant accounting for characteristics of yield loss increments to DSUB given to the plants with effective submergence at the vegetative and the reproductive phases.	Yes (R^2 is presented on p. 52)	No	Deterministic

<table>
<tr><th>Reference</th><th>Country</th><th>Methodology</th><th>Response variable</th><th>Water depth</th><th>Duration</th><th>Growth stage</th><th>Others</th><th>Rice variety</th><th>Equation</th><th>Model validation</th><th>Transferability assessment</th><th>Model type</th></tr>
<tr><td>Mekong River Commission Secretariat (2009)</td><td>Cambodia</td><td>Expert-based</td><td>Damage (USD/ha)</td><td>Yes</td><td>No</td><td>No</td><td>Rice variety; Timing of the flood</td><td>Early flood paddy & rainy season paddy</td><td>Ramp functions for different rice varieties and timings of the flood; equation was not reported, but can be approximated by:
$$D = \begin{cases} 0 & if\ wd \lt 1.0 \\ m * wd - b & if\ 1.0 \lt wd \lt SLCS \\ 1, & if\ wd \gt SLCS \end{cases}$$
where D = damage in USD/ha for a specific rice variety and timing of flood, with m = slope and b= intercept.

When timing of flood = June 1, the slope is:
$$m = \left(\frac{D_{max}}{SLCS - h_{min}}\right) = \frac{390}{3.5 - 1} = \frac{390}{2.5} = 156$$
where D_{max} = the duration-specific maximum damage (in USD/ha), SLCS = the starting level of complete submergence (in meter), and h_{min} = minimum damageable flood depth (in meter). The intercept b is calculated based on y=mx+b and point P(1|0):
$\mathrm{b} = \mathrm{y} - \mathrm{mx} = 0 - 156 * 1 = -156.$

<table><tr><th>Rice variety</th><th>Flood timing</th><th>D_{max} (USD/ha)</th><th>SLCS (meter)</th><th>h_{min} (meter)</th><th>m</th><th>b</th></tr><tr><td>Early flood paddy</td><td>June 1</td><td>675</td><td>3.5</td><td>1.0</td><td>270</td><td>–270</td></tr><tr><td>Early flood paddy</td><td>July 1</td><td>275</td><td>3.5</td><td>1.0</td><td>110</td><td>–110</td></tr><tr><td>Early flood paddy</td><td>Aug. 1</td><td>25</td><td>3.5</td><td>1.0</td><td>10</td><td>–10</td></tr><tr><td>Rainy season paddy</td><td>Sept. 1</td><td>390</td><td>3.5</td><td>1.0</td><td>156</td><td>–156</td></tr><tr><td>Rainy season paddy</td><td>Oct. 1</td><td>195</td><td>3.5</td><td>1.0</td><td>78</td><td>–78</td></tr><tr><td>Rainy season paddy</td><td>Nov. 1</td><td>195</td><td>3.5</td><td>1.0</td><td>78</td><td>–78</td></tr></table></td><td>No</td><td>No</td><td>Determi nistic</td></tr>
<tr><td>Mekong River Commission Secretariat (2009)</td><td>Lao PDR</td><td>Expert-based</td><td>Damage (USD/ha)</td><td>Yes</td><td>Yes (3 values)</td><td>No</td><td>No</td><td>Not reported</td><td>Ramp functions for different flood durations; equation was not reported, but can be approximated by:
$$D = \begin{cases} 0 & if\ wd \lt 0.5 \\ m * wd - b & if\ 0.5 \lt wd \lt SLCS \\ 1, & if\ wd \gt SLCS \end{cases}$$
where D = damage in USD/ha for a specific water depth (wd) in meter, with m = slope and b= intercept.

When duration = 10 days, the slope is:
$$m = \left(\frac{D_{max}}{SLCS - h_{min}}\right) = \frac{100}{3 - 0.5} = \frac{100}{2.5} = 40$$
where D_{max} = the duration-specific maximum damage (in USD/ha), SLCS = the starting level of complete submergence (in meter), and h_{min} = minimum damageable flood depth (in meter). The intercept b is calculated based on y=mx+b and point P(0.5|0):
$\mathrm{b} = \mathrm{y} - \mathrm{mx} = 0 - 40 * 0.5 = -20.$
<table><tr><th>Duration (days)</th><th>D_{max} (USD/ha)</th><th>SLCS (meter)</th><th>h_{min} (meter)</th><th>m</th><th>b</th></tr><tr><td>10</td><td>100</td><td>3.0</td><td>0.5</td><td>40</td><td>–20</td></tr><tr><td>15</td><td>400</td><td>3.0</td><td>0.5</td><td>160</td><td>–80</td></tr><tr><td>>30</td><td>670</td><td>3.0</td><td>0.5</td><td>268</td><td>–134</td></tr></table></td><td>No</td><td>No</td><td>Determi nistic</td></tr>
</table>

<table>
<tr><th>Reference</th><th>Country</th><th>Methodology</th><th>Response variable</th><th>Water depth</th><th>Duration</th><th>Growth stage</th><th>Others</th><th>Rice variety</th><th>Equation</th><th>Model validation</th><th>Transferability assessment</th><th>Model type</th></tr>
<tr><td>Mekong River Commission Secretariat (2009)</td><td>Thailand</td><td>Expert-based</td><td>Relative damage (in %)</td><td>Yes</td><td>Yes (4 values)</td><td>No</td><td>No</td><td>Not reported</td><td>Ramp functions for different flood durations; equation was not reported, but can be approximated by:
$LR = \begin{cases} 0 & if\ wd < 0.5 \\ m * wd - b & if\ 0.5 < wd < SLCS \\ 1, & if\ wd > SLCS \end{cases}$
where LR = loss ratio (in %), m = slope and b= intercept.

When duration = 7 days, the slope is:
$m = \left(\frac{LR_{max}}{SLCS - h_{min}}\right) = \frac{40}{1.5 - 0.5} = \frac{40}{1} = 40$
where LR_{max} = the duration-specific maximum loss ratio, SLCS = the starting level of complete submergence (in meter), and h_{min} = minimum damageable flood depth (in meter). The intercept b is calculated based on y=mx+b and point P(0.5|0): $b = y - mx = 0 - 40 * 0.5 = -20$.
<table><tr><th>Duration (days)</th><th>D_{max} (USD/ha)</th><th>SLCS (meter)</th><th>h_{min} (meter)</th><th>m</th><th>b</th></tr><tr><td>7</td><td>40</td><td>1.5</td><td>0.5</td><td>40</td><td>–20</td></tr><tr><td>9</td><td>65</td><td>1.5</td><td>0.5</td><td>65</td><td>–32.5</td></tr><tr><td>11</td><td>85</td><td>1.5</td><td>0.5</td><td>85</td><td>–42.5</td></tr><tr><td>13</td><td>100</td><td>1.5</td><td>0.5</td><td>100</td><td>–50</td></tr></table></td><td>No</td><td>No</td><td>Deterministic</td></tr>
<tr><td>Ganji et al. (2012)</td><td>Iran</td><td>Experimental</td><td>Loss rate (L) = “ratio of the number of damaged stems to total stems”</td><td>Yes (up to 0.45m)</td><td>No</td><td>Yes (4 classes)</td><td>Velocity, shear stress, Froude number, Reynolds number [separate models]</td><td>Not reported</td><td>Linear function, logarithmic function, quadratic function for different growth stages;
$L = a * ln(Re) + b$, where
L = crop loss magnitude in percent and
a and b = regression coefficients determined by experiment for different growth stages (given in Table 3, on p. 418).</td><td>Yes (R^2 is presented on p. 417)</td><td>No</td><td>Deterministic</td></tr>
<tr><td>Chau et al. (2015)</td><td>Vietnam</td><td>Empirical</td><td>Total damage (in VDN billion in 2010 prices) and susceptibility</td><td>Yes (4 classes)</td><td>No</td><td>Indirectly (3 scenarios)</td><td>No</td><td>Winter-spring rice, summer-autumn rice (only considered in cost-benefit-analysis)</td><td>The damage function by Messner et al. (2007) was used:
$Damage_{total} = \sum_{i=1}^{n}\sum_{j=1}^{m} D_{i,j}$
$= \sum_{i=1}^{n}\sum_{j=1}^{m} value_{i,j} \times susceptibility_{i,j}$ where
i = category of crops (with n crop types);
j = inundation depth (with m inundation classes);
D_{ij} = damage for crop i at inundation depth j;
$value_{ij}$ = yield per ha for crop i (based on previous year) * inundated area (at depth j) * crop sale price;
$susceptibility_{i,j} = f(E_{ij}, F_k)$ measured as percentage of crop yield (e.g. for rice) in flood year compared to crop yield in previous year (based on historical yield statistics; average yield loss per district and per inundation level was calculated);
F_k = inundation characteristics of flood class k (return periods k= 1:10-, 1:20-, 1:100-year flood);
E_{ij} = timing of the crop rotation (for rice) (p. 1754).</td><td>No</td><td>No</td><td>Deterministic</td></tr>
</table>

Reference	Country	Methodology	Response variable	Water depth	Duration	Growth stage	Others	Rice variety	Equation	Model validation	Transferability assessment	Model type
Kwak et al. (2015)	Bangladesh	Empirical expert-based	damage ratio (in %) = the area of rice damage / total area of rice fields	Yes	Yes (2 classes)	No	Minimum damageable flood depth threshold at 0.3m	Single-cropped rain-fed Aman rice	Piecewise linear functions; equation was not reported, but can be approximated by: $LR = \begin{cases} 0 & if\ wd < 0.3 \\ m * wd - b & if\ 0.3 < wd < SLCS \\ 1, & if\ wd > SLCS \end{cases}$ where LR = loss ratio (in %), m = slope and b= intercept. When duration = 8 days, the slope is: $m = \left(\frac{LR_{max} - LR_{min}}{SLCS - h_{min}}\right) = \frac{60 - 15}{1.05 - 0.3} = \frac{45}{0.75} = 60$ where LR_{max} and LR_{min} = the duration-specific maximum and minimum loss ratios, SLCS = the starting level of complete submergence, and h_{min} = minimum damageable flood depth. The intercept b is calculated based on y=mx+b and point $P(0.3 \mid 15)$: $\mathrm{b = y - mx} = 15 - 60 * 0.3 = -3.$ When duration = 16 days, the slope is: $m = \frac{100-25}{1.00-0.3} = \frac{75}{0.7} \approx 107.4$ and the intercept is $\mathrm{b = y - mx} = 25 - 107.4 * 0.3 = -7.14.$	No	No	Deterministic
Samantaray et al. (2015)	India	Experimental	Damage (%)	Yes (3 classes)	Yes (6 classes)	No	Rice variety	Normal, shallow, medium deep, and deep water rice	Equation was not reported, but lookup tables for four rice varieties were provided.	No	No	Deterministic
Shrestha (2016)	Philippines	Empirical expert-based	Yield loss (Yl)	Yes	Yes (5 classes)	Yes (4 classes)	No	Not reported	Piecewise linear functions; equation was not reported, but can be approximated for each growth stage by: $LR = \begin{cases} 0 & if\ wd < h_{min} \\ m_1 * wd - b_1 & if\ h_{min} < wd < x_1 \\ m_2 * wd - b_2 & if\ x_1 < wd < SLCS \\ 1, & if\ wd > SLCS \end{cases}$ where LR = loss ratio (in %), h_{min} = minimum damageable water depth, x1 = water depth at partial submergence, and SLCS = starting level of complete submergence. The line connecting $P_1(h_{min} \mid LR\ at\ h_{min})$ and $P_2(x_1 \mid LR\ at\ x_1)$ is defined by $y=m_1x+b_1$. The line connecting $P_2(x_1 \mid LR\ at\ x_1)$ and $P_3(SLCS \mid LR\ at\ SLCS)$ is defined by $y=m_2x+b_2$. The values are provided in the suppl. data.	Yes	No	Deterministic
Huizinga et al. (2017)	India	Not reported	Normalized damage factor	Yes	No	Yes (2 classes)	No	Not reported	Piecewise linear functions; equation was not reported, but data needed to recreate the functions is provided in the suppl. data.	No	No	Deterministic

Reference	Country	Methodology	Response variable	Water depth	Duration	Growth stage	Others	Rice variety	Equation	Model validation	Transferability assessment	Model type
Nguyen et al. (2017)	Vietnam	Empirical	Damage ratio (y)	Yes	No	No (functions are for the harvesting period)	h_{max} (defined as the water depth at which the damage ratio becomes 1)	Winter rice (used in Central Vietnam)	Quadratic function: $y = ax^2 + (1-a)x$, with $(0 \le a \le 1)$ and calibrated parameters: a=1, h_{max}=3.1; Exponential function: $y = \frac{1}{a-1}(a^x - 1)$, with $(a > 1)$ and calibrated parameters: a=431, h_{max}=2.5; and S-shape function: $y = \frac{1}{a-1}(a^x - 1)$, with $(a > 0, b > 1)$ and calibrated parameters: a=431, b=5.8, where y is the damage ratio, x=h/h_{max}, h = water depth, h_{max} = water depth at which the damage ratio becomes 1, and a and b are constants. a, b, and h_{max} were calibrated using the SCE-UA method.	Yes (with district-level damage data from five districts in the Thach Han River Basin, Quang Tri Province)	No	Deterministic
Win et al. (2018)	Myanmar	Empirical	Agricultural damage rate (ADR)	Yes	Yes (3 values)	Yes (3 classes)	Investment into a farmer's field (Kyats/ hectare)	Deep-water rice variety	$ADR = \frac{Agricultural\ damage\ value\ (Kyats/hectare)}{Agricultural\ gross\ income\ (kyats/hectare)}$ "ADR was reformed by lognormal transformations [...] to normalize its distribution." The resulting ADR model is $\ln(ADR) = 0.000007\,\mathrm{I} + 0.66\,\mathrm{FH} + 0.012\mathrm{FD} + 0\mathrm{d}_1 - 0.05\mathrm{d}_2 - 0.471\mathrm{d}_3 - 1.91$, where ADR = agricultural damage rate, I = investments into a farmer's field (Kyats/ hectare), FD = flood duration (days), FH = flood height (meter), and d_* are Boolean dummy variables (0 or 1) for the growth stage.	Yes (p. 698)	No	Deterministic
Federal Emergency Management Agency (FEMA) (2020)	United States of America	Empirical	Loss (L) in USD	No	Yes (3 values)	No	Calendar date of flood	Not reported	$L = A(pY_0 - H) * D(t) * R(t)$, where L = loss (USD), A = cultivated area (acres), P = price (USD/bushel), Y_0 = normal annual yield (bushels / acre), H I = harvest cost (USD / acre), D(t) = crop loss at day t of the year (% of maximum net revenue), and R(t) = the crop loss modifier for flood duration (percent of maximum potential loss).	No	No	Deterministic
Hendrawan and Komori (2021)	Indonesia	Modeling based on remote-sensing data	Yield change (Y)	Yes	Yes	No	Velocity	Monsoon rice crop	Three separate equations to predict y, the yield change (in %), were developed through multiple regressions: 1) x = max. water depth (in m): y = 0.52 + 0.29 · ln(x) 2) x = max. velocity (in m/s): y = 3.4 + 0.95 · ln(x) 3) x = max. duration (in days): y = 2 + 0.97 · ln(x) No model that integrates all predictors was presented.	Yes	No	Deterministic
Nguyen et al. (2021)	Vietnam (trained on secondary data)	Synthetic (using secondary data)	Damage ratio (y)	Yes (4 classes)	Yes (9 classes)	Yes (3 classes)	No	NA2 and NA6 (summer-autumn rice)	Synthetic lookup tables were developed based on global secondary global damage data from the literature and plant height of rice variety planted in Vietnam.	Yes	No	Deterministic
Shrestha (2021)	Myanmar	Empirical	Yield loss (%)	Yes	Yes (6 classes)	Yes (3 classes)	minimum damageable flood depth (h_min), starting level of complete submergence (SLCS)	Rainfed rice, with max. plant height of 130 cm	Yield Loss (%) = (h_flood − h_min) × (a + b × D_flood) if h_flood > SLCS, h_flood = flood depth at SLCS if Yield Loss < 0, Yield Loss = 0% if Yield Loss > 100, Yield Loss = 100%	Yes	Yes	Deterministic
Khairul (2022)	Bangladesh	Empirical	Percent rice yield damage (PRD) (in %)	Yes (5 values)	Yes (3 classes)	No (only maturity stage)	No	Boro rice	PRD_i = 100 ∗ RRY_i/MEY, where RRY_i is the reduced rice yield due to flood and MEY_i is the maximum expected normal rice yield.	Yes	No	Deterministic

Reference	Country	Methodology	Response variable	Water depth	Duration	Growth stage	Others	Rice variety	Equation	Model validation	Transferability assessment	Model type
									Linear: y = a + b*x; Logistic: $y = a/(1 + be^{-cx})$; Natural Logarithm: y = a + b*ln(x); Polynomial (3rd order): $y = ax^3 + bx^2 + cx + d$; Power: $y = a*x^b$ (p. 8). Parameters are provided in Table 4 (p. 10). The polynominal regression model performed best for 1-3 day-floods. The logistic model performed best for 4-7 and >7 day-floods (p. 10).			
Model developed in this study	Thailand, Myanmar	Empirical	Relative yield loss (in %)	Yes	No	No	No	Myanmar: Shrestha et al. 2021 & Win et al. 2018; Thailand: RD6 (56%) & White Jasmine 105 (38%)	Linear regression [Deterministic stage-damage function] (see Table 4)	Yes	Yes	Deterministic
Model developed in this study	Thailand, Myanmar	Empirical	Relative yield loss (in %)	Yes	No	No	No		Univariable Bayesian regression [Probabilistic stage-damage function] (see Table 4 and Suppl. Information Section 2.3)	Yes	Yes	Probabilistic
Model developed in this study	Thailand, Myanmar	Empirical	Relative yield loss (in %)	Yes	Yes	Yes	No		Multivariable Bayesian regression (see Table 4 and Suppl. Information Section 2.2)	Yes	Yes	Probabilistic
Model developed in this study	Thailand, Myanmar	Empirical	Relative yield loss (in %)	Yes	Yes	Yes	No		Random Forest (see Table 4 and Suppl. Information Section 2.1)	Yes	Yes	Probabilistic

S1.2 Household survey in Northeast Thailand

This section describes the collection of data needed for the model development. We conducted a household survey in the Lower Songkhram River Basin, in Northeast Thailand, from March 11-28, 2023, in collaboration with the Stockholm Environment Institute Asia and Nakhon Phanom University. Fig. S1 shows the selected villages on a map, and Table S2 gives an overview of the village selection criteria. The selected villages have a total population of 2,904 households. To achieve a sample with a confidence level of 95%, we had to survey at least 352 households, equivalent to 12% of all households, according to Yamane's formula (Yamane, 1967):

$$n = \frac{N}{1 + N * e^2} = \frac{2904}{1 + 2904 * 0.05^2} = 352$$

where n is the sample size, N is the population size, and e is the level of precision (e.g., a 95% confidence level would be p=0.2). We increased the sample size to 20 percent of the total population, which was 584 households, equivalent to a 96% confidence level. The target of interviewing 20 percent of the households per village resulted in village-level confidence levels ranging from 80 to 89 percent. Table S3 presents the number of households surveyed per village and the village-level confidence levels. Within each village, streets and houses within the selected streets were sampled randomly. If nobody was present in a selected house, the household in the neighboring house was interviewed. In participating households, the household head, defined as the person familiar with the household finances, was interviewed. The minimum age for participation was set at 20 years, the national majority age in Thailand.

A group of trained surveyors conducted face-to-face interviews and recorded the results in the open-source data collection software KoboToolbox. The household survey covered data beyond the flood damage data that is not used in the present paper. The data collection met the international standards and expectations regarding research ethics and integrity established at Nanyang Technological University (NTU) and was approved under NTU's Institutional Review Board (IRB) Protocol IRB-2022-1105.

Fig. S1: Map of villages in the Lower Songkhram River Basin, in Northeast Thailand, where the household survey was conducted. The inset map shows the Songkhram River Basin (in orange), delineated from a Digital Elevation Model (Wagenaar et al., n.d.), and the location of the main map (in blue). The administrative boundaries by the Royal Thai Survey Department (2022) and rivers and water bodies by GISTA (2018) were used. Sources of the village locations and the Ramsar site map are provided in Table S2. Base map: Powered by Esri (n.d.).

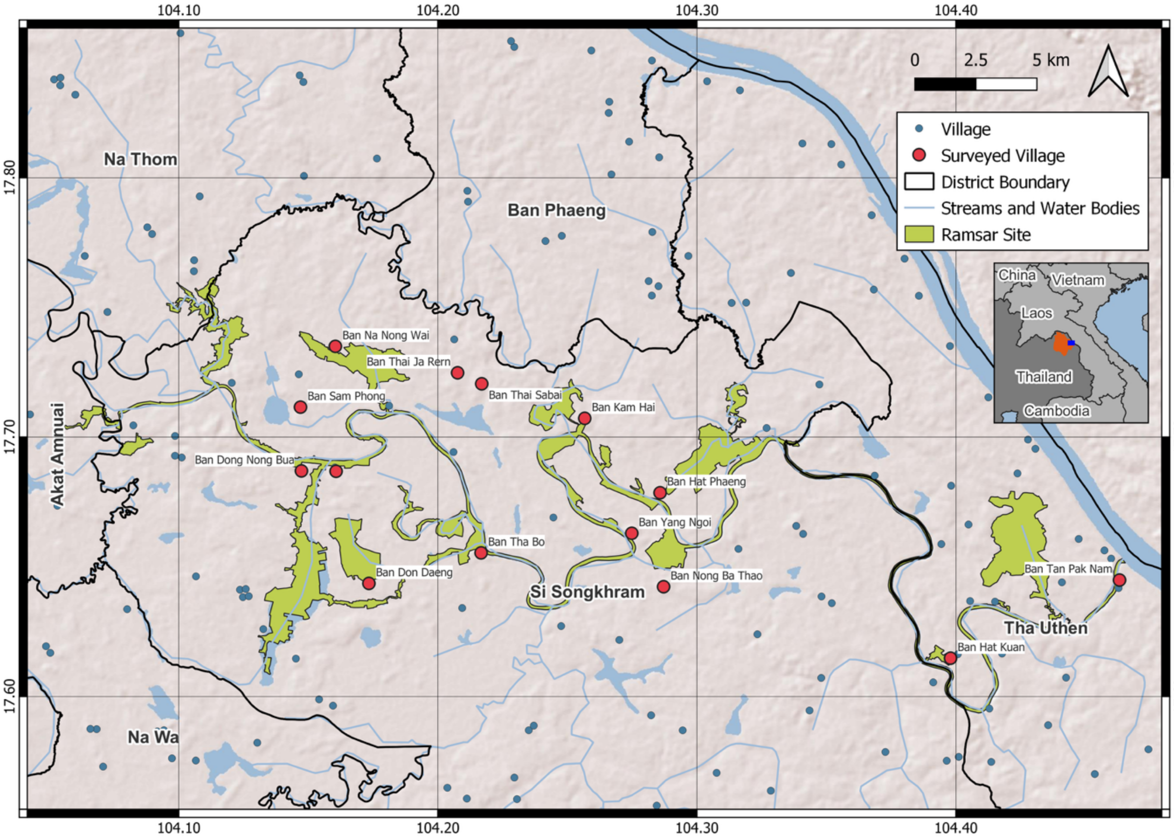


Table S2: Criteria and data for the selection of villages for the household survey. Applying selection criteria 1 to 6 (right column) led to a list of 13 villages in six subdistricts. Aiming to include two villages per subdistrict (criterium 7), we added two villages where SEI had established working relationships with the village heads (criterium 6).

Data	Year	Data (data format)	Source	Selection criteria
Village location	2017	village locations (shapefile)	(Naresuan University Geoinformatics Community and Sharing (NUGIS), 2014)	1. Villages located within a 5km radius of the Ramsar site. *Assessment in QGIS: Got intersection of Ramsar site (plus 5km in all directions) and villages.*
Ramsar site shape	2020	Ramsar site boundaries (shapefile)	(Ramsar Site Information Service (RSIS), 2020)	
Historical flood records	2013 - 2017	number of flood occurrences per village (yes/no for each year) (table)	(Thai Department of Disaster Prevention and Mitigation, Ministry of Interior, 2017)	2. Villages that experienced flooding in at least three years from 2013-2020. *Assessment in QGIS: Got intersection of flood extent and village points to assess if village experienced flooding.*
	2018 - 2020	maximum flood extent per year and village points (shapefiles)	*Flood extent:* (Geo-Informatics and Space Technology Development Agency (GISTDA), 2023) *Village points:* (Naresuan University Geoinformatics Community and Sharing (NUGIS), 2014)	
Community Forest Projects	2020	community forest project status per village (active, expired, none) (table)	(Royal Forest Department, Community Forest Management Promotion Section, 2022)	3. Villages that have a community forest that is actively managed (under an ongoing project by the Royal Forest Department or an expired project, which is usually passed on to the community afterwards).
Average annual village household income	2021	average annual household income in THB per village (excel)	*Household income:* 2021 Basic Needs (BMN) Data (Ministry of the Interior. Department of Community Development (MOI-CDD), 2021) *Minimum wage:* (Thai Ministry of Labor. Wage Committee, 2022)	4. Villages with a mean annual household income of less than THB 200,000 in 2021.[1]
	2021	village population statistics (excel)	(Bureau of Registration Administration Thailand (BORA), 2021)	
Access to subsidiary roads	2014	Roads (shapefile)	(Naresuan University Geoinformatics Community and Sharing (NUGIS), 2014)	5. Villages located within 1.5 km of a subsidiary road.
Focus group conversation subdistricts	2023	list of villages and subdistricts where SEI had conducted focus group discussions by Feb. 2023 (list)	List of subdistricts provided by SEI: Tha Bo Songkhram, Ban Kha, Si Songkhram, Sam Phong, Hat Phaeng, Chai Buri	6. Villages located in one of the six subdistricts where the SEI had conducted focus group discussions and hence had already established partnerships with the village heads or representatives of community-led organizations
List of selected villages	-	Not applicable	Not applicable	7. At least two villages per selected subdistrict should be included.

[1] This income threshold is slightly higher than two minimum wages per household. In 2022, the Wage Committee under the Ministry of Labor set a minimum wage per day for the Province of Nakhon Phanom at THB 335. Assuming 247 working days per year (based on the year 2023) and six days of annual leave (the minimum annual leave after one year of employment as per the annual leave policy), the minimum annual income is THB 80,735. For a household with two persons with minimum wages, the income would amount to THB 161,470. The international poverty line and the lower middle income class poverty line are equivalent to THB 10,658.00 and THB 18,068 per year respectively (WBG 2023).

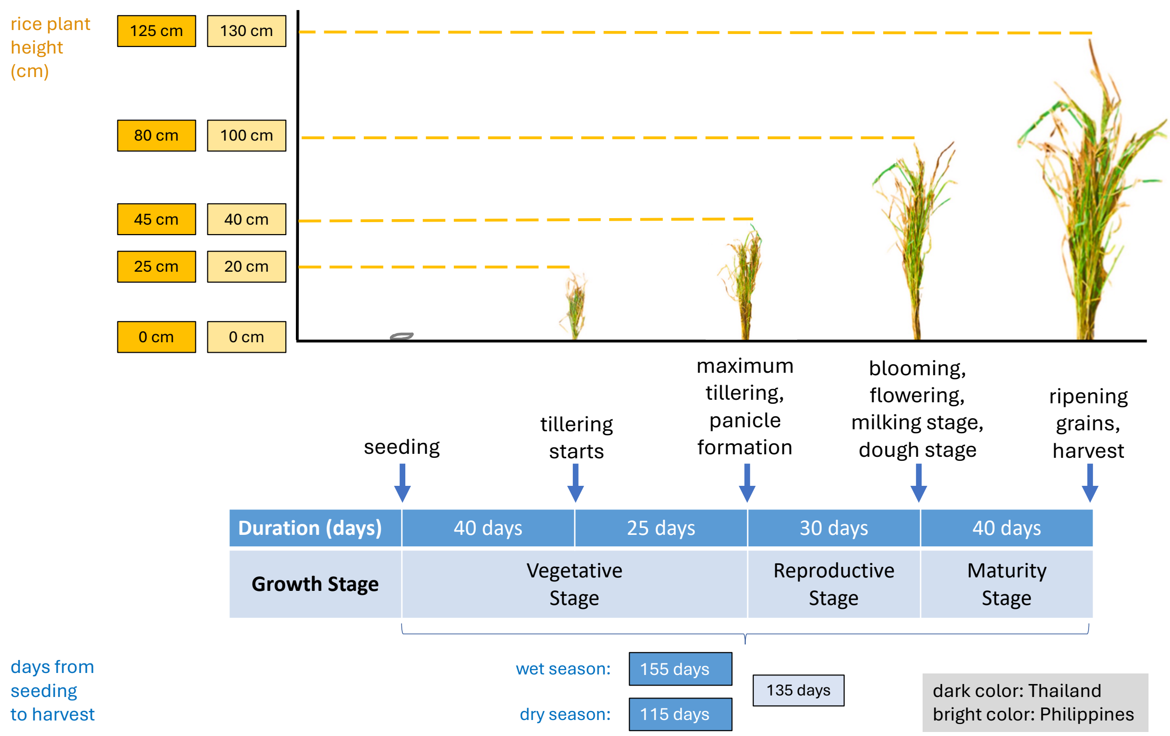
Table S3: Number of households surveyed per village in the Province of Nakhon Phanom, in Thailand, and Confidence Interval (CI). The total no. of households per village is based on the 2022 population statistics (Bureau of Registration Administration Thailand (BORA), 2021)

#	Village	Subdistrict, District	District	Total no. of households in the village	Target no. of households	No. of households surveyed	Difference of target and surveyed no.	CI
1	Ban Don Daeng	Tha Bo Songkhram	Si Songkhram	302	60	60	0	88.4%
2	Ban Tha Bo Songkhram	Tha Bo Songkhram		234	47	47	0	87.0%
3	Ban Tha Bo	Tha Bo Songkhram		262	52	52	0	87.6%
4	Ban Dong Nong Bua	Ban Kha		120	24	24	0	81.7%
5	Ban Tha Kong	Ban Kha		96	19	19	0	79.5%
6	Ban Yang Ngoi	Si Songkhram		197	39	38	-1	85.4%
7	Ban Nong Ba Thao	Si Songkhram		310	62	62	0	88.6%
8	Ban Na Nong Wai	Sam Phong		231	46	48	+2	87.2%
9	Ban Khok Klang	Sam Phong		95	19	19	0	79.5%
10	Ban Sam Phong	Sam Phong		165	33	33	0	84.4%
11	Ban Thai Sabai	Sam Phong		150	30	32	+2	84.3%
12	Ban Hat Phaeng	Hat Phaeng		147	29	30	+1	83.7%
13	Ban Kam Hai	Hat Phaeng		192	38	38	0	85.5%
14	Ban Tan Pak Nam	Chai Buri	Tha Uthen	200	40	41	+1	86.1%
15	Ban Hat Kuan	Chai Buri		203	41	41	0	86.0%
Total				**2904**	**579**	**584**	**+5**	96.3%

S1.3 Growth stages of rice plants

One predictor used in the developed flood damage models is the growth stage of the plants. The duration from seeding to harvest is 134 days in the wet season in Myanmar, which is in line with the duration of 135 days provided by the International Rice Research Institute. In Thailand, the plant growth duration in the wet season is 155 days, about 20 days longer than in Myanmar. The indicated plant height at each growth stage is in a similar range as in Myanmar, with slightly larger plants in the early growth stages and slightly smaller plants in the late growth stages (Fig. S2).

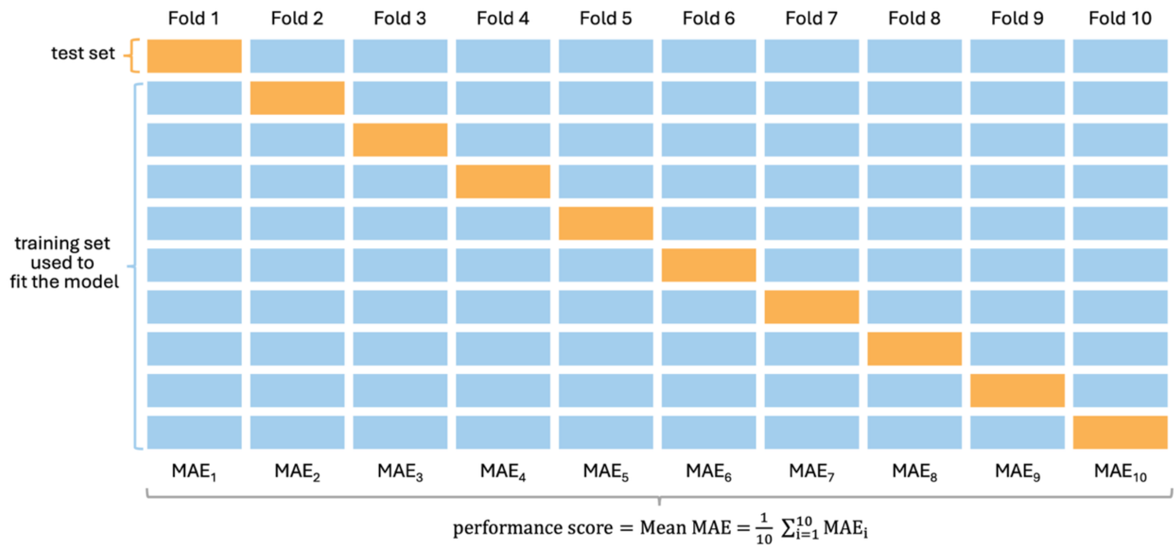
Fig. S2: Growth stages of rice plants and their durations (adapted from Shrestha et al., 2021). The data used for the Myanmar model (light-colored boxes) by Shrestha et al. (2021) is based on data by the International Rice Research Institute (IRRI, 2007) and the Bureau of Agricultural Statistics, Department of Agriculture, Philippines. The plant growth duration for the Philippines of 135 days is in line with the duration of 134 days for Myanmar, according to the survey by Shrestha et al. (n=174). The data for Thailand collected by the authors in a household survey (n=584) indicates the mean plant height (n=404) and the duration from seeding to harvest for the wet season (n=472) and the dry season (n=127).



S2 Model development

This section introduces each flood damage model developed in this study, including the Random Forest (RF) model, Bayesian Regression Model (BRM), and stage-damage functions (SDF) in a deterministic and a probabilistic version. The description of the developed models builds on previous studies on flood damage models for companies which inspired the methodological framework of the present study (Schoppa et al., 2020; Sieg et al., 2017). We compare the performance of these models with ramp functions found in the literature review (Shrestha et al., 2021). 10-fold Cross Validation is conducted as part of the model development (Fig. S3). For the 10-fold CV, we created 10 combinations of training and validation sets.

Fig. S3: Visualization of 10-fold cross validation (Figure adapted from James et al., 2013). The damage dataset was randomly split into 10 roughly equally large groups. Each of the ten test sets, also called hold-out sets or validation sets (shown in orange), served to test the model's performance. The remaining data was used to train the model (shown in blue). The model fitting and validation was repeated ten times. For each fold, we estimated three performance scores, one of which is the mean absolute error (MAE).



S2.1 Random Forest

Machine learning algorithms aim to identify patterns, classify data, or reveal relationships in large data sets. Decision tree methods stratify or segment the predictor variables into multiple subsets of the data, referred to as "regions." The ensemble of splitting rules used to divide the predictor space into regions can be represented by a tree. Decision tree-based models can combine multiple trees to make more accurate predictions (James et al., 2013).

One example within the family of decision tree methods is a Random Forest, which is an ensemble of tree-structured classifiers (Breiman, 2001). Supp. Fig. 4 visualizes the creation of Random Forests in a 10-fold CV. In a Random Forest, the input training data represents the root node of a single tree and is split recursively (branching) into subsamples (the tree nodes). Splitting is based on a threshold value of the predictor, leading to a subsample that minimizes heterogeneity in the response variable. The response value is obtained from the final subsamples (the leaf nodes). To predict the response variable for a given data point, the values of its predictor variables determine which leaf node is used. If the response variable is categorical, the model returns the most frequent class in the leaf node's subsample, also referred to as the mode (classification tree). For continuous response variables, the response value is the mean value of the leaf node's subsample (regression tree). The response variable (relative yield loss in percent) of the Random Forest models trained in this study is continuous. In the following, we therefore focus on regression trees (Sieg et al., 2017).

Random Forests use bootstrap sampling, also referred to as bagging, to select the bootstrap sample, which serves as the subsample for training a single tree. About one third of the training set is hold out, they are called Out-of-Bag (OOB) observations. The OOB sample is used internally to estimate the performance of the resulting model and to evaluate the variable importance (Sieg et al., 2017).

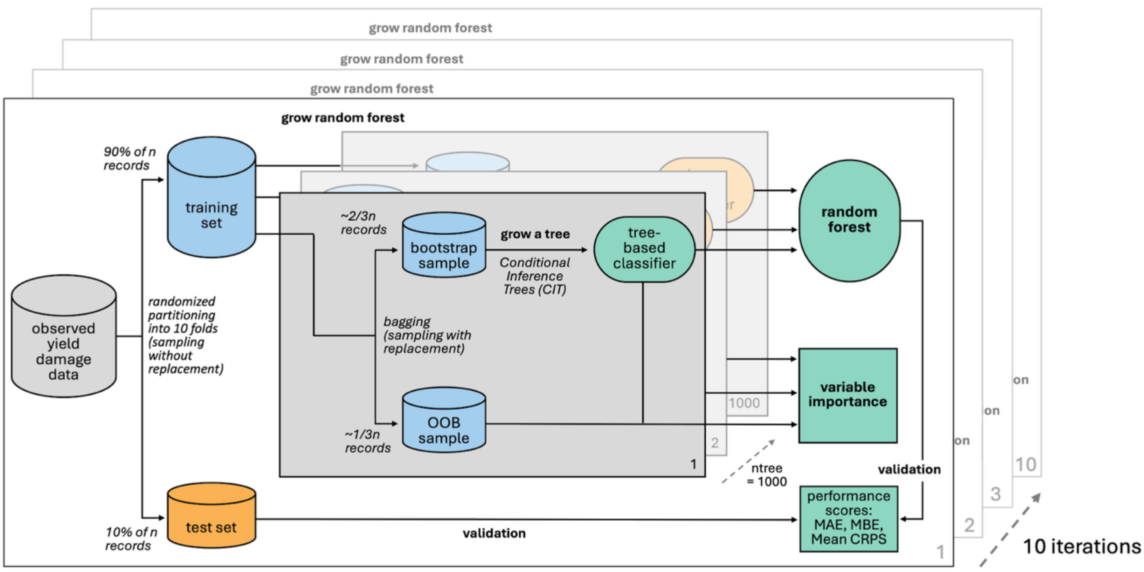
Different algorithms exist to build a single tree, like the Classification And Regression Tree (CART) algorithm, THAID, C4.5, and the Conditional Inference Tree (CIT) algorithm (Wei et al., 2015). The CART is a commonly used algorithm (Breiman et al., 1984). However, CART algorithms (Breiman et al., 1984) are prone to a variable selection bias, as they tends to favor continuous predictors with more potential splits (White and Liu, 1994). The CIT algorithm, developed by Hothorn et al. (2006), overcomes this limitation by employing unbiased recursive partitioning based on permutation tests.

The CART and the CIT algorithms differ in how they select and split variables (splitting criterion) and how they define leaf nodes (stop criterion). CART uses an exhaustive search on a random sample of m variables to identify the variable with the best split. The best split is the one that maximizes node impurity, measured as the mean square error of the response values in the subsample. Splitting in CART ends when a threshold of node impurity is met or no further splits are possible. To mitigate overfitting within each tree, OOB observations are held out. In contrast, CIT applies hypothesis testing at each node to assess the association between predictors and the response. In an RF of CITs such as partykit::cforest(), a random subset of predictors is considered at each split[2] (the number of predictors is defined by mtry), and the variable with the strongest association – determined by the smallest p-value of the hypothesis test – is chosen for splitting (Hothorn and Zeileis, 2023). If no significant association is found, splitting stops and the node becomes a leaf node (Sieg et al., 2017). The depth of the trees is regulated by mincriterion. The CIT algorithm splits only if p_value ≤ 1 – mincriterion. For example, when mincriterion = 0.9, the p-value must be < 0.1 for a split at that node (Hothorn and Zeileis, 2023). Hothorn et al. (2006) demonstrated that the CIT algorithm reduces the risk of overfitting by using statistical tests for variable selection and stopping criteria, enabling unbiased variable selection even when predictors differ in scale and splitting possibilities.

Early studies that used regression trees in flood damage modeling used the CART algorithm (Merz et al., 2013; Schröter et al., 2014), however, recent studies on flood damage modeling for companies recognized the value of CITs for datasets with variables that have different scales and splitting possibilities (Sieg et al., 2017; Sultana et al., 2018). Given that our dataset contains ordinal and continuous variables, we employed Random Forest models based on CIT. The Random Forest was created with R (version 4.4.2), a language and environment for statistical computing (R Core Team, 2024), using the cforest() function of the "partykit" package (version 1.2 – 20) (Hothorn and Zeileis, 2015). We trained an ensemble of 1,000 trees (n_{tree} = 1000) and set the number of predictor variables that are randomly selected at each split (m_{try}) to one-third of the number of predictors, following standard practice (Hastie et al., 2009). When $m_{try} > 0$, a random selection of m_{try} input variables, is performed in each node (Hothorn and Zeileis, 2023).

We use quantile regression forests, which provide probabilistic outputs rather than only a mean prediction (Meinshausen, 2006). Quantile estimates and the mean continuous ranked probability scores (CRPS), explained in detail below, are derived from the distribution of predictions of all trees in a Random Forest. "Usually unstopped and unpruned trees are used in random forests" (Hothorn and Zeileis, 2023). By setting mincriterion = 0, we allow the Conditional Inference Trees inside the forest to grow as deeply as possible, producing more leaf nodes, which improves the accuracy of the quantile estimates.

Fig. S4: Visualization of 10-fold CV and Random Forest (Figure adapted from Sieg et al., 2017)



[2] In a single CIT like partykit::ctree(), all predictors are considered at each node (Hothorn and Zeileis, 2023).

S2.2 Bayesian Regression

S2.2.1 Zero-and-one inflated beta regression

Bayesian data analysis is a method that derives a logic from data to provide a probability distribution of plausible answers to a question. The method uses probability theory to model things happening in the world or theoretical concepts like parameters. After defining a statistical model, Bayesian data analysis processes the data to generate inference. It is a tool to learn about something from the data that is not directly observable at first sight (McElreath, 2016).

We use Bayesian data analysis (for an introduction see Gelman et al., 2013; McElreath, 2016) to generate regression models to predict relative yield loss, with a zero-one-inflated-beta distribution and a logit link function. The logit link is the default for zero-one-inflated beta models (Bürkner, 2017a). Zero-one-inflated models are useful when the data contains many zeros (no loss) and ones (complete loss) that are not explained by the primary distribution of the response variable. The zero-one-inflated-beta distribution combines the beta distribution with a Bernoulli distribution to adequately model excess zeros and ones in the response variable (Ospina and Ferrari, 2010). The combined distribution has the following cumulative distribution function:

$$BEINF(y|\lambda, \gamma, \mu, \varphi) = \lambda \cdot F_{Bernoulli}(y|\gamma) + (1-\lambda) \cdot F_{Beta}(y|\mu, \varphi), \tag{S1}$$

with y being the response variable (the relative yield loss) and λ being the zero-one-inflation probability (e.g., the probability that the response is 0 or 1). The term $F_{Bernoulli}(y|\gamma)$ describes the CDF of the Bernoulli distribution with the parameter λ being the conditional one-inflation probability (the probability that the response is 1 rather than 0). The reparameterized beta distribution $F_{Beta}(y|\mu, \varphi)$ is defined by the mean (μ) and a precision parameter (φ) (Ospina and Ferrari, 2010; Schoppa et al., 2020).

To train Bayesian multilevel models (MLMs), we utilized the brms package (version 2.22.0) in R (version 4.4.2). Utilizing the probabilistic programming language Stan for Bayesian interference on the backend, the brms package enables the fitting of MLM models through an lme4-like formula syntax. MLMs predict the response variable *y* "through the linear combination *η* of predictors transformed by the inverse link function *f,* assuming a certain distribution *D* for *y*" (Bürkner, 2017b). The form of the MLM can be written as:

$$y \sim D(f(\eta_i), \theta). \tag{S2}$$

In this formula, D is the 'family,' f is the inverse link function, η is the combination of predictors, and i is the i-th data point. The parameter θ describes family-specific parameters that are estimated, e.g. the standard deviation σ in normal models. A key advantage of Bayesian Markov chain Monte Carlo (MCMC) sampling approaches compared to maximum likelihood approaches is that the former treat uncertainty as a parameter, instead of assuming that it is part of the error term. Consequently, the Bayesian models allow to evaluate uncertainty in the estimates, as they provide a distribution of predictions.

Table S4 summarizes the parameters that are estimated in the regression model. The mathematical derivation of the flood damage model is:

$$y_i \sim ZOIB(\mu_i, \phi_i, zoi_i, coi_i), \tag{S3}$$

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) and 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):

$$f(y_i) = \begin{cases} zoi_i \cdot (1 - coi_i), & if\ y_i = 0 \\ zoi_i \cdot coi_i, & if\ y_i = 1 \\ (1 - zoi_i) \cdot Beta(y_i;\ \mu_i, \phi_i), & if\ 0 < y_i < 1. \end{cases} \tag{S4}$$

Table S4: Overview of parameters, their interpretation and used link functions for the zero-one-inflated beta distribution (Bürkner, 2017a)

Parameter	Description	Interpretation	Link function	Scale
μ (mu)	Mean of the beta distribution	A larger mu indicates a higher expected relative yield loss.	Logit	$\mu \in (0,1)$
Φ (phi)	Precision (controls variance)	A larger phi means less variance, indicating that the	Log	$\Phi > 0$

		observations are more tightly clustered around the mean.		
zoi	Captures the probability that the relative yield loss is exactly 0 or 1 (zero-one-inflation probability). It is the probability that $y_i \in \{0,1\}$.	A higher zoi indicates a greater likelihood of observing the values zero or one.	Logit	$\text{zoi} \in (0,1)$
coi	Describes the probability that the relative yield loss is 1, given that the relative yield loss is either 0 or 1 (conditional one-inflation probability). It is the conditional probability that $y_i = 1$ given $y_i \in \{0,1\}$.	A higher coi suggests that, among the zero and one observations, ones are more prevalent than zeros.	Logit	$\text{coi} \in (0,1)$

In the following, we present the mathematical equations that build the foundation of the model. Each submodel uses linear predictors η that are transformed via a link function. Each linear predictor is modeled indirectly using a linear combination of predictors (including water depth, duration, and growth stage), and then transformed to ensure the result stays in the valid range, which is defined by the link function. For each submodel, the model computes a linear predictor η, which in general terms is denoted as

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots, \text{o} \quad \text{(S5)}$$

where β_0 is the intercept (the value of η when all predictors x_1, x_2 etc. are zero), the regression coefficients β_1, β_2 etc. (also called slopes or weights) quantify the effect of the independent variables x_1, x_2 etc. on the linear predictor η, and where x_1, x_2 etc. are the independent variables.

The linear predictor can take values from -∞ to +∞, but it should be constrained. In the next step, a link function is applied to transform the linear predictor η to stay within the valid bounds.

1. μ (mu), zoi, and coi can only take values in the range (0,1), hence, the logit link is used, which – for μ as an example parameter – would be denoted as:
   $$logit(\mu) = \eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots . \quad \text{(S6)}$$
   To simulate and interpret predictions, we are interested in the value of the parameter, here, μ, so we convert the formula back using the inverse logit function:
   $$\mu = \text{logit}^{-1}(\eta) = \frac{1}{1+e^{\eta}} \quad \text{(S7)}$$
2. The parameter Φ (phi) should be positive, therefore, the log link is used, with
   $$\Phi = e^{\eta}. \quad \text{(S8)}$$
   To interpret or simulate predictions for ϕ, we apply the inverse log function, which is
   $$\Phi = \exp(\eta). \quad \text{(S9)}$$

S2.2.2 Bayesian multivariate regression model

We fit two types of Bayesian generalized nonlinear multivariate multilevel models: a univariate model (with water depth as a predictor) and a multivariate model (with water depth, flood duration, and growth stage as predictors). The multivariate regression model is presented in this subsection and the univariable model is introduced in the following subsection. To build that model, we estimate the precision of the beta component (Φ) and the zero-one-inflation probability based on all available predictors. In contrast, the mean of the beta distribution (μ) and the conditional one inflation probability are estimated by the most influential predictor variables to reduce overfitting and improve predictive performance. The linear predictors with link functions are as follows:

1. Mean of the beta component (μ):
   $$logit(\mu_i) = \beta_0 + \beta_1 \cdot water\_depth_i + \beta_2 \cdot duration_i + \beta_3 \cdot growth\_stage_i \quad \text{(S10)}$$
2. Precision of the beta component (Φ):
   $$log(\phi_i) = \gamma_0 + \gamma_1 \cdot water\_depth_i + \gamma_2 \cdot duration_i \quad \text{(S11)}$$
3. Zero-one-inflation probability (zoi):
   $$logit(zoi_i) = \delta_0 + \delta_1 \cdot water\_depth_i + \delta_2 \cdot duration_i + \delta_3 \cdot growth\_stage_i \quad \text{(S12)}$$
4. Conditional one inflation probability (coi):
   $$logit(coi_i) = \alpha_0 + \alpha_1 \cdot water\_depth_i + \alpha_2 \cdot duration_i \quad \text{(S13)}$$

The R code to fit the model is as follows:

```
model_brm = brm(bf(loss_ratio ~ water_depth_cm + duration_days + growth_stage,          (S14)
                phi ~ water_depth_cm + duration_days,
                zoi ~ water_depth_cm + duration_days + growth_stage,
                coi ~ water_depth_cm + duration_days),
                data = train_data,
                family = zero_one_inflated_beta("logit"),
                chains = 2, iter = 2000, warmup = 200,
                control = list(adapt_delta = 0.95))
```

In the brms package, population-level parameters are not limited to have normal priors. For the population-level parameters, the default is that parameters have an improper flat prior over the reals. We used the default priors of the brms package, as no deviations occurred when using the priors and because the default priors can be vectorized which results in faster MCMC sampling (Bürkner, 2017b).

We selected the model (mod3) presented above based on a performance comparison of four multivariate regression model specifications (mod1, mod2, mod3, and mod4) with the following Bayesian model formulas:

mod1: (S15)

```
bf(loss_ratio ~ water_depth_cm + duration_days + growth_stage,
phi ~ water_depth_cm,
zoi ~ water_depth_cm,
coi ~ water_depth_cm)
```

mod2: (S16)

```
bf(loss_ratio ~ water_depth_cm + duration_days + growth_stage,
phi ~ water_depth_cm + duration_days,
zoi ~ water_depth_cm + duration_days,
coi ~ water_depth_cm + duration_days)
```

mod3: (S17)

```
bf(loss_ratio ~ water_depth_cm + duration_days + growth_stage,
phi ~ water_depth_cm + duration_days,
zoi ~ water_depth_cm + duration_days + growth_stage,
coi ~ water_depth_cm + duration_days)
```

mod4: (S18)

```
bf(loss_ratio ~ water_depth_cm + duration_days + growth_stage,
phi ~ water_depth_cm + duration_days + growth_stage,
zoi ~ water_depth_cm + duration_days + growth_stage,
coi ~ water_depth_cm + duration_days + growth_stage)
```

In the model comparison, data, family, chains, iterations, warmup, and control were the same across models (as presented in formula 13, but with 1000 iterations). The compared model specifications are based on different assumptions:

- mod1 includes only water_depth_cm as a predictor in all submodels for parsimony, assuming that water depth is the primary driver of the relative yield loss.
- mod4 adds duration_days to the phi, zoi, and coi submodels, assuming that duration adds explanatory power.
- mod6 further includes growth_stage in the zoi submodel.
- mod_all includes all three predictors (water_depth_cm, duration_days, growth_stage) in all submodels, representing the most complex specification.

Table S5 presents the results of the performance comparison. Based on expected log predictive density (ELPD) comparisons, mod2 significantly outperforms mod1, and mod3 significantly outperforms mod2, indicating that adding complexity to submodels beyond the most influential predictors may reduce predictive performance. The difference between mod3 and mod4 is not statistically significant, suggesting that fully parameterizing all components does not improve the model significantly. The results support a modeling approach in which complexity is allocated to components (like Φ and zoi) where it demonstrably improves model fit, while more parsimonious specifications are used for parameters like μ and coi.

Table S5: Comparison of multiple Bayesian Regression Models, based on the expected log predictive density (ELPD) and the standard error of ELPD. The table presents the metrics for two probabilistic stage-damage functions (SDF-prob) and four multivariate regression models (mod1 to mod4). Based on the comparison, SDF-prob-1 and mod3 were selected for the analysis.

Comparison	Compared model	Difference in ELPD	Standard Error of ELPD	Better performing model	Does the model perform significantly better?
SDF-prob-1 vs SDF-prob-2	SDF-prob-2	-7.9	1.9	SDF (prob) 1	Yes
mod1 vs SDF-prob-1	SDF-prob-1	-15.7	4.8	mod1	Yes
mod2 vs mod1	mod1	-16.9	6.3	mod2	Yes
mod3 vs mod2	mod2	-20.3	6.6	mod3	Yes
mod4 vs mod3	mod4	-2.4	1.6	mod3	No

S2.3 Stage-damage functions (SDFs)

We compare the multivariable models introduced above to univariable stage-damage functions (SDF), which predict flood-induced loss based on water depth. The SDF constitute a standard approach in flood loss modeling (Merz et al., 2010). We use a deterministic and a probabilistic version of the SDF for the evaluation of the performance improvement of multivariable and probabilistic models separately.

In line with previous studies on flood-induced asset loss (Schoppa et al., 2020; Schröter et al., 2014; Wagenaar et al., 2017), we use a square root SDF, which has outperformed linear and polynomial forms previously (Elmer et al., 2010).

S2.3.1 The deterministic SDF

The deterministic SDF is a simple, least square regression, where the relative yield loss is defined as:

$$relative\ yield\ loss = \alpha + \beta\sqrt{water\ depth} + \varepsilon, \tag{S19}$$

where relative yield loss is the observed loss ratio, α the intercept, β the regression coefficient, and ε is the error. In the model fitting process, values of α and β are identified that lead to the smallest error sum of squares (ESS), calculated as:

$$ESS = \sum_{i=1}^{n}\left(relative\ yield\ loss_i - \widehat{relative\ yield\ loss_i}\right)^2, \tag{S20}$$

where the difference of the observed and modeled relative loss ($relative\ yield\ loss_i - \widehat{relative\ yield\ loss_i}$) describes the error. The model was fit with the R stats package.

S2.3.2 The probabilistic SDF

The probabilistic SDF is a Bayesian regression, where relative yield loss is defined by the zero-one-inflated Beta distribution

$$y_i \sim ZOIB(\mu_i, \phi_i, zoi_i, coi_i), \tag{S21}$$

and where the variables are defined as described in Section 2.2.2 and Table S5. The following logit link function was used

$$logit(\mu_i) = \alpha + \beta * water\ depth_i. \tag{S22}$$

The relative yield loss is bounded to 0% to 100% and yield loss starts to occur at a water depth of 2 cm. We compared the performance of two forms of the Bayesian regression and found that the probabilistic SDF (SDF-prob-1) outperformed the probabilistic square root SDF (SDF-prob-2) (Suppl. Table5). The models were defined as follows, with the same Bayesian regression specifications as used for the BRM model comparison:

SDF-prob-1: (S23)

```
bf(loss_ratio ~ water_depth_cm,
                phi ~ water_depth_cm,
                zoi ~ water_depth_cm,
                coi ~ water_depth_cm),
```

SDF-prob-2: (S24)

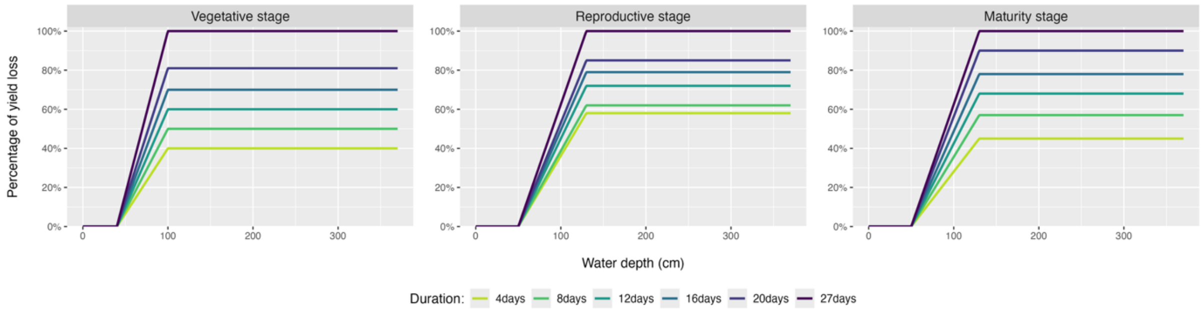
```
bf(loss_ratio ~ sqrt(water_depth_cm),
                phi ~ water_depth_cm,
```

```
zoi ~ water_depth_cm,
coi ~ water_depth_cm),
```

S2.4 Ramp functions by Shrestha et al. (2021)

The models described above were compared with status quo reference functions from the literature. The selected reference functions are ramp functions developed for Myanmar by Shrestha et al. (2021) (Fig. S5). Separate functions exist for three growth stages and six flood durations, leading to a total of 18 functions. Yield loss starts to occur at the minimum damageable flood depth (h_{min}); it increases linearly up to the water depth where the plant is fully underwater (the starting level of complete submergence or SLCS). Depending on growth stage and flood duration, the maximum relative yield loss (yield $loss_{max}$) varies. The ramp functions are based on empirical data for Myanmar (Shrestha et al., 2021).

Fig. S5: Flood damage model for rice in Myanmar based on ramp functions (Figure adapted from Shrestha et al., 2021)



S3 Model validation

We assess the model performance of each model, using k-fold cross-validation (CV), with k=10. As part of the cross-region validation, we assessed the performance of the localized models across regions. In addition, we tested the performance of the generalized models in each region as part of the 10-fold CV.

Each model's performance is validated by calculating three performance metrics:

1. the mean absolute error (MAE), which indicates the accuracy of a predicted value by averaging the difference between the observation and the estimate across all observations in the validation set. The MAE is the sum of absolute errors, defined as the absolute difference between the observed and estimated values, divided by the size of the validation set (n),

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|obs_i - pred_i|, \tag{S25}$$

2. the mean bias error (MBE), measuring the mean bias in the model's predictions and evaluates whether the model tends to under- or overestimate the observed values. A negative MBE means that the model is overpredicting, a positive MBE means that the model is underpredicting, and zero indicates no bias:

$$MBE = \frac{1}{n}\sum_{i=1}^{n} obs_i - pred_i, \text{ and} \tag{S26}$$

3. the continuous ranked probability score (CRPS), which is a scoring metric to evaluate the performance of probabilistic models that provide a distribution of predictions. Hence, the CRPS does not evaluate a point estimate, but it evaluates the full distribution of predictions by jointly considering its sharpness (the concentration of the predictive distribution) and calibration (the statistical agreement of observations and model predictions). The CRPS is a metric that enables a direct comparison of point predictions and probabilistic predictions, as it generalizes the MAE (Gneiting and Katzfuss, 2014; Matheson and Winkler, 1976). The CRPS for a given observation obs_i is defined as:

$$CRPS_i(F_i, obs_i) = \int_{-\infty}^{\infty}(F_i(x) - 1\{obs_i \le x\})^2 dx, \tag{S27}$$

where F_i is the cumulative density of the predictive distribution $f_i(x)$ and 1{obs ≤ x} is the indicator function, which is one if obs ≤ x and zero otherwise. The calculation of the CRPS for predictive distributions generated by the probabilistic models, see Jordan et al. (2019) and Krüger et al. (2021). As the relative loss is limited to values in the range [0, 1], CRPS values are within the same interval, with lower values indicating better model performance. One CRPS is calculated per observation in the validation set. For each fold, one mean CRPS is calculated. The overall model performance score is the mean of the mean CRPS. The performance scores selected for the model evaluation are aligned with previous assessments of flood damage model performance (Schoppa et al., 2020).

S4 Supplementary results

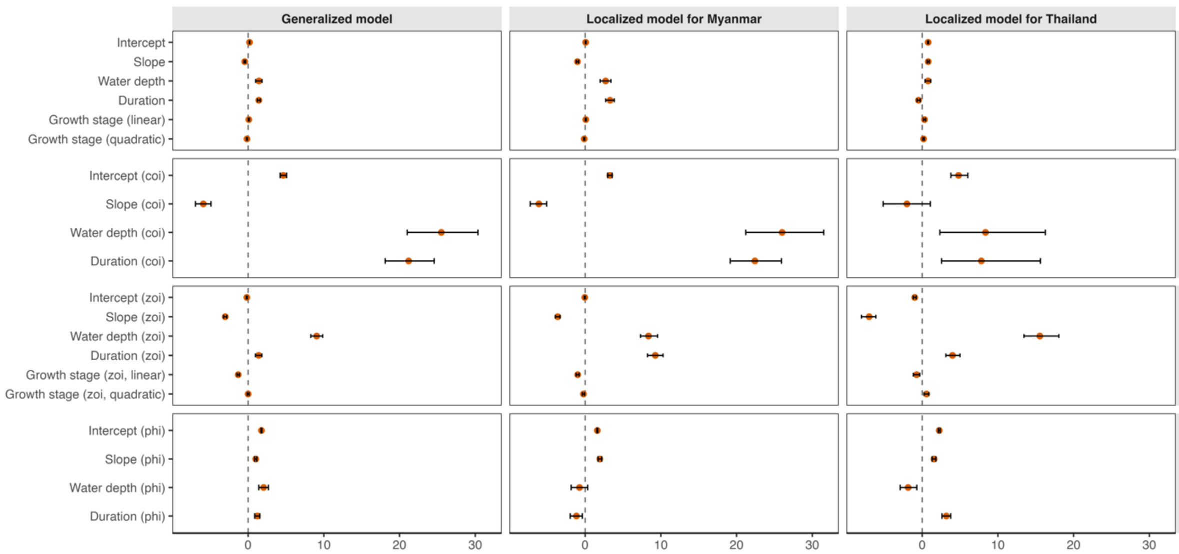
S4.1 Performance scores

Table S6 provides the performance scores (MAE, MBE, and Mean CRPS) obtained from the conducted model performance and transferability assessments. It covers the models developed by the authors – deterministic and probabilistic SDF, multivariate BRM and RF model – as generalized and localized models. The approaches used encompass 10-fold cross-validation (10-fold CV), Leaven-nothing out (LNO), and cross-region validation (CRV). The performance comparison of the ramp function from the literature and the models trained with the dataset by Shrestha et al. (2021) is presented in Table S7. The model performance for floods with different characteristics is shown in Fig. S7.

S4.2 Variable importance: Multivariable Bayesian Regression Model coefficients

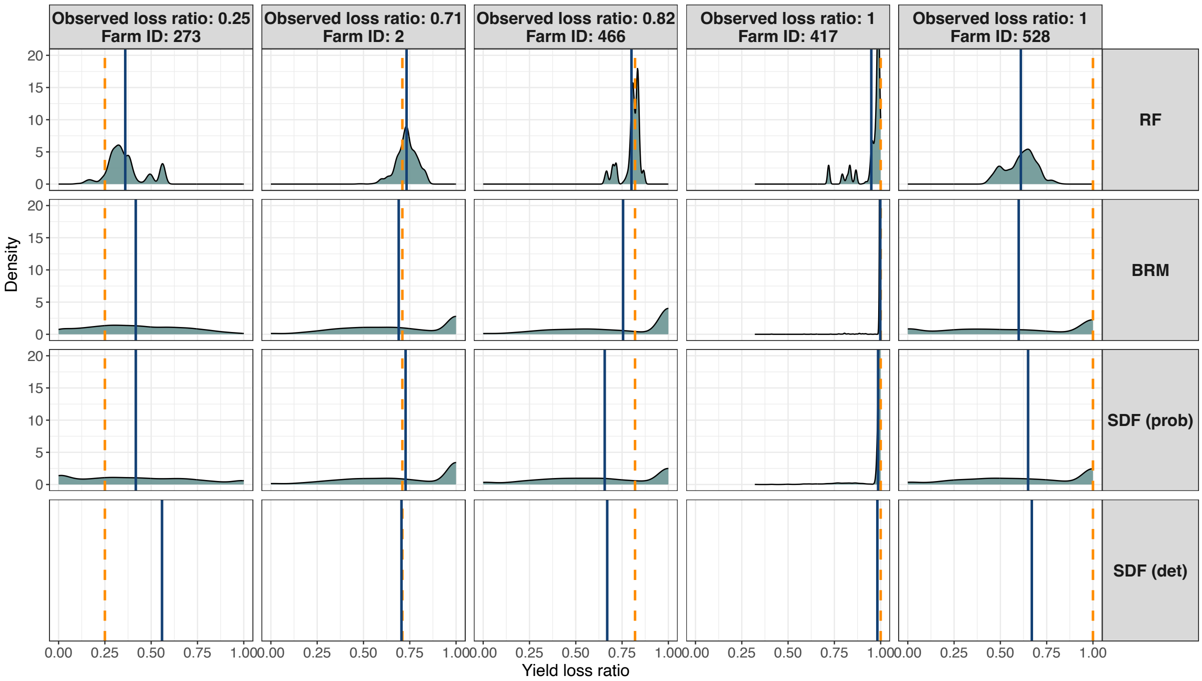
The coefficients of the multivariable Bayesian regression (mod3 presented above) shown in Fig. S6 reveal submodel- and region-specific effects. In the generalized model, water depth and duration both have positive coefficients. In the localized model for Myanmar, water depth and duration have also positive coefficients. In contrast, the Thailand model has a positive water depth coefficient and a negative duration coefficient. These results suggest that while water depth is a consistent predictor across contexts, the role of duration varies between regions. Growth stage was found to be an important attribute for loss explanation in the literature. However, in all our model definitions, growth stage has the least coefficients and has a non-zero linear dependence only to zero-and-one inflation.

Fig. S6: Multivariable Bayesian Regression Model coefficients. The Figure presents posterior mean estimates and 50% credible intervals for all parameters across four submodels – μ, ϕ, zoi, and coi – for the generalized model and two localized models (Myanmar and Thailand).



S4.3 Comparison of model predictions and observations

Fig. S7: Predictions (for the deterministic model) and predictive densities (for probabilistic models) of relative yield loss for five randomly sampled farms. The figure shows predictions and observations generated with the generalized Random Forest (RF) model, the Bayesian Regression Model (BRM), and the probabilistic and deterministic stage-damage functions (SDF). The plots were created with the generalized models trained on all the data (Leave-Nothing-Out). Dashed orange lines indicate the observed relative yield loss. Solid blue lines indicate the prediction of the deterministic model and the mean of the predicted distributions of the probabilistic models.



S4.4 Model performance

Table S6: Results of the performance evaluation and spatial transferability assessment for flood damage models created in this study. The mean across ten folds is shown for 10-fold CV.

Model type	Model name in R	Model category	Calibration	Validation	Approach	MAE	MBE	Mean CRPS
RF	model_rf_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar	10-fold CV	0.218	-0.005	0.180
BRM	model_brm_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar	10-fold CV	0.223	0.010	0.135
SDF (prob)	model_sdf_prob_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar	10-fold CV	0.253	-0.011	0.155
SDF (det)	model_sdf_det_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar	10-fold CV	0.268	-0.018	-
RF	model_rf_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar & Thailand	10-fold CV	0.203	-0.001	0.124
BRM	model_brm_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar & Thailand	10-fold CV	0.223	0.002	0.142
SDF (prob)	model_sdf_prob_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar & Thailand	10-fold CV	0.244	0.005	0.154
SDF (det)	model_sdf_det_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Myanmar & Thailand	10-fold CV	0.263	0.004	-
RF	model_rf_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Thailand	10-fold CV	0.144	0.015	0.106
BRM	model_brm_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Thailand	10-fold CV	0.166	-0.003	0.114
SDF (prob)	model_sdf_prob_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Thailand	10-fold CV	0.186	0.052	0.128
SDF (det)	model_sdf_det_generalized_CV	Generalized model	fit with all the data excluding the training data for CV	Thailand	10-fold CV	0.185	0.066	-
RF	model_rf_generalized	Generalized model	fit with all the data	-	LNO	-	-	-
BRM	model_brm_generalized	Generalized model	fit with all the data	-	LNO	-	-	-
SDF (prob)	model_sdf_prob_generalized	Generalized model	fit with all the data	-	LNO	-	-	-
SDF (det)	model_sdf_det_generalized	Generalized model	fit with all the data	-	LNO	-	-	-
RF	model_rf_trained_MM_CV	Localized model for Myanmar	fit with the Myanmar data excluding the training data for CV	Myanmar	10-fold CV	0.220	0.002	0.179
BRM	model_brm_trained_MM_CV	Localized model for Myanmar	fit with the Myanmar data excluding the training data for CV	Myanmar	10-fold CV	0.209	0.002	0.130
SDF (prob)	model_sdf_prob_trained_MM_CV	Localized model for Myanmar	fit with the Myanmar data excluding the training data for CV	Myanmar	10-fold CV	0.253	0.000	0.156
SDF (det)	model_sdf_det_trained_MM_CV	Localized model for Myanmar	fit with the Myanmar data excluding the training data for CV	Myanmar	10-fold CV	0.256	-0.004	-
RF	model_rf_trained_MM	Localized model for Myanmar	fit with all the Myanmar data	Thailand	CRV	0.192	-0.009	0.146
BRM	model_brm_trained_MM	Localized model for Myanmar	fit with all the Myanmar data	Thailand	CRV	0.196	-0.074	0.172
SDF (prob)	model_sdf_prob_trained_MM	Localized model for Myanmar	fit with all the Myanmar data	Thailand	CRV	0.200	0.054	0.150
SDF (det)	model_sdf_det_trained_MM	Localized model for Myanmar	fit with all the Myanmar data	Thailand	CRV	0.262	0.059	-
RF	model_rf_trained_TH_CV	Localized model for Thailand	fit with the Thailand data excluding the training data for CV	Thailand	10-fold CV	0.148	0.002	0.117
BRM	model_brm_trained_TH_CV	Localized model for Thailand	fit with the Thailand data excluding the training data for CV	Thailand	10-fold CV	0.156	0.012	0.103
SDF (prob)	model_sdf_prob_trained_TH_CV	Localized model for Thailand	fit with the Thailand data excluding the training data for CV	Thailand	10-fold CV	0.155	0.020	0.101
SDF (det)	model_sdf_det_trained_TH_CV	Localized model for Thailand	fit with the Thailand data excluding the training data for CV	Thailand	10-fold CV	0.178	0.015	-
RF	model_rf_trained_TH	Localized model for Thailand	fit with all the Thailand data	Myanmar	CRV	0.281	-0.034	0.247
BRM	model_brm_trained_TH	Localized model for Thailand	fit with all the Thailand data	Myanmar	CRV	0.288	-0.024	0.193
SDF (prob)	model_sdf_prob_trained_TH	Localized model for Thailand	fit with all the Thailand data	Myanmar	CRV	0.272	-0.045	0.187
SDF (det)	model_sdf_det_trained_TH	Localized model for Thailand	fit with all the Thailand data	Myanmar	CRV	0.285	-0.100	-

Table S7: Results of the performance evaluation and spatial transferability assessment for the ramp functions by Shrestha et al. 2021 and for flood damage models developed in this study re-trained with the dataset published by Shrestha et al. 2021. The mean across ten folds is shown for 10-fold CV.

Model type	Model name in R	Model category	Calibration	Validation	Approach	MAE	MBE	Mean CRPS
Ramp function	model_ramp_trained_MM	Localized model for Myanmar	Model from the literature (Shrestha et al., 2021)	Myanmar & Thailand	-	0.233	0.053	-
Ramp function	model_ramp_trained_MM	Localized model for Myanmar	Model from the literature (Shrestha et al., 2021)	Myanmar (Shrestha et al. 2021 data)	-	0.235	0.032	-
Ramp function	model_ramp_trained_MM	Localized model for Myanmar	Model from the literature (Shrestha et al., 2021)	Myanmar (all the data)	-	0.227	0.054	-
Ramp function	model_ramp_trained_MM	Localized model for Myanmar	Model from the literature (Shrestha et al., 2021)	Thailand	CRV	0.257	0.049	-
RF	model_rf_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data	Thailand	CRV	0.198	0.070	0.154
BRM	model_brm_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data	Thailand	CRV	0.199	-0.057	0.175
SDF (prob)	model_sdf_prob_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data	Thailand	CRV	0.211	0.108	0.149
SDF (det)	model_sdf_det_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data	Thailand	CRV	0.291	0.046	-
RF	model_rf_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data excluding the training data for CV	Myanmar (Shrestha)	10-fold CV	0.238	-0.005	0.199
BRM	model_brm_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data excluding the training data for CV	Myanmar (Shrestha)	10-fold CV	0.232	-0.010	0.151
SDF (prob)	model_sdf_prob_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data excluding the training data for CV	Myanmar (Shrestha)	10-fold CV	0.284	0.004	0.178
SDF (det)	model_sdf_det_trained_MM_Shrestha	Localized model for Myanmar (Shrestha)	fit with the Myanmar (Shrestha) data excluding the training data for CV	Myanmar (Shrestha)	10-fold CV	0.284	0.000	-

Fig. S8: Model performance for flood events with specific characteristics. Data was partitioned into groups based on relative yield loss (low, medium, high, complete), water depth (shallow, medium, deep), duration (short, medium, long), and growth stage (vegetative, reproductive, maturity). Relative yield loss groups were created as equal-sized partitions, while water depth and duration are categorized based on the 25th and 75th percentiles.

S4.5 Model reporting: Lookup tables for generalized flood damage models for rice

In this section, we provide lookup tables for the generalized models developed in this study, including the deterministic SDF (Table S8), probabilistic SDF (Table S9), BRM (Table S10), and RF model (Table S11).

Table S8: Lookup table for the deterministic stage-damage function

Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss
2–9	5.5	32.2
10–19	14.5	38.8
20–29	24.5	43.87
30–39	34.5	47.96
40–49	44.5	51.47
50–59	54.5	54.61
60–69	64.5	57.47
70–79	74.5	60.11
80–89	84.5	62.57
90–99	94.5	64.9
100–109	104.5	67.1
110–119	114.5	69.2
120–129	124.5	71.21
130–139	134.5	73.14
140–149	144.5	75
150–159	154.5	76.8
160–169	164.5	78.53
170–179	174.5	80.22
180–189	184.5	81.86
190–199	194.5	83.45
200–209	204.5	85.01
210–219	214.5	86.52
220–229	224.5	88
230–239	234.5	89.45
240–249	244.5	90.87
250–259	254.5	92.26
260–269	264.5	93.62
270–279	274.5	94.96
280–289	284.5	96.27
290–299	294.5	97.56
300–309	304.5	98.83
>300		100

Table S9: Lookup table for the probabilistic stage-damage function

Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (median)	Relative yield loss (q25)	Relative yield loss (q75)
2–9	5.5	27.32	17.59	39.5
10–19	14.5	29.29	19.15	42.01
20–29	24.5	29.98	20.06	42.32
30–39	34.5	31.61	20.89	44.5
40–49	44.5	34.19	22.68	46.38
50–59	54.5	38.19	26.1	50.55
60–69	64.5	42.34	30.16	54.96
70–79	74.5	46.96	34.7	60.32
80–89	84.5	53.04	40.97	68.37
90–99	94.5	59.35	46.67	79.67
100–109	104.5	65.96	53.39	82.98
110–119	114.5	73.1	59.38	86.55
120–129	124.5	77.46	63.68	88.73
130–139	134.5	87.19	71.01	93.59
140–149	144.5	100	79.85	100
150–159	154.5	100	82.31	100
160–169	164.5	100	84.68	100
170–179	174.5	100	86.29	100
180–189	184.5	100	89.79	100
190–199	194.5	100	93.83	100
>200		100	100	100

Table S10: Lookup table for the Bayesian Regression Model (BRM)

Duration (days)	Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (median)	Relative yield loss (q25)	Relative yield loss (q75)
		Vegetative stage			
4	2–19	10.5	29.67	9.83	53.39
4	20–39	29.5	28.81	7.84	51.82
4	40–59	49.5	29.02	4.91	53.82
4	60–79	69.5	27.68	0	51.87
4	80–99	89.5	33.01	0	60.48
4	100–119	109.5	45.3	10.36	91.73
4	120–139	129.5	61.54	25.9	100
4	140–159	149.5	100	45.91	100
4	160–179	169.5	100	62.22	100
4	>180		100	100	100
8	2–19	10.5	31.26	10.28	54.28
8	20–39	29.5	31.3	9.47	54.33
8	40–59	49.5	31.54	5.85	55.85
8	60–79	69.5	34.8	6.26	60.78
8	80–99	89.5	41.01	11.24	73.47
8	100–119	109.5	57.96	26.06	100
8	120–139	129.5	100	41.48	100
8	140–159	149.5	100	55.85	100
8	160–179	169.5	100	71.34	100
8	>180		100	100	100
12	2–19	10.5	32.33	11.59	55.03
12	20–39	29.5	32.55	11.26	56.7
12	40–59	49.5	35.64	11.47	61.06
12	60–79	69.5	42.26	15.39	69.93
12	80–99	89.5	53.47	24.38	100
12	100–119	109.5	70.87	37.89	100
12	120–139	129.5	100	49.99	100
12	140–159	149.5	100	61.24	100
12	160–179	169.5	100	81.44	100
12	>170		100	100	100
16	2–19	10.5	35.51	13.94	57.53
16	20–39	29.5	36.61	14.46	60.62
16	40–59	49.5	40.36	16.72	65.58
16	60–79	69.5	50.86	25.07	83.85
16	80–99	89.5	63.46	34.39	100
16	100–119	109.5	86.11	44.95	100
16	120–139	129.5	100	56.86	100
16	140–159	149.5	100	70.19	100
16	>170		100	100	100
20	2–19	10.5	36.63	16.04	59.31
20	20–39	29.5	40.88	19.9	65.08
20	40–59	49.5	47.34	23.51	75.39
20	60–79	69.5	57	31.99	100
20	80–99	89.5	72.78	42.62	100
20	100–119	109.5	100	50.25	100
20	120–139	129.5	100	58.18	100
20	140–159	149.5	100	72.35	100
20	>160		100	100	100

Duration (days)	Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (median)	Relative yield loss (q25)	Relative yield loss (q75)
			Reproductive stage		
4	2–19	10.5	39.91	18.32	61.69
4	20–39	29.5	40.33	18.72	61.11
4	40–59	49.5	42.47	20.23	62.88
4	60–79	69.5	41.59	18.61	62.31
4	80–99	89.5	44.98	21.75	66.67
4	100–119	109.5	51.89	28.35	74.96
4	120–139	129.5	58.74	35.07	92.84
4	140–159	149.5	70.13	44.23	100
4	160–179	169.5	85.72	51.24	100
4	180–199	189.5	100	60.22	100
4	>220		100	100	100
8	2–19	10.5	41.15	20.18	62.82
8	20–39	29.5	42.04	21.51	63.98
8	40–59	49.5	44.67	22.53	64.67
8	60–79	69.5	46.2	23.03	66.36
8	80–99	89.5	50.98	28.56	73.12
8	100–119	109.5	55.82	34.21	81.66
8	120–139	129.5	63.34	41.18	100
8	140–159	149.5	78.63	51.51	100
8	160–179	169.5	100	56.06	100
8	180–199	189.5	100	65.54	100
8	>220		100	100	100
12	2–19	10.5	43.59	22.4	65.16
12	20–39	29.5	43.27	23.04	63.54
12	40–59	49.5	46.86	26.13	67.66
12	60–79	69.5	49.71	28.26	70.71
12	80–99	89.5	54.54	34.47	77.82
12	100–119	109.5	62.21	42.28	94.48
12	120–139	129.5	71.85	47.85	100
12	140–159	149.5	82.62	53.7	100
12	160–179	169.5	100	60.3	100
12	180–199	189.5	100	67.71	100
12	>220		100	100	100
16	2–19	10.5	46.56	26.08	65.98
16	20–39	29.5	47	25.87	67.86
16	40–59	49.5	49.75	28.95	69.27
16	60–79	69.5	53.03	33.61	73.22
16	80–99	89.5	59.07	38.58	84.14
16	100–119	109.5	65.92	44.71	100
16	120–139	129.5	73.53	50.75	100
16	140–159	149.5	84.1	56.52	100
16	160–179	169.5	100	61.75	100
16	180–199	189.5	100	70.25	100
16	>210		100	100	100
20	2–19	10.5	47.97	26.17	68.48
20	20–39	29.5	50.28	29.64	70.72
20	40–59	49.5	54.77	34.64	73.87
20	60–79	69.5	57.19	37.48	78.3
20	80–99	89.5	62.98	43.1	88.31
20	100–119	109.5	68.06	48.13	100
20	120–139	129.5	79.14	54.44	100
20	140–159	149.5	90	59.46	100
20	160–179	169.5	100	63.46	100
20	180–199	189.5	100	74.33	100
20	>210		100	100	100

Duration (days)	Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (median)	Relative yield loss (q25)	Relative yield loss (q75)
		Maturity stage			
4	2–19	10.5	36.3	17.72	59.15
4	20–39	29.5	38.87	19.38	60.51
4	40–59	49.5	39.35	20.52	59.78
4	60–79	69.5	41.42	23.83	61.23
4	80–99	89.5	43.9	25.84	63.44
4	100–119	109.5	48.45	28.21	68.1
4	120–139	129.5	50.78	31.83	72.42
4	140–159	149.5	57.27	37.66	81.77
4	160–179	169.5	63.46	43.03	100
4	180–199	189.5	70.61	47.09	100
4	>280		100	100	100
8	2–19	10.5	38.83	20.32	60.17
8	20–39	29.5	39.45	21.83	60.91
8	40–59	49.5	41.89	22.91	62.05
8	60–79	69.5	44.67	26.12	63.55
8	80–99	89.5	45.85	27.68	66.01
8	100–119	109.5	50.53	32.51	70.22
8	120–139	129.5	55.38	36.72	77.97
8	140–159	149.5	59.95	40.74	88.3
8	160–179	169.5	66.14	44.5	100
8	180–199	189.5	71.32	49.52	100
8	>270		100	100	100
12	2–19	10.5	40.42	21.93	61.65
12	20–39	29.5	43	24.14	62.52
12	40–59	49.5	44.63	25.81	63.21
12	60–79	69.5	46.71	28.6	66.28
12	80–99	89.5	49.92	30.99	68.58
12	100–119	109.5	54.14	35.85	74.89
12	120–139	129.5	57.3	38.35	79.49
12	140–159	149.5	62.9	43.49	96.61
12	160–179	169.5	68.67	48.5	100
12	180–199	189.5	75.02	51.75	100
12	>270		100	100	100
16	2–19	10.5	43.23	24.54	63.21
16	20–39	29.5	44.35	25.78	63.62
16	40–59	49.5	47.47	28.55	66.67
16	60–79	69.5	48.9	30.37	67.63
16	80–99	89.5	52.41	34.94	70.47
16	100–119	109.5	56.36	38.2	76.22
16	120–139	129.5	60.5	42.13	83.42
16	140–159	149.5	64.32	46.4	100
16	160–179	169.5	69.2	48.78	100
16	180–199	189.5	77.93	54.13	100
16	>270		100	100	100
20	2–19	10.5	45.17	25.59	64.72
20	20–39	29.5	46.29	27.09	65.18
20	40–59	49.5	48.3	30.53	67.23
20	60–79	69.5	51.41	34.03	70.06
20	80–99	89.5	55.08	37.99	73.54
20	100–119	109.5	57.84	40.89	77.4
20	120–139	129.5	61.79	44.49	84.18
20	140–159	149.5	65.81	47.78	100
20	160–179	169.5	71.88	53.06	100
20	180–199	189.5	80.31	57.07	100
20	>270		100	100	100

Table S11: Lookup table for the Random Forest (RF) model (trained on Myanmar & Thailand data)

Duration (days)	Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (mean)	Relative yield loss (q25)	Relative yield loss (q75)
			Vegetative stage		
4	2–19	10.5	44.53	35.5	51.05
4	20–39	29.5	40.73	34.43	44.99
4	40–59	49.5	40.1	33.87	44.38
4	60–79	69.5	41.16	34.83	44.38
4	80–99	89.5	42.38	36.48	44.99
4	100–119	109.5	52.94	42.14	61.82
4	120–139	129.5	53.41	42.86	60
4	140–159	149.5	63.22	47.07	75.17
4	160–179	169.5	79.41	61.75	94.67
4	180–199	189.5	80.6	61.75	98.33
4	>200		81.01	61.75	98.58
8	2–19	10.5	47.45	37.44	53.03
8	20–39	29.5	43.67	36.54	48.48
8	40–59	49.5	42.93	36.48	47.07
8	60–79	69.5	43.48	36.54	47.32
8	80–99	89.5	44.31	37.24	48.48
8	100–119	109.5	52.38	41.07	60.09
8	120–139	129.5	52.72	41.07	59.62
8	140–159	149.5	62.47	46.13	75.13
8	160–179	169.5	78.8	58.37	94.67
8	180–199	189.5	79.99	58.37	98.33
8	>200		80.41	58.37	98.58
12	2–19	10.5	59.05	48.96	68.02
12	20–39	29.5	55.57	44.99	64.98
12	40–59	49.5	55.33	44.52	64.94
12	60–79	69.5	55.89	44.99	64.94
12	80–99	89.5	56.8	45.27	65.59
12	100–119	109.5	64.91	59.24	70.06
12	120–139	129.5	65.52	59.24	70.31
12	140–159	149.5	72.04	61.75	82.9
12	160–179	169.5	85.96	71.89	98.11
12	180–199	189.5	87.61	72.78	98.58
12	>200		88.14	72.78	98.67
16	2–19	10.5	68.26	62.81	74.77
16	20–39	29.5	66	61.95	73.72
16	40–59	49.5	66.22	61.95	73.72
16	60–79	69.5	67.04	61.98	73.99
16	80–99	89.5	67.91	62.15	74.77
16	100–119	109.5	72.41	65.85	80.19
16	120–139	129.5	73.37	66.28	82.74
16	140–159	149.5	75.94	67.97	83.42
16	160–179	169.5	89.53	85.18	98.33
16	180–199	189.5	91.69	89.35	98.67
16	>200		92.29	93.72	98.67
20	2–19	10.5	75.34	67.69	83.52
20	20–39	29.5	73.22	66.4	83.52
20	40–59	49.5	73.42	66.41	83.52
20	60–79	69.5	75.43	68.02	84.29
20	80–99	89.5	76.81	71.89	84.96
20	100–119	109.5	83.18	79.9	87.37
20	120–139	129.5	83.54	80.75	88.75
20	140–159	149.5	81.84	75.26	86.67
20	160–179	169.5	92.58	89.62	98.4
20	180–199	189.5	94.76	94.69	98.67
20	>200		95.47	97.86	98.72

Duration (days)	Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (mean)	Relative yield loss (q25)	Relative yield loss (q75)
Reproductive stage					
4	2–19	10.5	45.99	35.55	55.04
4	20–39	29.5	41.9	32.08	51.29
4	40–59	49.5	41.07	31.98	48.93
4	60–79	69.5	41.5	33.51	48.4
4	80–99	89.5	42.22	35.25	48.93
4	100–119	109.5	57.85	49.45	65.27
4	120–139	129.5	56.78	49.72	62.04
4	140–159	149.5	66.84	56.88	73.89
4	160–179	169.5	79.37	66.52	92.78
4	180–199	189.5	81.88	66.76	95.4
4	>200		82.57	66.76	96.98
8	2–19	10.5	51.28	40.22	57.63
8	20–39	29.5	47.28	38.83	55.33
8	40–59	49.5	46.35	38.31	53.72
8	60–79	69.5	46.43	38.38	53.26
8	80–99	89.5	46.87	39.11	53.46
8	100–119	109.5	58.94	54.52	64.73
8	120–139	129.5	57.66	53.72	61.31
8	140–159	149.5	66.79	56.92	73.89
8	160–179	169.5	79.15	63.36	92.78
8	180–199	189.5	81.66	63.97	95.4
8	>200		82.36	63.97	96.98
12	2–19	10.5	59.29	52.49	67.78
12	20–39	29.5	55.63	48.35	63.48
12	40–59	49.5	55.19	46.96	63.35
12	60–79	69.5	55.27	45.87	63.35
12	80–99	89.5	55.7	46.85	63.48
12	100–119	109.5	64.78	59.14	70.1
12	120–139	129.5	64.25	59.14	69.12
12	140–159	149.5	71.47	62.05	75.69
12	160–179	169.5	83.28	73.89	92.78
12	180–199	189.5	86.66	73.89	95.9
12	>200		87.61	73.89	98.46
16	2–19	10.5	68.67	63.46	73.94
16	20–39	29.5	66.22	61.98	73.66
16	40–59	49.5	66.26	61.55	73.66
16	60–79	69.5	66.56	61.71	73.89
16	80–99	89.5	66.99	61.85	73.89
16	100–119	109.5	72.92	68.87	77.87
16	120–139	129.5	72.72	68.38	77.93
16	140–159	149.5	74.38	69.76	77.93
16	160–179	169.5	85.93	78.86	93.73
16	180–199	189.5	90.8	89.12	97.22
16	>200		92.03	92.26	98.69
20	2–19	10.5	72.14	65.14	79.44
20	20–39	29.5	69.83	63.63	79.44
20	40–59	49.5	69.87	63.46	79.44
20	60–79	69.5	71.05	63.71	80.23
20	80–99	89.5	71.66	64.16	80.49
20	100–119	109.5	79.07	75.25	82.81
20	120–139	129.5	80.06	75.83	84.14
20	140–159	149.5	75.58	71.3	80.23
20	160–179	169.5	87.31	82.21	93.34
20	180–199	189.5	92.95	91.75	97.51
20	>200		94.39	93.73	98.76

Duration (days)	Water depth range (cm)	Water depth midpoint (cm)	Relative yield loss (mean)	Relative yield loss (q25)	Relative yield loss (q75)
Maturity stage					
4	2–19	10.5	39.63	30.69	47.92
4	20–39	29.5	36.61	29.87	40.48
4	40–59	49.5	36.2	29.66	39.57
4	60–79	69.5	37.64	31.2	41.43
4	80–99	89.5	38.85	32.5	42.92
4	100–119	109.5	46.2	38.36	52.23
4	120–139	129.5	46.12	39	52.2
4	140–159	149.5	55.1	40.97	60
4	160–179	169.5	69	44.6	92.78
4	180–199	189.5	70.39	44.6	94.67
4	>200		70.73	44.6	95.36
8	2–19	10.5	41.56	33.04	49.86
8	20–39	29.5	38.52	31.2	43.33
8	40–59	49.5	38.01	30.77	41.14
8	60–79	69.5	39.02	31.7	42.14
8	80–99	89.5	40.12	34.42	44.71
8	100–119	109.5	47.87	40.8	55.55
8	120–139	129.5	47.78	41.12	55.6
8	140–159	149.5	56.12	42.92	59.32
8	160–179	169.5	69.4	45.11	92.78
8	180–199	189.5	70.79	45.11	94.67
8	>200		71.13	45.11	95.36
12	2–19	10.5	56.63	44.1	71.08
12	20–39	29.5	53.73	40.48	67.48
12	40–59	49.5	53.61	40.48	67.39
12	60–79	69.5	54	40.48	67.65
12	80–99	89.5	54.89	42.02	69.16
12	100–119	109.5	61.64	52.89	71.41
12	120–139	129.5	61.95	54.25	71.37
12	140–159	149.5	67.87	56.12	75.13
12	160–179	169.5	78.95	61.38	92.78
12	180–199	189.5	80.92	61.38	95.9
12	>200		81.44	61.38	98.69
16	2–19	10.5	64.18	56.12	73.28
16	20–39	29.5	62.32	56.12	73.17
16	40–59	49.5	62.47	56.12	73.17
16	60–79	69.5	62.81	56.12	73.28
16	80–99	89.5	63.48	56.12	73.28
16	100–119	109.5	67.4	57.28	74.2
16	120–139	129.5	67.28	57.78	74.2
16	140–159	149.5	71.24	61.51	76.01
16	160–179	169.5	83.06	72.82	93.76
16	180–199	189.5	85.92	75.55	97.64
16	>200		86.57	75.55	98.8
20	2–19	10.5	66.61	56.12	75.2
20	20–39	29.5	64.89	56.12	74.87
20	40–59	49.5	64.99	56.12	74.87
20	60–79	69.5	65.87	56.12	76.2
20	80–99	89.5	66.64	56.12	76.55
20	100–119	109.5	71.11	58.38	80.07
20	120–139	129.5	71.56	60.68	80.76
20	140–159	149.5	72.35	64.74	81.28
20	160–179	169.5	84.44	79.71	93.34
20	180–199	189.5	87.73	82.19	98.08
20	>200		88.44	82.19	99

Supplementary references

Breiman, L.: Random Forests, Machine Learning, 45, 5–32, 2001.

Breiman, L., Friedman, J., Olshen, R., and Stone, C. J.: Classification and Regression Trees, 1st ed., Chapman and Hall/CRC, https://doi.org/10.1201/9781315139470, 1984.

Bureau of Registration Administration Thailand (BORA): Population Statistics for 2021: Village Level (โครงสร้างข้อมูลสถิติจำนวนประชากร: ระดับหมู่บ้าน), 2021.

Bürkner, P.-C.: brms (2.22.0): Special Family Functions for brms Models, 2017a.

Bürkner, P.-C.: brms: An R Package for Bayesian Multilevel Models using Stan, J. Stat. Soft., 80, https://doi.org/10.18637/jss.v080.i01, 2017b.

Chau, V. N., Cassells, S., and Holland, J.: Economic impact upon agricultural production from extreme flood events in Quang Nam, central Vietnam, Nat Hazards, 75, 1747–1765, https://doi.org/10.1007/s11069-014-1395-x, 2015.

Dutta, D., Herath, S., and Musiake, K.: A mathematical model for flood loss estimation, Journal of Hydrology, 277, 24–49, https://doi.org/10.1016/S0022-1694(03)00084-2, 2003.

Elmer, F., Thieken, A. H., Pech, I., and Kreibich, H.: Influence of flood frequency on residential building losses, Nat. Hazards Earth Syst. Sci., 10, 2145–2159, https://doi.org/10.5194/nhess-10-2145-2010, 2010.

ESRI: ESRI Shaded Relief, n.d.

Federal Emergency Management Agency (FEMA): Hazus Flood Model Technical Manual 2.1: Multi-hazard Loss Estimation Methodology Flood Model, 2020.

Ganji, Z., Shokoohi, A., and Samani, J. M. V.: Developing an agricultural flood loss estimation function (case study: Rice), Natural Hazards, 64, 405–419, https://doi.org/10.1007/s11069-012-0250-1, 2012.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., and Rubin, D. B.: Bayesian Data Analysis, 3rd ed., Chapman and Hall/CRC, 2013.

Geo-Informatics and Space Technology Development Agency (GISTDA): Thailand Flood Monitoring System, 2023.

GISTA The Thai Space Agency: Thailand - Inland Waters, 2018.

Gneiting, T. and Katzfuss, M.: Probabilistic Forecasting, Annu. Rev. Stat. Appl., 1, 125–151, https://doi.org/10.1146/annurev-statistics-062713-085831, 2014.

Hastie, T., Tibshirani, R., and Friedman, J.: The Elements of Statistical Learning, Springer New York, New York, NY, https://doi.org/10.1007/978-0-387-84858-7, 2009.

Hendrawan, V. S. A. and Komori, D.: Developing flood vulnerability curve for rice crop using remote sensing and hydrodynamic modeling, International Journal of Disaster Risk Reduction, 54, https://doi.org/10.1016/j.ijdrr.2021.102058, 2021.

Hothorn, T. and Zeileis, A.: partykit: A Modular Toolkit for Recursive Partytioning in R, Journal of Machine Learning Research, 16, 3905–3909, 2015.

Hothorn, T. and Zeileis, A.: partykit: A Toolkit for Recursive Partytioning, https://doi.org/10.32614/CRAN.package.partykit, 2023.

Hothorn, T., Hornik, K., and Zeileis, A.: Unbiased Recursive Partitioning: A Conditional Inference Framework, Journal of Computational and Graphical Statistics, 15, 651–674, https://doi.org/10.1198/106186006X133933, 2006.

Huizinga, J., de Moel, H., and Szewczyk, W.: Global flood depth-damage functions: methodology and the database with guidelines., Publications Office of the European Union, Luxembourg, 2017.

Hussain, Sk. G.: Decision support system for assessing rice yield losses from annual flooding in Bangladesh. A dissertation submitted to the Graduate Division of the University of Hawaii in partial fulfillment to the requirements for the Degree of Doctor of Philosophy in Agronomy and Soil Science, 1995.

Intarathaiwong, S. and Vudhivanich, V.: Study on rice yield reduction due to flooding, Kasetsart Engineering Journal, 10, 97–107, 1996.

James, G., Witten, D., Hastie, T., and Tibshirani, R.: An introduction to statistical learning with applications in R, 1st ed., Springer Science+Business Media, New York, USA, 426 pp., https://doi.org/10.1007/978-1-4614-7138-7_1, 2013.

Jordan, A., Krüger, F., and Lerch, S.: Evaluating Probabilistic Forecasts with **scoringRules**, J. Stat. Soft., 90, https://doi.org/10.18637/jss.v090.i12, 2019.

Kotera, A. and Nawata, E.: Role of plant height in the submergence tolerance of rice: A simulation analysis using an empirical model, Agricultural Water Management, 89, 49–58, https://doi.org/10.1016/j.agwat.2006.12.002, 2007.

Krüger, F., Lerch, S., Thorarinsdottir, T., and Gneiting, T.: Predictive Inference Based on Markov Chain Monte Carlo Output, Int Statistical Rev, 89, 274–301, https://doi.org/10.1111/insr.12405, 2021.

Kwak, Y., Arifuzzanman, B., and Iwami, Y.: Prompt Proxy Mapping of Flood Damaged Rice Fields Using MODIS-Derived Indices, Remote Sensing, 7, 15969–15988, https://doi.org/10.3390/rs71215805, 2015.

Matheson, J. E. and Winkler, R. L.: Scoring Rules for Continuous Probability Distributions, Management Science, 22, 1087–1096, https://doi.org/10.1287/mnsc.22.10.1087, 1976.

McElreath, R.: Statistical Rethinking: A Bayesian Course with Examples in R and Stan, 1st ed., Chapman and Hall/CRC, New York, USA, 2016.

Meinshausen, N.: Quantile Regression Forests, Journal of Machine Learning Research, 7, 983–999, 2006.

Mekong River Commission Secretariat (MRCS): Flood Damages, Benefits and Flood Risk in Focal Areas The Flood Management and Mitigation Programme, Component 2: Structural Measures & Flood Proofing in the Lower Mekong Basin. Draft Final Report, Volume 2C, 2009.

Merz, B., Kreibich, H., Schwarze, R., and Thieken, A.: Review article "Assessment of economic flood damage," Nat. Hazards Earth Syst. Sci., 10, 1697–1724, https://doi.org/10.5194/nhess-10-1697-2010, 2010.

Merz, B., Kreibich, H., and Lall, U.: Multi-variate flood damage assessment: a tree-based data-mining approach, Nat. Hazards Earth Syst. Sci., 13, 53–64, https://doi.org/10.5194/nhess-13-53-2013, 2013.

Ministry of the Interior. Department of Community Development (MOI-CDD): 2021 Basic Needs Data. Translated from Thai: ข้อมูลความจำเป็นพื้นฐาน (จปฐ). The data was made available., 2021.

Naresuan University Geoinformatics Community and Sharing (NUGIS): Free and Open Source GIS Data: (7) Village Location, (10) Roads, 2014.

Nguyen, N. Y., Ichikawa, Y., and Ishidaira, H.: Establishing flood damage functions for agricultural crops using estimated inundation depth and flood disaster statistics in data-scarce regions, Hydrological Research Letters, 11, 12–18, https://doi.org/10.3178/hrl.11.12, 2017.

Nguyen, N. Y., Kha, D. D., and Ichikawa, Y.: Developing a multivariable lookup table function for estimating flood damages of rice crop in Vietnam using a secondary research approach, International Journal of Disaster Risk Reduction, 58, 102208, https://doi.org/10.1016/j.ijdrr.2021.102208, 2021.

Ospina, R. and Ferrari, S. L. P.: Inflated beta distributions, Stat Papers, 51, 111–126, https://doi.org/10.1007/s00362-008-0125-4, 2010.

R Core Team: R: A Language and Environment for Statistical Computing, 2024.

Ramsar Site Information Service (RSIS): Lower Songkhram River. Ramsar Site Boundaries (shapefile), 2020.

Royal Forest Department, Community Forest Management Promotion Section: List of community forests receiving subsidies: Community forest management activities to develop quality of life for Fiscal year 2020-2022, including 805 community forests (translated). รายชื่อป่าชุมชนที่ได้รับเงินอุดหนุน กิจกรรมบริหารจัดการป่าชุมชนเพื่อพัฒนาคุณภาพชีวิต ปีงบประมาณ พ.ศ. 2563 จ ำนวน 805 ป่าชุมชน, 2022.

Royal Thai Survey Department: Thailand: Subnational Administrative Boundaries. Updated: 27 January 2022, 2022.

Samantaray, D., Chatterjee, C., Singh, R., Gupta, P. K., and Panigrahy, S.: Flood risk modeling for optimal rice planning for delta region of Mahanadi river basin in India, Nat Hazards, 76, 347–372, https://doi.org/10.1007/s11069-014-1493-9, 2015.

Schoppa, L., Sieg, T., Vogel, K., Zöller, G., and Kreibich, H.: Probabilistic Flood Loss Models for Companies, Water Resources Research, 56, e2020WR027649, https://doi.org/10.1029/2020WR027649, 2020.

Schröter, K., Kreibich, H., Vogel, K., Riggelsen, C., Scherbaum, F., and Merz, B.: How useful are complex flood damage models?, Water Resources Research, 50, 3378–3395, https://doi.org/10.1002/2013WR014396, 2014.

Shrestha, B. B., Okazumi, T., Miyamoto, M., and Sawano, H.: Flood damage assessment in the Pampanga River basin of the Philippines, J. Flood Risk Manag., 9, 355–369, https://doi.org/10.1111/jfr3.12174, 2016.

Shrestha, B. B., Kawasaki, A., and Zin, W. W.: Development of flood damage functions for agricultural crops and their applicability in regions of Asia, Journal of Hydrology: Regional Studies, 36, 100872, https://doi.org/10.1016/j.ejrh.2021.100872, 2021.

Sieg, T., Vogel, K., Merz, B., and Kreibich, H.: Tree-based flood damage modeling of companies: Damage processes and model performance, Water Resources Research, 53, 6050–6068, https://doi.org/10.1002/2017WR020784, 2017.

Sultana, Z., Sieg, T., Kellermann, P., Müller, M., and Kreibich, H.: Assessment of Business Interruption of Flood-Affected Companies Using Random Forests, Water, 10, 1049, https://doi.org/10.3390/w10081049, 2018.

Thai Department of Disaster Prevention and Mitigation, Ministry of Interior: Flood Statistics: Recurring droughts and floods, 2017.

Thai Ministry of Labor. Wage Committee: Royal Gazette Announcement of the Wage Committee. Minimum wage rate (No. 11). Volume 139, Special Section 221 D. 19 September 2022, 2022.

Wagenaar, D., De Jong, J., and Bouwer, L. M.: Multi-variable flood damage modelling with limited data using supervised learning approaches, Nat. Hazards Earth Syst. Sci., 17, 1683–1696, https://doi.org/10.5194/nhess-17-1683-2017, 2017.

Wagenaar, D., Kasmalkar, I., and Lallemant, D.: HAZDEM: Hazard Analysis Zones global Digital Elevation Model: 30m x 30m, Disaster Risk Analytics for Society Lab, Earth Observatory of Singapore, Nanyang Technological University, n.d.

Wei, P., Lu, Z., and Song, J.: Variable importance analysis: A comprehensive review, Reliability Engineering & System Safety, 142, 399–432, https://doi.org/10.1016/j.ress.2015.05.018, 2015.

White, A. P. and Liu, W. Z.: Bias in information-based measures in decision tree induction, Mach Learn, 15, 321–329, https://doi.org/10.1007/BF00993349, 1994.

Win, S., Zin, W. W., Kawasaki, A., and San, Z. M. L. T.: Establishment of flood damage function models: A case study in the Bago River Basin, Myanmar, International Journal of Disaster Risk Reduction, 28, 688–700, https://doi.org/10.1016/j.ijdrr.2018.01.030, 2018.

World Bank Group (WBG): Poverty & Equity Brief: East Asia & Pacific. Thailand, 2023.

Yamane, T.: Statistics, An Introductory Analysis, 2nd ed., Harper and Row/John Weatherhill, Inc., New York, Evanston & London / Tokyo, 1967.