

TITLE

Floods as a window of opportunity: When and why extreme events trigger adaptation

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1 **Abstract**

2 Disasters can open windows of opportunity for climate adaptation—moments when heightened
3 public attention makes it possible to advance policies and measures that would otherwise
4 struggle to gain traction. Yet whether and how floods shape public adaptation discourse remains
5 unclear. Here, we quantify how flood severity influences media coverage on 12 adaptation
6 measures across 274 German districts from 2000–2020, using 625,813 news articles and daily
7 streamflow observations from 1,238 gauging stations. Through two-way fixed-effects models, we
8 find that floods significantly increase adaptation coverage across all hazard severity levels, with
9 extreme floods producing 26 times the effect of minor ones. However, this coverage is selective:
10 structural measures (e.g., dikes, dams) and warning systems dominate, while financial and
11 nature-based solutions receive proportionally less coverage, particularly during severe events. In
12 general, post-flood discourse follows a three-phase cycle: an immediate increase in coverage to
13 structural measures, a gradual shift toward financial recovery, and a return to baseline within 8 to
14 12 weeks. However, repeated floods alter this pattern. With successive events occurring in the
15 same district or neighboring districts, discourse becomes more diverse and shifts beyond
16 structural responses, with greater attention to financial preparedness measures. This suggests a
17 learning process in which societies move from reliance on single solutions toward a broader
18 portfolio of adaptation options. Together, our results demonstrate that floods create windows of
19 attention in news media. Yet, these are systematically biased, potentially narrowing the range of
20 adaptation options considered in the public debate.

21 **Significance Statement**

22 Floods repeatedly expose societies to the limits of existing protection, opening windows of
23 opportunity: moments of heightened public attention when communities are more receptive to
24 adopting adaptation measures that would otherwise face institutional inertia or political resistance.
25 Yet the discourse they trigger may not prepare communities for future risks. Analyzing 625,813
26 German news over two decades, we show that floods reliably open media windows for adaptation
27 discussion—but these windows are dominated by structural defenses such as dikes, while
28 nature-based and financial measures receive proportionally less attention. Repeated flooding
29 gradually diversifies discourse on financial preparedness, and flooding in neighboring districts
30 generates similar spillover effects. These findings reveal a systematic structural bias in post-
31 disaster public discourse that may constrain the adaptation options societies consider.

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34 1. Introduction

35 Historically, disasters such as floods have motivated fundamental social, economic, and political
36 transformations (1, 2). Scholars have used concepts such as “focusing events”(3) or “windows of
37 opportunity” (4, 5) to explain how crises can create conditions for change. These frameworks
38 posit that disasters create periods when policy and implementation changes are more likely to be
39 adopted (4).

40 However, such windows do not automatically translate into transformation. As argued by (6),
41 disasters lead to societal change only when they are interpreted, framed, and mobilized as
42 signals of the need for change. This process unfolds in part through media discourse (7). By
43 emphasizing or downplaying certain topics, media can influence which adaptation options
44 become visible, when, and for how long. Media coverage also influences the acceptability of
45 different adaptation strategies (8) and shapes individual behavior, such as mobility choices (9)
46 and climate-related investments (10).

47 In the context of increasing climate extremes, it is more important than ever to ask what drives
48 adaptation discourse. Previous research shows that extreme events increase attention to climate
49 risks (11–13), while hazard characteristics such as event magnitude and disaster frequency
50 shape post-disaster adaptation policies(4, 14, 15). However, how these characteristics translate
51 into the *emergence, type, persistence, and spillover* of adaptation discourse remains poorly
52 understood. In particular, it is unclear whether repeated events or experiences in nearby regions
53 trigger local adaptation coverage. Without this evidence, we cannot explain whether disaster
54 experience accumulates into longer-term societal learning—or whether each flood triggers the
55 same narrow focus on structural measures.

56 Despite advances in NLP-based discourse studies, three critical gaps remain. First, studies often
57 treat adaptation coverage as a single category (16, 17), obscuring which specific measures (e.g.,
58 nature-based solutions) gain or lose attention. Second, except for a few exceptions (18, 19),
59 studies fail to link media coverage systematically to flood physical characteristics using
60 hydrometric observations; instead, they often rely on disaster impact databases (20) or media-
61 defined event boundaries (18), limiting causal inference. Third, little is known about how
62 sequences of events shape adaptation discourse: in particular, whether and how repeated or
63 spatially connected floods (i.e., events in the same basin) cumulatively trigger the emergence,
64 persistence, or fading of adaptation discourse in the media.

65 Here, we address these gaps by investigating how floods shape media coverage on adaptation
66 across four dimensions. First, we examine **emergence**: whether and to what extent flood severity
67 increases adaptation discourse, and whether this relationship is linear or dependent on the
68 severity level. Second, we examine **composition**: which specific adaptation measures (e.g.,
69 structural, financial, nature-based, governance, and relocation options) gain or lose coverage as
70 flood severity escalates. Third, we examine **persistence**: how the temporal structure of post-flood
71 discourse unfolds, and whether coverage dynamics differ systematically across adaptation
72 categories. Fourth, we examine **spillover**: whether flood experience in neighboring districts within
73 the same river basin influences local adaptation discourse.

74 To investigate this, we use Germany as a case study, where two decades of severe flooding and
75 an active policy debate on adaptation provide a suitable empirical context. We link hydrological
76 flood records from 1,238 gauging stations (CAMELS-DE; (29)) to a corpus of 625,813 German
77 news articles covering floods from 2000–2020, classifying articles by adaptation measure type
78 using a supervised text classification model (SetFit (21)) and geolocating them to 274 NUTS-3
79 districts. Using two-way fixed-effects models that compare flood weeks against non-flood weeks
80 within the same district, we estimate how flood severity shapes both the volume and composition
81 of adaptation discourse across four dimensions: emergence, composition, persistence, and

82 spillover. fig. 1 summarizes the distribution of flood adaptation coverage across time, measures,
83 and districts.

84 Our results indicate that flood-triggered media windows are real, severity-dependent, and
85 temporally structured but also biased towards specific measures. Structural measures dominate
86 coverage immediately after floods, while financial and nature-based options are crowded out
87 precisely when public attention peaks. However, this bias is not unchangeable: repeated flood
88 experience and floods occurring in neighboring districts gradually shift discourse toward financial
89 preparedness, suggesting a slow learning mechanism that unfolds over years and across
90 administrative boundaries.

91 2. Results

92 2.1 Flood severity opens media windows, but not for all adaptation measures

93 Results are organized around the four dimensions: emergence, composition, persistence, and
94 spillover. The key outcome variable is Flood Adaptation Coverage (FAC) — the weekly count of
95 adaptation-related news articles mentioning a district, log-transformed to account for the
96 temporally skewed distribution of article counts. To examine discourse composition, we use two
97 measures: Shannon entropy, which captures how evenly coverage is distributed across the five
98 adaptation categories (higher values indicate more diverse discourse), and category shares,
99 which track the proportion of coverage to each category in a given week. Readers are referred to
100 the Methods section for in-depth details and model specifications.

101 We found that flood severity is positively and significantly associated with FAC at every severity
102 level: minor ($\beta = 0.013$, $P < 0.001$), moderate ($\beta = 0.072$, $P < 0.001$), major ($\beta = 0.087$, $P <$
103 0.001), severe ($\beta = 0.215$, $P < 0.001$), and extreme ($\beta = 0.340$, $P < 0.001$) (tbl. 1). The
104 relationship is nonlinear: each increase in severity roughly doubles the effect size, with extreme
105 floods producing 26 times the effect of minor floods (fig. 2A) — suggesting that severity does not
106 simply scale attention up uniformly, but accelerates it in ways that compound across thresholds.
107 In particular, an extreme flood is associated with a 40% increase in FAC in the affected district
108 relative to a non-flood week. These results remain stable when accounting for observed
109 economic losses and fatalities (*SI Appendix*, Table S2).

110 We also tested whether gradual, cumulative exposure to floods can substitute for an acute
111 triggering event. It cannot. Districts experiencing an extreme flood produce an average of 14.7
112 adaptation-related articles per district-week; districts with high accumulated flood exposure over
113 the preceding 12 weeks but no ongoing event produce just 1.0 article — a 14-fold gap (*SI*
114 *Appendix*, Table S1). These findings suggest that windows for adaptation discourse are event-
115 triggered: past flood experience alone does not sustain media discourse in the absence of a
116 current flood.

117 Having established that floods reliably increase the *volume* of adaptation coverage, we also
118 investigate what *kind* of coverage floods generate — and which options are crowded out.

119 Floods trigger the largest increases in coverage for dikes and levees ($\beta = 0.059$, $P < 0.001$),
120 followed by retention basins ($\beta = 0.044$, $P < 0.001$) and warning systems ($\beta = 0.027$, $P < 0.001$).
121 Together, these three adaptation measures account for around three-quarters of the total flood-
122 driven increase in FAC across all 12 measures (fig. 3A). Flood walls ($\beta = 0.016$), flood insurance
123 ($\beta = 0.011$), and financial support ($\beta = 0.010$) form a middle group with a modest but significant
124 increase in FAC. The remaining six measures — land-use restrictions, flood-risk policies, channel
125 modifications, permeable surfaces, floodplain restoration, and voluntary relocation — show either
126 minimal or no significant flood-driven increase (*SI Appendix*, Table S3 and Fig. S5). This pattern
127 holds after rescaling each measure against its own non-flood baseline (*SI Appendix*, Figs. S2, S3,
128 and S9): measures that dominate flood-week coverage also dominate the *increase relative to*

129 *normal weeks*, confirming that structural measures attract more attention after floods rather than
130 simply receiving more coverage at all times.

131 This structural dominance becomes even more pronounced as flood severity increases.
132 Structural measures receive significantly more coverage after floods at all five severity levels (all
133 $P < 0.005$), while financial and nature-based measures lag further behind with each step up in
134 severity. Warning systems see increased coverage even after minor floods. Coverage of financial
135 measures only increases meaningfully after severe or extreme floods, suggesting that public
136 debate about financial preparedness is reserved for the most damaging events. The media
137 coverage for nature-based solutions is inconsistent for any severity level, and relocation coverage
138 shows no significant response at any level (tbl. 1).

139 Severe and extreme floods do broaden coverage in one sense: during non-flood weeks, media
140 attention concentrates heavily on one or two measure types, whereas after severe floods, more
141 categories receive at least some coverage (Shannon entropy: 0.14 vs. 0.41; *SI Appendix*, Table
142 S4). Yet this broadening is not proportionally neutral. Structural coverage increases its share from
143 45% to 59%, and governance — driven by warning systems — quadruples from 3% to 13%.
144 Financial coverage, by contrast, drops from 25% to 11%, and nature-based coverage from 12%
145 to 4%. The surge in media attention that severe floods create is therefore not neutral: it amplifies
146 some adaptation options while crowding out others. Coverage breakdowns for all 12 individual
147 measures across flood severity levels are shown in *SI Appendix*, Fig. S15.

148 **2.2 Post-flood discourse follows a three-phase cycle and fades within 8–12 weeks**

149 To trace how FAC composition evolves after floods, we tracked the share of each adaptation
150 category from 4 weeks before to 12 weeks after each severe or extreme flood event. Three
151 phases (t to t+2, t+2 to t+8, t+8 to t+12) are visible (fig. 3B and fig. 4).

152 In the first 2 weeks after a flood (Phase 1), structural coverage surges from 45% to 59%, driven
153 by sharp increases in dikes and retention basins—particularly after severe and extreme
154 floodsfig. 4. Warning system coverage spikes immediately at the moment of the flood but returns
155 to baseline within 1 week. Financial and nature-based categories decline in their proportional
156 share during this phase, not because they receive fewer articles in absolute terms, but because
157 structural coverage grows so rapidly that it disproportionately dominates available media attention
158 (*SI Appendix*, Fig. S13).

159 In weeks 2 through 8 (Phase 2), financial and governance shares gradually recover as
160 compensation programs and policy debates enter the coverage. Financial support and flood
161 insurance coverage rise only in the weeks following severe floods, suggesting that financial
162 preparedness enters public debate with a delay relative to the immediate structural response.
163 Nature-based measures and relocation attract no meaningful increase in coverage during this
164 phase, regardless of flood severity.

165 After week 8 (Phase 3), FAC on all adaptation categories return toward pre-flood levels, though
166 structural coverage remains slightly elevated and financial coverage slightly depressed relative to
167 the week before the flood—a pattern visible across all flood severity levels (*SI Appendix*, Fig.
168 S12). The adaptation categories differ, however, in how quickly they return to baseline: structural
169 and financial measures remain elevated for up to 8 weeks after a flood, whereas warning systems
170 return to baseline within 1 week (*SI Appendix*, Fig. S6).

171 Together, these three phases reveal that the media window opened by floods is both time-limited
172 and systematically selective: physical protection dominates the immediate aftermath, financial
173 recovery enters only once the acute crisis narrative fades, and nature-based and relocation
174 options never gain meaningful attention, even as overall public attention declines.

175 **2.3 Prior flood experience gradually shifts discourse from structural to financial measures**
176 The previous section showed how a single flood event shapes the composition of adaptation
177 discourse in the immediate aftermath. Here, we examine whether the baseline composition of
178 adaptation measures in a specific district varies with the number of flood events.

179 To do so, we use an interaction model of current flood severity, cumulative prior flood occurrence,
180 and their interaction (*SI Appendix*, Table S5). We found that cumulative flood occurrence alone
181 does not predict discourse diversity, measured here as higher Shannon entropy ($\beta = 0.0001$, $P =$
182 0.730). However, the interaction between current severity and cumulative occurrence is positive
183 and significant ($\beta = 0.0004$, $P = 0.002$) (*SI Appendix*, Table S5). When a flood occurs, districts
184 with more previous floods produce a broader, more evenly distributed mix of adaptation coverage
185 than districts experiencing a similar flood for the first time.

186 The effect is stronger for recent floods than for distant ones. The count of major floods in the
187 preceding year yields a per-event effect roughly three times larger ($\beta = 0.035$) than the full-period
188 count ($\beta = 0.012$), suggesting that the diversifying effect of prior flood experience is concentrated
189 in recent events, with older floods contributing progressively less to current discourse (*SI*
190 *Appendix*, Fig. S7 and Table S6).

191 fig. 5A illustrates this pattern: districts with more prior major floods show consistently higher
192 Shannon entropy (i.e., discourse diversity), across all temporal windows examined — the
193 preceding year, the preceding two years, and the full study period — suggesting that the
194 diversifying effect of flood experience is not an artifact of any particular time horizon. When
195 considering the individual measures (fig. 5B), we found that the shift is directional. With
196 increasing flood history, coverage of financial support and flood insurance rises, while attention to
197 dikes and retention basins declines. Over time, repeated floods gradually shift public discourse
198 away from a purely structural focus toward a greater emphasis on financial preparedness (*SI*
199 *Appendix*, Fig. S8).

200 Experienced economic damage from the European Flood Impact dataset reinforces this pattern
201 regardless of flood severity. Cumulative economic loss history significantly predicts discourse
202 diversification ($\beta = 0.016$, $P < 0.001$; *SI Appendix*, Table S2), confirming that the learning
203 mechanism is driven by felt impact, not just by how often or how severely a district floods.

204 **2.4 Flooding in neighboring districts spreads adaptation discourse across administrative** 205 **boundaries**

206 Finally, we tested whether floods occurring in other districts within the same river basin affect
207 local FAC composition. Floods occurring within the same basin significantly broaden local
208 adaptation discourse (Shannon entropy: $\beta = 0.018$, $P < 0.001$; *SI Appendix*, Table S7), with effect
209 sizes comparable to those of local flooding. When broken down by adaptation category, flooding
210 in neighboring districts within the same river basin increases coverage of financial measures most
211 strongly ($\beta = 0.007$, $P < 0.001$), while structural coverage shows no significant change. Flooding
212 elsewhere in the same river basin is thus associated with increased local discussion of financial
213 preparedness, suggesting that proximity to flood events, not just direct experience, shapes
214 adaptation discourse (*SI Appendix*, Fig. S9 and Tables S7–S8).

215 **3. Discussion**

216 Our findings demonstrate that floods reliably open media windows for adaptation discourse — but
217 these windows are biased, amplifying structural defenses while crowding out financial and nature-
218 based options precisely when public attention peaks.

219 **Floods open real but severity-dependent media windows.** The monotonic relationship
220 between flood severity and adaptation coverage—spanning a 26-fold range from minor to
221 extreme events—demonstrates that the window-of-opportunity mechanism operates along a

222 continuous severity gradient rather than a simple binary threshold. This finding extends the
223 literature on “focusing events” (22–24) by showing that even minor floods generate measurable
224 increases in adaptation discourse, although the effects grow rapidly with severity. The
225 nonlinearity also explains why previous studies using aggregate flood indicators may have
226 underestimated the contribution of moderate events to cumulative adaptation discourse.

227 **The discourse window is selective.** While severe floods do broaden adaptation coverage in
228 absolute terms — more categories receive some attention than during non-flood weeks — the
229 relative composition shifts sharply toward structural and governance measures at the expense of
230 financial and nature-based options. The window opens wider, but unevenly: structural measures
231 capture a disproportionately larger share of the expanded attention, crowding out financial and
232 nature-based options precisely when public attention peaks. This pattern aligns with availability
233 heuristics (25) and media framing dynamics that privilege visible, tangible, and politically
234 uncontroversial solutions in crisis contexts (13). The three-phase post-flood cycle we document—
235 structural surge, financial recovery, and return to baseline—provides a temporal structure for
236 understanding how this filtering operates: the immediate crisis narrative favors physical
237 protection. By the time discourse diversifies, overall media coverage has already faded.

238 **Repeated experience offers a partial corrective.** The finding that cumulative flood
239 experience—both direct and through basin-level spillover—shifts the discourse toward financial
240 measures suggests a form of collective flood memory: repeated exposure gradually recalibrates
241 which adaptation options are discussed, operating as a slow corrective to the acute structural
242 bias. This is consistent with theories of social learning in hazard contexts (26–28), where
243 repeated exposure enables communities to move beyond immediate crisis responses toward
244 more comprehensive risk management strategies. The spatial spillover finding suggests that
245 media reporting at the river basin scale can transmit adaptation-relevant information across
246 administrative boundaries, a mechanism that has received little attention in the adaptation
247 communication literature.

248 A notable feature of this learning mechanism is that the recency of flood occurrence matters as
249 much as cumulative quantity. The one-year window of major flood occurrence produces an effect
250 roughly three times larger per event than the full-period count ($\beta = 0.035$ vs. $\beta = 0.012$),
251 suggesting that societies do not accumulate flood experience in a simple additive way. Instead,
252 recent events appear to activate a form of collective risk memory that fades over time, consistent
253 with theoretical accounts of availability-based risk perception and the psychological literature on
254 the recency effect in hazard salience. The window during which flood experience can diversify
255 adaptation discourse may therefore be narrower than previously assumed—communication
256 strategies designed to leverage prior flood experience need to be activated quickly after
257 subsequent events to be effective.

258 Some limitations should be noted. First, our analysis covers 2000–2020 due to the availability of
259 the CAMELS-DE dataset and thus does not capture the 2021 Ahr Valley flood, which may have
260 changed German adaptation discourse. Second, our NLP-based media classification operates at
261 the sentence level and captures mentions of adaptation measures rather than evaluations of their
262 implementation or effectiveness. Third, the two-way fixed effects framework estimates average
263 effects and cannot account for heterogeneity in media market structure or editorial orientation.

264 Despite these limitations, our results have clear implications for climate adaptation governance.
265 The systematic structural bias in post-flood discourse suggests that media windows, while
266 valuable for raising adaptation salience, are not self-correcting in the short term. If crisis-driven
267 public attention is to be leveraged for comprehensive adaptation planning, financial, nature-
268 based, and governance options must be actively introduced into the discourse during the narrow
269 window when media attention peaks. The finding that flood experience gradually diversifies
270 discourse offers cautious optimism—but the time scale of this learning (years, not weeks) implies

271 that relying on experiential learning alone will be insufficient to keep pace with accelerating
272 climate risks.

273 **4. Methods**

274 **4.1 Study Design and Data Sources**

275 We linked two primary datasets at the NUTS-3 district \times week level to construct a panel spanning
276 June 2000 to January 2020 (274 districts, 1,026 weeks, 281,124 district-week observations).
277 Flood events were identified using daily streamflow observations from the CAMELS-DE dataset,
278 covering 1,582 German catchments (29). For each catchment, floods were defined as the annual
279 maximum daily discharge within hydrological years (November–October) and classified into five
280 severity levels (minor, moderate, major, severe, extreme) using empirical return periods based on
281 Weibull plotting positions (30, 31), with class boundaries at 5, 10, 20, and 50 years. Gauges with
282 more than 35 missing daily observations or fewer than 30 valid hydrological years per year were
283 excluded from the analysis. Media data were drawn from a corpus of 215 million German news
284 articles from over 350 outlets (2000–2020), using a news aggregator database ([www.wiso-](http://www.wiso-net.de)
285 [net.de](http://www.wiso-net.de)). Then it was filtered to over 2.5 million articles that mention flood-related keywords within
286 the first five sentences, following the inverted pyramid principle in journalism.

287 **4.2 Quantification of Flood Adaptation Coverage**

288 We developed a typology of 12 flood adaptation measures across five categories: structural
289 (dikes, flood walls, channel modifications, retention basins), nature-based (floodplain restoration,
290 permeable surfaces), financial (insurance, financial support), governance (warning systems, land-
291 use restrictions, risk policies), and relocation (Table S9 in SI Appendix).

292 To identify articles reporting on these measures, we designed a multi-step filtering and
293 classification pipeline applied to a corpus of German news articles described above. The corpus
294 was first filtered using flood-related keywords (*Flut*, *Hochwasser*, *Starkregen*), yielding 2,508,345
295 articles. To remove noise, we retained only those articles containing at least one keyword
296 associated with a specific adaptation measure category (Table S9 in SI Appendix), reducing the
297 sample to 625,813 articles. To ensure that relevant articles were not inadvertently excluded at
298 this stage, we manually reviewed a random sample of 100 articles that matched the flood
299 keywords but none of the adaptation-related keywords. Additionally, duplicate articles with a
300 Jaccard similarity greater than 0.8 were removed to avoid duplicates from news agencies or
301 press releases shared across multiple outlets.

302 The retained articles were then split into sentences and classified using SetFit, a supervised
303 learning approach based on fine-tuned sentence transformers (paraphrase-multilingual-mpnet-
304 base-v2;(32)). For each adaptation measure, we constructed manually curated training sets
305 comprising both positive and negative examples drawn from the original corpus and augmented
306 with synthetic data. This process identified 191,166 articles as reporting on at least one
307 adaptation measure.

308 Positively classified articles were then geolocated to NUTS-3 districts using named-entity
309 recognition. Location entities were matched to GeoNames coordinates
310 (<https://www.geonames.org/>). Hierarchical clustering of the location entities was applied to
311 distinguish flood-relevant locations from incidental mentions (e.g., newspaper headquarters)
312 based on (33). Flood adaptation coverage (FAC) was operationalized as article counts per
313 district-week, with $\log(1 + n)$ as the primary dependent variable. Full details on classifier training,
314 validation metrics, and example texts are provided in the SI Appendix.

315 **4.3 Statistical Framework**

316 All models use two-way fixed effects (TWFE) of the form $Y_{it} = \beta \cdot \text{Flood}_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$, where α_i
317 are district fixed effects absorbing time-invariant regional characteristics, and γ_t are time fixed
318 effects absorbing national-level temporal trends. Standard errors are clustered at the NUTS-3

319 level. The identifying variation is within-district temporal deviation: we compare FAC in weeks with
320 versus without flood occurrence within the same district, net of national trends. Our specification
321 uses continuous weekly flood count regressors rather than a binary absorbing treatment indicator,
322 which avoids the negative-weighting concerns associated with staggered difference-in-differences
323 designs (34, 35). Article counts are heavily right-skewed (skewness ranges from 13.9 to 58.0
324 across all categories and measure-level counts, with a modal value of zero); we therefore apply
325 the $\log(1 + x)$ transformation as the primary dependent variable.

326 For compositional analyses, we use category and measure shares and Shannon entropy.
327 Shannon entropy measures how evenly FAC is distributed across the five adaptation categories:
328 $H = -\sum p_i \ln(p_i)$, where p_i is the share of total adaptation articles belonging to category i . Values
329 range from 0 (all articles concentrated in a single category) to $\ln(5) \approx 1.61$ (perfectly even
330 distribution across all five categories). Category shares are modeled using OLS with two-way
331 fixed effects, following standard practice in large panel settings (36, 37). This linear specification
332 is appropriate given that conditional shares remain well within the unit interval.

333 To measure cumulative flood experience, we constructed rolling backward-looking counts of
334 major-or-above flood weeks within defined temporal windows (1-year, 2-year, and full study
335 period), each lagged by one week to avoid simultaneity. These variables capture whether districts
336 with more prior flood exposure produce different adaptation discourse patterns when a new flood
337 occurs. For the basin-level spillover analysis, we identified all other NUTS-3 districts sharing the
338 same major river basin as each focal district and computed cumulative flood intensity across
339 those neighboring districts over the preceding 12 weeks. This variable captures whether flooding
340 observed elsewhere in the same river system is associated with changes in local adaptation
341 discourse, independent of local flood occurrence.

342 For models examining cumulative experience and basin spillover, week fixed effects are replaced
343 with year and month fixed effects to avoid collinearity with rolling exposure windows (see SI
344 Appendix, Table S17). The event window spans eight weeks before to twelve weeks after each
345 flood event ($t = -8$ to $t = +12$). Because panel construction constraints mean that not all events
346 have eight full weeks of pre-event observations, only $t = -4$ to $t = -2$ are available as estimable
347 pre-period coefficients across the full event sample, with $t = -1$ serving as the reference category
348 following standard event-study convention. Pre-event parallel trends were formally tested by
349 applying a joint Wald test to all estimable pre-period coefficients ($t = -4$ to $t = -2$, with $t = -1$ as
350 the reference category). We fail to reject the null of jointly zero pre-period effects ($F = 1.00$, $df = 3$,
351 $P = 0.39$, standard errors clustered at NUTS-3), supporting the identifying assumption of the
352 event-study design. All models were estimated using the `fixest` package in R (38). Detailed
353 variable construction is reported in the SI Appendix 4.

354 We conducted extensive robustness checks on all core results. The severity–coverage
355 relationship is robust to alternative dependent variable specifications, including rate per million
356 inhabitants and top-percentile trimming (SI Appendix, Table S15). Under NUTS-1 clustering, the
357 extreme flood coefficient loses significance only in the raw-count specification ($P = 0.176$); the
358 log-transformed specification used throughout the main analysis remains significant, confirming
359 that this sensitivity is driven by the right-skewed distribution of raw counts rather than by the
360 clustering choice (SI Appendix, Table S16). Results are also robust to replacing calendar-week
361 fixed effects with year and month fixed effects (SI Appendix, Table S17). Dose-response analysis
362 confirms a monotonic increase in coverage with flood intensity (SI Appendix, Table S13), and
363 temporal sensitization tests show modest increases in flood responsiveness over the study
364 period, driven primarily by governance coverage (SI Appendix, Table S14). Results are also
365 robust to five alternative spatial linking strategies between river catchments and NUTS-3 districts,
366 with coefficient variation across methods of 8.6% for the severe tier on which substantive
367 conclusions rest (SI Appendix, Table S18).

368 **Acknowledgments**

369 The CAMELS-DE hydrological dataset is publicly available via Loritz et al. (2024)
370 [https://doi.org/10.5281/zenodo.13837553]. The severity-calibrated flood event dataset, the
371 analysis panel (comprising NUTS-3 weekly article counts and flood variables), and all underlying
372 analysis code will be made available on Zenodo upon publication.

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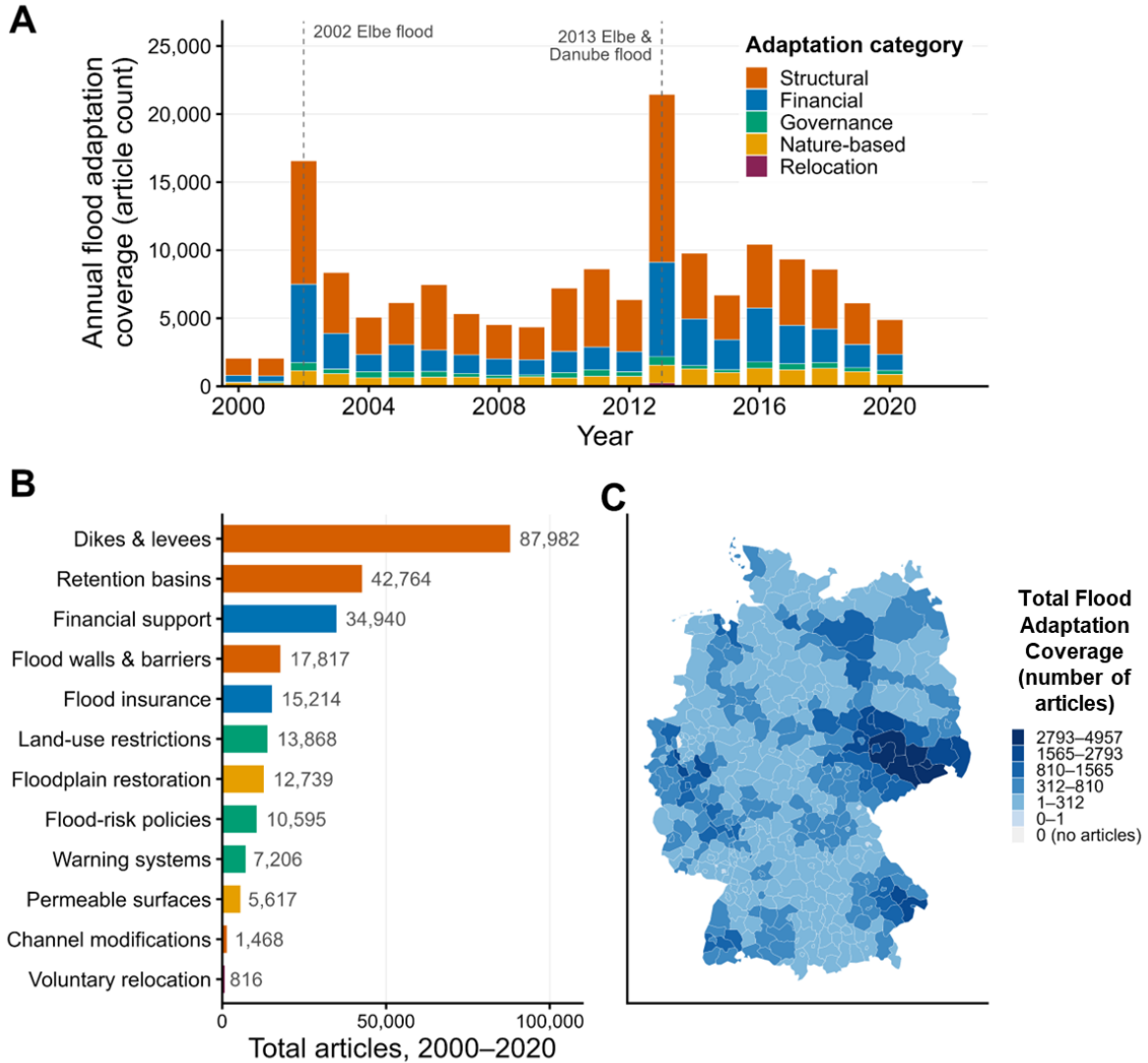
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459 **Figures and Tables**

460 Each on separate pages (use the manual page breaks from the formatbar).

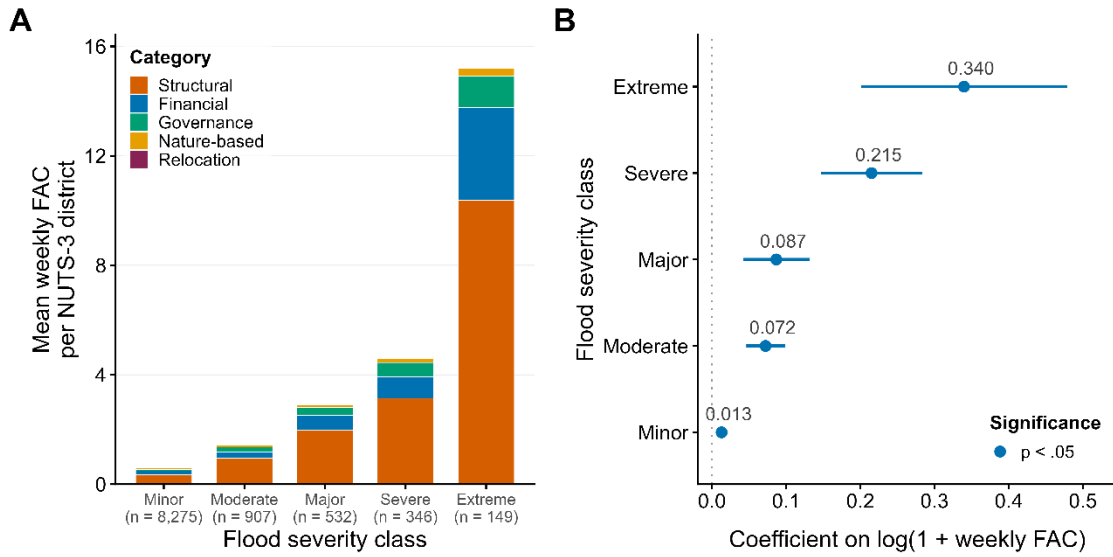


461

462 **Figure 1: Flood adaptation coverage (FAC) in German news media, 2000–2020**

463 (A) Annual FAC article counts stacked by adaptation category. Spikes correspond to major
 464 floods: the 2002 Elbe flood and the 2013 Elbe and Danube floods. Structural measures (orange)
 465 dominate coverage in all years, with financial measures (blue) forming the second largest
 466 category. (B) Total FAC articles per adaptation measure between 2000 and 2020. Dikes and
 467 levees (87,982 articles) and retention basins (42,764 articles) account for the largest share of all
 468 adaptation coverage, followed by financial support (34,940 articles). (C) Spatial distribution of
 469 total FAC articles across 274 NUTS-3 (Nomenclature of territorial units for statistics) districts.
 470 Districts in southeastern Germany, particularly those along the Elbe and Danube river systems,
 471 show the highest cumulative coverage.

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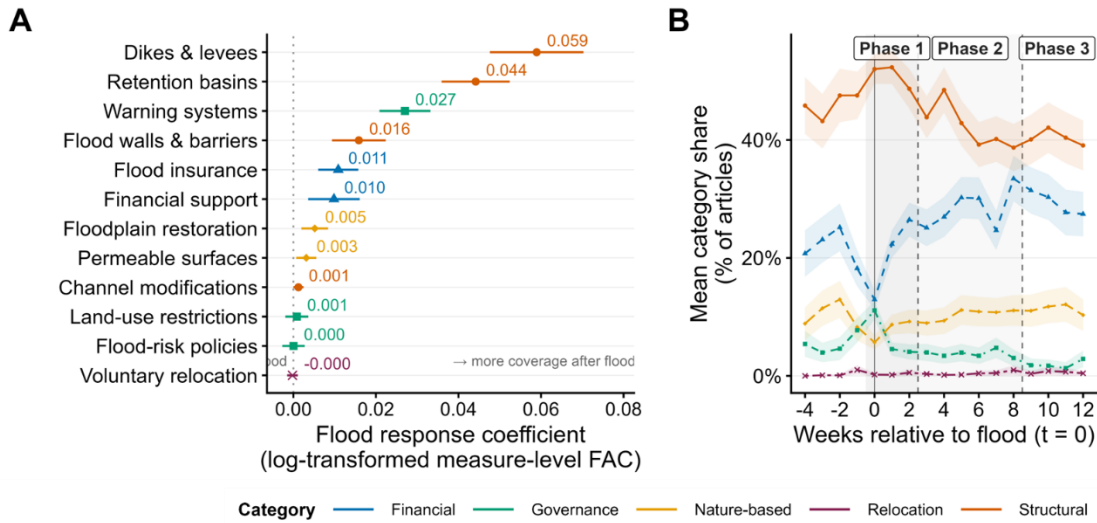


473

474 **Figure 2: Volume of flood adaptation coverage (FAC) by hazard severity**

475 (A) Mean weekly FAC per NUTS-3 district by flood severity class, stacked by adaptation
 476 category. Sample sizes are shown below the class labels. (B) Regression coefficients from two-
 477 way fixed effects models of $\log(1 + \text{weekly FAC})$ on severity class counts, with NUTS-3 district
 478 and calendar week fixed effects. Horizontal bars show 95% confidence intervals (standard errors
 479 clustered at the district level). Filled circles indicate statistical significance at $p < .05$; open circles
 480 indicate nonsignificance. All five severity classes are statistically significant ($p < .001$).
 481 Coefficients approximate proportional changes: an extreme flood increases FAC by
 482 approximately 40% relative to non-flood weeks in the same district.

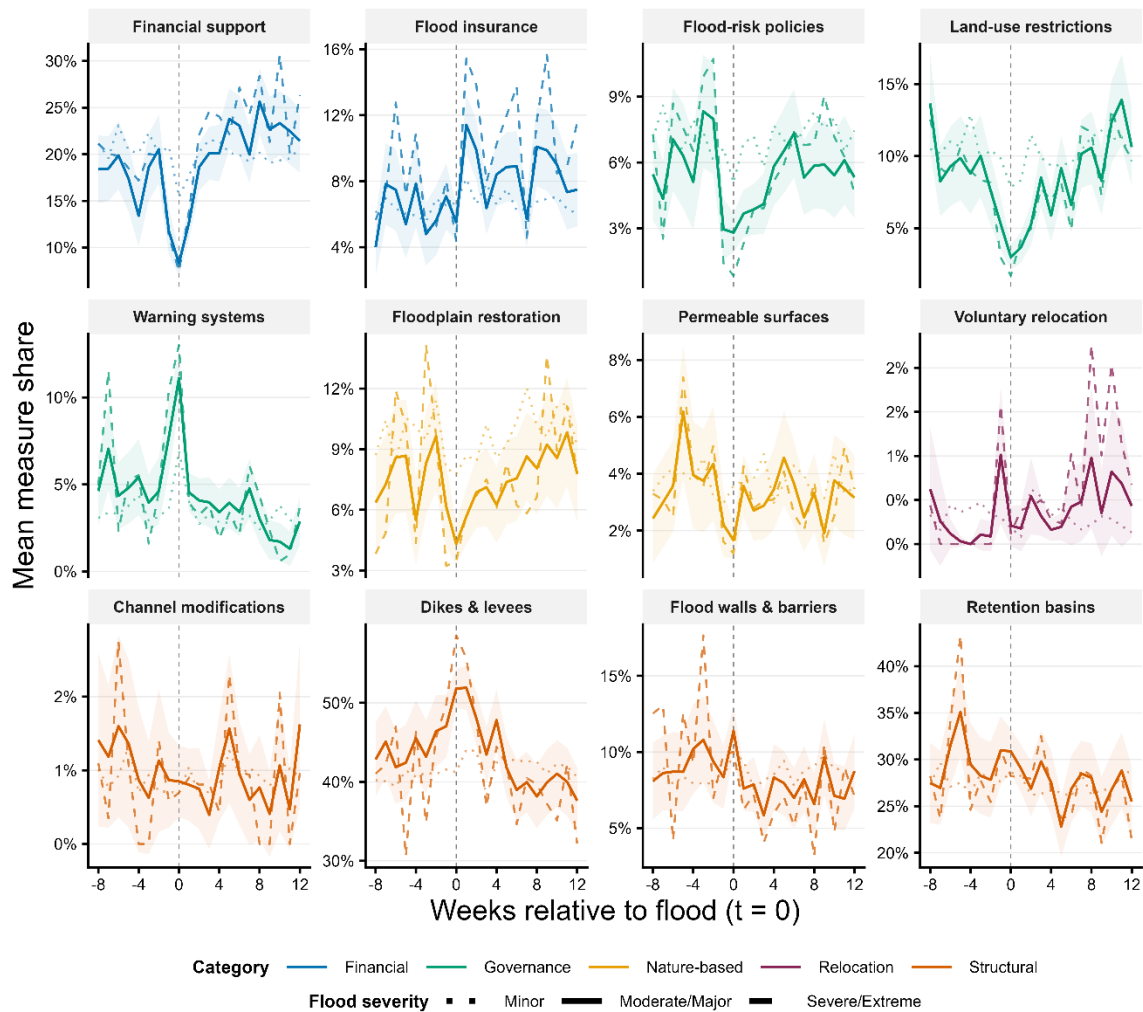
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484

485 **Figure 3: Measure-level flood responses and post-flood discourse dynamics**

486 (A) Flood response coefficients for 12 individual adaptation measures, estimated from two-way
 487 fixed effects models of $\log(1 + \text{measure-level FAC})$ on a binary flood indicator and 12-week
 488 cumulative flood intensity, with NUTS-3 district and calendar week fixed effects (standard errors
 489 clustered at district level). Positive values indicate greater coverage following a flood event;
 490 negative values indicate reduced coverage. Dikes and levees, retention basins, and warning
 491 systems produce the three largest positive responses. (B) Mean share of articles devoted to each
 492 adaptation category (% of all adaptation articles) in the weeks around severe and extreme flood
 493 events ($t = 0$), with 95% confidence ribbons. Three post-flood phases are visible: Phase 1 (t to
 494 $t+2$), in which structural coverage surges; Phase 2 ($t+2$ to $t+8$), in which financial and governance
 495 coverage gradually recovers; and Phase 3 ($t+8$ to $t+12$), in which shares return toward pre-flood
 496 levels.

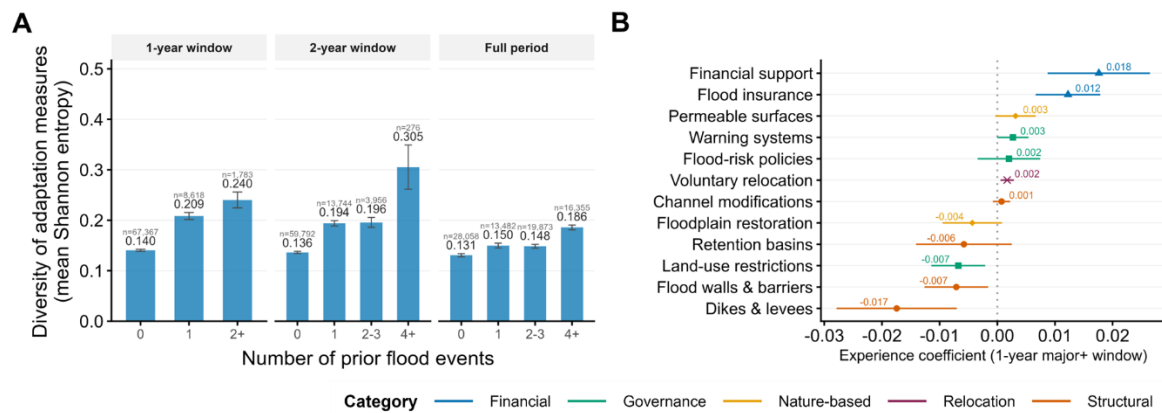


497

498 **Figure 4: Post-flood adaptation measure trajectories by flood severity**

499 Each panel shows the mean weekly share of one adaptation measure from four weeks before to
500 twelve weeks after a flood event ($t = 0$, dashed vertical line). The event window extends from $t =$
501 -8 to $t = +12$ weeks relative to flood occurrence. Flat pre-event trajectories are confirmed by a
502 joint Wald test on pre-period coefficients ($t = -4$ to $t = -2$, with $t = -1$ as reference; $F = 1.00$, $df =$
503 3 , $P = 0.39$), supporting the identifying assumption of the event-study design. Solid lines:
504 moderate and major floods; dashed lines: severe and extreme floods; dotted lines: minor floods.
505 Shaded ribbons around the solid line show 95% confidence intervals for the moderate/major
506 group. Colors indicate adaptation category. Y-axes are scaled independently for each measure to
507 maximize readability; note that scales differ across panels.

508



509

510 **Figure 5: Cumulative flood occurrence and discourse diversification**

511 (A) Mean Shannon entropy by bins of prior major-or-above flood occurrence, across three
 512 temporal windows (within a 1-year window, within a 2-year window, and over the full study period
 513 (2000–2020)). Error bars show 95% confidence intervals. Higher entropy indicates a more even
 514 distribution of FAC across adaptation categories. Districts with more prior major floods
 515 consistently show higher discourse diversity. Sample sizes shown below bin labels. (B) Effect of
 516 1-year cumulative major flood occurrence on individual adaptation measure shares, estimated
 517 from two-way fixed effects models (standard errors clustered at district level). Positive values
 518 indicate the measure gains share with flood experience; negative values indicate share loss.
 519 Financial support and flood insurance gain share with cumulative flood occurrence, while dikes
 520 and retention basins lose share. Together, panels A and B indicate that repeated flood
 521 occurrence gradually shifts public discourse away from a purely structural framing toward one
 522 that includes financial preparedness.

523

524 **Table 1:** Effect of flood severity on weekly flood adaptation coverage (FAC) by adaptation
 525 category

<i>DV: log(1+articles)</i>	<i>Minor</i>	<i>Moderate</i>	<i>Major</i>	<i>Severe</i>	<i>Extreme</i>
<i>Total</i>	0.013*** (0.002)	0.072*** (0.013)	0.087*** (0.023)	0.215*** (0.035)	0.340*** (0.071)
<i>Structural</i>	0.006** (0.002)	0.037** (0.012)	0.056** (0.019)	0.205*** (0.036)	0.320*** (0.071)
<i>Financial</i>	0.001 (0.001)	0.004 (0.005)	0.015 (0.012)	0.055* (0.022)	0.188** (0.057)
<i>Governance</i>	0.004*** (0.001)	0.013* (0.006)	0.032** (0.011)	0.074*** (0.018)	0.113* (0.044)
<i>Nature-based</i>	0.001 (0.001)	0.007* (0.003)	-0.009* (0.005)	0.027* (0.011)	0.025 (0.025)
<i>Relocation</i>	0.000 (0.000)	0.001 (0.001)	0.004 (0.004)	-0.003 (0.002)	0.009 (0.008)

526 Each cell reports the coefficient (β) from a separate two-way fixed-effects regression of log-
 527 transformed weekly article counts, $\log(1 + \text{articles})$, on the count of flood events of a given
 528 severity class in that district-week. The dependent variable (DV) measures the number of
 529 adaptation-related news articles that mentioned a given district in a given week, log-transformed
 530 to account for the temporally skewed distribution of article counts. Positive values indicate greater
 531 adaptation coverage during flood weeks than during non-flood weeks in the same district. Flood
 532 severity is classified by empirical return periods: minor (< 5 years), moderate (5–10 years), major
 533 (10–20 years), severe (20–50 years), and extreme (≥ 50 years). All models include NUTS-3
 534 district and calendar-week fixed effects; standard errors in parentheses are clustered at the
 535 NUTS-3 level. Full model output in *SI Appendix*, Tables S13–S18. † $P < .10$, * $P < .05$, ** $P < .01$,
 536 *** $P < .001$.

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Supporting Information for
Floods as a window of opportunity: When and why extreme events
trigger adaptation

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This PDF file includes:

- I . Sentence-Level Classification of Flood Adaptation Measures
- II. Variable Construction
- III. Supplementary Figures (Figures S1 to S15)
- IV. Supplementary Tables (Tables S1 to S18)

I. Sentence-Level Classification of Flood Adaptation Measures Using Few-Shot Multilingual Transformers

First, we identified candidate documents from our sample of 2,508,345 articles by filtering those that mention at least one keyword from Table S10. To assess the robustness of the keyword pre-filtering step, we manually reviewed a random sample of 100 documents excluded during filtering; 23 were identified as potentially relevant false negatives (23%), with misclassifications confined almost entirely to the financial support category and no relevant documents identified in any other adaptation category. Additionally, duplicate articles with a Jaccard similarity greater than 0.8 were removed to avoid duplicates from news agencies or press releases shared across multiple outlets. Based on this, 625,813 articles were identified.

Sentence-level classification of flood adaptation measures was implemented using SetFit (Tunstall et al., 2022), a few-shot learning framework built on contrastive fine-tuning of sentence transformers. All classifiers shared the same pre-trained backbone, paraphrase-multilingual-mpnet-base-v2 (Reimers & Gurevych, 2020), a multilingual transformer. A separate binary classifier was trained for each of the 12 adaptation measures in Table S11, yielding 12 independent models.

For each classifier, a manually curated training set was constructed comprising between 20 and 48 positive examples and 16–20 negative examples, all at the sentence level and written in German. A total of 663 samples was manually annotated. Positive examples were domain-specific sentences explicitly referencing the target measure (e.g., dike construction, flood insurance contracts); negative examples included both thematically unrelated sentences and semantically adjacent but non-matching flood-related sentences, to encourage precise decision boundaries. Training followed the standard SetFit procedure to fine-tune the sentence encoder (3 epochs, 20 iterations) followed by fitting a logistic classification head on the resulting embeddings.

Inference was performed on sentence-level splits of the pre-filtered article corpus, with each classifier applied only to the subset of articles pre-selected by the corresponding adaptation-measure keywords.

Each model was evaluated on a stratified held-out sample of 100 sentences, drawn from the classified corpus by binning predicted probabilities into 10 equal-width intervals (0.1-step) and sampling up to 10 sentences per bin. This stratified design ensured that sentences spanning the full range of model confidence were represented in the evaluation. Sampled sentences were manually labelled by human annotators. Standard classification metrics (accuracy, precision, recall, F1 score) were computed against these human labels.

II. Variable Construction

To identify the relationship between flood events and adaptation discourse, we linked flood event data to flood adaptation coverage (FAC) at the NUTS-3 district \times calendar week level, constructing a balanced panel spanning June 2000 to January 2020 (274 NUTS-3 districts \times 1,026 weeks = 281,124 district-week observations). Region-weeks without flood events received zeros for all flood variables; region-weeks without FAC received zeros for article counts. This section documents the construction of all variables used in the analysis.

5.1 Flood Exposure Variables

For each region-week, we aggregated catchment-level flood classifications (described in Section 2.4 of the main text) into the following variables.

Binary severity indicators. For each of the five severity classes (minor: $T < 5$ year; moderate: $T = 5\text{--}10$ year; major: $T = 10\text{--}20$ year; severe: $T = 20\text{--}50$ year; extreme: $T \geq 50$ year), we defined a binary indicator equal to 1 if at least one gauging station assigned to the NUTS-3 district exceeded that severity threshold during the calendar week. A district-week may have multiple active indicators if different gauging stations recorded floods of different severities in the same week.

Severity count variables. For each severity class, we counted the number of distinct flood events at or above the corresponding threshold within each district-week (n_{minor} , n_{moderate} , n_{major} , n_{severe} , n_{extreme}). These serve as the primary regressors in the severity–coverage models (Table 1 in the main text), allowing us to estimate the marginal effect of an additional flood event at each severity level.

Weekly maximum severity score. A single continuous measure ($\text{weekly_max_severity}$) that collapses the multi-tier structure into a weighted composite: minor = 1, moderate = 2, major = 4, severe = 8, extreme = 16. This variable is used in compositional analyses where a single severity index is preferred over five separate count variables.

Weekly flood intensity. The sum of all return period values across gauging stations within a district-week (weekly_intensity). Unlike $\text{weekly_max_severity}$, which uses ordinal weights, this variable reflects the cumulative hydrological magnitude of all concurrent flood events.

- Cumulative flood experience. We constructed rolling backward-looking counts of flood weeks within defined temporal windows, each lagged by one week to avoid simultaneity:
- $\text{roll_major_52wk_lag}$: count of weeks with major-or-above floods in the preceding 52 weeks (1-year window)
- $\text{roll_major_104wk_lag}$: 2-year window
- $\text{roll_major_156wk_lag}$: 3-year window
- $\text{roll_major_260wk_lag}$: 5-year window
- $\text{cum_floods_major_lag}$: full-period cumulative count from the start of the panel
- $\text{cum_floods_any_lag}$: full-period count including all severity levels

These variables are used in the experience–diversification analysis (Result Section “Repeated Flood Occurrence Shifts Discourse Toward Financial Measures”) to test whether districts with more flood history produce more diverse adaptation coverage.

12-week cumulative intensity. The sum of weekly_intensity over the preceding 12 weeks ($\text{intensity_past_12wk}$), used as a control variable in binary flood effect models to separate acute from accumulated effects.

Basin-level spillover intensity. For each NUTS-3 district, we identified all other districts sharing the same major river basin and computed the cumulative weekly_intensity across those neighbouring districts over the preceding 12 weeks (basin_intensity_12wk). This variable captures hydrological spillover — the possibility that flooding observed in nearby districts within the same river system may affect local adaptation discourse even before local flooding occurs.

5.2 Adaptation Coverage Variables

Adaptation articles classified at the sentence level (described in Section 4 of this appendix) are aggregated to the NUTS-3 \times week level.

Article counts. We computed raw article counts at three levels of aggregation: total FAC articles (n_articles), articles by adaptation category (five categories: structural, financial, governance, nature-based, relocation), and articles by individual measure (12 measures, listed in Table S9). Each article is counted once per district-week even if multiple sentences within the article mention adaptation measures.

Log-transformed counts. Because article counts are heavily right-skewed (skewness > 10 for most measures, with the modal value being zero), we applied $\log(1 + x)$ transformation to all count variables before use as dependent variables. This is the primary DV specification throughout the analysis. Skewness diagnostics for all variables are reported in the replication materials.

Rate per million. To account for secular growth in the WISO news database over the study period, we computed a normalised rate defined as articles per million WISO articles published in the same calendar year. This variable is used as an alternative DV in robustness checks (Table S16).

Min-max normalized counts. For cross-measure comparability, we applied min-max normalization to $\log(1 + x)$ counts for each measure independently, rescaling to $[0, 1]$. A coefficient of 0.05 on a min-max variable means that a flood moves the measure by 5% of its own full observed range. This transformation removes the dominance of high-volume measures (e.g., dikes: max = 238 articles/week) over low-volume ones (e.g., permeable surfaces: max = 14) and is used in supplementary analyses (Figs. S2, S3, S9, S10).

5.3 Compositional Variables

Compositional variables are computed only for district-weeks with at least one adaptation article ($N = 81,160$).

Category and measure shares. For each district-week, the share of category c is defined as $\text{share}_c = n_{\text{articles}_c} / n_{\text{articles_total}}$, where n_{articles_c} is the count of articles mentioning at least one measure in category c . Measure-level shares are defined analogously. Because articles may mention measures from multiple categories, shares do not necessarily sum to exactly 1.0.

Shannon entropy. Captures how evenly coverage is distributed across the five adaptation categories: $H = -\sum p_i \ln(p_i)$, where p_i is the share of total adaptation articles belonging to category i . Values range from 0 (all articles in a single category) to $\ln(5) \approx 1.61$ (perfectly even distribution). Shannon entropy is more sensitive to the number of categories represented.

Herfindahl-Hirschman Index (HHI). Measures concentration: $\text{HHI} = \sum p_i^2$, where p_i is defined as above. Values range from 0.2 (five equal shares) to 1.0 (single-category dominance). HHI is more sensitive to the dominance of the largest category. Shannon and HHI are used as complementary dependent variables in the compositional analyses (Sections 3.3–3.5 of the main text).

Structural and nonstructural shares. A binary decomposition: structural_share is the share of structural articles; nonstructural_share = $1 - \text{structural_share}$. Used in basin spillover models (Table S7).

5.4 Fixed Effects and Clustering

All models include two-way fixed effects. NUTS-3 district fixed effects (α_i) absorb time-invariant regional characteristics such as geography, population, media market structure, and baseline flood exposure. Time fixed effects (γ_t) absorb national-level temporal trends in media coverage, flood occurrence, and seasonal patterns. For severity–coverage models (Sections 3.1–3.3), we used calendar-week fixed effects (1,026 dummies). For experience and spillover models (Sections 3.4–3.5), we replaced week FE with year fixed effects (20) and calendar-month fixed effects (12) to avoid collinearity with the rolling experience windows, which vary at the week level within years. The robustness of this choice is tested in Table S18. Standard errors are clustered at the NUTS-3 district level throughout, and NUTS-1 clustering is tested as a robustness check in Table S17.

III. Supplementary Figures

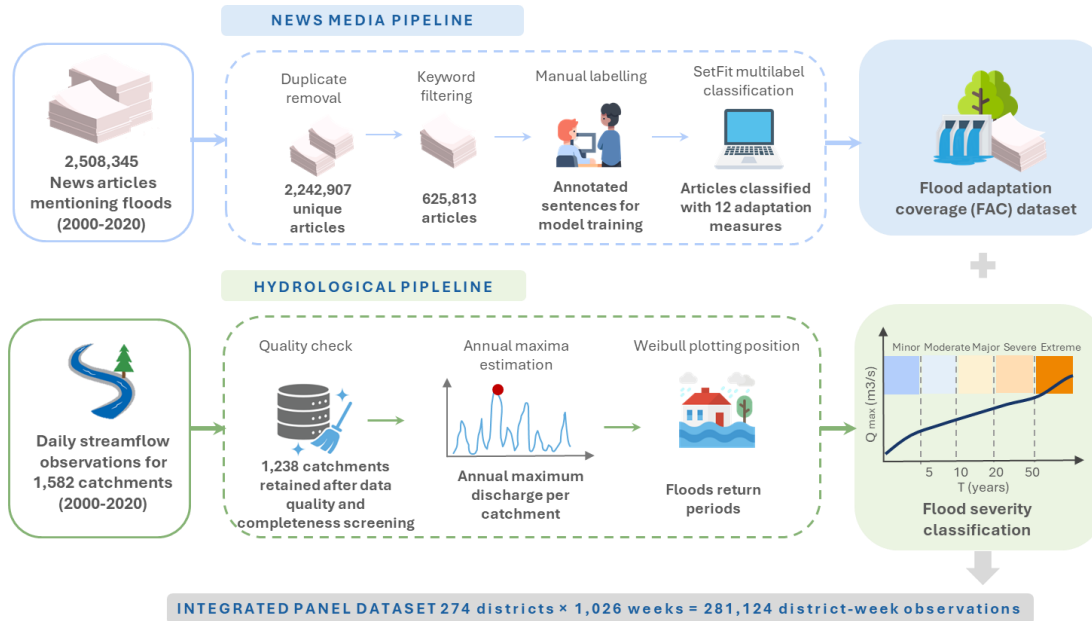


Fig. S1. Overview of the integrated data pipeline.

The news-media pipeline (top) processes flood-related news articles through duplicate removal, keyword filtering, manual labelling, and multi-label classification to produce the Flood Adaptation Coverage (FAC) dataset. The hydrological pipeline (bottom) processes daily streamflow observations through quality control, annual-maxima estimation, and Weibull plotting-position analysis to derive flood return periods and a five-class flood severity classification. The two streams are combined into an integrated district-week panel dataset.

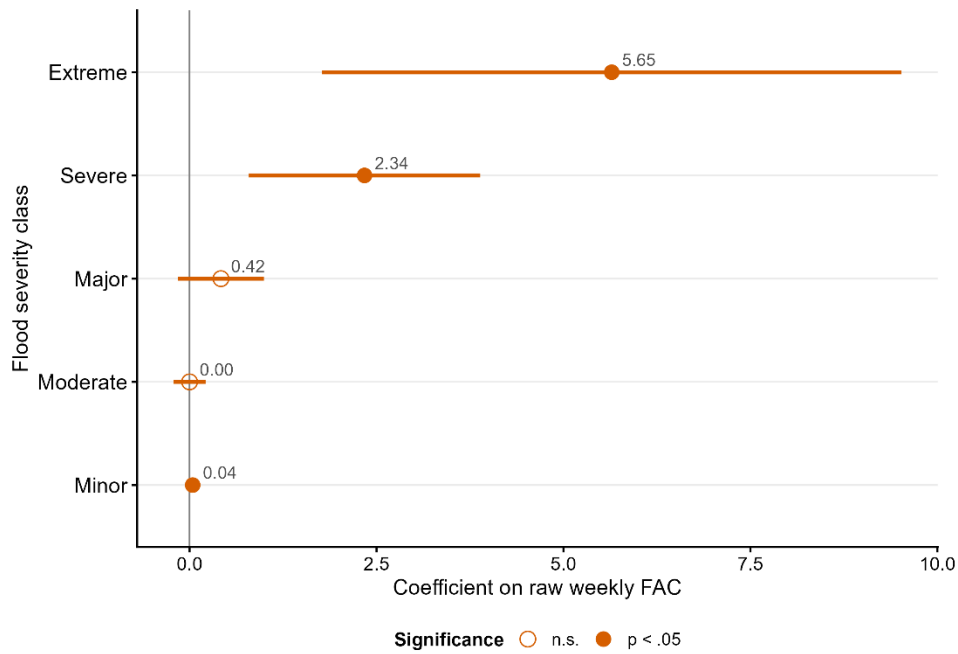


Fig. S2. Raw-count severity coefficients

Coefficients from a two-way FE panel regression of raw (untransformed) weekly adaptation article counts on flood severity class counts, with NUTS-3 district and calendar week fixed effects. Horizontal bars show 95% CIs (SE clustered at NUTS-3). Moderate and major floods are not statistically significant ($P > .05$), indicating compression due to right-skewed article distributions. Compare with main text Fig. 1B (log-transformed DV), where all five severity classes are significant.

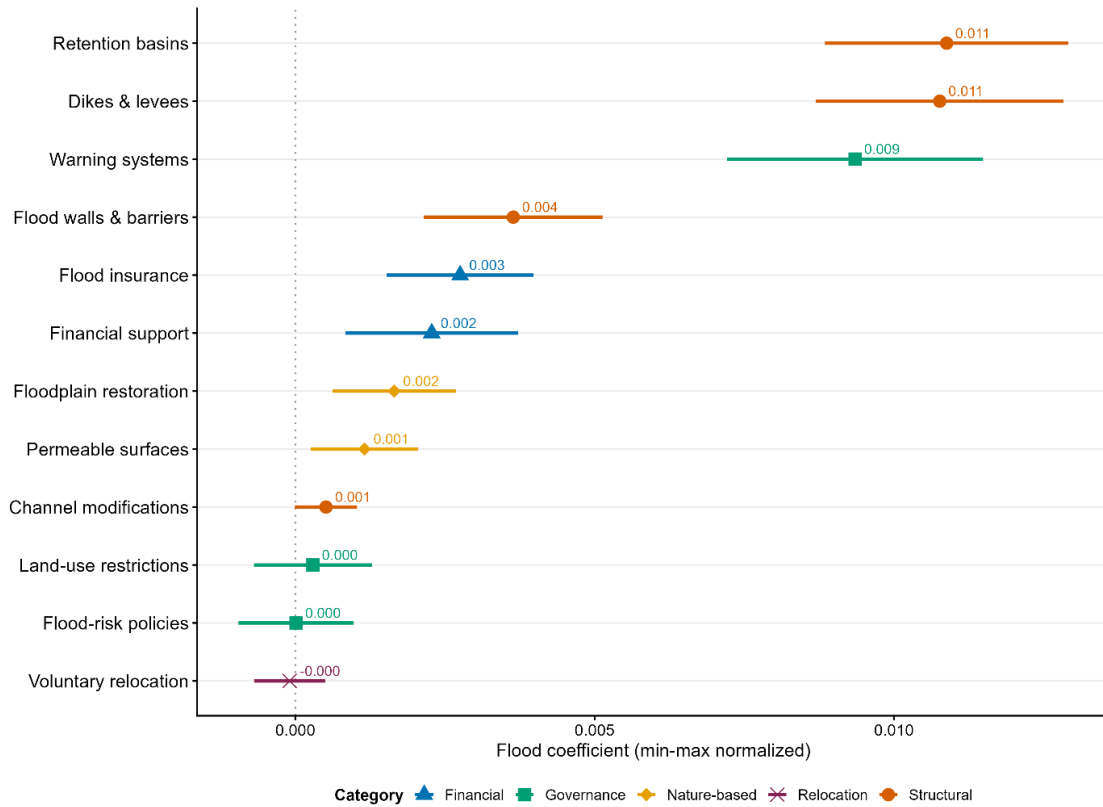


Fig. S3. Min-max normalized flood response coefficients by adaptation measure

Flood response coefficients estimated from two-way FE models using min-max normalized $\log(1 + \text{articles})$ as the dependent variable. Min-max rescales each measure independently to $[0, 1]$, so a coefficient of 0.01 means a flood moves the measure by 1% of its own full range. Under this normalization, retention basins (0.011), dikes (0.011), and warning systems (0.009) are nearly identical in responsiveness, indicating that the absolute dominance of dikes in the log specification (Fig. 2A) is partly volume-driven.

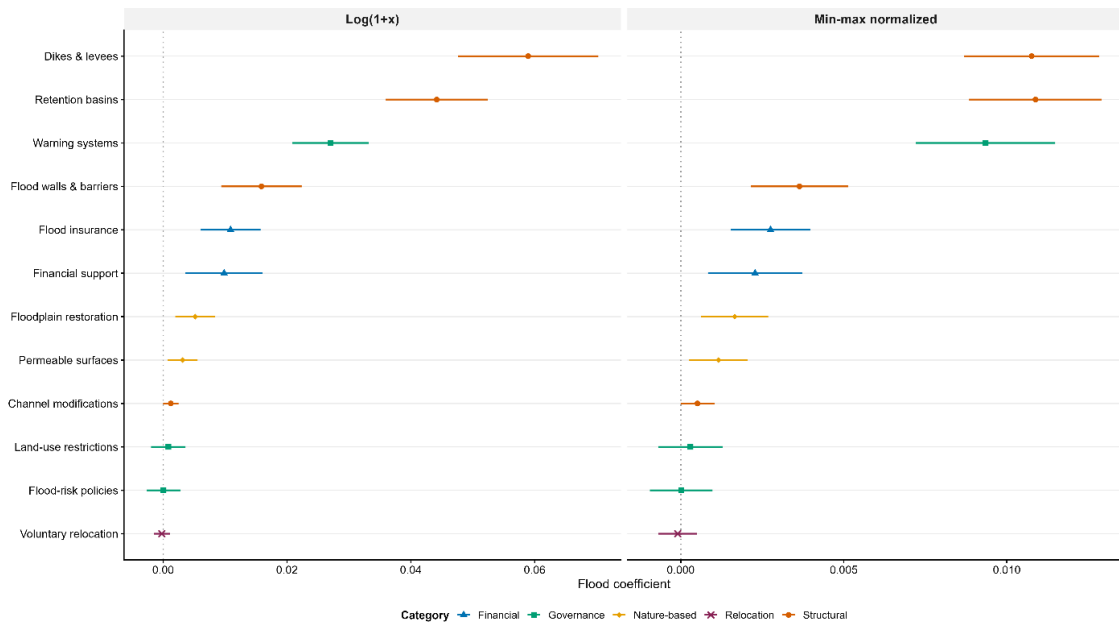


Fig. S4. Log(1 + x) vs. min-max normalized flood coefficients: side-by-side comparison

Left panel: log(1 + articles) coefficients (as in Fig. 2A). Right panel: min-max normalized coefficients (as in Fig. S3). If rankings differ substantially, apparent dominance of structural measures in the log specification reflects absolute coverage volume rather than proportional flood responsiveness.

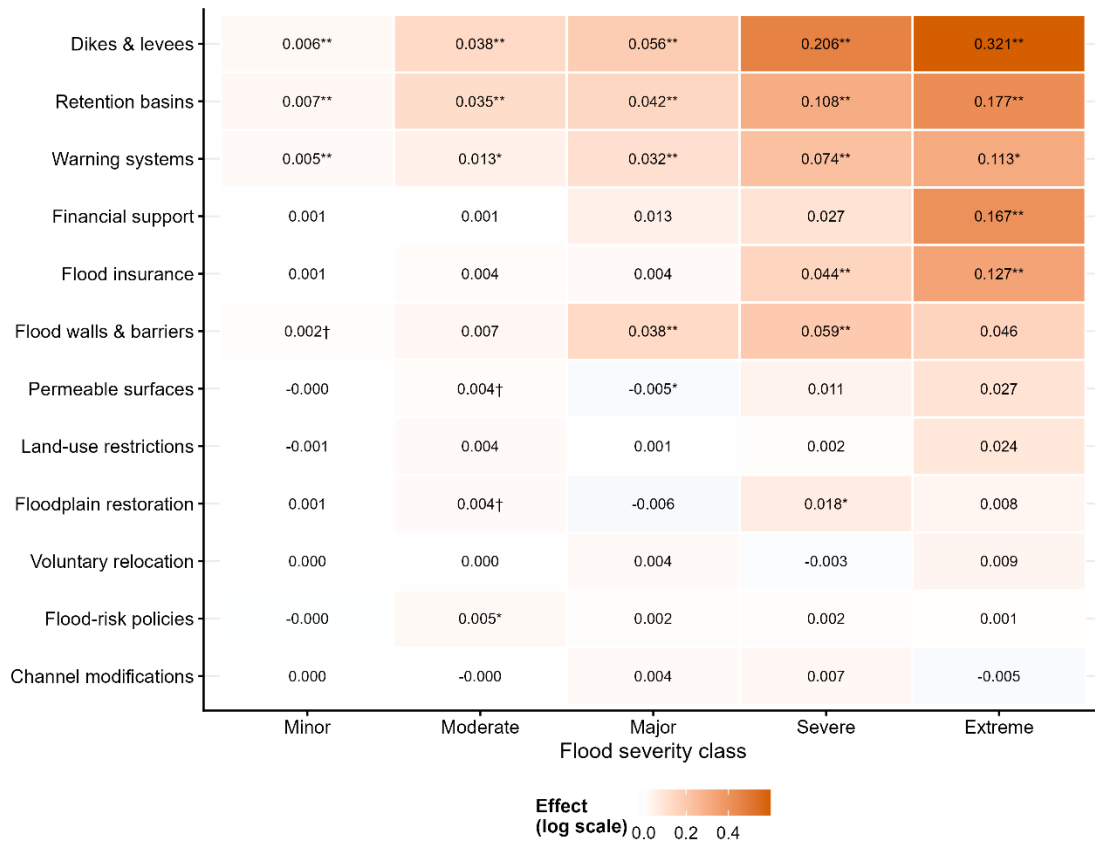


Fig. S5. Severity–measure heatmap

Coefficients from $\log(1 + \text{articles})$ models with NUTS-3 and week FE, showing how each of the 12 adaptation measures responds to each severity class. Cell values are point estimates with significance markers († $P < 0.10$, * $P < 0.05$, ** $P < 0.01$). The colour scale is log-compressed to improve readability. Measures are ordered by total coefficient magnitude (bottom to top). Orange borders indicate outlier coefficients ($|\beta| > 0.5$).

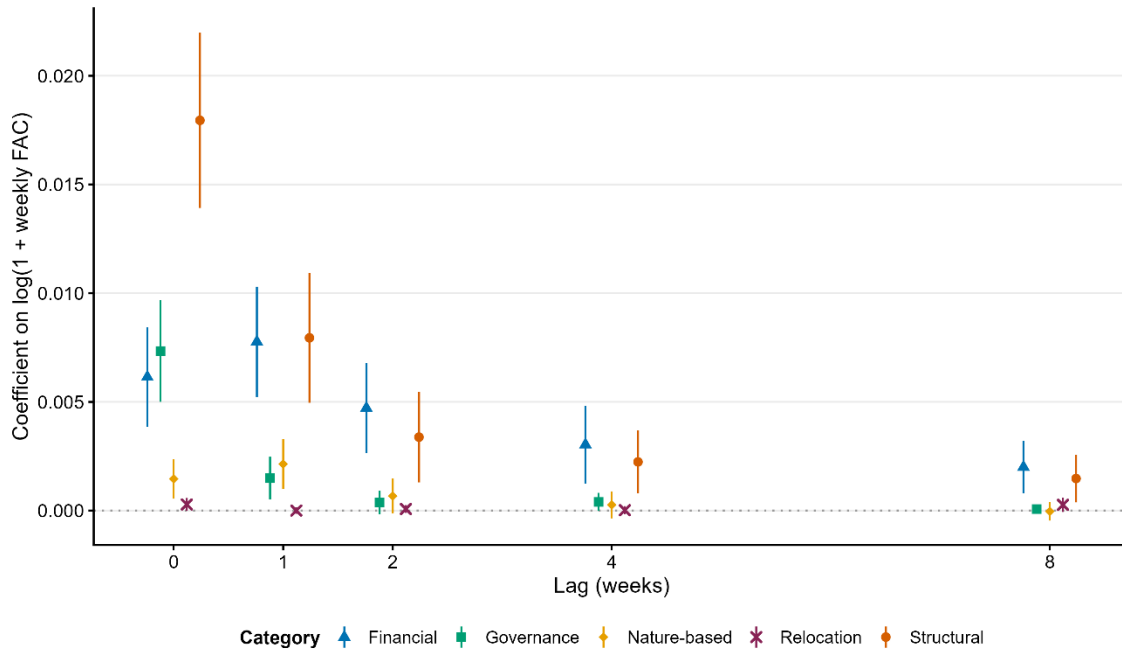


Fig. S6. Lag structure by adaptation category

Distributed lag coefficients (contemporaneous, 1-week, 2-week, 4-week, 8-week) for each adaptation category, estimated from $\log(1 + \text{category articles}) \sim \text{weekly_intensity} + \text{lag terms} \mid \text{NUTS-3} + \text{week FE}$. Structural and financial categories show persistent effects up to 8 weeks. Warning systems (governance) decay within 1 week. This temporal persistence structures the three-phase post-flood discourse cycle described in the main text.

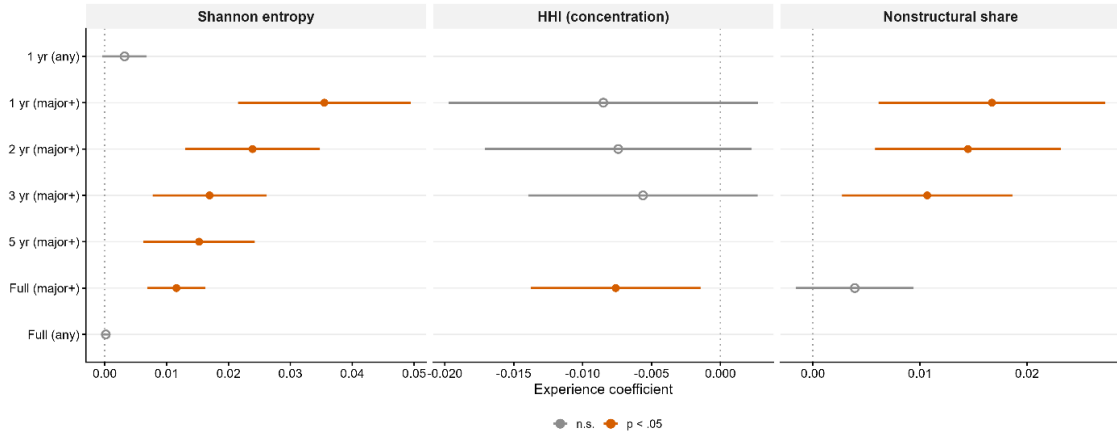


Fig. S7. Experience window comparison for Shannon entropy, HHI, and nonstructural share

Coefficients on cumulative flood experience measured over different temporal windows (1-year any, 1-year major+, 2-year major+, 3-year major+, 5-year major+, full-period major+, full-period any) from FE models predicting Shannon entropy (left), HHI (centre), and nonstructural share (right). The 1-year major+ window produces the largest per-event effect for Shannon entropy. Only major-or-above floods yield significant experience coefficients.

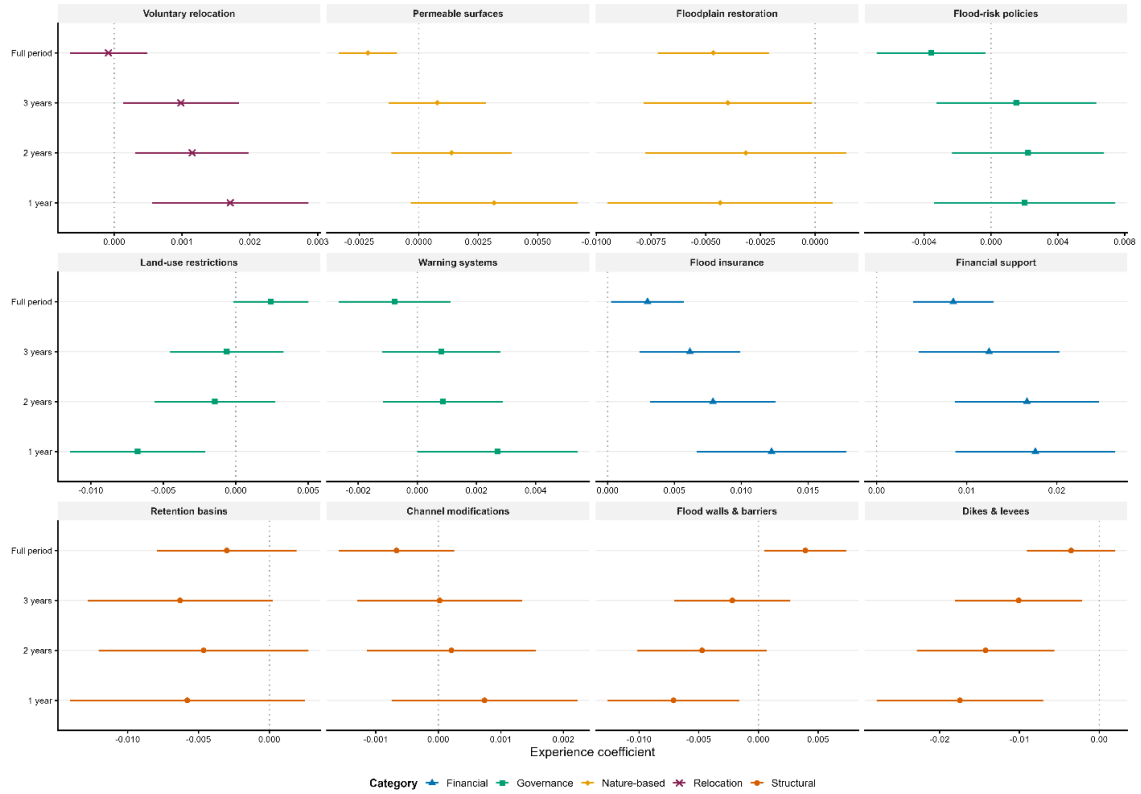


Fig. S8. Experience coefficients by individual adaptation measure across temporal windows
 Effect of cumulative major+ flood experience on individual measure shares, estimated from two-way FE models across four temporal windows (1-year, 2-year, 3-year, full period). Each panel shows one measure; horizontal axis shows the experience coefficient. Financial support and flood insurance gain share with flood experience, while dikes and retention basins lose share.

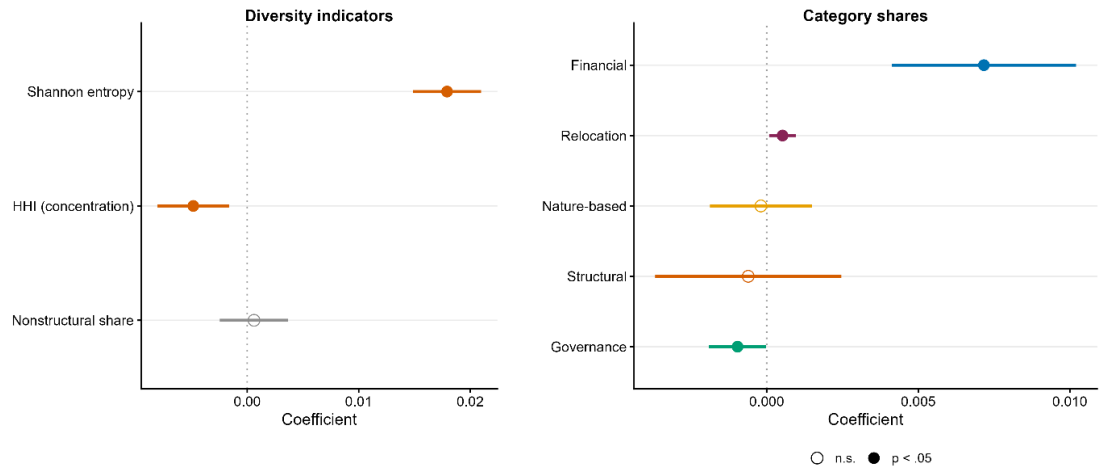


Fig. S9. Basin-level spillover: diversity indicators and category shares

Left panel: coefficients of basin_intensity_12wk on nonstructural share, HHI, and Shannon entropy. Right panel: coefficients on individual category shares. Financial coverage is the primary beneficiary of basin-level spillover. All models include NUTS-3, year, and month FE. Filled circles: $P < .05$; open circles: not significant.

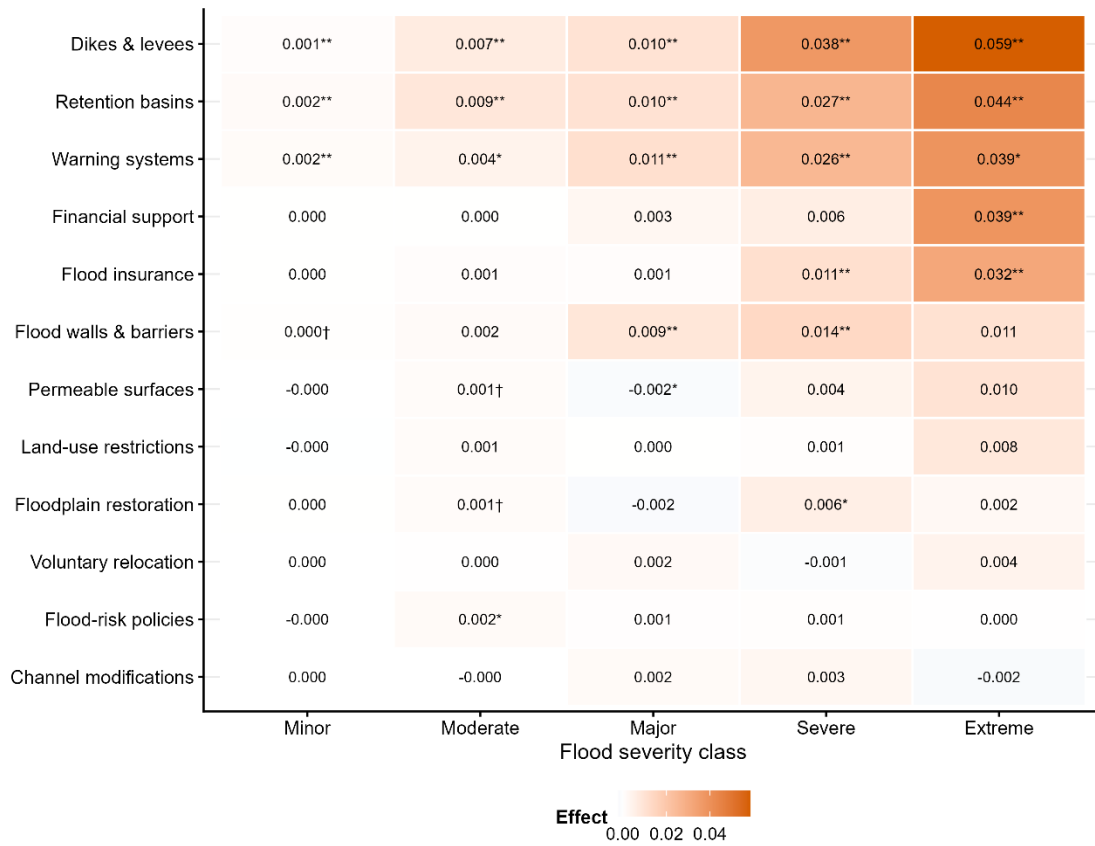


Fig. S10. Min-max normalized severity–measure heatmap

As Fig. S5, but using min-max normalized $\log(1 + \text{articles})$ as the dependent variable. Each measure is rescaled to [0, 1] independently. Compare with Fig. S5 to assess whether severity–responsiveness patterns are driven by absolute volume differences across measures.

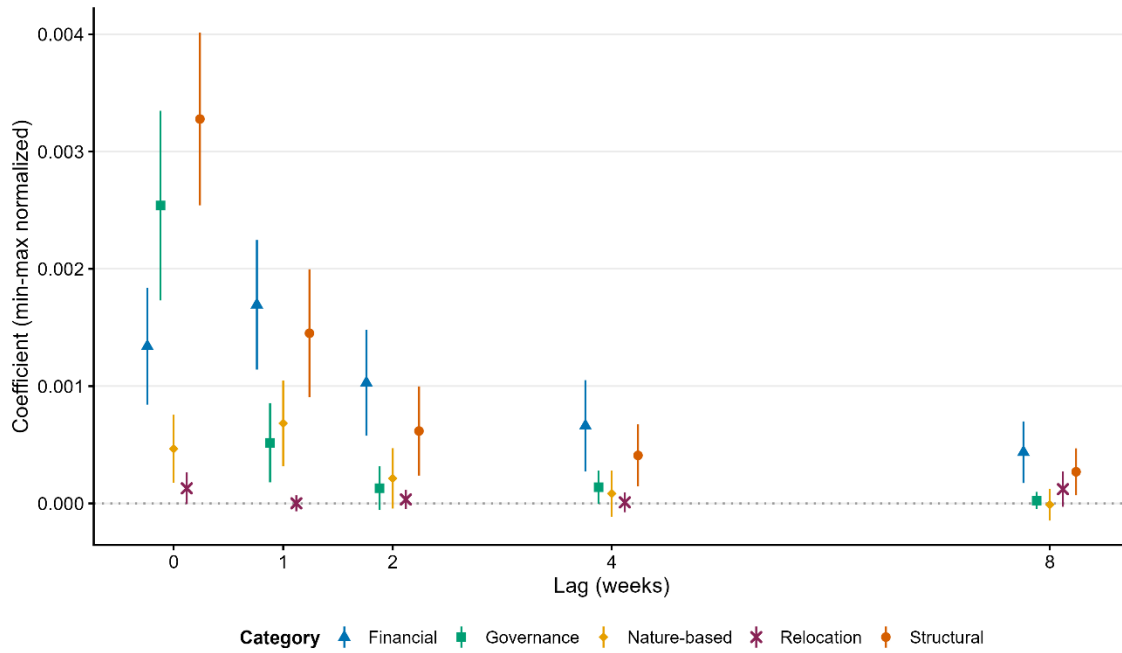


Fig. S11. Min-max normalized lag structure by category

As Fig. S6, but using min-max normalized DVs. Shows proportional response within each category's own range.

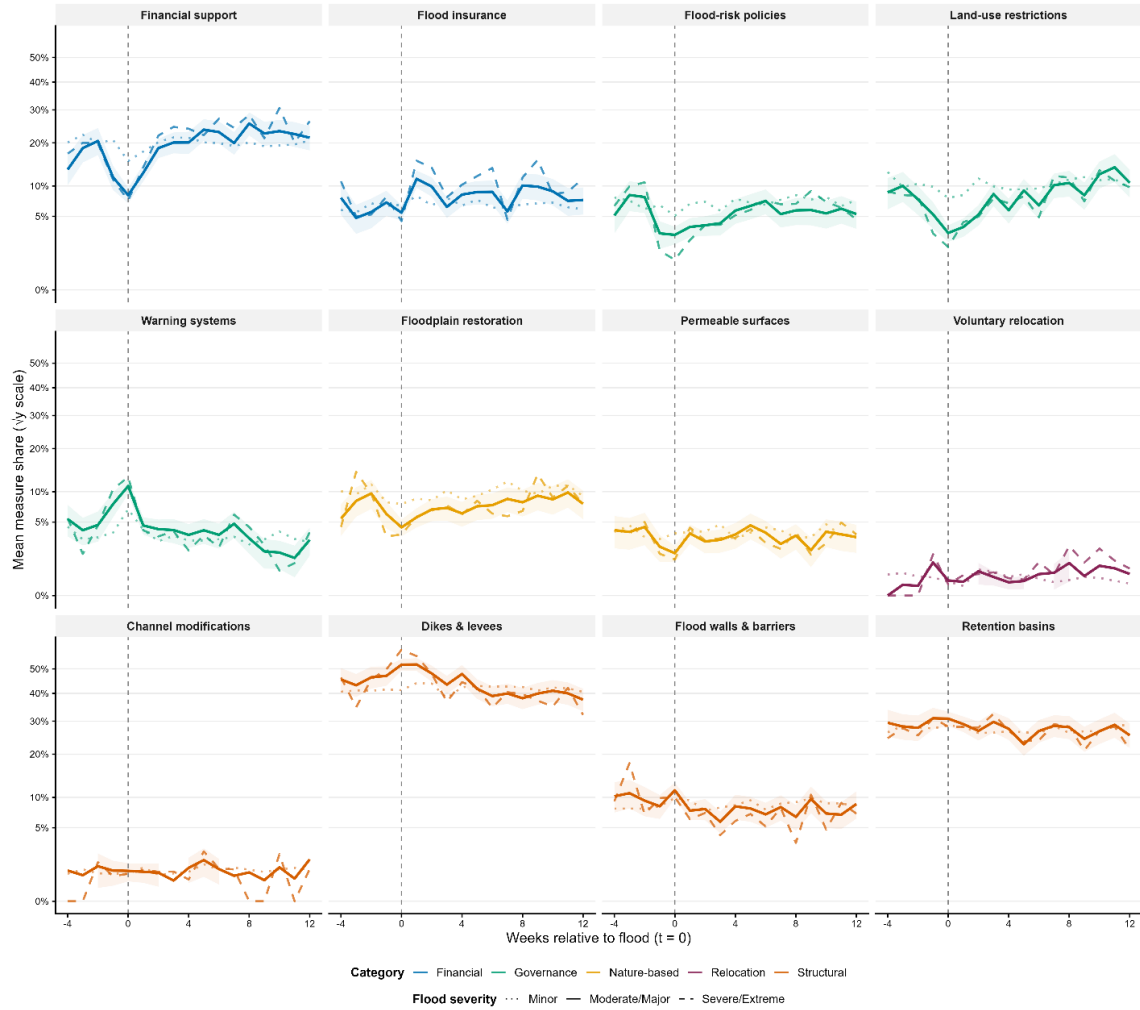


Fig. S12. Post-flood measure trajectories with common square-root y-axis

As Fig. 3, but with a common fixed square-root y-axis across all 12 panels to enable cross-measure magnitude comparison. This version sacrifices within-panel readability for low-share measures but reveals the relative scale of dike and retention basin responses compared to all other measures.

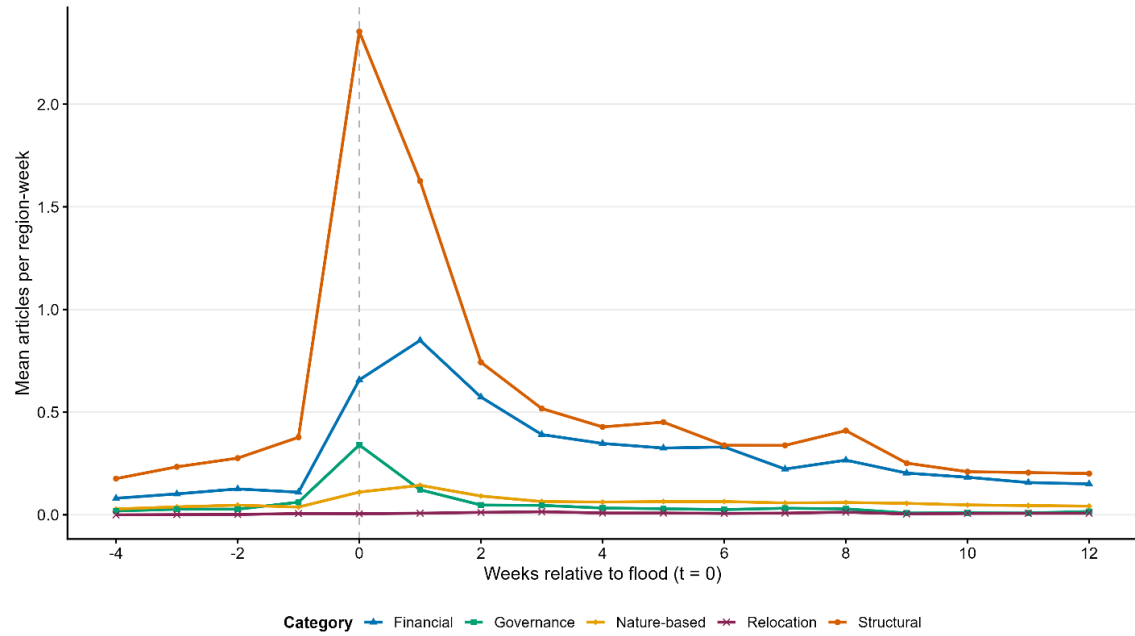


Fig. S13. Absolute post-flood article counts by adaptation category

Mean absolute (not share) article counts per region-week around significant flood events, by adaptation category. Unlike the share trajectories in Fig. 2B, this figure shows that all categories increase in absolute terms after a flood—the share decline of financial and nature-based categories reflects proportional crowding-out, not an absolute decrease.

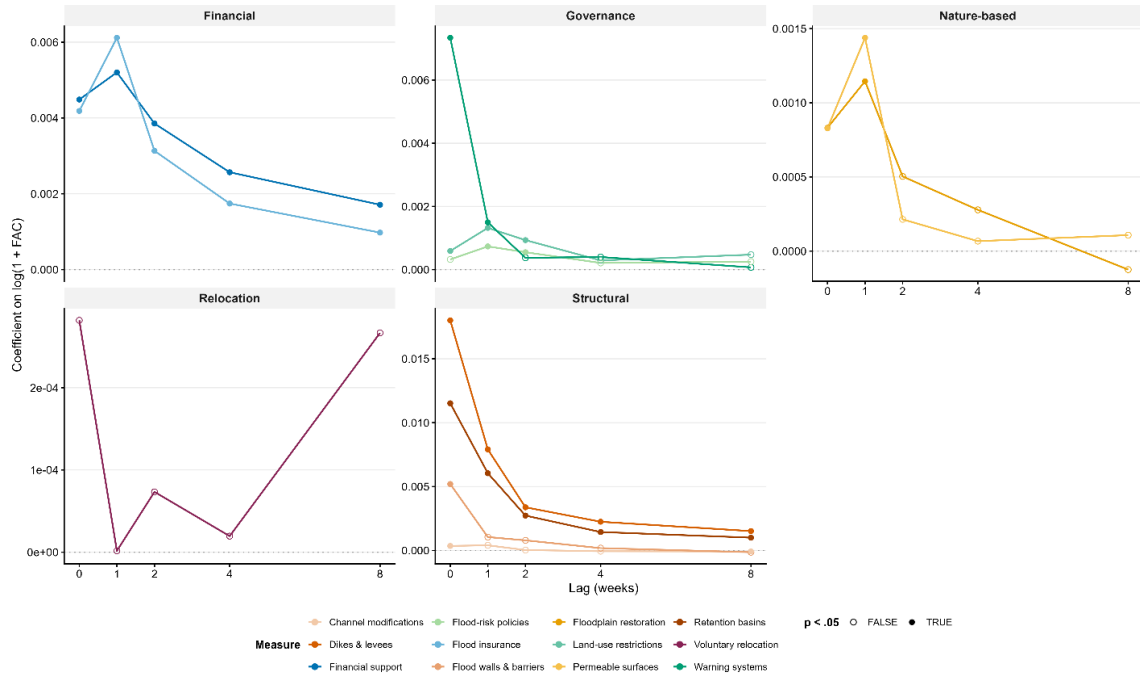


Fig. S14. Lag structure by individual adaptation measure

Distributed lag coefficients for each of the 12 individual measures, faceted by adaptation category. Each line shows one measure's response from contemporaneous (lag 0) through 8-week lag. Filled circles: $P < .05$; open circles: not significant.

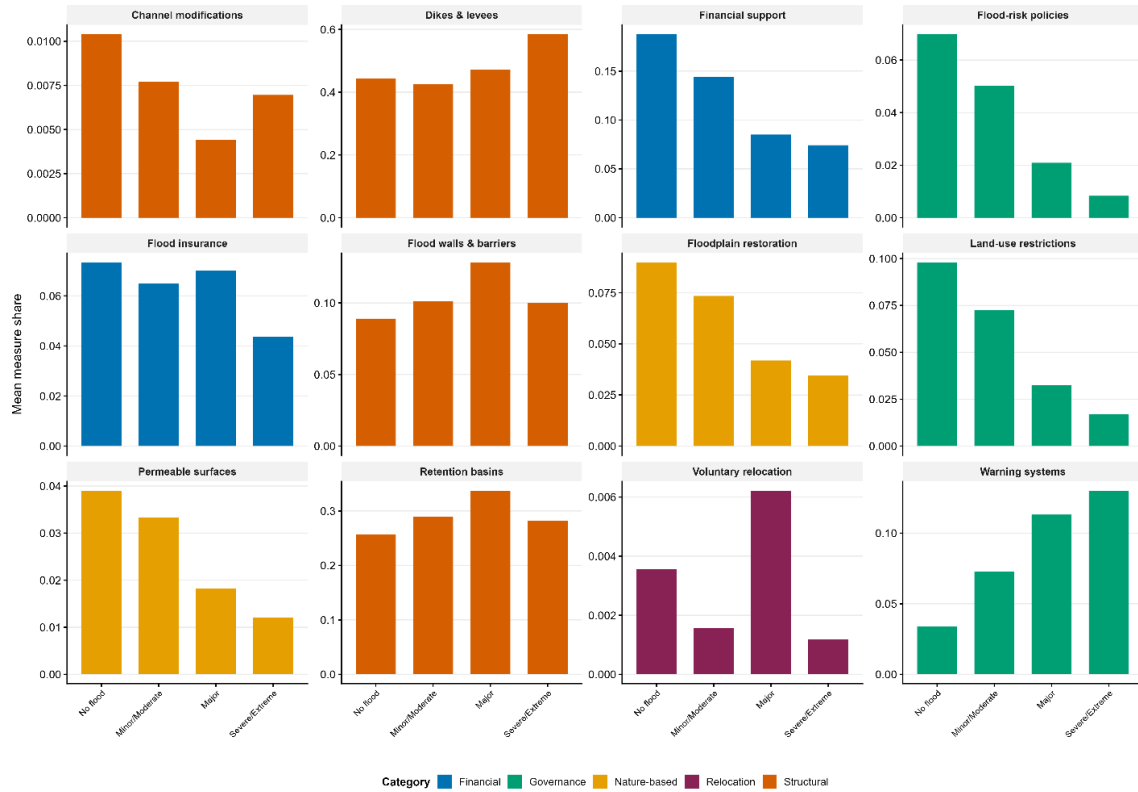


Fig. S15. Adaptation measure shares by flood severity

Mean share of each individual adaptation measure across severity (no flood, minor/moderate, major, severe/extreme), for district-weeks with at least one article. Faceted by measure; fill colour indicates adaptation category.

IV. Supplementary Tables

Table S1. Flood Adaptation Coverage for Acute Floods and Cumulative Flood Occurrence

This table compares mean weekly flood adaptation coverage (FAC) between district-weeks experiencing an acute flood of a given severity class and district-weeks with high cumulative flood intensity but no current flood event. Current extreme floods are followed by a coverage volume of approximately 14.7 articles per district-week, compared with 1.0 article in districts with equivalent cumulative intensity but no ongoing flood. This confirms that adaptation coverage is mainly triggered by acute events and cannot be substituted by gradual cumulative flood occurrence.

Category	n	Mean articles	Mean log(1+articles)	Mean articles per million
Current extreme	149	14.745	1.597	1.774
Current severe	346	5.159	0.916	0.544
Current major	532	3.267	0.725	0.327
High cumulative intensity (cumulative return period \geq 8), no current flood	12,697	1.017	0.307	0.120
High cumulative intensity (cumulative return period \geq 4), no current flood	18,340	0.498	0.199	0.049

Note. Region-week observations from 274 NUTS-3 districts between 2000–2020. Cumulative intensity is the sum of flood return periods over the preceding 12 weeks.

Table S2. Economic Losses and Fatalities as Predictors of Adaptation Coverage

This table tests whether recorded economic losses and fatalities from the European Flood Impact dataset add explanatory power beyond hydrological severity. Panel A examines whether concurrent losses and fatalities predict FAC volume beyond return periods. Panel B tests whether losses reshape the composition of discourse. Panel C examines whether cumulative loss history predicts discourse diversification.

Panel A: Losses and fatalities beyond hydrological severity

Within the subsample of district-weeks experiencing either a hydrological flood event (identified from gauging station records) or a recorded impact event, both economic losses and fatalities significantly predict FAC volume beyond return-period-based severity. Adding log(losses) increases the within-R² from 0.010 to 0.054, and the loss coefficient is highly significant ($\beta = 1.666$, $P < 0.001$). Importantly, the severity coefficient remains significant and stable across all specifications ($\beta = 0.451$ – 0.515), confirming that hydrological severity and economic losses capture partly independent dimensions of flood impact. We retain hydrological severity as the primary measure throughout because (i) it provides complete, systematic coverage of all flood events from 1,582 gauging stations, whereas impact records cover only a subset of documented events, and (ii) the severity gradient on which the main substantive conclusions rest is robust to the inclusion of loss variables.

Model	Severity β	SE	Loss β	Fatality β	R ² _{within}
M0: Severity only	0.451***	(0.114)	—	—	0.010
M1: + log(losses)	0.514***	(0.115)	1.666***	—	0.054
M2: + fatalities	0.507***	(0.116)	—	11.533***	0.048
M3: + both	0.515***	(0.116)	1.429**	1.957	0.054

Note. Dependent variable (DV): total articles. Two-way fixed effects (FE) (NUTS-3 + week). standard errors (SE) clustered at NUTS-3. *** $P < 0.001$, ** $P < 0.01$.

Panel B: Losses reshape discourse composition

Among district-weeks with recorded impact events, $\log(\text{losses})$ significantly increases Shannon entropy ($\beta = 0.064$, $P = 0.044$) but not the Herfindahl–Hirschman Index (HHI) ($\beta = -0.003$, $P = 0.958$), suggesting that losses broaden the range of categories discussed without reducing dominance of the largest category. At the category level, losses significantly increase the financial share ($\beta = 0.072$, $P < 0.001$) and significantly decrease the governance share ($\beta = -0.041$, $P = 0.006$), while structural coverage is unaffected. This indicates that economic damage—rather than water levels alone—activates financial discourse in the aftermath of floods.

DV	Loss β	SE	P
Shannon entropy	0.064*	(0.031)	0.044
HHI (concentration)	-0.003	(0.051)	0.958
Financial share	0.072***	(0.021)	< 0.001
Structural share	-0.012	(0.032)	0.703
Nature-based share	0.018	(0.014)	0.183
Governance share	-0.041**	(0.015)	.006
Relocation share	0.004	(0.006)	.510

Note. All models include maximum weekly severity ($\text{weekly_max_severity}$, see Panel C). FE: NUTS-3 + year + month. SE clustered at NUTS-3. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Panel C: Cumulative loss history and discourse diversification

Cumulative economic loss history independently predicts discourse diversification. Districts with greater cumulative prior losses show significantly higher Shannon entropy ($\beta = 0.016$, $P < 0.001$), even after controlling for current severity. The interaction between severity and cumulative losses is not significant ($\beta = -0.0004$, $P = 0.559$), indicating that the loss-history effect operates independently of current flood characteristics. At the category level, the interaction of severity with cumulative loss history is significant for structural ($\beta = 0.0018$, $P = 0.002$), financial ($\beta = 0.0009$, $P = 0.028$), and nature-based ($\beta = 0.0008$, $P = 0.007$) shares, indicating that costly flood experience amplifies the responsiveness of these categories to subsequent floods.

Model	Term	β	SE	P	Within R ²
Base	weekly_max_severity	0.025***	(0.002)	< 0.001	0.005
+ loss history	weekly_max_severity	0.025***	(0.002)	< 0.001	0.008
	log_cum_losses	0.016***	(0.002)	< 0.001	
× interaction	weekly_max_severity	0.025***	(0.002)	< 0.001	0.008
	log_cum_losses	0.016***	(0.002)	< 0.001	
	severity × losses	-0.000	(0.001)	0.559	

Category	Interaction β	SE	P
Structural	0.0018**	(0.001)	0.002
Financial	0.0009*	(0.000)	0.028
Nature-based	0.0008**	(0.000)	0.007
Governance	-0.0008	(0.001)	0.147
Relocation	-0.0001	(0.000)	0.066

Note. DV: Shannon entropy (upper) or category share (lower). FE: NUTS-3 + year + month. SE clustered at NUTS-3. Cumulative losses: $\log(1 + \text{total prior losses in million EUR})$, lagged one year. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Table S3. Flood Response Coefficients and Lag Persistence

This table ranks the 12 individual adaptation measures by their flood response coefficient and reports lag persistence. Panel A uses $\log(1+x)$ DVs; Panel B uses min-max normalized DVs for cross-measure comparability.

Panel A: $\log(1+x)$ dependent variable

Category	Measure	Flood β	SE	P	Significant lags	Max lag
STRUCTURAL	Dikes & levees	0.059***	(0.006)	< 0.001	5	8
STRUCTURAL	Retention basins	0.044***	(0.004)	< 0.001	5	8
STRUCTURAL	Flood walls	0.016***	(0.003)	< 0.001	1	0
STRUCTURAL	Channel modification	0.001	(0.001)	0.053	2	8
FINANCIAL	Flood insurance	0.011***	(0.002)	< 0.001	5	8
FINANCIAL	Financial support	0.010**	(0.003)	0.002	5	8
GOVERNANCE	Warning systems	0.027***	(0.003)	< 0.001	2	1
GOVERNANCE	Land-use restriction	0.001	(0.001)	0.557	3	2
GOVERNANCE	Flood-risk policies	0.000	(0.001)	0.978	2	2
NATURE-BASED	Floodplain restoration	0.005**	(0.002)	0.002	2	1
NATURE-BASED	Permeable surfaces	0.003*	(0.001)	0.012	2	1
RELOCATION	Voluntary relocation	-0.000	(0.001)	0.755	0	—

Panel B: Min-max normalized dependent variable

Category	Measure	Flood β	SE	P	Sig. lags	Max lag
STRUCTURAL	Retention basins	0.011***	(0.001)	< 0.001	5	8
STRUCTURAL	Dikes & levees	0.011***	(0.001)	< 0.001	5	8
GOVERNANCE	Warning systems	0.009***	(0.001)	< 0.001	2	1
STRUCTURAL	Flood walls	0.004***	(0.001)	< 0.001	1	0
FINANCIAL	Flood insurance	0.003***	(0.001)	< 0.001	5	8
FINANCIAL	Financial support	0.002**	(0.001)	0.002	5	8
NATURE-BASED	Floodplain restoration	0.002**	(0.001)	0.002	2	1
NATURE-BASED	Permeable surfaces	0.001*	(0.000)	0.012	2	1
STRUCTURAL	Channel modification	0.001	(0.000)	0.053	2	8
GOVERNANCE	Land-use restriction	0.000	(0.001)	0.557	3	2
GOVERNANCE	Flood-risk policies	0.000	(0.000)	0.978	2	2
RELOCATION	Voluntary relocation	-0.000	(0.000)	0.755	0	—

Note. Flood β : coefficient on a binary flood indicator (equal to 1 in weeks with any flood) from measure-level models with 12-week cumulative intensity control and NUTS-3 + week FE. SE clustered at NUTS-3. Min-max rescales each measure's $\log(1+x)$ to $[0,1]$ independently. *** P < 0.001, ** P < 0.01, * P < 0.05.

Table S4. Adaptation Coverage Composition by Flood Severity

Mean category shares, HHI, and Shannon entropy across severity groups, conditional on at least one article. Shannon entropy increases from 0.14 in non-flood weeks to 0.41 in severe/extreme flood weeks.

Severity	Financial	Structural	Nature-based	Governance	Relocation	HHI	Shannon	n
No flood	0.251	0.450	0.123	0.034	0.004	0.765	0.144	77,961
Minor/Moderate	0.198	0.428	0.102	0.073	0.002	0.678	0.191	2,643
Major	0.147	0.476	0.055	0.113	0.006	0.593	0.324	256
Severe/Extreme	0.112	0.588	0.043	0.130	0.001	0.622	0.406	300

Note. Shares are mean proportions conditional on the total article count > 0. HHI: 0 = diversity, 1 = dominance. Shannon: 0 = single category, $\ln(5) \approx 1.61$ = perfect evenness.

Table S5. Interaction: Current Flood Severity × Cumulative Flood Experience

The interaction term is positive and significant ($\beta = 0.0004$, $P = .002$), indicating that districts with more flood history produce more diverse adaptation coverage when experiencing a flood of a given severity.

Term	β	SE	t	P	
weekly_max_severity		0.0168	(0.003)	5.97	< 0.001
cum_floods_any_lag		0.0001	(0.000)	0.34	0.730
severity × cum_floods		0.0004	(0.000)	3.17	0.002

Note. DV: Shannon entropy. FE: NUTS-3 + year + month. SE clustered at NUTS-3. N = 81,160. Row terms: weekly maximum severity score (weekly_max_severity); cumulative count of prior flood weeks, lagged one week (cum_floods_any_lag); and their interaction (severity × cum_floods).

Table S6. Experience Window Comparison: Shannon Entropy

The 1-year major+ window produces the largest per-event effect ($\beta = 0.035$), roughly three times larger than the full-period count ($\beta = 0.012$). Counting all floods regardless of severity produces no significant experience effect.

Experience window	Exp. β	SE	P	N	Within R ²	
Severity only		—	—	—	81,160	0.005
1 yr (any)	0.003	(0.002)	0.079	79,403	0.006	
1 yr (major+)	0.035***	(0.007)	< 0.001	79,403	0.008	
2 yr (major+)	0.024***	(0.006)	< 0.001	77,768	0.008	
3 yr (major+)	0.017***	(0.005)	< 0.001	74,206	0.007	
5 yr (major+)	0.015***	(0.005)	< 0.001	67,424	0.008	
Full (major+)	0.012***	(0.002)	< 0.001	81,160	0.007	
Full (any)	0.000	(0.000)	0.611	81,160	0.005	

Note. DV: Shannon entropy. All models include weekly_max_severity + NUTS-3 + year + month fixed effects. Standard errors clustered at NUTS-3. *** P < 0.001.

Table S7. Basin-Level Flood Spillover and Discourse Diversity

Basin-level flooding significantly increases Shannon entropy and reduces HHI, with effect sizes comparable to local flooding.

DV	Severity β	Basin β	Basin SE	Basin P
Nonstructural share	-0.014***	0.001	(0.002)	0.699
HHI (concentration)	-0.014***	-0.005**	(0.002)	0.004
Shannon entropy	0.018***	0.018***	(0.002)	< 0.001

Note. FE: NUTS-3 + year + month. SE clustered at NUTS-3. *** P < 0.001, ** P < 0.01.

Table S8. Basin-Level Spillover by Adaptation Category

Financial coverage is the primary beneficiary of basin-level spillover ($\beta = 0.007$, $P < .001$), while structural coverage shows no significant response.

Category	Basin β	SE	P
Financial	0.007***	(0.002)	< 0.001
Structural	-0.001	(0.002)	0.699
Nature-based	-0.000	(0.001)	0.825
Governance	-0.001*	(0.000)	0.047
Relocation	0.001*	(0.000)	0.022

Note. DV: category share. All models include weekly_max_severity + NUTS-3 + year + month FE. SE clustered at NUTS-3. *** $P < 0.001$, * $P < 0.05$.

Table S9. Overview of Adaptation Typology Considered

Measure	Definition	IPCC Class
Insurance	Financial protection mechanisms, including flood insurance, elemental damage insurance, and other insurance products that provide coverage for flood-related damages.	Economic
Financial support	Economic assistance measures including funding programs, grants, subsidies, financial aid, compensation, and state support for flood prevention, response, or recovery.	Economic
Dikes	Engineered embankments or barriers constructed along riverbanks or coastlines to prevent water from flooding adjacent land areas during high water events.	Engineered and Built Environment
Flood walls and barriers	Fixed structural protective walls or barriers designed to prevent floodwater from entering protected areas, typically constructed of concrete or masonry materials.	Engineered and Built Environment
Channel modifications	Physical alterations to rivers or watercourses, including straightening, deepening, or widening of channels to increase water flow capacity and reduce flood risk.	Engineered and Built Environment
Reservoirs and retention basin	Water storage facilities, including retention basins, polders, reservoirs, and other structures designed to temporarily hold and regulate floodwater, reducing peak flows downstream.	Engineered and Built Environment
Floodplain restoration	Restoration or reactivation of natural floodplains and riparian areas, including re-meandering of rivers and expansion of overflow areas to allow natural water retention.	Ecosystem-based Adaptation
Permeable surfaces	Water-permeable surfaces and infiltration areas, including unsealing of surfaces and sustainable drainage systems that allow rainwater to infiltrate into the ground rather than creating surface runoff.	Ecosystem-based Adaptation
Communication and warning systems	Early warning systems, real-time monitoring systems, and communication infrastructure designed to detect flooding conditions and alert populations to impending flood events.	Technological
Land-use restrictions	Planning and regulatory measures that restrict development or land use in flood-prone areas, including zoning laws, building prohibitions, and spatial planning regulations.	Laws and Regulations
Risk policies	Strategic, legal, and policy frameworks for flood risk management, including flood protection strategies, directives, regulations, and comprehensive risk management plans.	Laws and Regulations
Relocation	Voluntary resettlement or managed retreat of populations and infrastructure from flood-prone areas to reduce exposure to flood hazards.	Misc.
	Household emergency preparedness	(discarded)

Training programs	(discarded)
Public participation in flood planning	(discarded)
Building adaptations and flood-proofing	(discarded)
Reforestation and afforestation	(discarded)
Sediment management	(discarded)
Infrastructure protection (roads, electricity, utilities)	(discarded)

Note. The IPCC Class column maps each measure to the corresponding category of adaptation options assessed in the IPCC Sixth Assessment Report, Working Group II (IPCC, 2022). Measures marked “discarded” were considered but not retained in the analysis (see main text).

Table S10. Keywords used for filtering adaptation-related articles

This table lists the German-language keywords used to pre-filter the full flood article corpus for each of the 12 adaptation measures. For each measure, articles were retained if they contained at least one of the listed keywords. This list of synonyms was compiled using synonym dictionaries and co-occurrence analysis: candidate terms were drawn from German synonym dictionaries and expanded with terms that frequently co-occurred with each measure in the flood corpus, then manually reviewed and pruned to retain measure-specific vocabulary.

Measure	Keywords
Insurance	hochwasserversicherung', 'elementarversicherung', 'elementarschadenversicherung', 'versicherung', 'versicherungsschutz', 'wohngebäudeversicherung', 'naturgefahrenversicherung', 'überschwemmungsversicherung', 'versicherungspflicht', 'pflichtversicherung'
Financial support	'finanzielle unterstützung', 'förderprogramm', 'fördermittel', 'zuschuss', 'subvention', 'subventionen', 'finanzhilfe', 'finanzielle entschädigung', 'schadensersatz', 'soforthilfe', 'aufbauhilfe', 'staatliche unterstützung', 'finanzspritze', 'finanzielle hilfe'
Dikes	deich', 'deiche', 'damm', 'dämme'
Flood walls and barriers	schutzmauer', 'hochwassermauer', 'schutzwand', 'schutzwände', 'flutmauer', 'ufermauer', 'hochwasserschutzwand', 'kaimauer'
Channel modifications	begradigen', 'begradigung', 'gewässervertief', 'flussvertief', 'flussverbreiter', 'sohlvertie'
Reservoirs and retention basin	rückhaltebecke', 'staubecken', 'stausee', 'hochwasserspeicher', 'retentionsbecken', 'regenrückhaltebecken', 'polder', 'retention', 'rückhalteraum', 'entlastungsbecken', 'auffangbecken', 'ausgleichsbecken'
Floodplain restoration	renaturierung', 'auenreaktivierung', 'gewässerrenaturierung', 'renaturierung', 'deichrückverlegung', 'gewässerrückbau', 'flussrenaturierung', 'remäandrierung', 'wiederherstellung', 'überschwemmungsfläche'
Permeable surfaces	versickerungsfläche', 'versickerungsfähige fläche', 'wasserdurchlässige fläche', 'flächenentsiegelung', 'schwamm', 'regenwassermanagement', 'regenwasserversickerung', 'versicker', 'infrastruktur', 'sickerfähige fläche', 'retention'
Communication and warning systems	frühwarnsystem', 'warnsystem', 'hochwasserwarndienst', 'warndienst', 'alarmsystem', 'hochwasseralarm', 'meldesystem', 'frühwarnung', 'warnapp', 'sirene', 'sirenen', 'warn-app', 'katwarn', 'nina', 'echtzeitüberwachung', 'echtzeitpegelmessung', 'hochwasserüberwachung'
Land-use restrictions	flächennutzung', 'flächennutzungsplan', 'bebauungsplan', 'baurecht', 'bauverbot', 'baubeschränkung', 'bauplanung', 'raumplanung', 'raumordnung', 'siedlungsentwicklung', 'bauliche beschränkung', 'nutzungsbeschränkung', 'bauauflagen', 'bebauungsverbot'
Risk policies	hochwasserrisikomanagement', 'risikomanagement', 'hochwasserschutzkonzept', 'schutzkonzept', 'hochwasserrisikomanagementplan', 'risikomanagementplan', 'hochwasserschutzstrategie', 'hochwasserrichtlinie', 'wasserrahmenrichtlinie', 'hochwasserschutzgesetz', 'wasserhaushaltsgesetz', 'landeswassergesetz', 'hochwasservorsorge'
Relocation	freiwillige umsiedlung', 'umsiedlung', 'umsiedelung', 'siedlungsrückzug', 'freiwilliger umzug', 'freiwillige enteignung'

Table S11. Classification performance and article counts by adaptation measure

This table reports SetFit classifier performance and the number of articles retained at each classification stage for all 12 adaptation measures. Columns 2–5 report standard binary classification metrics evaluated against human-annotated labels from 100 texts per class. Columns 6–7 report article counts after keyword-based pre-filtering and after supervised classification respectively, illustrating the reduction attributable to each step.

Class	Accuracy	Precision	Recall	F1	After keyword filter	After supervised classification
Insurance	0.82	0.67	0.84	0.75	48,475	24,052
Financial support	0.86	0.95	0.76	0.84	79,709	40,832
Dikes	0.85	0.70	0.90	0.78	151,566	82,202
Flood walls and barriers	0.92	0.75	0.88	0.81	23,321	15,796
Channel modifications	0.86	0.77	0.86	0.81	2,558	1,229
Reservoirs and retention basin	0.78	0.70	0.76	0.72	61,722	34,499
Floodplain restoration	0.84	0.72	0.85	0.78	26,341	10,742
Permeable surfaces	0.91	0.65	0.86	0.74	62,955	5,691
Communication and warning systems	0.89	0.89	0.66	0.76	29,940	8,668
Land-use restrictions	0.81	0.68	0.80	0.74	21,044	13,237
Risk policies	0.84	0.76	0.71	0.74	23,272	8,316
Relocation	0.75	0.60	1.00	0.75	1,911	997

Table S12. Example training sentences for each SetFit classifier

This table provides illustrative training examples for each of the 12 binary SetFit classifiers. For each adaptation measure, three positive and two negative sentence-level examples are shown. The full training sets for all 12 classifiers are provided in the replication code.

Adaptation measure	Label	Example training sentence (German)
Insurance	Positive	Viele Hausbesitzer schließen eine Hochwasserversicherung ab, um Schäden finanziell abzusichern.
	Positive	Elementarschadensversicherungen bieten Schutz gegen Überschwemmungen und Hochwasser.
	Positive	Nach der Flutkatastrophe stieg die Nachfrage nach Hochwasserversicherungen stark an.
	Negative	Wie Bayern wurde auch Sachsen von schweren Hochwassern und Überschwemmungen heimgesucht.
	Negative	Beim Verein am Vorhaller Weg hat man sich an die Aufräumarbeiten gemacht.
Financial support	Positive	Die Gemeinde stellt Fördermittel für den Wiederaufbau nach dem Hochwasser bereit.
	Positive	Betroffene Hausbesitzer können Soforthilfe beim zuständigen Amt beantragen.
	Positive	Das Förderprogramm unterstützt Kommunen bei der Finanzierung von Schutzmaßnahmen.
	Negative	Die Feuerwehr pumpte das Wasser aus den Kellern.
	Negative	Der Damm wurde nach dem letzten Hochwasser um zwei Meter erhöht.
Dikes	Positive	Die Stadt investiert Millionen in den Bau neuer Schutzdeiche.
	Positive	Entlang des Flusses wurden die Flussdeiche verstärkt und saniert.
	Positive	Der Seedeich an der Nordseeküste schützt seit Jahrhunderten das Hinterland.
	Negative	Zehntausende Tote im Himalaja, Hunderttausende Obdachlose am Mississippi.
	Negative	Im PNP-Interview zieht er Bilanz. Herr Götz, das Jahrhunderthochwasser ist nun bald eineinhalb Jahre her.
Flood walls and barriers	Positive	Eine massive Flutmauer schützt die Altstadt vor Überschwemmungen.
	Positive	Mobile Hochwasserschutzwände wurden installiert.
	Positive	Die Hochwasserschutzwand besteht aus Glaselementen.
	Negative	Ein Rückhaltebecken wurde oberhalb der Stadt gebaut.
	Negative	Die Versicherung übernimmt die Schäden durch das Hochwasser nur teilweise.
Channel modifications	Positive	Durch die Flussbegradigung wurde die Fließgeschwindigkeit des Wassers erhöht.
	Positive	Die Gewässervertiefung ermöglicht einen besseren Abfluss bei Starkregen.
	Positive	Experten fordern eine Rücknahme früherer Flussbegradigung.
	Negative	Die Hochwasserschutzmauer am Rheinufer wurde verstärkt.
	Negative	Sandsäcke wurden entlang der Straßen aufgestapelt, um das Wasser aufzuhalten.
Reservoirs and retention basins	Positive	Ein neues Hochwasserrückhaltebecken wurde oberhalb des Ortes errichtet.
	Positive	Der gesteuerte Polder ist Teil eines modernen Hochwassermanagements.
	Positive	Flutpolder werden nur bei extremen Wasserständen aktiviert.
	Negative	Nach dem Hochwasser standen zahlreiche Häuser unter Wasser.
	Negative	Mobile Hochwasserschutzwände schützen die Altstadt.
Floodplain restoration	Positive	Die Deichrückverlegung schafft neue Auenflächen für natürliche Überflutung.
	Positive	Die Flussrenaturierung stellt natürliche Mäander und Auenbereiche wieder her.
	Positive	Durch Gewässerrenaturierung werden Lebensräume und Retentionsflächen wiederhergestellt.

	Negative	Der Damm wurde nach dem Hochwasser erhöht.
	Negative	Die Flussbegradigung beschleunigt den Abfluss.
Permeable surfaces	Positive	Die Schwammstadt-Maßnahmen verbessern die Versickerung in urbanen Gebieten.
	Positive	Versickerungsfähige Oberflächen reduzieren den Oberflächenabfluss.
	Positive	Nachhaltige Regenwasserbewirtschaftung sorgt für eine effiziente Nutzung von Regenwasser.
	Negative	Die Flussrenaturierung verlangsamt den Abfluss.
	Negative	Die Fußballmannschaft gewann das Heimspiel.
Communication and warning systems	Positive	Das Frühwarnsystem informiert rechtzeitig über steigende Pegelstände.
	Positive	Sensoren überwachen den Pegelstand kontinuierlich.
	Positive	Wetterwarnungen werden per App und SMS weitergegeben.
	Negative	Ein Rückhaltebecken wurde oberhalb der Stadt gebaut.
	Negative	Die Schäden durch die Überschwemmung waren erheblich.
Land-use restrictions	Positive	Der Bebauungsplan untersagt neue Wohnbebauung in ausgewiesenen Überschwemmungsgebieten.
	Positive	Raumordnungsrechtliche Vorgaben begrenzen die Siedlungsentwicklung in Risikolagen.
	Positive	Bauverbote in der Überflutungszone wurden durch neue Vorschriften verschärft.
	Negative	Das Frühwarnsystem informiert die Bevölkerung bei Pegelanstieg.
	Negative	Die Baukosten sind deutlich gestiegen.
Risk policies	Positive	Die Gemeinde hat eine umfassende Schutzstrategie für Risikogebiete entwickelt.
	Positive	Das Schutzkonzept integriert technische und naturbasierte Maßnahmen.
	Positive	Der Hochwasserrisikomanagementplan legt Prioritäten und Verantwortlichkeiten fest.
	Negative	Nach dem Unwetter standen viele Keller unter Wasser.
	Negative	Im Sommer steigen die Temperaturen an.
Relocation	Positive	Ein Umsiedlungsprogramm unterstützt Familien beim Umzug aus gefährdeten Gebieten.
	Positive	Freiwillige Umsiedlung wird in enger Abstimmung mit den Betroffenen umgesetzt.
	Positive	Bürger können sich für ein freiwilliges Wegzugsprogramm anmelden.
	Negative	Die Flussrenaturierung verlangsamt den Abfluss.
	Negative	Das Ministerium stellte neue Fördermittel vor.

Robustness Checks and Sensitivity Analyses

This section reports robustness analyses testing the sensitivity of the main results to alternative model specifications (Tables S13–S18) and to alternative spatial linking strategies between river catchments and NUTS-3 administrative districts (Table A1).

Table S13. Dose-Response

Tests whether the severity–coverage relationship follows a continuous dose-response pattern. Weekly flood intensity enters linearly; 12-week cumulative intensity is binned into categories (reference: 0). Results confirm a monotonically increasing relationship for total FAC and for each category separately.

Category	Intensity β	Cum 1–3	Cum 4–7	Cum 8–15	Cum 16–31	Cum 32+
Total	0.187***	0.059*	0.126*	0.147	0.699*	1.175*
Structural	0.140***	0.019	0.042	0.018	0.177	0.339
Financial	0.024**	0.034***	0.061**	0.079*	0.468*	0.744*
Governance	0.019***	0.001	0.004	0.012*	0.012	0.041
Nature-based	0.002*	0.004*	0.009**	0.011*	0.038*	0.061
Relocation	0.000	0.001	0.002	0.002	0.016	0.003

Note. DV: category article counts. Two-way FE (NUTS-3 + week). SE clustered at NUTS-3. Reference category: the 12-week cumulative intensity bin = 0. *** P < 0.001, ** P < 0.01, * P < 0.05.

Table S14. Temporal Sensitization: Flood Effect × Year Interaction

Temporal sensitization refers to whether the strength of the flood–coverage relationship changes over the study period. Tests whether the flood–coverage relationship has changed over the 2000–2020 study period. The interaction of weekly intensity with year_centered is significant and positive for total FAC ($\beta = 0.013$, $P = 0.017$) under year+month FE, indicating that the same flood intensity produces somewhat more coverage in later years. The effect is driven primarily by governance coverage ($\beta = 0.001$, $P = 0.013$). Under week FE, the interaction is absorbed and not identifiable.

Category	Fixed-effects specification	Intensity β	Year β	Intensity × Year β	Int. P
Total	Week	—	—	−0.001	0.818
Total	Year+month	0.279***	0.010***	0.013*	0.017
Structural	Year+month	0.189***	0.003**	0.007	0.088
Financial	Year+month	0.044***	0.003***	0.000	0.940
Governance	Year+month	0.025***	0.000*	0.001*	0.013
Nature-based	Year+month	0.004***	0.002***	0.000	0.892
Relocation	Year+month	0.000	0.000*	0.000	0.501

Note. DV: category article counts. The flood effect is the coefficient on weekly flood intensity (Intensity β). Year_centered = year − 2010. SE clustered at NUTS-3. Under week FE, year_centered is absorbed; only the interaction is identifiable. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Table S15. Alternative Dependent Variables

Re-estimates the severity–coverage model using three DVs: $\log(1 + \text{articles})$, articles per million inhabitants, and raw counts with top-1% trimming ($\text{articles} \leq 15$). All specifications produce qualitatively identical severity gradients. Under the rate per million, moderate and major floods lose significance due to population normalization. Under trimming, extreme floods lose significance because the trimming threshold removes the most informative observations.

DV specification	Minor	Moderate	Major	Severe	Extreme
log(1 + articles)	0.013***	0.072***	0.087***	0.215***	0.340***
Rate per million	0.004**	0.008	0.017	0.216*	0.801*
Trimmed (≤ 15)	0.056***	0.179*	0.265*	0.468***	0.008

Note. Two-way FE (NUTS-3 + week). SE clustered at NUTS-3. Trimming excludes district-weeks above the 99th percentile (> 15 articles). *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Table S16. Clustering Sensitivity: NUTS-3 vs. NUTS-1

Compares standard errors from NUTS-3-level (401 clusters) and NUTS-1-level (16 clusters) clustering. NUTS-1 clustering produces larger standard errors, and the extreme flood coefficient loses significance at the 5% level ($P = 0.176$). All other severity coefficients remain significant at conventional levels under both clustering schemes.

Severity class	Coef.	NUTS-3 SE	NUTS-3 P	NUTS-1 SE	NUTS-1 P
Minor	0.042	(0.013)	0.002**	(0.019)	0.042*
Moderate	0.000	(0.110)	0.997	(0.098)	0.997
Major	0.420	(0.293)	0.153	(0.262)	0.130
Severe	2.340	(0.789)	0.003**	(0.894)	0.019*
Extreme	5.646	(1.976)	0.004**	(3.972)	0.176

Note. DV: raw article counts. Two-way FE (NUTS-3 + week). Point estimates are identical; only SEs differ. *** $P < .001$, ** $P < .01$, * $P < .05$.

Table S17. Fixed Effects Specification: Week vs. Year + Month

Compares Shannon diversity models using calendar-week FE (1,083 time dummies) versus year + month FE (20 + 12 dummies). The severity coefficient is larger under year+month FE (0.025 vs. 0.016), likely because week FE absorb more within-year variation. The cumulative experience coefficient is not significant under either specification. Results are qualitatively robust.

FE specification	Severity β	Severity P	Cum. experience β	Cum. exp. P
Calendar week	0.016***	< .001	0.000	0.691
Year + month	0.025***	< .001	0.000	0.611

Note. DV: Shannon entropy. Both models include NUTS-3 FE + cum_floods_any_lag. SE clustered at NUTS-3. *** P < 0.001.

Table S18. Robustness of Results to Alternative Spatial Linking Strategies

Assigning flood records derived from the discharge time series of the gauges available from CAMELS-DE to NUTS-3 administrative districts requires a spatial linking decision. River catchments do not follow administrative boundaries, and a gauge station measures discharge at a single point at the catchment outlet, while the impacts of corresponding floods may be felt upstream across the entire extent of the flooded area. To evaluate the effect of this choice, we assess the sensitivity of the main results to five possible choices of spatial linking between river catchments and administrative boundaries.

Linking strategies

M0 – Catchment largest overlap (baseline): Each river catchment is assigned to the single NUTS-3 district with which it shares the largest overlapping area. This yields 10,209 flood-affected region-weeks across 274 districts.

M1/M2 – Gauge point-in-polygon: Gauge location identifies the containing district. 11,238 flood-affected region-weeks across 312 districts.

M3a/M3b/M3c – Catchment overlap thresholds ($\geq 10\%$ / $\geq 30\%$ / $\geq 50\%$): Many-to-many assignment at varying overlap thresholds, yielding 14,145 / 11,381 / 9,688 flood-affected region-weeks respectively.

Method	Minor	Moderate	Major	Severe	Extreme	Flood-weeks	R ² w
M1/M2 Gauge point	0.018***	0.090***	0.130***	0.225***	0.462***	11,238	0.006
M0 Largest overlap	0.013***	0.072***	0.087***	0.215***	0.340***	10,209	0.004
M3a Overlap $\geq 10\%$	0.009***	0.050***	0.046**	0.172***	0.262***	14,145	0.005
M3b Overlap $\geq 30\%$	0.012***	0.063***	0.066***	0.210***	0.348***	11,381	0.005
M3c Overlap $\geq 50\%$	0.013***	0.080***	0.100***	0.214***	0.400***	9,688	0.004
CV (%)	23.8	21.0	36.5†	8.6‡	19.3	—	—

Note. DV: $\log(1 + n_{\text{articles}})$. FE: NUTS-3 + week. SE clustered at NUTS-3. N = 435,887. Bold row (M0) = baseline. CV = coefficient of variation across methods. † Highest CV (driven by M3a). ‡ Lowest CV (severe category most stable). *** P < 0.001, ** P < 0.01.

Method selection

We use method M0 (catchment largest overlap) as the primary linking strategy for three reasons. First, it is the most conservative approach: at 10,209 flood-affected region-weeks it avoids over-attributing flood exposure to districts where only a small, potentially upstream portion of a catchment overlaps the administrative boundary. Second, comparison with M3b ($\geq 30\%$ threshold, 11,381 flood-weeks) confirms that relaxing the one-to-one constraint while maintaining a substantive overlap requirement yields nearly identical coefficients for severe and extreme events (n_{severe} : 0.215 vs. 0.210; n_{extreme} : 0.340 vs. 0.348), indicating M0 does not suppress signal by being overly restrictive. Third, M0 avoids the threshold choice inherent in M3a–c, and the sensitivity analysis confirms results are not meaningfully altered across the 30–50% overlap range. The gauge-point methods (M1/M2), while producing the largest coefficients, cover 312 NUTS-3 districts compared to 274 under M0; the additional 38 districts likely reflect gauge placements near administrative boundaries rather than genuine additional flood exposure, making M0 the more spatially grounded choice.



Supporting Information for

Floods as a window of opportunity: When and why extreme events trigger adaptation

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This PDF file includes:

- I . Sentence-Level Classification of Flood Adaptation Measures
- II. Variable Construction
- III. Supplementary Figures (Figures S1 to S15)
- IV. Supplementary Tables (Tables S1 to S18)

I. Sentence-Level Classification of Flood Adaptation Measures Using Few-Shot Multilingual Transformers

First, we identified candidate documents from our sample of 2,508,345 articles by filtering those that mention at least one keyword from Table S10. To assess the robustness of the keyword pre-filtering step, we manually reviewed a random sample of 100 documents excluded during filtering; 23 were identified as potentially relevant false negatives (23%), with misclassifications confined almost entirely to the financial support category and no relevant documents identified in any other adaptation category. Additionally, duplicate articles with a Jaccard similarity greater than 0.8 were removed to avoid duplicates from news agencies or press releases shared across multiple outlets. Based on this, 625,813 articles were identified.

Sentence-level classification of flood adaptation measures was implemented using SetFit (Tunstall et al., 2022), a few-shot learning framework built on contrastive fine-tuning of sentence transformers. All classifiers shared the same pre-trained backbone, paraphrase-multilingual-mpnet-base-v2 (Reimers & Gurevych, 2020), a multilingual transformer. A separate binary classifier was trained for each of the 12 adaptation measures in Table S11, yielding 12 independent models.

For each classifier, a manually curated training set was constructed comprising between 20 and 48 positive examples and 16–20 negative examples, all at the sentence level and written in German. A total of 663 samples was manually annotated. Positive examples were domain-specific sentences explicitly referencing the target measure (e.g., dike construction, flood insurance contracts); negative examples included both thematically unrelated sentences and semantically adjacent but non-matching flood-related sentences, to encourage precise decision boundaries. Training followed the standard SetFit procedure to fine-tune the sentence encoder (3 epochs, 20 iterations) followed by fitting a logistic classification head on the resulting embeddings.

Inference was performed on sentence-level splits of the pre-filtered article corpus, with each classifier applied only to the subset of articles pre-selected by the corresponding adaptation-measure keywords.

Each model was evaluated on a stratified held-out sample of 100 sentences, drawn from the classified corpus by binning predicted probabilities into 10 equal-width intervals (0.1-step) and sampling up to 10 sentences per bin. This stratified design ensured that sentences spanning the full range of model confidence were represented in the evaluation. Sampled sentences were manually labelled by human annotators. Standard classification metrics (accuracy, precision, recall, F1 score) were computed against these human labels.

II. Variable Construction

To identify the relationship between flood events and adaptation discourse, we linked flood event data to flood adaptation coverage (FAC) at the NUTS-3 district \times calendar week level, constructing a balanced panel spanning June 2000 to January 2020 (274 NUTS-3 districts \times 1,026 weeks = 281,124 district-week observations). Region-weeks without flood events received zeros for all flood variables; region-weeks without FAC received zeros for article counts. This section documents the construction of all variables used in the analysis.

5.1 Flood Exposure Variables

For each region-week, we aggregated catchment-level flood classifications (described in Section 2.4 of the main text) into the following variables.

Binary severity indicators. For each of the five severity classes (minor: $T < 5$ year; moderate: $T = 5\text{--}10$ year; major: $T = 10\text{--}20$ year; severe: $T = 20\text{--}50$ year; extreme: $T \geq 50$ year), we defined a binary indicator equal to 1 if at least one gauging station assigned to the NUTS-3 district exceeded that severity threshold during the calendar week. A district-week may have multiple active indicators if different gauging stations recorded floods of different severities in the same week.

Severity count variables. For each severity class, we counted the number of distinct flood events at or above the corresponding threshold within each district-week (n_{minor} , n_{moderate} , n_{major} , n_{severe} , n_{extreme}). These serve as the primary regressors in the severity–coverage models (Table 1 in the main text), allowing us to estimate the marginal effect of an additional flood event at each severity level.

Weekly maximum severity score. A single continuous measure ($\text{weekly_max_severity}$) that collapses the multi-tier structure into a weighted composite: minor = 1, moderate = 2, major = 4, severe = 8, extreme = 16. This variable is used in compositional analyses where a single severity index is preferred over five separate count variables.

Weekly flood intensity. The sum of all return period values across gauging stations within a district-week (weekly_intensity). Unlike $\text{weekly_max_severity}$, which uses ordinal weights, this variable reflects the cumulative hydrological magnitude of all concurrent flood events.

- Cumulative flood experience. We constructed rolling backward-looking counts of flood weeks within defined temporal windows, each lagged by one week to avoid simultaneity:
- $\text{roll_major_52wk_lag}$: count of weeks with major-or-above floods in the preceding 52 weeks (1-year window)
- $\text{roll_major_104wk_lag}$: 2-year window
- $\text{roll_major_156wk_lag}$: 3-year window
- $\text{roll_major_260wk_lag}$: 5-year window
- $\text{cum_floods_major_lag}$: full-period cumulative count from the start of the panel
- $\text{cum_floods_any_lag}$: full-period count including all severity levels

These variables are used in the experience–diversification analysis (Result Section “Repeated Flood Occurrence Shifts Discourse Toward Financial Measures”) to test whether districts with more flood history produce more diverse adaptation coverage.

12-week cumulative intensity. The sum of weekly_intensity over the preceding 12 weeks ($\text{intensity_past_12wk}$), used as a control variable in binary flood effect models to separate acute from accumulated effects.

Basin-level spillover intensity. For each NUTS-3 district, we identified all other districts sharing the same major river basin and computed the cumulative weekly_intensity across those neighbouring districts over the preceding 12 weeks (basin_intensity_12wk). This variable captures hydrological spillover — the possibility that flooding observed in nearby districts within the same river system may affect local adaptation discourse even before local flooding occurs.

5.2 Adaptation Coverage Variables

Adaptation articles classified at the sentence level (described in Section 4 of this appendix) are aggregated to the NUTS-3 \times week level.

Article counts. We computed raw article counts at three levels of aggregation: total FAC articles (n_articles), articles by adaptation category (five categories: structural, financial, governance, nature-based, relocation), and articles by individual measure (12 measures, listed in Table S9). Each article is counted once per district-week even if multiple sentences within the article mention adaptation measures.

Log-transformed counts. Because article counts are heavily right-skewed (skewness > 10 for most measures, with the modal value being zero), we applied $\log(1 + x)$ transformation to all count variables before use as dependent variables. This is the primary DV specification throughout the analysis. Skewness diagnostics for all variables are reported in the replication materials.

Rate per million. To account for secular growth in the WISO news database over the study period, we computed a normalised rate defined as articles per million WISO articles published in the same calendar year. This variable is used as an alternative DV in robustness checks (Table S16).

Min-max normalized counts. For cross-measure comparability, we applied min-max normalization to $\log(1 + x)$ counts for each measure independently, rescaling to $[0, 1]$. A coefficient of 0.05 on a min-max variable means that a flood moves the measure by 5% of its own full observed range. This transformation removes the dominance of high-volume measures (e.g., dikes: max = 238 articles/week) over low-volume ones (e.g., permeable surfaces: max = 14) and is used in supplementary analyses (Figs. S2, S3, S9, S10).

5.3 Compositional Variables

Compositional variables are computed only for district-weeks with at least one adaptation article ($N = 81,160$).

Category and measure shares. For each district-week, the share of category c is defined as $\text{share}_c = n_articles_c / n_articles_total$, where $n_articles_c$ is the count of articles mentioning at least one measure in category c . Measure-level shares are defined analogously. Because articles may mention measures from multiple categories, shares do not necessarily sum to exactly 1.0.

Shannon entropy. Captures how evenly coverage is distributed across the five adaptation categories: $H = -\sum p_i \ln(p_i)$, where p_i is the share of total adaptation articles belonging to category i . Values range from 0 (all articles in a single category) to $\ln(5) \approx 1.61$ (perfectly even distribution). Shannon entropy is more sensitive to the number of categories represented.

Herfindahl-Hirschman Index (HHI). Measures concentration: $HHI = \sum p_i^2$, where p_i is defined as above. Values range from 0.2 (five equal shares) to 1.0 (single-category dominance). HHI is more sensitive to the dominance of the largest category. Shannon and HHI are used as complementary dependent variables in the compositional analyses (Sections 3.3–3.5 of the main text).

Structural and nonstructural shares. A binary decomposition: structural_share is the share of structural articles; nonstructural_share = $1 - \text{structural_share}$. Used in basin spillover models (Table S7).

5.4 Fixed Effects and Clustering

All models include two-way fixed effects. NUTS-3 district fixed effects (α_i) absorb time-invariant regional characteristics such as geography, population, media market structure, and baseline flood exposure. Time fixed effects (γ_t) absorb national-level temporal trends in media coverage, flood occurrence, and seasonal patterns. For severity–coverage models (Sections 3.1–3.3), we used calendar-week fixed effects (1,026 dummies). For experience and spillover models (Sections 3.4–3.5), we replaced week FE with year fixed effects (20) and calendar-month fixed effects (12) to avoid collinearity with the rolling experience windows, which vary at the week level within years. The robustness of this choice is tested in Table S18. Standard errors are clustered at the NUTS-3 district level throughout, and NUTS-1 clustering is tested as a robustness check in Table S17.

III. Supplementary Figures

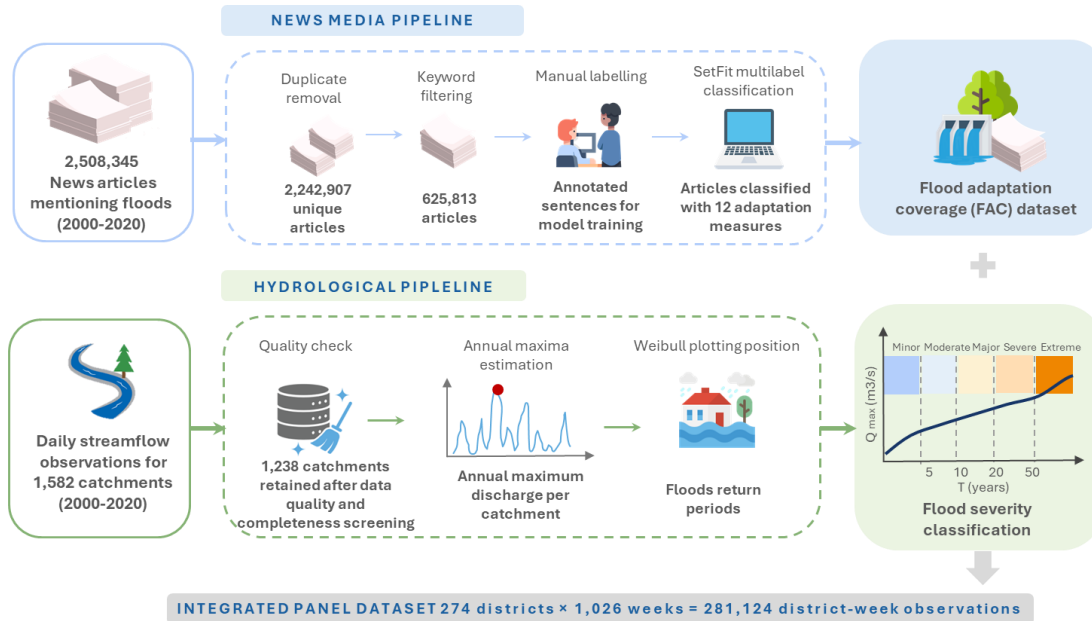


Fig. S1. Overview of the integrated data pipeline.

The news-media pipeline (top) processes flood-related news articles through duplicate removal, keyword filtering, manual labelling, and multi-label classification to produce the Flood Adaptation Coverage (FAC) dataset. The hydrological pipeline (bottom) processes daily streamflow observations through quality control, annual-maxima estimation, and Weibull plotting-position analysis to derive flood return periods and a five-class flood severity classification. The two streams are combined into an integrated district-week panel dataset.

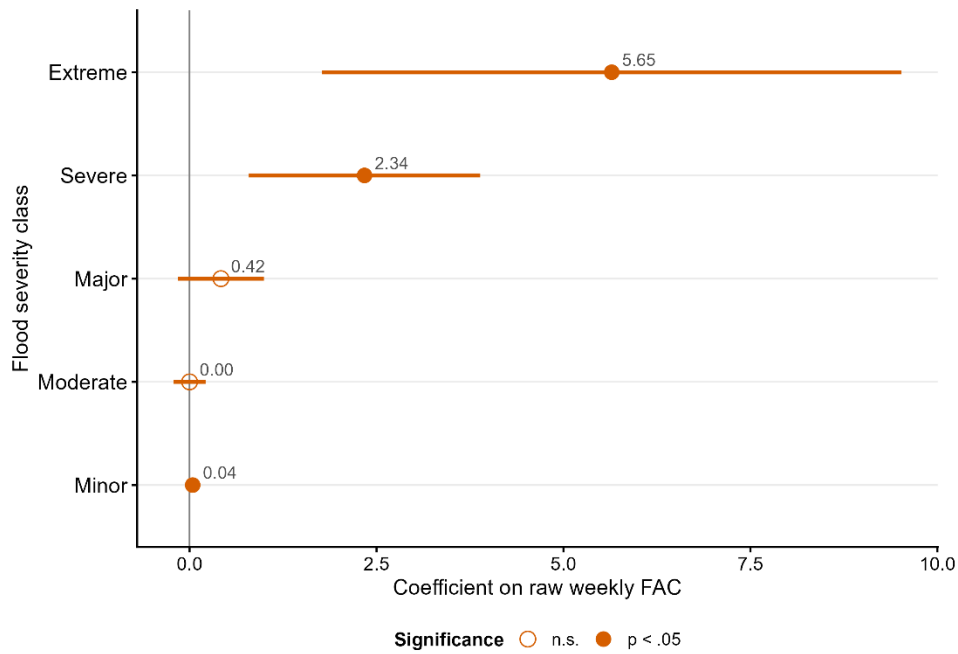


Fig. S2. Raw-count severity coefficients

Coefficients from a two-way FE panel regression of raw (untransformed) weekly adaptation article counts on flood severity class counts, with NUTS-3 district and calendar week fixed effects. Horizontal bars show 95% CIs (SE clustered at NUTS-3). Moderate and major floods are not statistically significant ($P > .05$), indicating compression due to right-skewed article distributions. Compare with main text Fig. 1B (log-transformed DV), where all five severity classes are significant.

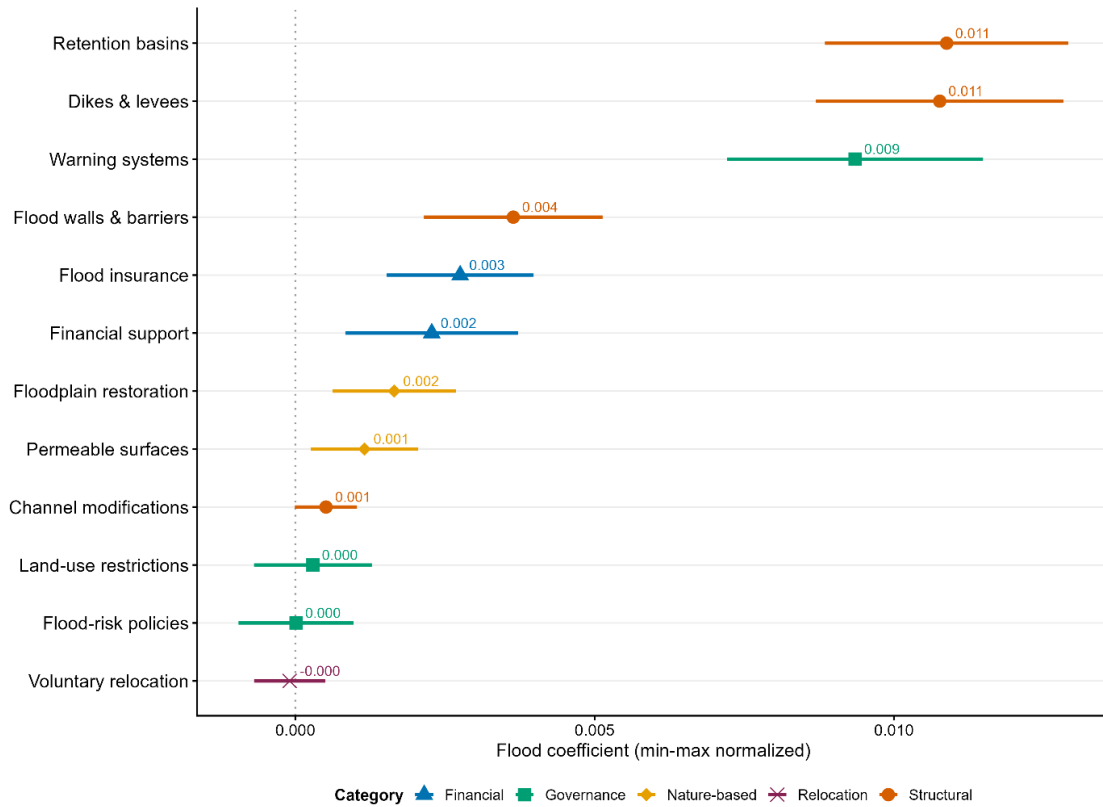


Fig. S3. Min-max normalized flood response coefficients by adaptation measure

Flood response coefficients estimated from two-way FE models using min-max normalized $\log(1 + \text{articles})$ as the dependent variable. Min-max rescales each measure independently to $[0, 1]$, so a coefficient of 0.01 means a flood moves the measure by 1% of its own full range. Under this normalization, retention basins (0.011), dikes (0.011), and warning systems (0.009) are nearly identical in responsiveness, indicating that the absolute dominance of dikes in the log specification (Fig. 2A) is partly volume-driven.

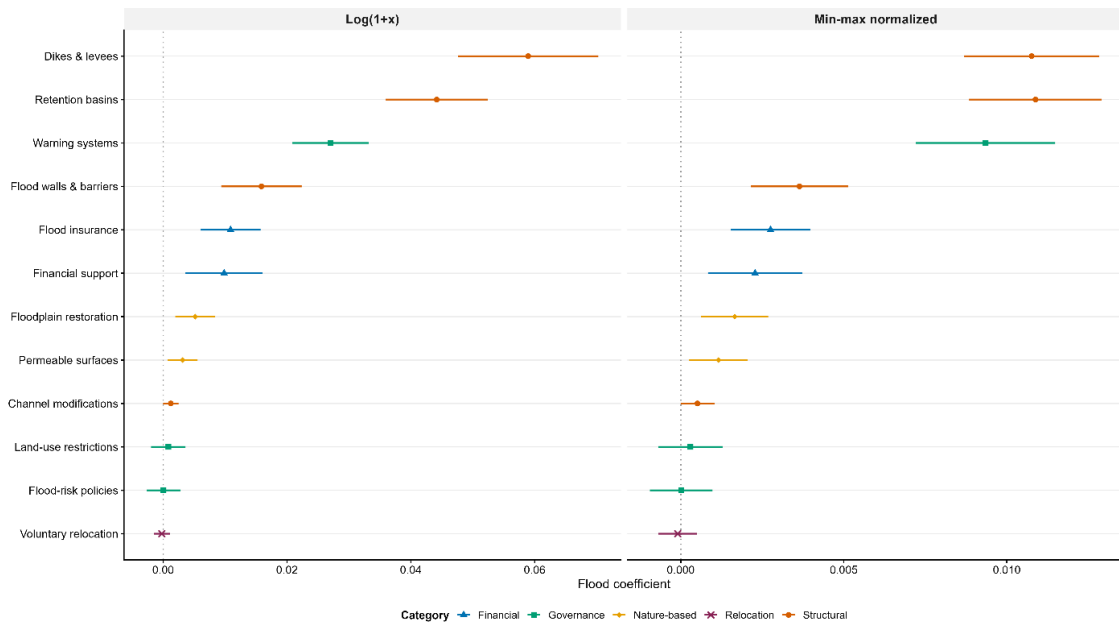


Fig. S4. Log(1 + x) vs. min-max normalized flood coefficients: side-by-side comparison

Left panel: log(1 + articles) coefficients (as in Fig. 2A). Right panel: min-max normalized coefficients (as in Fig. S3). If rankings differ substantially, apparent dominance of structural measures in the log specification reflects absolute coverage volume rather than proportional flood responsiveness.

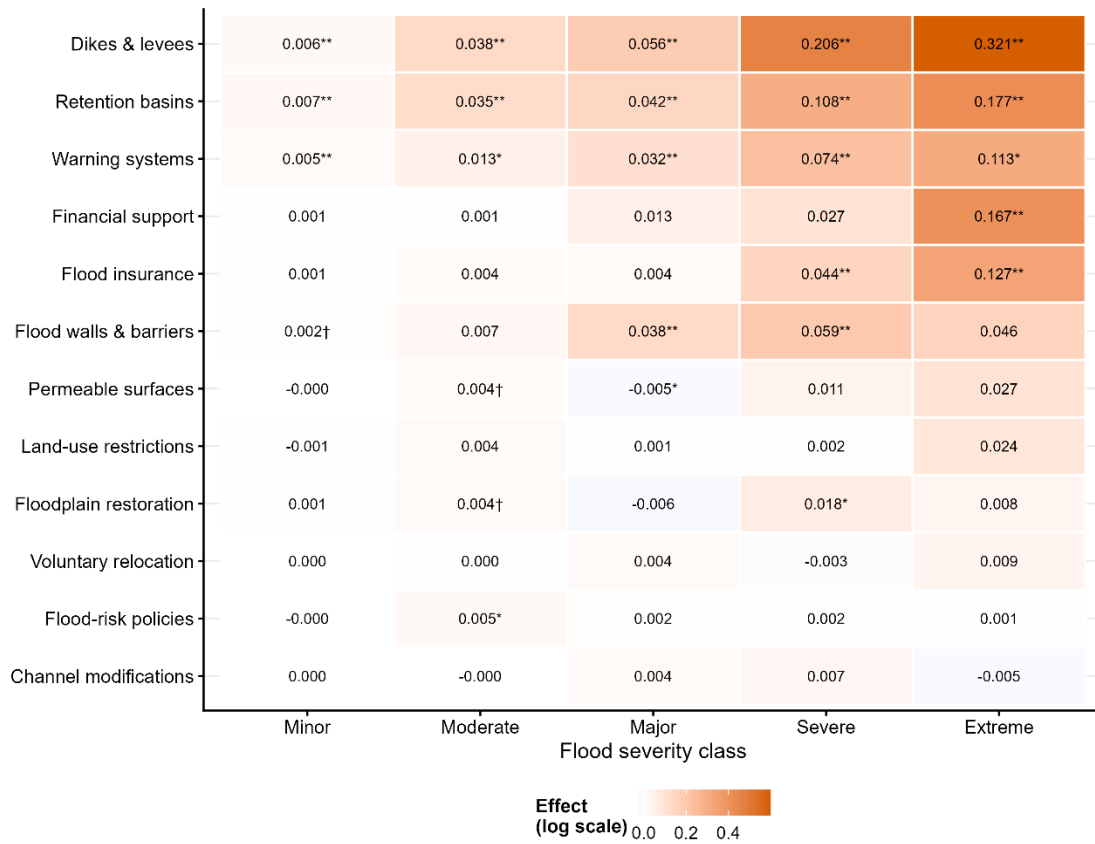


Fig. S5. Severity–measure heatmap

Coefficients from $\log(1 + \text{articles})$ models with NUTS-3 and week FE, showing how each of the 12 adaptation measures responds to each severity class. Cell values are point estimates with significance markers († $P < 0.10$, * $P < 0.05$, ** $P < 0.01$). The colour scale is log-compressed to improve readability. Measures are ordered by total coefficient magnitude (bottom to top). Orange borders indicate outlier coefficients ($|\beta| > 0.5$).

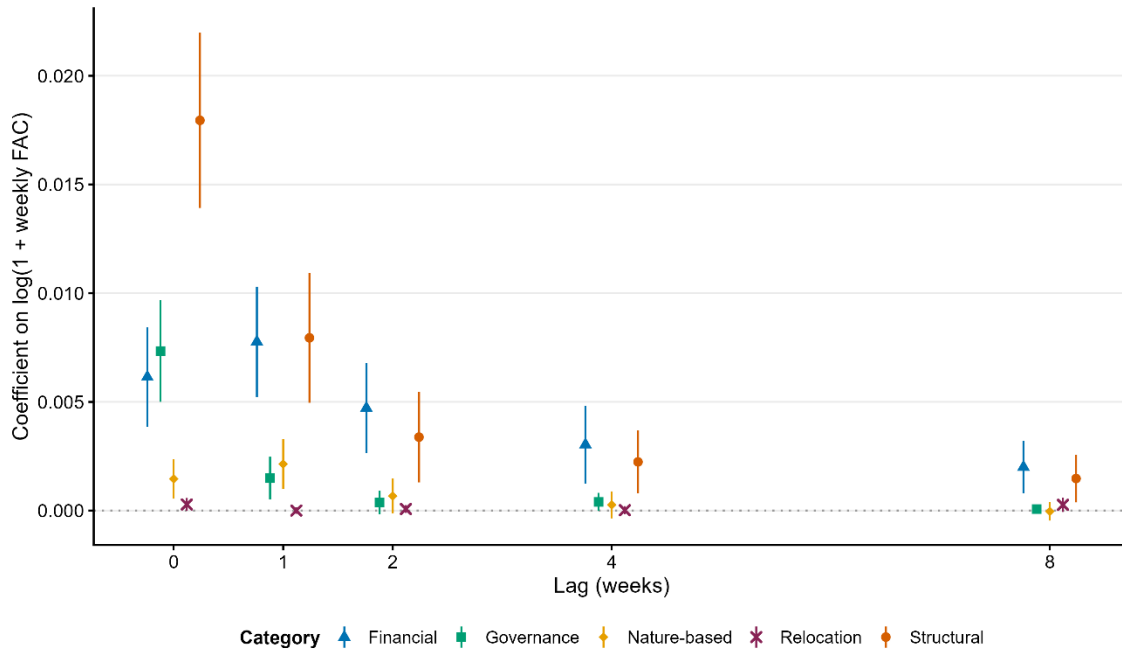


Fig. S6. Lag structure by adaptation category

Distributed lag coefficients (contemporaneous, 1-week, 2-week, 4-week, 8-week) for each adaptation category, estimated from $\log(1 + \text{category articles}) \sim \text{weekly_intensity} + \text{lag terms} \mid \text{NUTS-3} + \text{week FE}$. Structural and financial categories show persistent effects up to 8 weeks. Warning systems (governance) decay within 1 week. This temporal persistence structures the three-phase post-flood discourse cycle described in the main text.

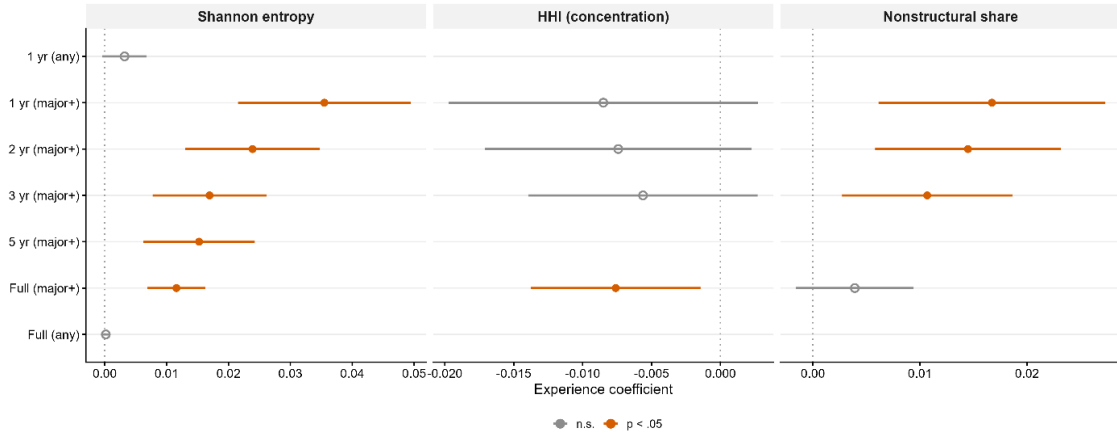


Fig. S7. Experience window comparison for Shannon entropy, HHI, and nonstructural share

Coefficients on cumulative flood experience measured over different temporal windows (1-year any, 1-year major+, 2-year major+, 3-year major+, 5-year major+, full-period major+, full-period any) from FE models predicting Shannon entropy (left), HHI (centre), and nonstructural share (right). The 1-year major+ window produces the largest per-event effect for Shannon entropy. Only major-or-above floods yield significant experience coefficients.

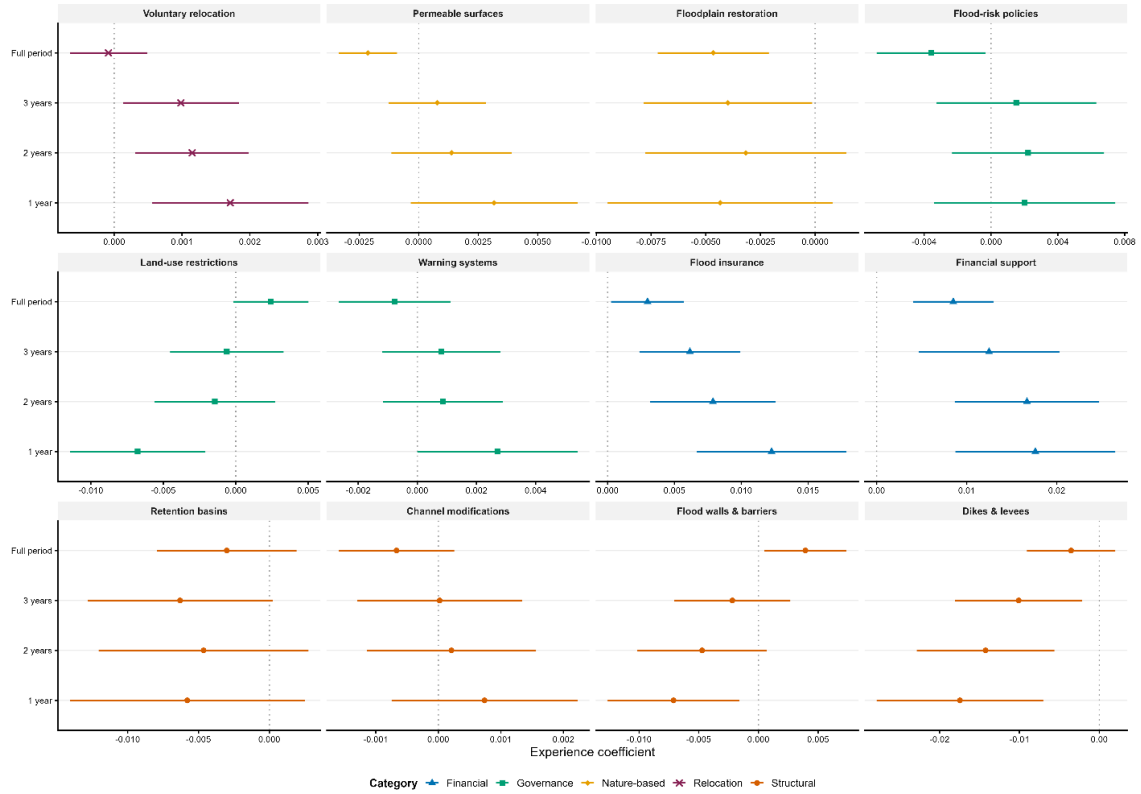


Fig. S8. Experience coefficients by individual adaptation measure across temporal windows
 Effect of cumulative major+ flood experience on individual measure shares, estimated from two-way FE models across four temporal windows (1-year, 2-year, 3-year, full period). Each panel shows one measure; horizontal axis shows the experience coefficient. Financial support and flood insurance gain share with flood experience, while dikes and retention basins lose share.

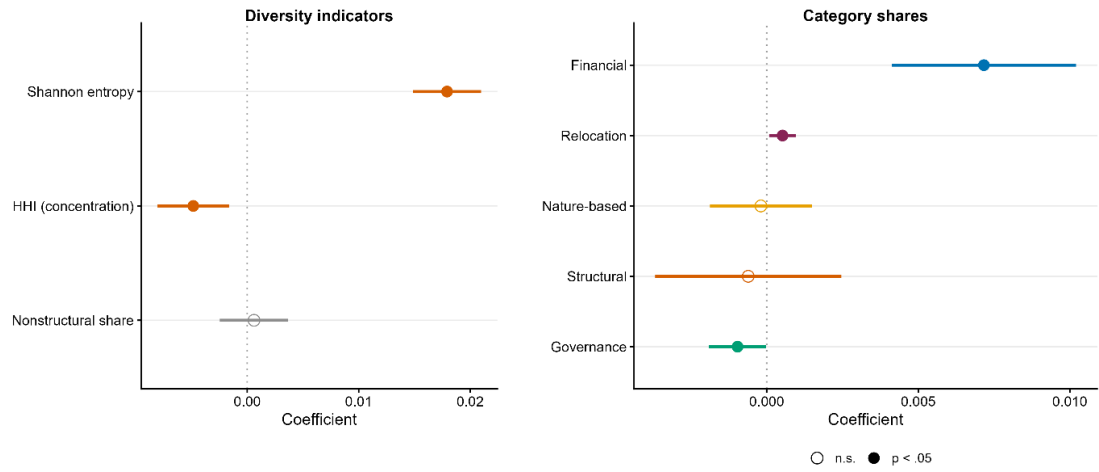


Fig. S9. Basin-level spillover: diversity indicators and category shares

Left panel: coefficients of basin_intensity_12wk on nonstructural share, HHI, and Shannon entropy. Right panel: coefficients on individual category shares. Financial coverage is the primary beneficiary of basin-level spillover. All models include NUTS-3, year, and month FE. Filled circles: $P < .05$; open circles: not significant.

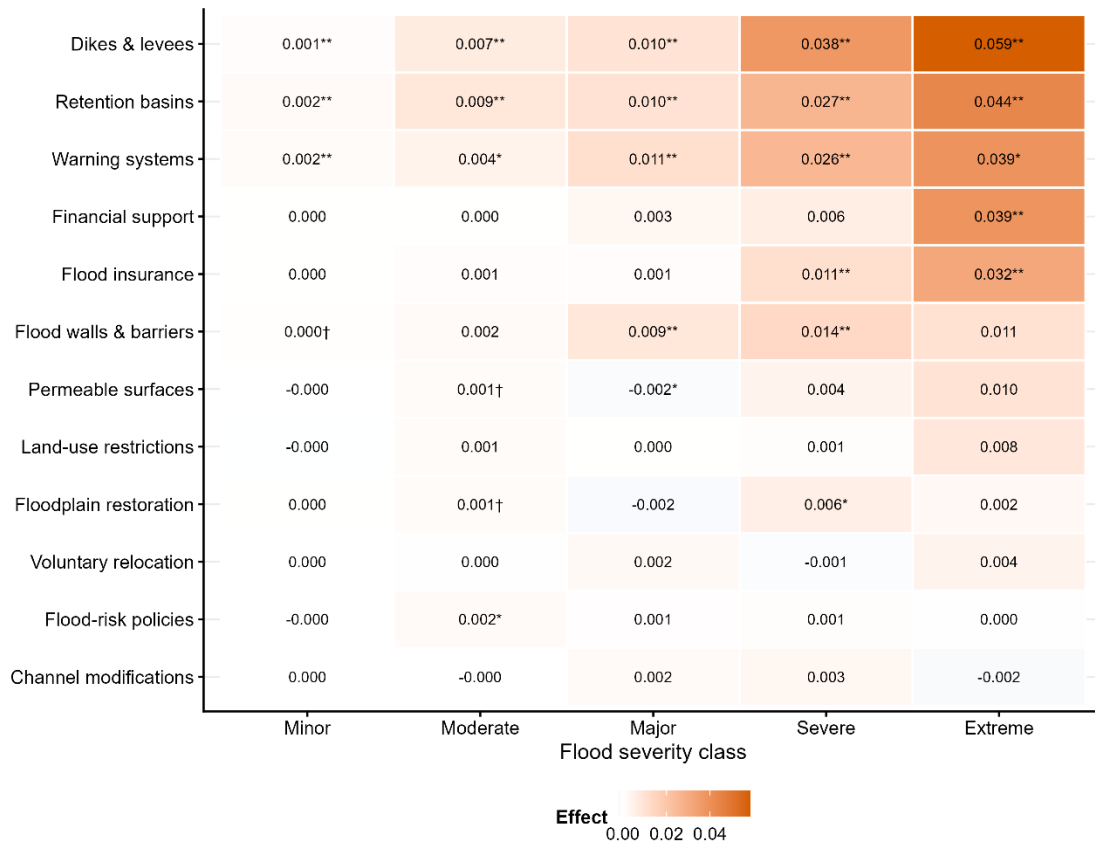


Fig. S10. Min-max normalized severity–measure heatmap

As Fig. S5, but using min-max normalized $\log(1 + \text{articles})$ as the dependent variable. Each measure is rescaled to [0, 1] independently. Compare with Fig. S5 to assess whether severity–responsiveness patterns are driven by absolute volume differences across measures.

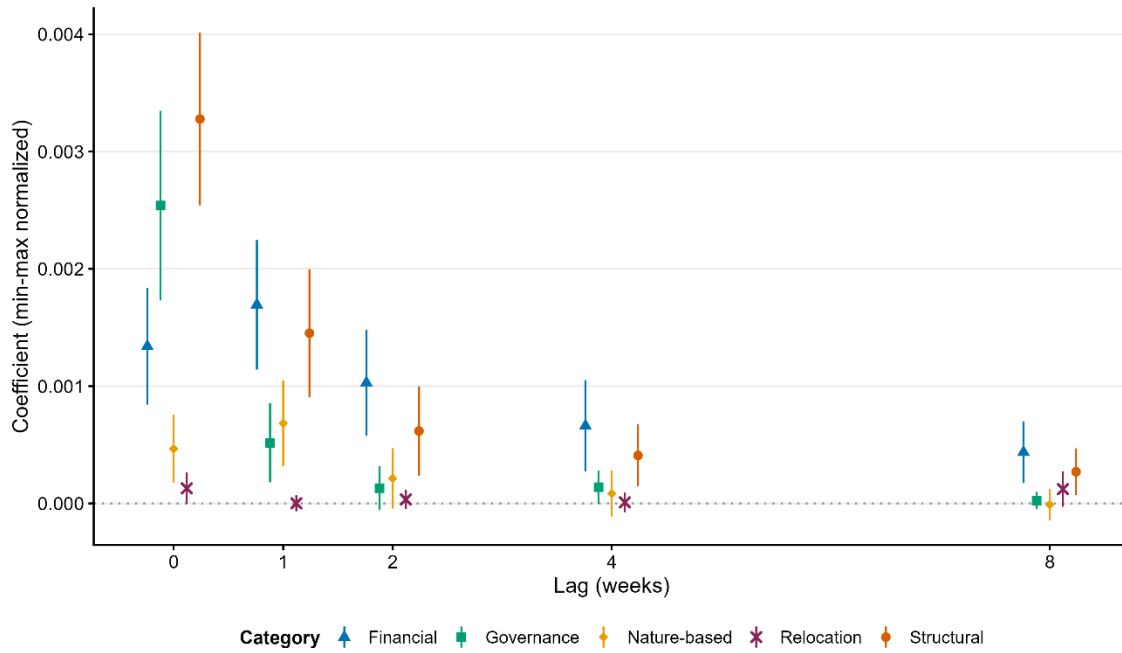


Fig. S11. Min-max normalized lag structure by category

As Fig. S6, but using min-max normalized DVs. Shows proportional response within each category's own range.

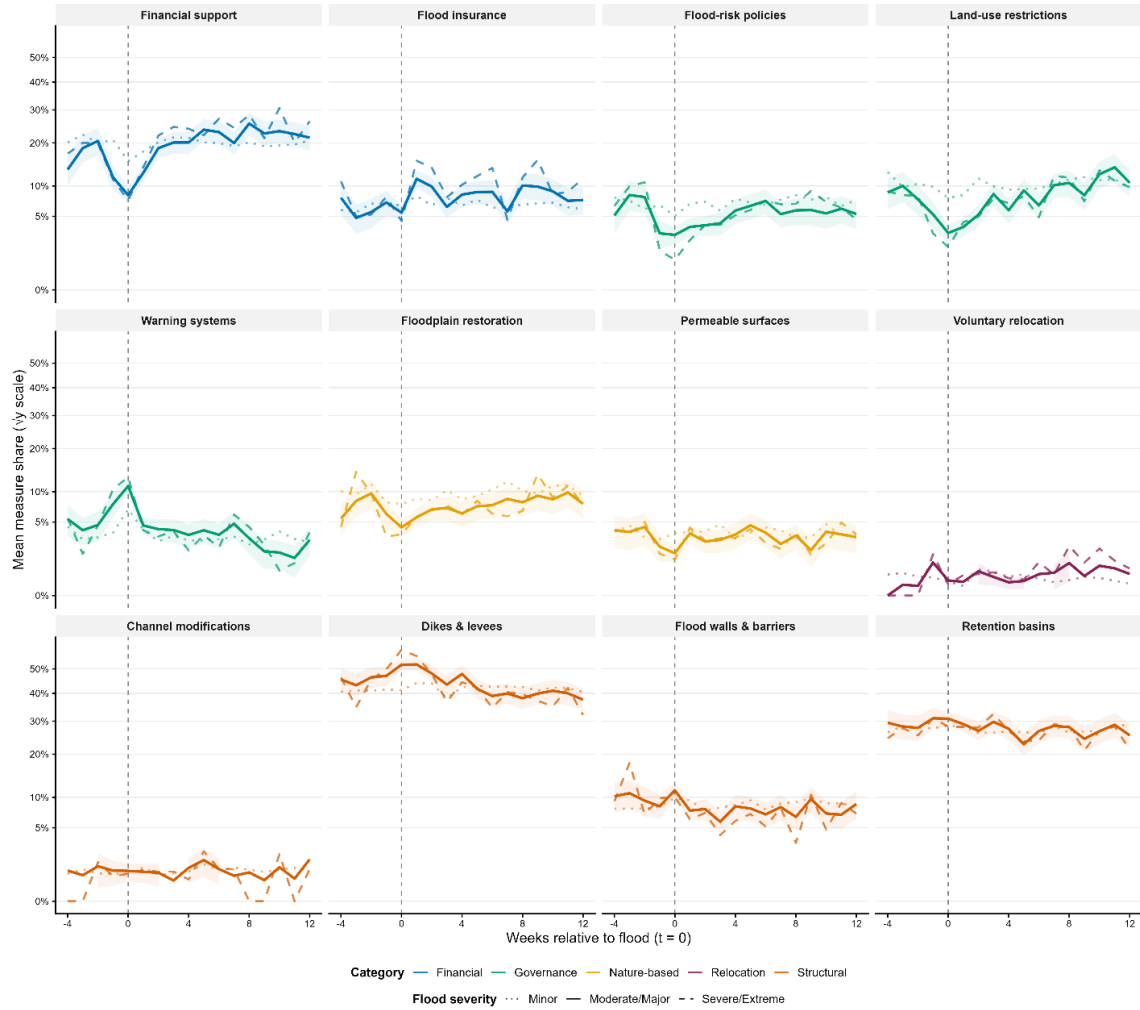


Fig. S12. Post-flood measure trajectories with common square-root y-axis

As Fig. 3, but with a common fixed square-root y-axis across all 12 panels to enable cross-measure magnitude comparison. This version sacrifices within-panel readability for low-share measures but reveals the relative scale of dike and retention basin responses compared to all other measures.

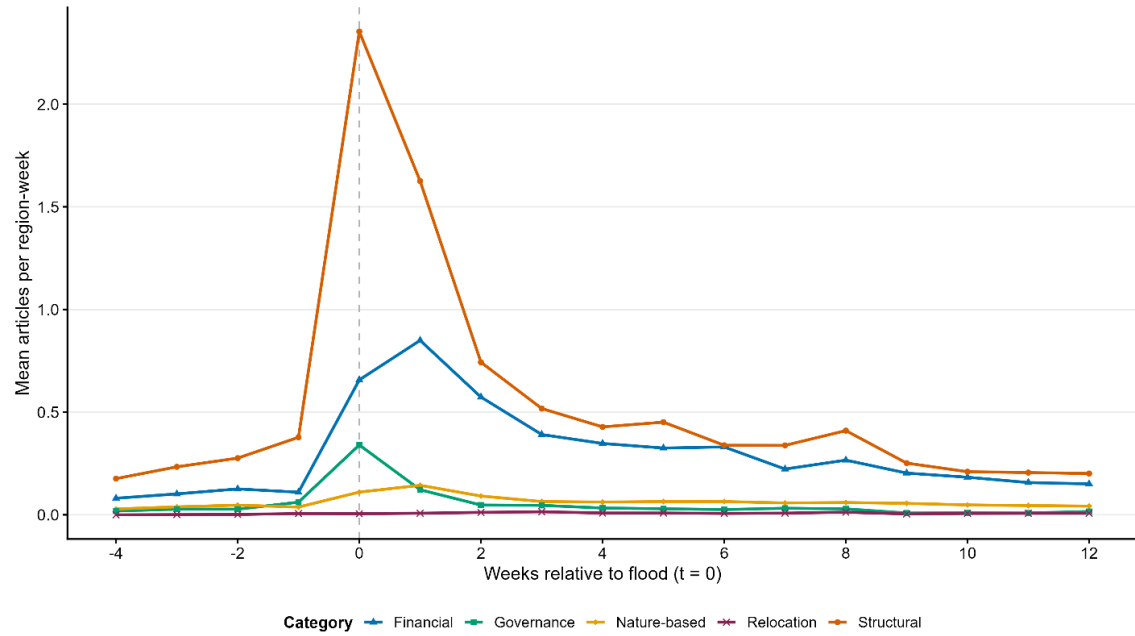


Fig. S13. Absolute post-flood article counts by adaptation category

Mean absolute (not share) article counts per region-week around significant flood events, by adaptation category. Unlike the share trajectories in Fig. 2B, this figure shows that all categories increase in absolute terms after a flood—the share decline of financial and nature-based categories reflects proportional crowding-out, not an absolute decrease.

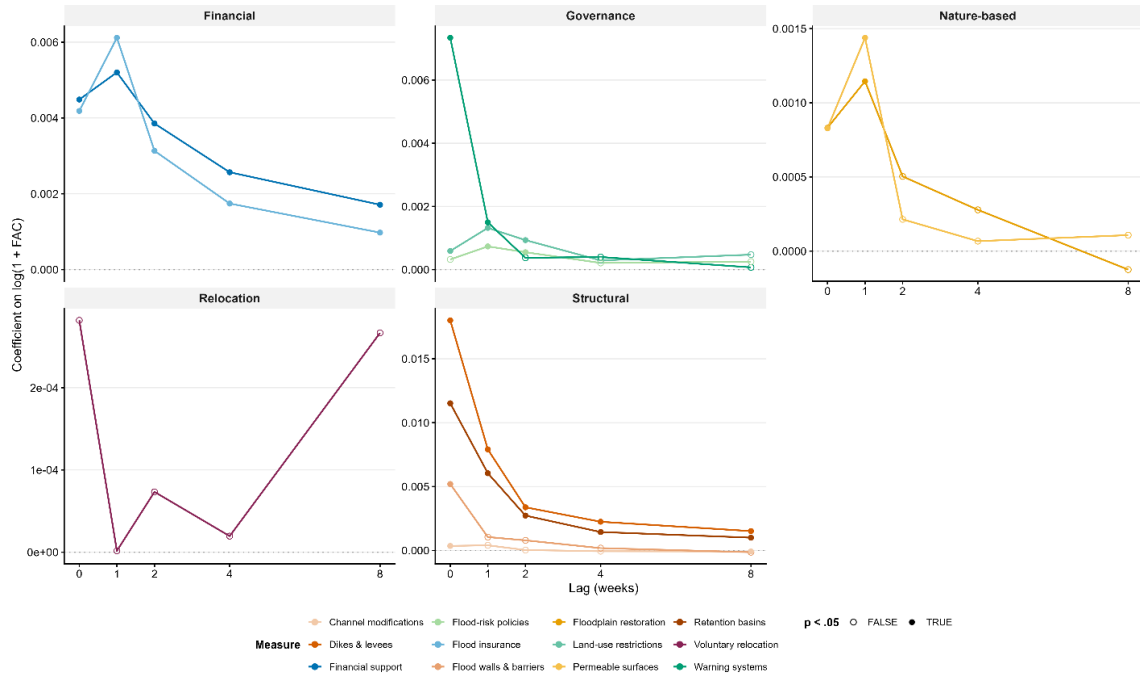


Fig. S14. Lag structure by individual adaptation measure

Distributed lag coefficients for each of the 12 individual measures, faceted by adaptation category. Each line shows one measure's response from contemporaneous (lag 0) through 8-week lag. Filled circles: $P < .05$; open circles: not significant.

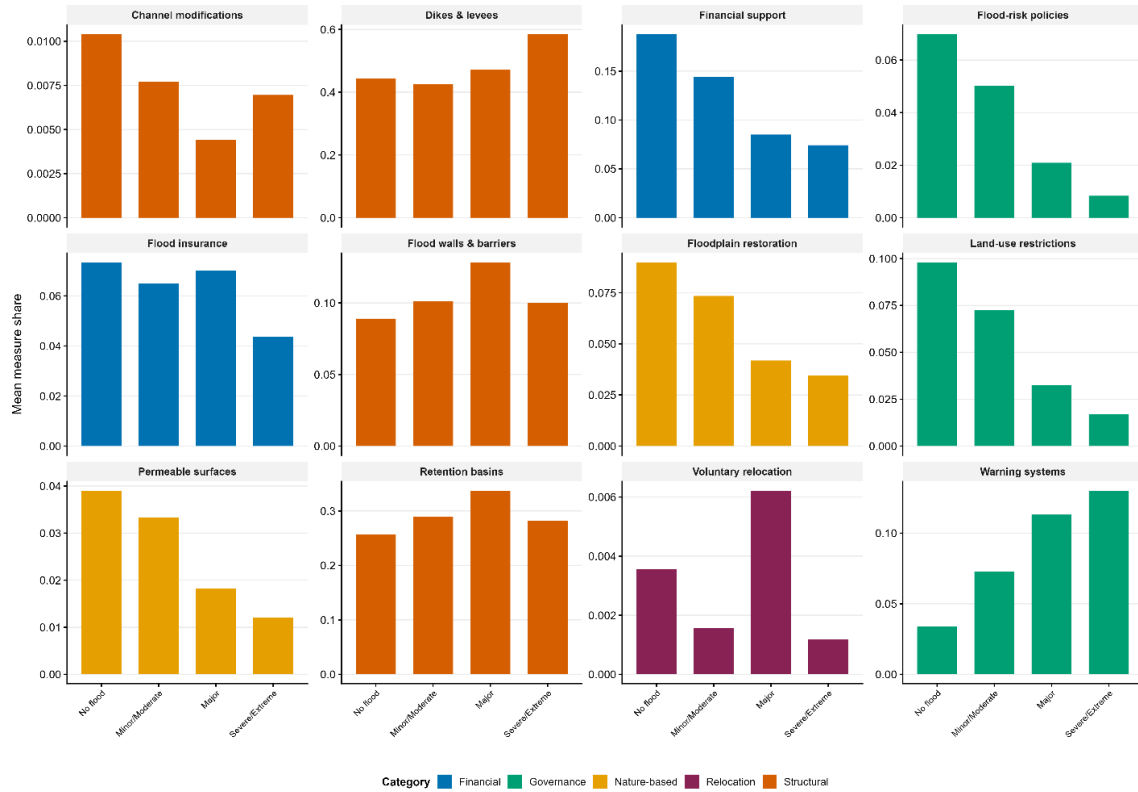


Fig. S15. Adaptation measure shares by flood severity

Mean share of each individual adaptation measure across severity (no flood, minor/moderate, major, severe/extreme), for district-weeks with at least one article. Faceted by measure; fill colour indicates adaptation category.

IV. Supplementary Tables

Table S1. Flood Adaptation Coverage for Acute Floods and Cumulative Flood Occurrence

This table compares mean weekly flood adaptation coverage (FAC) between district-weeks experiencing an acute flood of a given severity class and district-weeks with high cumulative flood intensity but no current flood event. Current extreme floods are followed by a coverage volume of approximately 14.7 articles per district-week, compared with 1.0 article in districts with equivalent cumulative intensity but no ongoing flood. This confirms that adaptation coverage is mainly triggered by acute events and cannot be substituted by gradual cumulative flood occurrence.

Category	n	Mean articles	Mean log(1+articles)	Mean articles per million
Current extreme	149	14.745	1.597	1.774
Current severe	346	5.159	0.916	0.544
Current major	532	3.267	0.725	0.327
High cumulative intensity (cumulative return period \geq 8), no current flood	12,697	1.017	0.307	0.120
High cumulative intensity (cumulative return period \geq 4), no current flood	18,340	0.498	0.199	0.049

Note. Region-week observations from 274 NUTS-3 districts between 2000–2020. Cumulative intensity is the sum of flood return periods over the preceding 12 weeks.

Table S2. Economic Losses and Fatalities as Predictors of Adaptation Coverage

This table tests whether recorded economic losses and fatalities from the European Flood Impact dataset add explanatory power beyond hydrological severity. Panel A examines whether concurrent losses and fatalities predict FAC volume beyond return periods. Panel B tests whether losses reshape the composition of discourse. Panel C examines whether cumulative loss history predicts discourse diversification.

Panel A: Losses and fatalities beyond hydrological severity

Within the subsample of district-weeks experiencing either a hydrological flood event (identified from gauging station records) or a recorded impact event, both economic losses and fatalities significantly predict FAC volume beyond return-period-based severity. Adding $\log(\text{losses})$ increases the within- R^2 from 0.010 to 0.054, and the loss coefficient is highly significant ($\beta = 1.666$, $P < 0.001$). Importantly, the severity coefficient remains significant and stable across all specifications ($\beta = 0.451\text{--}0.515$), confirming that hydrological severity and economic losses capture partly independent dimensions of flood impact. We retain hydrological severity as the primary measure throughout because (i) it provides complete, systematic coverage of all flood events from 1,582 gauging stations, whereas impact records cover only a subset of documented events, and (ii) the severity gradient on which the main substantive conclusions rest is robust to the inclusion of loss variables.

Model	Severity β	SE	Loss β	Fatality β	R^2_{within}
M0: Severity only	0.451***	(0.114)	—	—	0.010
M1: + $\log(\text{losses})$	0.514***	(0.115)	1.666***	—	0.054
M2: + fatalities	0.507***	(0.116)	—	11.533***	0.048
M3: + both	0.515***	(0.116)	1.429**	1.957	0.054

Note. Dependent variable (DV): total articles. Two-way fixed effects (FE) (NUTS-3 + week). standard errors (SE) clustered at NUTS-3. *** $P < 0.001$, ** $P < 0.01$.

Panel B: Losses reshape discourse composition

Among district-weeks with recorded impact events, $\log(\text{losses})$ significantly increases Shannon entropy ($\beta = 0.064$, $P = 0.044$) but not the Herfindahl–Hirschman Index (HHI) ($\beta = -0.003$, $P = 0.958$), suggesting that losses broaden the range of categories discussed without reducing dominance of the largest category. At the category level, losses significantly increase the financial share ($\beta = 0.072$, $P < 0.001$) and significantly decrease the governance share ($\beta = -0.041$, $P = 0.006$), while structural coverage is unaffected. This indicates that economic damage—rather than water levels alone—activates financial discourse in the aftermath of floods.

DV	Loss β	SE	P
Shannon entropy	0.064*	(0.031)	0.044
HHI (concentration)	-0.003	(0.051)	0.958
Financial share	0.072***	(0.021)	< 0.001
Structural share	-0.012	(0.032)	0.703
Nature-based share	0.018	(0.014)	0.183
Governance share	-0.041**	(0.015)	.006
Relocation share	0.004	(0.006)	.510

Note. All models include maximum weekly severity (`weekly_max_severity`, see Panel C). FE: NUTS-3 + year + month. SE clustered at NUTS-3. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Panel C: Cumulative loss history and discourse diversification

Cumulative economic loss history independently predicts discourse diversification. Districts with greater cumulative prior losses show significantly higher Shannon entropy ($\beta = 0.016$, $P < 0.001$), even after controlling for current severity. The interaction between severity and cumulative losses is not significant ($\beta = -0.0004$, $P = 0.559$), indicating that the loss-history effect operates independently of current flood characteristics. At the category level, the interaction of severity with cumulative loss history is significant for structural ($\beta = 0.0018$, $P = 0.002$), financial ($\beta = 0.0009$, $P = 0.028$), and nature-based ($\beta = 0.0008$, $P = 0.007$) shares, indicating that costly flood experience amplifies the responsiveness of these categories to subsequent floods.

Model	Term	β	SE	P	Within R ²
Base	weekly_max_severity	0.025***	(0.002)	< 0.001	0.005
+ loss history	weekly_max_severity	0.025***	(0.002)	< 0.001	0.008
	log_cum_losses	0.016***	(0.002)	< 0.001	
× interaction	weekly_max_severity	0.025***	(0.002)	< 0.001	0.008
	log_cum_losses	0.016***	(0.002)	< 0.001	
	severity × losses	-0.000	(0.001)	0.559	

Category	Interaction β	SE	P
Structural	0.0018**	(0.001)	0.002
Financial	0.0009*	(0.000)	0.028
Nature-based	0.0008**	(0.000)	0.007
Governance	-0.0008	(0.001)	0.147
Relocation	-0.0001	(0.000)	0.066

Note. DV: Shannon entropy (upper) or category share (lower). FE: NUTS-3 + year + month. SE clustered at NUTS-3. Cumulative losses: $\log(1 + \text{total prior losses in million EUR})$, lagged one year. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Table S3. Flood Response Coefficients and Lag Persistence

This table ranks the 12 individual adaptation measures by their flood response coefficient and reports lag persistence. Panel A uses log(1+x) DVs; Panel B uses min-max normalized DVs for cross-measure comparability.

Panel A: Log(1+x) dependent variable

Category	Measure	Flood β	SE	P	Significant lags	Max lag
STRUCTURAL	Dikes & levees	0.059***	(0.006)	< 0.001	5	8
STRUCTURAL	Retention basins	0.044***	(0.004)	< 0.001	5	8
STRUCTURAL	Flood walls	0.016***	(0.003)	< 0.001	1	0
STRUCTURAL	Channel modification	0.001	(0.001)	0.053	2	8
FINANCIAL	Flood insurance	0.011***	(0.002)	< 0.001	5	8
FINANCIAL	Financial support	0.010**	(0.003)	0.002	5	8
GOVERNANCE	Warning systems	0.027***	(0.003)	< 0.001	2	1
GOVERNANCE	Land-use restriction	0.001	(0.001)	0.557	3	2
GOVERNANCE	Flood-risk policies	0.000	(0.001)	0.978	2	2
NATURE-BASED	Floodplain restoration	0.005**	(0.002)	0.002	2	1
NATURE-BASED	Permeable surfaces	0.003*	(0.001)	0.012	2	1
RELOCATION	Voluntary relocation	-0.000	(0.001)	0.755	0	—

Panel B: Min-max normalized dependent variable

Category	Measure	Flood β	SE	P	Sig. lags	Max lag
STRUCTURAL	Retention basins	0.011***	(0.001)	< 0.001	5	8
STRUCTURAL	Dikes & levees	0.011***	(0.001)	< 0.001	5	8
GOVERNANCE	Warning systems	0.009***	(0.001)	< 0.001	2	1
STRUCTURAL	Flood walls	0.004***	(0.001)	< 0.001	1	0
FINANCIAL	Flood insurance	0.003***	(0.001)	< 0.001	5	8
FINANCIAL	Financial support	0.002**	(0.001)	0.002	5	8
NATURE-BASED	Floodplain restoration	0.002**	(0.001)	0.002	2	1
NATURE-BASED	Permeable surfaces	0.001*	(0.000)	0.012	2	1
STRUCTURAL	Channel modification	0.001	(0.000)	0.053	2	8
GOVERNANCE	Land-use restriction	0.000	(0.001)	0.557	3	2
GOVERNANCE	Flood-risk policies	0.000	(0.000)	0.978	2	2
RELOCATION	Voluntary relocation	-0.000	(0.000)	0.755	0	—

Note. Flood β : coefficient on a binary flood indicator (equal to 1 in weeks with any flood) from measure-level models with 12-week cumulative intensity control and NUTS-3 + week FE. SE clustered at NUTS-3. Min-max rescales each measure's log(1+x) to [0,1] independently. *** P < 0.001, ** P < 0.01, * P < 0.05.

Table S4. Adaptation Coverage Composition by Flood Severity

Mean category shares, HHI, and Shannon entropy across severity groups, conditional on at least one article. Shannon entropy increases from 0.14 in non-flood weeks to 0.41 in severe/extreme flood weeks.

Severity	Financial	Structural	Nature-based	Governance	Relocation	HHI	Shannon	n
No flood	0.251	0.450	0.123	0.034	0.004	0.765	0.144	77,961
Minor/Moderate	0.198	0.428	0.102	0.073	0.002	0.678	0.191	2,643
Major	0.147	0.476	0.055	0.113	0.006	0.593	0.324	256
Severe/Extreme	0.112	0.588	0.043	0.130	0.001	0.622	0.406	300

Note. Shares are mean proportions conditional on the total article count > 0. HHI: 0 = diversity, 1 = dominance. Shannon: 0 = single category, $\ln(5) \approx 1.61$ = perfect evenness.

Table S5. Interaction: Current Flood Severity × Cumulative Flood Experience

The interaction term is positive and significant ($\beta = 0.0004$, $P = .002$), indicating that districts with more flood history produce more diverse adaptation coverage when experiencing a flood of a given severity.

Term	β	SE	t	P	
weekly_max_severity		0.0168	(0.003)	5.97	< 0.001
cum_floods_any_lag		0.0001	(0.000)	0.34	0.730
severity × cum_floods		0.0004	(0.000)	3.17	0.002

Note. DV: Shannon entropy. FE: NUTS-3 + year + month. SE clustered at NUTS-3. N = 81,160. Row terms: weekly maximum severity score (weekly_max_severity); cumulative count of prior flood weeks, lagged one week (cum_floods_any_lag); and their interaction (severity × cum_floods).

Table S6. Experience Window Comparison: Shannon Entropy

The 1-year major+ window produces the largest per-event effect ($\beta = 0.035$), roughly three times larger than the full-period count ($\beta = 0.012$). Counting all floods regardless of severity produces no significant experience effect.

Experience window	Exp. β	SE	P	N	Within R ²
Severity only	—	—	—	81,160	0.005
1 yr (any)	0.003	(0.002)	0.079	79,403	0.006
1 yr (major+)	0.035***	(0.007)	< 0.001	79,403	0.008
2 yr (major+)	0.024***	(0.006)	< 0.001	77,768	0.008
3 yr (major+)	0.017***	(0.005)	< 0.001	74,206	0.007
5 yr (major+)	0.015***	(0.005)	< 0.001	67,424	0.008
Full (major+)	0.012***	(0.002)	< 0.001	81,160	0.007
Full (any)	0.000	(0.000)	0.611	81,160	0.005

Note. DV: Shannon entropy. All models include weekly_max_severity + NUTS-3 + year + month fixed effects. Standard errors clustered at NUTS-3. *** P < 0.001.

Table S7. Basin-Level Flood Spillover and Discourse Diversity

Basin-level flooding significantly increases Shannon entropy and reduces HHI, with effect sizes comparable to local flooding.

DV	Severity β	Basin β	Basin SE	Basin P
Nonstructural share	-0.014***	0.001	(0.002)	0.699
HHI (concentration)	-0.014***	-0.005**	(0.002)	0.004
Shannon entropy	0.018***	0.018***	(0.002)	< 0.001

Note. FE: NUTS-3 + year + month. SE clustered at NUTS-3. *** P < 0.001, ** P < 0.01.

Table S8. Basin-Level Spillover by Adaptation Category

Financial coverage is the primary beneficiary of basin-level spillover ($\beta = 0.007$, $P < .001$), while structural coverage shows no significant response.

Category	Basin β	SE	P
Financial	0.007***	(0.002)	< 0.001
Structural	-0.001	(0.002)	0.699
Nature-based	-0.000	(0.001)	0.825
Governance	-0.001*	(0.000)	0.047
Relocation	0.001*	(0.000)	0.022

Note. DV: category share. All models include weekly_max_severity + NUTS-3 + year + month FE. SE clustered at NUTS-3. *** $P < 0.001$, * $P < 0.05$.

Table S9. Overview of Adaptation Typology Considered

Measure	Definition	IPCC Class
Insurance	Financial protection mechanisms, including flood insurance, elemental damage insurance, and other insurance products that provide coverage for flood-related damages.	Economic
Financial support	Economic assistance measures including funding programs, grants, subsidies, financial aid, compensation, and state support for flood prevention, response, or recovery.	Economic
Dikes	Engineered embankments or barriers constructed along riverbanks or coastlines to prevent water from flooding adjacent land areas during high water events.	Engineered and Built Environment
Flood walls and barriers	Fixed structural protective walls or barriers designed to prevent floodwater from entering protected areas, typically constructed of concrete or masonry materials.	Engineered and Built Environment
Channel modifications	Physical alterations to rivers or watercourses, including straightening, deepening, or widening of channels to increase water flow capacity and reduce flood risk.	Engineered and Built Environment
Reservoirs and retention basin	Water storage facilities, including retention basins, polders, reservoirs, and other structures designed to temporarily hold and regulate floodwater, reducing peak flows downstream.	Engineered and Built Environment
Floodplain restoration	Restoration or reactivation of natural floodplains and riparian areas, including re-meandering of rivers and expansion of overflow areas to allow natural water retention.	Ecosystem-based Adaptation
Permeable surfaces	Water-permeable surfaces and infiltration areas, including unsealing of surfaces and sustainable drainage systems that allow rainwater to infiltrate into the ground rather than creating surface runoff.	Ecosystem-based Adaptation
Communication and warning systems	Early warning systems, real-time monitoring systems, and communication infrastructure designed to detect flooding conditions and alert populations to impending flood events.	Technological
Land-use restrictions	Planning and regulatory measures that restrict development or land use in flood-prone areas, including zoning laws, building prohibitions, and spatial planning regulations.	Laws and Regulations
Risk policies	Strategic, legal, and policy frameworks for flood risk management, including flood protection strategies, directives, regulations, and comprehensive risk management plans.	Laws and Regulations
Relocation	Voluntary resettlement or managed retreat of populations and infrastructure from flood-prone areas to reduce exposure to flood hazards.	Misc.
	Household emergency preparedness	(discarded)

Training programs	(discarded)
Public participation in flood planning	(discarded)
Building adaptations and flood-proofing	(discarded)
Reforestation and afforestation	(discarded)
Sediment management	(discarded)
Infrastructure protection (roads, electricity, utilities)	(discarded)

Note. The IPCC Class column maps each measure to the corresponding category of adaptation options assessed in the IPCC Sixth Assessment Report, Working Group II (IPCC, 2022). Measures marked “discarded” were considered but not retained in the analysis (see main text).

Table S10. Keywords used for filtering adaptation-related articles

This table lists the German-language keywords used to pre-filter the full flood article corpus for each of the 12 adaptation measures. For each measure, articles were retained if they contained at least one of the listed keywords. This list of synonyms was compiled using synonym dictionaries and co-occurrence analysis: candidate terms were drawn from German synonym dictionaries and expanded with terms that frequently co-occurred with each measure in the flood corpus, then manually reviewed and pruned to retain measure-specific vocabulary.

Measure	Keywords
Insurance	hochwasserversicherung', 'elementarversicherung', 'elementarschadenversicherung', 'versicherung', 'versicherungsschutz', 'wohngebäudeversicherung', 'naturgefahrenversicherung', 'überschwemmungsversicherung', 'versicherungspflicht', 'pflichtversicherung'
Financial support	'finanzielle unterstützung', 'förderprogramm', 'fördermittel', 'zuschuss', 'subvention', 'subventionen', 'finanzhilfe', 'finanzielle entschädigung', 'schadensersatz', 'soforthilfe', 'aufbauhilfe', 'staatliche unterstützung', 'finanzspritze', 'finanzielle hilfe'
Dikes	deich', 'deiche', 'damm', 'dämme'
Flood walls and barriers	schutzmauer', 'hochwassermauer', 'schutzwand', 'schutzwände', 'flutmauer', 'ufermauer', 'hochwasserschutzwand', 'kaimauer'
Channel modifications	begradigen', 'begradigung', 'gewässervertief', 'flussvertief', 'flussverbreiter', 'sohlvertief'
Reservoirs and retention basin	rückhaltebecke', 'staubecken', 'stausee', 'hochwasserspeicher', 'retentionsbecken', 'regenrückhaltebecken', 'polder', 'retention', 'rückhalteraum', 'entlastungsbecken', 'auffangbecken', 'ausgleichsbecken'
Floodplain restoration	renaturierung', 'auenreaktivierung', 'gewässerrenaturierung', 'renaturierung', 'deichrückverlegung', 'gewässerrückbau', 'flussrenaturierung', 'remäandrierung', 'wiederherstellung', 'überschwemmungsfläche'
Permeable surfaces	versickerungsfläche', 'versickerungsfähige fläche', 'wasserdurchlässige fläche', 'flächenentsiegelung', 'schwamm', 'regenwassermanagement', 'regenwasserversickerung', 'versicker', 'infrastruktur', 'sickerfähige fläche', 'retention'
Communication and warning systems	frühwarnsystem', 'warnsystem', 'hochwasserwarndienst', 'warndienst', 'alarmsystem', 'hochwasseralarm', 'meldesystem', 'frühwarnung', 'warnapp', 'sirene', 'sirenen', 'warn-app', 'katwarn', 'nina', 'echtzeitüberwachung', 'echtzeitpegelmessung', 'hochwasserüberwachung'
Land-use restrictions	flächennutzung', 'flächennutzungsplan', 'bebauungsplan', 'baurecht', 'bauverbot', 'baubeschränkung', 'bauplanung', 'raumplanung', 'raumordnung', 'siedlungsentwicklung', 'bauliche beschränkung', 'nutzungsbeschränkung', 'bauauflagen', 'bebauungsverbot'
Risk policies	hochwasserrisikomanagement', 'risikomanagement', 'hochwasserschutzkonzept', 'schutzkonzept', 'hochwasserrisikomanagementplan', 'risikomanagementplan', 'hochwasserschutzstrategie', 'hochwasserrichtlinie', 'wasserrahmenrichtlinie', 'hochwasserschutzgesetz', 'wasserhaushaltsgesetz', 'landeswassergesetz', 'hochwasservorsorge'
Relocation	freiwillige umsiedlung', 'umsiedlung', 'umsiedelung', 'siedlungsrückzug', 'freiwilliger umzug', 'freiwillige enteignung'

Table S11. Classification performance and article counts by adaptation measure

This table reports SetFit classifier performance and the number of articles retained at each classification stage for all 12 adaptation measures. Columns 2–5 report standard binary classification metrics evaluated against human-annotated labels from 100 texts per class. Columns 6–7 report article counts after keyword-based pre-filtering and after supervised classification respectively, illustrating the reduction attributable to each step.

Class	Accuracy	Precision	Recall	F1	After keyword filter	After supervised classification
Insurance	0.82	0.67	0.84	0.75	48,475	24,052
Financial support	0.86	0.95	0.76	0.84	79,709	40,832
Dikes	0.85	0.70	0.90	0.78	151,566	82,202
Flood walls and barriers	0.92	0.75	0.88	0.81	23,321	15,796
Channel modifications	0.86	0.77	0.86	0.81	2,558	1,229
Reservoirs and retention basin	0.78	0.70	0.76	0.72	61,722	34,499
Floodplain restoration	0.84	0.72	0.85	0.78	26,341	10,742
Permeable surfaces	0.91	0.65	0.86	0.74	62,955	5,691
Communication and warning systems	0.89	0.89	0.66	0.76	29,940	8,668
Land-use restrictions	0.81	0.68	0.80	0.74	21,044	13,237
Risk policies	0.84	0.76	0.71	0.74	23,272	8,316
Relocation	0.75	0.60	1.00	0.75	1,911	997

Table S12. Example training sentences for each SetFit classifier

This table provides illustrative training examples for each of the 12 binary SetFit classifiers. For each adaptation measure, three positive and two negative sentence-level examples are shown. The full training sets for all 12 classifiers are provided in the replication code.

Adaptation measure	Label	Example training sentence (German)
Insurance	Positive	Viele Hausbesitzer schließen eine Hochwasserversicherung ab, um Schäden finanziell abzusichern.
	Positive	Elementarschadensversicherungen bieten Schutz gegen Überschwemmungen und Hochwasser.
	Positive	Nach der Flutkatastrophe stieg die Nachfrage nach Hochwasserversicherungen stark an.
	Negative	Wie Bayern wurde auch Sachsen von schweren Hochwassern und Überschwemmungen heimgesucht.
	Negative	Beim Verein am Vorhaller Weg hat man sich an die Aufräumarbeiten gemacht.
Financial support	Positive	Die Gemeinde stellt Fördermittel für den Wiederaufbau nach dem Hochwasser bereit.
	Positive	Betroffene Hausbesitzer können Soforthilfe beim zuständigen Amt beantragen.
	Positive	Das Förderprogramm unterstützt Kommunen bei der Finanzierung von Schutzmaßnahmen.
	Negative	Die Feuerwehr pumpte das Wasser aus den Kellern.
	Negative	Der Damm wurde nach dem letzten Hochwasser um zwei Meter erhöht.
Dikes	Positive	Die Stadt investiert Millionen in den Bau neuer Schutzdeiche.
	Positive	Entlang des Flusses wurden die Flussdeiche verstärkt und saniert.
	Positive	Der Seedeich an der Nordseeküste schützt seit Jahrhunderten das Hinterland.
	Negative	Zehntausende Tote im Himalaja, Hunderttausende Obdachlose am Mississippi.
	Negative	Im PNP-Interview zieht er Bilanz. Herr Götz, das Jahrhunderthochwasser ist nun bald eineinhalb Jahre her.
Flood walls and barriers	Positive	Eine massive Flutmauer schützt die Altstadt vor Überschwemmungen.
	Positive	Mobile Hochwasserschutzwände wurden installiert.
	Positive	Die Hochwasserschutzwand besteht aus Glaselementen.
	Negative	Ein Rückhaltebecken wurde oberhalb der Stadt gebaut.
	Negative	Die Versicherung übernimmt die Schäden durch das Hochwasser nur teilweise.
Channel modifications	Positive	Durch die Flussbegradigung wurde die Fließgeschwindigkeit des Wassers erhöht.
	Positive	Die Gewässervertiefung ermöglicht einen besseren Abfluss bei Starkregen.
	Positive	Experten fordern eine Rücknahme früherer Flussbegradigung.
	Negative	Die Hochwasserschutzmauer am Rheinufer wurde verstärkt.
	Negative	Sandsäcke wurden entlang der Straßen aufgestapelt, um das Wasser aufzuhalten.
Reservoirs and retention basins	Positive	Ein neues Hochwasserrückhaltebecken wurde oberhalb des Ortes errichtet.
	Positive	Der gesteuerte Polder ist Teil eines modernen Hochwassermanagements.
	Positive	Flutpolder werden nur bei extremen Wasserständen aktiviert.
	Negative	Nach dem Hochwasser standen zahlreiche Häuser unter Wasser.
	Negative	Mobile Hochwasserschutzwände schützen die Altstadt.
Floodplain restoration	Positive	Die Deichrückverlegung schafft neue Auenflächen für natürliche Überflutung.
	Positive	Die Flussrenaturierung stellt natürliche Mäander und Auenbereiche wieder her.
	Positive	Durch Gewässerrenaturierung werden Lebensräume und Retentionsflächen wiederhergestellt.

	Negative	Der Damm wurde nach dem Hochwasser erhöht.
	Negative	Die Flussbegradigung beschleunigt den Abfluss.
Permeable surfaces	Positive	Die Schwammstadt-Maßnahmen verbessern die Versickerung in urbanen Gebieten.
	Positive	Versickerungsfähige Oberflächen reduzieren den Oberflächenabfluss.
	Positive	Nachhaltige Regenwasserbewirtschaftung sorgt für eine effiziente Nutzung von Regenwasser.
	Negative	Die Flussrenaturierung verlangsamt den Abfluss.
	Negative	Die Fußballmannschaft gewann das Heimspiel.
Communication and warning systems	Positive	Das Frühwarnsystem informiert rechtzeitig über steigende Pegelstände.
	Positive	Sensoren überwachen den Pegelstand kontinuierlich.
	Positive	Wetterwarnungen werden per App und SMS weitergegeben.
	Negative	Ein Rückhaltebecken wurde oberhalb der Stadt gebaut.
	Negative	Die Schäden durch die Überschwemmung waren erheblich.
Land-use restrictions	Positive	Der Bebauungsplan untersagt neue Wohnbebauung in ausgewiesenen Überschwemmungsgebieten.
	Positive	Raumordnungsrechtliche Vorgaben begrenzen die Siedlungsentwicklung in Risikolagen.
	Positive	Bauverbote in der Überflutungszone wurden durch neue Vorschriften verschärft.
	Negative	Das Frühwarnsystem informiert die Bevölkerung bei Pegelanstieg.
	Negative	Die Baukosten sind deutlich gestiegen.
Risk policies	Positive	Die Gemeinde hat eine umfassende Schutzstrategie für Risikogebiete entwickelt.
	Positive	Das Schutzkonzept integriert technische und naturbasierte Maßnahmen.
	Positive	Der Hochwasserrisikomanagementplan legt Prioritäten und Verantwortlichkeiten fest.
	Negative	Nach dem Unwetter standen viele Keller unter Wasser.
	Negative	Im Sommer steigen die Temperaturen an.
Relocation	Positive	Ein Umsiedlungsprogramm unterstützt Familien beim Umzug aus gefährdeten Gebieten.
	Positive	Freiwillige Umsiedlung wird in enger Abstimmung mit den Betroffenen umgesetzt.
	Positive	Bürger können sich für ein freiwilliges Wegzugsprogramm anmelden.
	Negative	Die Flussrenaturierung verlangsamt den Abfluss.
	Negative	Das Ministerium stellte neue Fördermittel vor.

Robustness Checks and Sensitivity Analyses

This section reports robustness analyses testing the sensitivity of the main results to alternative model specifications (Tables S13–S18) and to alternative spatial linking strategies between river catchments and NUTS-3 administrative districts (Table A1).

Table S13. Dose-Response

Tests whether the severity–coverage relationship follows a continuous dose-response pattern. Weekly flood intensity enters linearly; 12-week cumulative intensity is binned into categories (reference: 0). Results confirm a monotonically increasing relationship for total FAC and for each category separately.

Category	Intensity β	Cum 1–3	Cum 4–7	Cum 8–15	Cum 16–31	Cum 32+
Total	0.187***	0.059*	0.126*	0.147	0.699*	1.175*
Structural	0.140***	0.019	0.042	0.018	0.177	0.339
Financial	0.024**	0.034***	0.061**	0.079*	0.468*	0.744*
Governance	0.019***	0.001	0.004	0.012*	0.012	0.041
Nature-based	0.002*	0.004*	0.009**	0.011*	0.038*	0.061
Relocation	0.000	0.001	0.002	0.002	0.016	0.003

Note. DV: category article counts. Two-way FE (NUTS-3 + week). SE clustered at NUTS-3. Reference category: the 12-week cumulative intensity bin = 0. *** P < 0.001, ** P < 0.01, * P < 0.05.

Table S14. Temporal Sensitization: Flood Effect × Year Interaction

Temporal sensitization refers to whether the strength of the flood–coverage relationship changes over the study period. Tests whether the flood–coverage relationship has changed over the 2000–2020 study period. The interaction of weekly intensity with year_centered is significant and positive for total FAC ($\beta = 0.013$, $P = 0.017$) under year+month FE, indicating that the same flood intensity produces somewhat more coverage in later years. The effect is driven primarily by governance coverage ($\beta = 0.001$, $P = 0.013$). Under week FE, the interaction is absorbed and not identifiable.

Category	Fixed-effects specification	Intensity β	Year β	Intensity × Year β	Int. P
Total	Week	—	—	-0.001	0.818
Total	Year+month	0.279***	0.010***	0.013*	0.017
Structural	Year+month	0.189***	0.003**	0.007	0.088
Financial	Year+month	0.044***	0.003***	0.000	0.940
Governance	Year+month	0.025***	0.000*	0.001*	0.013
Nature-based	Year+month	0.004***	0.002***	0.000	0.892
Relocation	Year+month	0.000	0.000*	0.000	0.501

Note. DV: category article counts. The flood effect is the coefficient on weekly flood intensity (Intensity β). Year_centered = year - 2010. SE clustered at NUTS-3. Under week FE, year_centered is absorbed; only the interaction is identifiable. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Table S15. Alternative Dependent Variables

Re-estimates the severity–coverage model using three DVs: $\log(1 + \text{articles})$, articles per million inhabitants, and raw counts with top-1% trimming ($\text{articles} \leq 15$). All specifications produce qualitatively identical severity gradients. Under the rate per million, moderate and major floods lose significance due to population normalization. Under trimming, extreme floods lose significance because the trimming threshold removes the most informative observations.

DV specification	Minor	Moderate	Major	Severe	Extreme
log(1 + articles)	0.013***	0.072***	0.087***	0.215***	0.340***
Rate per million	0.004**	0.008	0.017	0.216*	0.801*
Trimmed (≤ 15)	0.056***	0.179*	0.265*	0.468***	0.008

Note. Two-way FE (NUTS-3 + week). SE clustered at NUTS-3. Trimming excludes district-weeks above the 99th percentile (> 15 articles). *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Table S16. Clustering Sensitivity: NUTS-3 vs. NUTS-1

Compares standard errors from NUTS-3-level (401 clusters) and NUTS-1-level (16 clusters) clustering. NUTS-1 clustering produces larger standard errors, and the extreme flood coefficient loses significance at the 5% level ($P = 0.176$). All other severity coefficients remain significant at conventional levels under both clustering schemes.

Severity class	Coef.	NUTS-3 SE	NUTS-3 P	NUTS-1 SE	NUTS-1 P
Minor	0.042	(0.013)	0.002**	(0.019)	0.042*
Moderate	0.000	(0.110)	0.997	(0.098)	0.997
Major	0.420	(0.293)	0.153	(0.262)	0.130
Severe	2.340	(0.789)	0.003**	(0.894)	0.019*
Extreme	5.646	(1.976)	0.004**	(3.972)	0.176

Note. DV: raw article counts. Two-way FE (NUTS-3 + week). Point estimates are identical; only SEs differ. *** $P < .001$, ** $P < .01$, * $P < .05$.

Table S17. Fixed Effects Specification: Week vs. Year + Month

Compares Shannon diversity models using calendar-week FE (1,083 time dummies) versus year + month FE (20 + 12 dummies). The severity coefficient is larger under year+month FE (0.025 vs. 0.016), likely because week FE absorb more within-year variation. The cumulative experience coefficient is not significant under either specification. Results are qualitatively robust.

FE specification	Severity β	Severity P	Cum. experience β	Cum. exp. P
Calendar week	0.016***	< .001	0.000	0.691
Year + month	0.025***	< .001	0.000	0.611

Note. DV: Shannon entropy. Both models include NUTS-3 FE + cum_floods_any_lag. SE clustered at NUTS-3. *** P < 0.001.

Table S18. Robustness of Results to Alternative Spatial Linking Strategies

Assigning flood records derived from the discharge time series of the gauges available from CAMELS-DE to NUTS-3 administrative districts requires a spatial linking decision. River catchments do not follow administrative boundaries, and a gauge station measures discharge at a single point at the catchment outlet, while the impacts of corresponding floods may be felt upstream across the entire extent of the flooded area. To evaluate the effect of this choice, we assess the sensitivity of the main results to five possible choices of spatial linking between river catchments and administrative boundaries.

Linking strategies

M0 – Catchment largest overlap (baseline): Each river catchment is assigned to the single NUTS-3 district with which it shares the largest overlapping area. This yields 10,209 flood-affected region-weeks across 274 districts.

M1/M2 – Gauge point-in-polygon: Gauge location identifies the containing district. 11,238 flood-affected region-weeks across 312 districts.

M3a/M3b/M3c – Catchment overlap thresholds ($\geq 10\%$ / $\geq 30\%$ / $\geq 50\%$): Many-to-many assignment at varying overlap thresholds, yielding 14,145 / 11,381 / 9,688 flood-affected region-weeks respectively.

Method	Minor	Moderate	Major	Severe	Extreme	Flood-weeks	R ² w
M1/M2 Gauge point	0.018***	0.090***	0.130***	0.225***	0.462***	11,238	0.006
M0 Largest overlap	0.013***	0.072***	0.087***	0.215***	0.340***	10,209	0.004
M3a Overlap $\geq 10\%$	0.009***	0.050***	0.046**	0.172***	0.262***	14,145	0.005
M3b Overlap $\geq 30\%$	0.012***	0.063***	0.066***	0.210***	0.348***	11,381	0.005
M3c Overlap $\geq 50\%$	0.013***	0.080***	0.100***	0.214***	0.400***	9,688	0.004
<i>CV (%)</i>	23.8	21.0	36.5 [†]	8.6 [‡]	19.3	—	—

Note. DV: $\log(1 + n_{\text{articles}})$. FE: NUTS-3 + week. SE clustered at NUTS-3. N = 435,887. Bold row (M0) = baseline. CV = coefficient of variation across methods. [†] Highest CV (driven by M3a). [‡] Lowest CV (severe category most stable). *** P < 0.001, ** P < 0.01.

Method selection

We use method M0 (catchment largest overlap) as the primary linking strategy for three reasons. First, it is the most conservative approach: at 10,209 flood-affected region-weeks it avoids over-attributing flood exposure to districts where only a small, potentially upstream portion of a catchment overlaps the administrative boundary. Second, comparison with M3b ($\geq 30\%$ threshold, 11,381 flood-weeks) confirms that relaxing the one-to-one constraint while maintaining a substantive overlap requirement yields nearly identical coefficients for severe and extreme events (n_{severe} : 0.215 vs. 0.210; n_{extreme} : 0.340 vs. 0.348), indicating M0 does not suppress signal by being overly restrictive. Third, M0 avoids the threshold choice inherent in M3a–c, and the sensitivity analysis confirms results are not meaningfully altered across the 30–50% overlap range. The gauge-point methods (M1/M2), while producing the largest coefficients, cover 312 NUTS-3 districts compared to 274 under M0; the additional 38 districts likely reflect gauge placements near administrative boundaries rather than genuine additional flood exposure, making M0 the more spatially grounded choice.