
**Memory sources shape flood risk perception and agricultural decision among
farmers in a drought-oriented irrigation district**

Bo Hu ^a, Shuang Song ^{b c #}, Yijia Wang ^d, Xiao Zhang ^e, Yanxu Liu ^e, Shuai Wang ^e,
Liuna Geng ^{a #}, Patrick Roberts ^b

^a School of Social and Behavioral Sciences, Nanjing University, Nanjing, China;

^b Department of Co-evolution of Land Use and Urbanisation, Max Planck Institute
of Geoanthropology, Jena, Germany;

^c State Key Laboratory of Earth Surface Processes and Disaster Risk Reduction,
Faculty of Geographical Science, Beijing Normal University, Beijing, China;

^d School of Geography, South China Normal University, Guangzhou, China;

^e Key Laboratory of Land Consolidation and Rehabilitation, Land Consolidation and
Rehabilitation Center (Land Science and Technology Innovation Center), Ministry of
Natural Resources, Beijing, China

Correspondence concerning this article should be addressed to:

Shuang Song, song@gea.mpg.de;

Liuna Geng, gengliuna@nju.edu.cn.

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Data Availability Statement

Data will be made available on request.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics statement

Approval for all studies was granted by the Institutional Review Board of Nanjing University and performed in accordance with the principles of the Declaration of Helsinki (NJUPSY202507035). All participants provided informed consent before the study.

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Abstract

5 Irrigation districts that have long been managed around water scarcity are
6 increasingly confronted with rapid-onset flooding, creating new challenges for
7 agricultural flood risk management. This study examines how personal disaster
8 experience, village communication, and social media shape farmers' perceptions of
9 future flood loss and planting intentions in the Hetao Irrigation District of Bayannur
10 City, Inner Mongolia Autonomous Region, China. The case is analytically important
11 because recent flood shocks emerged in a historically drought-oriented human-water
12 system. Based on a field survey of 591 farmers and analyzed using linear and
13 generalized linear mixed-effects models, the results indicate that personal disaster
14 experience is the strongest predictor of future flood loss perception and is also
15 associated with lower willingness to expand cultivated land. Media-based disaster
16 comparison significantly increases perceived future drought loss but does not further
17 increase perceived flood loss. Community disaster communication does not directly
18 heighten flood risk perception, yet it is positively associated with plans to expand
19 production. The study identifies which information channels make flood loss salient
20 and consequential for farm planning after recent events. The findings show that recent
21 flood memory now dominates local risk cognition in this drought-oriented irrigation
22 system. Flood risk management in such settings should combine recent lived experience,
23 locally specific guidance on waterlogging and drainage, and community-based
24 recovery support to strengthen agricultural resilience.

25 *Keywords:* flood risk perception; farmers; community communication; social media;

26 collective memory

27

1. Introduction

28 Floods are among the most disruptive hazards affecting agriculture, and their
29 consequences are expected to intensify as climate change increases the frequency of
30 extreme precipitation and compound hydroclimatic events (Calvin et al., 2023;
31 Diffenbaugh et al., 2017; Fischer & Knutti, 2015). These pressures threaten agricultural
32 production and food security both locally and, through increasingly complex supply
33 chains, at the global scale (Davis et al., 2020; Piao et al., 2010). For farming households,
34 flood risk is a question of anticipation and judgment. Farmers decide whether to
35 maintain production under uncertainty, and these decisions depend on how future
36 hazards are perceived (Jianjun et al., 2015; Mase et al., 2017). Understanding how
37 people perceive risk is crucial for managing flood risk in agricultural regions (Etana et
38 al., 2021; Galarza-Villamar et al., 2024).

39 Risk perception is a subjective construct: individuals' assessments of future
40 hazards depend on objective probabilities, prior experience, and cultural context (Slovic
41 & Weber, 2002; Weber & Hsee, 1998). Flood risk perception is therefore closely tied
42 to livelihood expectations (Adger, 2006). It influences not only how hazards are
43 interpreted, but also whether households feel confident enough to maintain or expand
44 production after a damaging season (Grothmann & Patt, 2005; Jianjun et al., 2015;
45 Mase et al., 2017).

46 This issue is especially important in irrigation districts whose water management
47 institutions were historically organized around drought prevention rather than flood
48 adaptation. In such settings, long-term human-water interactions have strengthened
49 technical routines and social coordination for managing water scarcity, while the
50 capacities needed to anticipate and recover from rapid-onset flooding have often
51 remained less developed. As climate variability increases, these systems may

52 experience abrupt shifts from scarcity-oriented thinking to flood-related concern
53 (Sivapalan et al., 2012; H. Wang et al., 2024; Zscheischler et al., 2018). The resulting
54 transition is not merely hydrological. It also reshapes memory, risk judgment, and
55 livelihood planning (Pahl-Wostl, 2009).

56 Existing research shows that disaster experience is a strong predictor of risk
57 perception, but it also suggests that perceptions are filtered through social
58 communication and mediated information (Botzen et al., 2009; Duinen et al., 2015;
59 Ntim-Amo et al., 2022). The Social Amplification of Risk Framework highlights how
60 risk signals are shaped by different communication stations rather than simply read off
61 from hazard statistics (Kasperson et al., 1988). Related work on collective memory in
62 flood risk research further suggests that experience, communication, and repeated
63 exposure influence which hazards remain cognitively available and decision-relevant
64 over time (Candia et al., 2018; Hirst et al., 2018; Hirst & Coman, 2018; Monteil et al.,
65 2020; Song et al., 2021). However, many studies of agricultural risk examine first-hand
66 experience, village interaction, or media exposure separately. Prior work has advanced
67 understanding of each channel in isolation, but a critical gap remains in explaining how
68 their interactions reshape risk perceptions in socio-hydrological systems undergoing
69 rapid regime shifts. The gap is particularly pronounced in large irrigation districts,
70 where institutional legacies of water-scarcity management shape how emerging flood
71 risks are understood (Di Baldassarre et al., 2013). In rural China, digital platforms and
72 acquaintance networks increasingly coexist as risk information environments, making
73 this a particularly relevant setting for examining multiple channels simultaneously
74 (Chung, 2011; McDonald, 2016).

75 The Hetao Irrigation District in Bayannur, Inner Mongolia, China, provides a case
76 of this transition. As a typical arid irrigation district in the upper Yellow River basin,

77 agricultural production in Hetao has long depended on canal diversion, gravity
78 irrigation, and collective water allocation, with irrigation serving as the primary
79 technical and institutional means by which recurrent drought stress is buffered in
80 everyday farming (Bai et al., 2017; White et al., 2020). Drought has therefore
81 historically been the dominant, yet relatively familiar and partly manageable, hazard
82 within the local human-water system. Yet this same system is not insulated from the
83 risks posed by excess water. Under recent conditions of intensified summer rainfall and
84 more abrupt drought–flood variability, flooding has emerged as a distinct threat that
85 established irrigation routines are less able to absorb. When heavy rainfall exceeds field
86 drainage capacity, damage to field ridges and canals can disrupt both irrigation and
87 runoff conveyance, thereby increasing crop loss and complicating post-disaster
88 recovery. In this historically drought-oriented irrigation district, excess water now
89 threatens agricultural production through mechanisms that differ fundamentally from
90 the more familiar challenge of drought.

91 This study addresses that gap by comparing three information channels: personal
92 disaster experience, community disaster communication, and media-based disaster
93 comparison. We ask two questions. First, how do these channels shape farmers'
94 perceptions of future flood loss and future drought loss? Second, how do they relate to
95 anticipated planting decisions? The paper contributes to current discussions on human-
96 water interactions and flood resilience in three ways: it brings a flood-centered
97 perspective to a major irrigation district, compares first-hand and second-hand
98 information channels within the same empirical model, shows why recent flood
99 memory matters for agricultural resilience in systems undergoing rapid hydrological
100 change, and demonstrates that personal experience, community discussion, and media
101 comparison are associated with different management-relevant outcomes.

102

103

2. Methods

2.1 Study area and recent flood setting

105 Bayannur lies in western Inner Mongolia along the upper Yellow River. The
106 municipality covers approximately 6.4×10^4 km², and its irrigated agricultural area along
107 the Yellow River exceeds 7×10^3 km². The Hetao Irrigation District has supported
108 agriculture for more than two thousand years through large-scale canal diversion and
109 gravity irrigation (ICID, 2019; J. Liu et al., 2015). Major crops include sunflower,
110 maize, and tomato, and agricultural livelihoods remain deeply tied to irrigation
111 infrastructure, water allocation, and collective canal management. For most farmers in
112 Hetao, drought has traditionally been the most salient climatic concern. Crop
113 performance depends on access to Yellow River water, and irrigation scarcity can raise
114 pumping costs, intensify soil-salinity stress, and reduce yields over time (Bai et al.,
115 2017; White et al., 2020). Because drought is familiar and partly manageable through
116 established irrigation practices, it is embedded in everyday production knowledge.

117 The recent flood shocks of 2024 and 2025 changed this balance. According to
118 publicly available meteorological reports (Li, 2025), 2024 was an exceptionally wet
119 year in Inner Mongolia, with annual precipitation 41.6% above the 1991–2020
120 climatological mean and the highest since 1961. Heavy rainfall episodes during the
121 2024 flood season increased the risk of urban and farmland waterlogging in parts of
122 Bayannur and the Hetao irrigation area. In July 2025, another extreme rainfall event
123 affected Inner Mongolia; Wuyuan recorded a maximum 1-hour rainfall of 83.4 mm,
124 exceeding its historical extreme, and subsequent reports described crop lodging and
125 emergency drainage in affected farmland. In low-lying fields, intense summer rainfall
126 could quickly create standing water, crop lodging, and losses that were difficult to offset

127 through familiar drought adaptation routines. Flood impacts were amplified by shallow
128 groundwater and the interdependence of canals. In this context, flood risk should not
129 be understood as the inverse of drought. The two hazards differ in timing, visibility, and
130 perceived controllability. Drought in Hetao is familiar, monitored, and partly governed
131 through irrigation scheduling. Flooding is more abrupt, harder to control at the plot
132 level, and more likely to be experienced as an immediate shock. This difference matters
133 for risk perception because farmers may respond more strongly to a recently
134 experienced hazard that disrupts established expectations of how the water system
135 normally works (Brown et al., 2018; Sutcliffe et al., 2024).

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137 **2.2 Analytical approach**

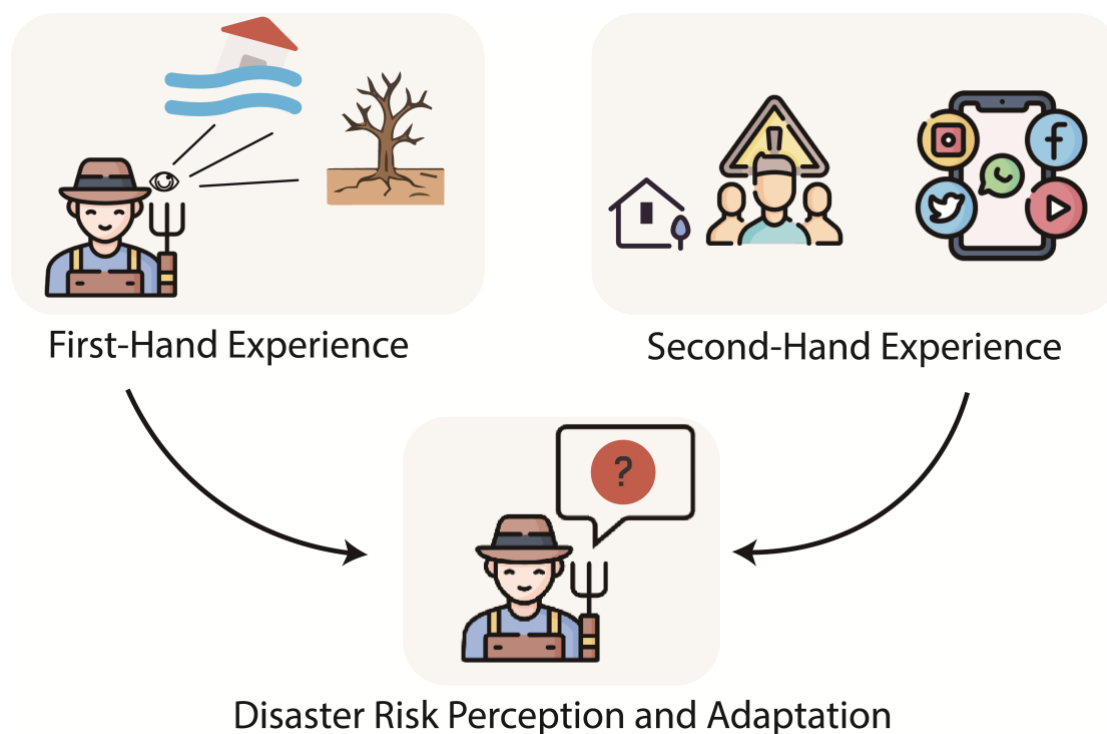
138 The analysis treats risk perception as the outcome of three intertwined information
139 channels. The first is personal disaster experience, which captures first-hand memory
140 of severe losses caused by water shortage or flooding. When recent flood impacts are
141 vivid, emotionally intense, and economically costly, they are likely to make future flood
142 loss more salient and more consequential in subsequent production planning (Botzen et
143 al., 2009; Ntim-Amo et al., 2022).

144 The second channel is community disaster communication. Village-level
145 discussion can amplify risk when negative stories circulate widely, but it can also
146 stabilize expectations by providing information, coordination, and a sense of collective
147 efficacy (Adger, 2003; Conley & Udry, 2010). In an irrigation district, where coping
148 with excess water often requires collective action or shared infrastructure, community
149 interaction may therefore influence planting decisions even when it does not directly
150 raise perceived risk (Hua et al., 2024; G. Wang & Xu, 2024).

151 The third channel is media-based disaster comparison. Short-video platforms,

152 messaging apps, and television circulate highly visual disaster content that can intensify
153 attention to hazards experienced elsewhere (Bathaiy et al., 2021; Spence et al., 2012).
154 These mediated signals may be especially influential when local first-hand memory is
155 weak. By comparing flood and drought outcomes in the same models, we can assess
156 whether second-hand information mainly amplifies hazards that are not currently
157 dominant in local experience. Figure 1 summarizes this analytical framing.

158 This channel-based perspective links risk perception to the social maintenance of
159 memory. First-hand losses can make a hazard immediately salient, community
160 discussion can keep that memory active in everyday conversation, and social media can
161 introduce additional disaster examples that reframe what farmers regard as serious or
162 likely. The key question, therefore, concerns not the possession of risk information itself,
163 but the channel through which particular hazards remain salient during production
164 decisions.



165

166 Figure 1. Analytical framing of how first-hand and second-hand information channels

167 shape risk perception and planting decisions.

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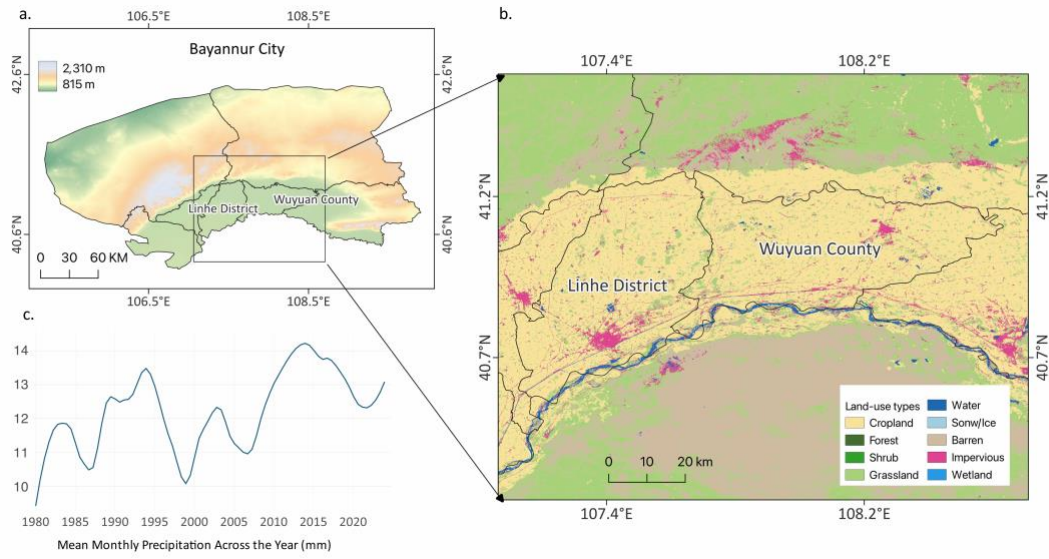
169 **2.3 Survey and sample**

170 The study is based on a field survey conducted from July to August 2025 in the
171 Hetao Irrigation District of Bayannur (Figure 2). A multistage stratified convenience
172 sampling strategy was used to cover villages with different geographical locations,
173 irrigation conditions, and local development contexts. We selected 107 villages from
174 Linhe District and Wuyuan County, which are broadly representative of the central
175 agricultural area of Hetao. Trained interviewers carried out face-to-face household
176 surveys using a structured questionnaire.

177 Questionnaires were excluded if respondents were not primarily engaged in local
178 agriculture or if responses were missing on key explanatory or outcome variables. After
179 screening, 591 valid questionnaires remained¹. The sample reflects the demographic
180 composition of the local farming population, including pronounced ageing. Male
181 household heads accounted for 64.7% of respondents, and farmers aged 50-69 formed
182 the largest age group (63.7%). Nearly half of respondents had primary school education
183 or below. The average cultivated land area was 55.62 mu (1 mu = 0.0667 ha; SD =
184 54.27). Table 1 reports the sample characteristics.

185

¹ As the maximum analytical sample; the demographic counts in Table 1 sum to 597 because it reports descriptive characteristics on the full set of completed questionnaires, six of which were subsequently excluded from the regression analyses because of missingness on focal independent variables (personal disaster experience, community disaster communication, or media-based disaster comparison). Effective sample sizes vary slightly across models (498 to 522) because, although missing values on control variables were imputed (see Section 2.4), missing values on the focal outcomes were not imputed and observations were retained model by model.



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Figure 2. Study villages and historical precipitation in the Hetao Irrigation District. (a) Location of the surveyed area. (b) Detailed spatial distribution of the surveyed sites within the Bayannur Hetao irrigation region. (c) Long-term changes in annual precipitation in Bayannur.

192 Table 1. Participant Demographics

Variable	Category	n	Percent(%)	Mean	SD
Age ^a	25–49	76	12.7		
	50–69	380	63.7		
	70+	100	16.8		
	NA	41	6.8		
Gender	Female	211	35.3		
	Male	386	64.7		
Education	Elementary school and below	252	42.2		
	Middle school	237	39.7		
	High school	55	9.2		
	College	8	1.3		
	NA	45	7.5		
Labor force (n) ^b		559		2.35	0.9
Land area (mu) ^c		591		55.62	54.27
Perceived social status		522		2.87	0.91

193 Note: ^a The high proportion of elderly individuals is due to the distinct aging of the
194 local farming population; ^b Labor force refers to the number of individuals in the
195 interviewed households who are engaged in agricultural farming; ^c 1 mu = 0.0667
196 hectare.

197

198 **2.4 Measures**

199 Two dependent variables capture future hazard perception. Regarding the
200 dependent variables of this study, similar to earlier studies (Botzen et al., 2009; Hansson
201 & Ferguson, 2011; Ntim-Amo et al., 2022; Spence et al., 2011), perceived future
202 drought loss was measured by asking farmers how likely they thought it was that their
203 crops would suffer losses due to drought or water shortage in the future. Perceived
204 future flood loss used the parallel question for flooding. Both variables were recorded
205 on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Although this
206 paper focuses on flood risk, retaining drought as a parallel outcome allows us to assess
207 whether information channels shape the dominant local hazard differently from a

208 comparison hazard.

209 Anticipated production behavior was measured through planting plans for the next
210 5 years. Respondents indicated whether they planned to maintain, expand, or reduce
211 planting scale. For modelling purposes, these responses were recoded into three binary
212 variables corresponding to each decision tendency. The intention measure does not
213 substitute for observed future behavior, but it is informative about the direction of
214 planned adjustment under recent flood experience.

215 The models also include controls for age, gender, education, household labor force,
216 cultivated land area, and perceived social status. These variables help account for
217 demographic and resource differences that may shape both perception and production
218 planning. Perceived social status is included because subjective social position has been
219 consistently linked to risk perception and economic decision-making. Individuals who
220 perceive themselves as occupying higher positions on the social ladder may differ in
221 perceived resources, risk appraisal, and behavioral responses to shocks; related
222 evidence links subjective social rank to cognition and behavior, and shows that risk
223 appraisal, self-efficacy, and risk preferences shape farmers' adaptation, technology
224 adoption, and post-disaster recovery decisions (Kraus et al., 2013; E. M. Liu, 2013;
225 Peng et al., 2018; Wens et al., 2021). Annual household income was collected during
226 fieldwork but showed substantial missingness and was not retained in the final models.
227 Nonresponse on income is unlikely to be missing completely at random, as income
228 questions are sensitive and cognitively demanding, and prior survey-methodological
229 evidence indicates that nonresponse may be concentrated among both low- and high-
230 income respondents; studies in rural China also report substantial item nonresponse for
231 household income questions (Jabkowski & Piekut, 2024; Wan & Yu, 2023). Missing
232 values in the control variables were imputed using mean substitution for continuous

233 variables and mode substitution for categorical variables so that the focal predictors
234 could be estimated on a consistent analytical sample. An analysis involving the
235 sequential exclusion of control variables indicates that the main results were not
236 affected by the inclusion of these variables. Even with these controls, the models do not
237 capture every factor relevant to future production planning. Household debt, land tenure,
238 access to machinery, drainage equipment, and off-farm income may also shape both
239 perceived risk and adaptive capacity. The empirical goal is therefore to identify how
240 information channels are associated with risk perception and planned adjustment, not
241 to claim a fully exhaustive explanation of farming behavior.

242 Regarding the independent variables of this study, similar to earlier studies (Le
243 Dang et al., 2014; Udmale et al., 2014; Xu et al., 2020), personal disaster experience
244 was measured by asking farmers whether they had been affected by natural disasters in
245 the past. The item was, "Have you ever experienced severe yield reduction or total
246 harvest failure due to water shortage or flooding?". We used a five-point scale (1 =
247 Strongly disagree, 5 = Strongly agree). Community disaster communication measured
248 the frequency of farmers' interaction with community members in real life. The question
249 was, "How often do you discuss local disaster-related issues when chatting with
250 neighbors?". We used a four-point scale (1 = Never discuss, 4 = Frequently discuss).
251 Media-based disaster comparison measured farmers' comparative severity judgments
252 between mediated and first-hand disaster experience. Specifically, it captured how
253 severe the disasters depicted on social-media platforms appeared relative to the
254 respondent's own lived experience. The item was, "How do the disasters you see on
255 Kuaishou, WeChat, and TV news in other regions compare to those you have personally
256 experienced?". We used a five-point scale (1 = My experience was more severe, 5 =
257 What I saw in the media was more severe).

258 2.5 Statistical analysis

259 Considering that the data has a significant nested spatial structure, where farmers
 260 are nested within villages and farmers in the same village are influenced by similar
 261 geomorphological and social environments. This study adopted Linear Mixed-Effects
 262 Models for parameter estimation. The model form is as follows:

$$263 \quad Y_{ij} = \beta_0 + \beta_1 X_{ij} + \mu_j + \varepsilon_{ij}$$

264 Y_{ij} is the dependent variable (perceived future disaster risk) for the i -th farmer in
 265 the j -th village; X_{ij} is the vector of explanatory variables at the farmer level; μ_j is the
 266 random intercept at the village level to account for differences in the social environment
 267 of the villages; and ε_{ij} is the residual term.

268 When the outcome variable is categorical, we employed Generalized Linear
 269 Mixed-Effects Models for parameter estimation. The model form is as follows:

$$270 \quad \text{logit}(p_{ij}) = \ln\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_0 + \beta_1 X_{ij} + u_j$$

271 p_{ij} represents the probability that the i -th farmer in the j -th village exhibits a
 272 specific outcome (willingness for anticipated planting decision); X_{ij} is the vector of
 273 explanatory variables at the farmer level; μ_j is the random intercept at the village level
 274 to account for differences in the social environment of the villages; and ε_{ij} is the
 275 residual term. All analyses were carried out in R version 4.4.1 (R Core Team, 2024)
 276 using the following packages: lme4 (version 1.1-35.5; Bates et al., 2015) for fitting
 277 linear and generalized linear mixed-effects models, lmerTest (version 3.1-3;
 278 Kuznetsova et al., 2017) for approximate degrees-of-freedom and p-values for fixed
 279 effects, performance (version 0.12.3; Lüdtke et al., 2021) for marginal and conditional
 280 R^2 statistics, tidyverse (version 2.0.0; Wickham et al., 2019) for data cleaning and
 281 visualization, and mice (version 3.16.0; Buuren & Groothuis-Oudshoorn, 2011) for

282 inspecting missingness patterns. Linear mixed-effects models for the continuous risk-
283 perception outcomes were estimated by restricted maximum likelihood (REML), and
284 generalized linear mixed-effects models for the binary planting-intention outcomes
285 were estimated by maximum likelihood with the Laplace approximation. The random-
286 intercept variance σ^2 at the village level was 0.21 for the future drought loss model,
287 0.10 for the future flood loss model, 0.04 for plan-maintain, 0.36 for plan-expand, and
288 0.27 for plan-reduce, all consistent with non-trivial between-village clustering and
289 justifying the inclusion of village random intercepts. Variance inflation factors for all
290 fixed effects were below 1.5, indicating no problematic multicollinearity.

291

3. Results and Discussion

292 Table 2 reports the mixed-model results. Across all models, personal disaster
293 experience is the most consistent predictor. Its association with future flood loss
294 perception is positive ($\beta = 0.599$, $p < 0.001$), and the coefficient is larger than that for
295 future drought loss ($\beta = 0.255$, $p < 0.001$). Waterlogging and crop lodging, produce a
296 different kind of memory than drought scarcity. They are highly abrupt visible, and
297 difficult to offset through routine management. The stronger flood coefficient suggests
298 that recent flood events have recalibrated farmers' expectations of what the local water
299 environment can do. For farmers in Hetao, recent flood losses represent high-
300 consequence memories that transform risk from abstract statistics into concrete
301 reference points (Pachur et al., 2012; Weber, 2006). The associated tendency toward
302 production contraction also reflects loss aversion. Farmers who have experienced
303 severe losses prefer reducing exposure over maintaining or expanding scale, consistent
304 with evidence from flood-affected agricultural communities elsewhere (Lindell & Perry,
305 2012; Ricart et al., 2025).

306 Personal disaster experience is also associated with anticipated planting

307 adjustment. Farmers reporting stronger experience are less willing to expand cultivated
308 land ($\beta = -0.355$, $p < 0.01$) and more willing to reduce scale ($\beta = 0.402$, $p < 0.01$). This
309 suggests that flood memory is not confined to cognitive appraisal; it is linked to
310 defensive livelihood planning. For agricultural flood resilience, reduced exposure may
311 be a rational response to recent flood losses. This is consistent with a broader pattern in
312 natural hazard research in which elevated risk perception does not automatically
313 translate into preparedness or investment (Wachinger et al., 2013). Persistent
314 contraction after flood shocks may weaken local production capacity if recovery
315 support is insufficient.

316

317 Table 2. Mixed effects model for disaster risk perception and planting decisions.

	Future Drought Loss	Future Flood Loss	Plan to Maintain	Plan to Expand	Plan to Reduce
(Intercept)	1.389*** (0.394)	0.930** (0.350)	1.229 (0.810)	-2.474* (1.248)	-2.755** (1.058)
Age	-0.047 (0.057)	-0.023 (0.051)	0.065 (0.113)	-0.450** (0.167)	0.260 (0.148)
Gender (Ref Female)	-0.162 (0.113)	0.018 (0.101)	0.044 (0.224)	-0.302 (0.325)	0.133 (0.282)
Education	0.002 (0.078)	-0.065 (0.070)	-0.254 (0.149)	0.304 (0.210)	0.141 (0.189)
Labor Force	-0.031 (0.059)	-0.059 (0.053)	0.248 (0.132)	-0.178 (0.201)	-0.251 (0.166)
Land Area	0.044 (0.057)	-0.048 (0.051)	-0.252* (0.109)	0.114 (0.143)	0.284* (0.124)
Social Status	-0.004 (0.064)	0.066 (0.057)	0.109 (0.129)	0.011 (0.188)	-0.146 (0.162)
Personal Disaster Experience	0.255*** (0.046)	0.599*** (0.041)	-0.022 (0.094)	-0.355** (0.128)	0.402** (0.144)
Community Disaster Communication	-0.009 (0.054)	0.077 (0.049)	-0.183 (0.115)	0.445* (0.197)	-0.017 (0.138)
Media-based disaster comparison	0.177*** (0.041)	0.053 (0.036)	0.004 (0.080)	-0.020 (0.121)	0.008 (0.100)
Marginal R^2	0.103	0.318	0.057	0.144	0.100
Conditional R^2	0.240	0.388	0.111	0.291	0.215
AIC	1695.164	1564.062	613.981	363.231	453.443
BIC	1746.071	1614.875	660.816	410.066	500.278
Num. obs.	514	510	522	522	522
Num. groups: village	107	107	106	106	106

318 Note. * $p < .05$. ** $p < .01$. *** $p < .001$. Missing values in control variables were
319 imputed before analysis: mean substitution for continuous controls and mode
320 substitution for categorical controls. The significance results for the primary predictor
321 variables (excluding control variables) are displayed in bold. A total of 107 distinct
322 village-level clusters in the final dataset, which are used as the random-intercept
323 grouping in all mixed-effects models; sample sizes per model vary slightly because not
324 every cluster contributed observations to every outcome.

325

326 Community disaster communication shows a different pattern. It is not
327 significantly associated with perceived future flood or drought loss, but it has a positive
328 association with plans to expand production ($\beta = 0.445$, $p < 0.05$). This suggests that
329 village discussion functions less as a panic mechanism and more as a coordination
330 resource, contrary to accounts that emphasize community rumour and collective
331 anxiety as the primary product of disaster communication (Tierney et al., 2006).
332 Evidence from flood-prone communities elsewhere supports this more nuanced reading:
333 in European settings, dense local ties can simultaneously enhance self-efficacy and
334 mobilize mutual support, even while sometimes downplaying formal risk estimates
335 (Babcicky & Seebauer, 2017; Hudson et al., 2020). In flood-vulnerable rural Asia,
336 different forms of social capital tend to function at different stages of the hazard cycle
337 (Azad & Pritchard, 2023).

338 In Hetao, where agricultural production depends on shared irrigation infrastructure,
339 community communication plausibly may function primarily as social support and as a
340 source of collective efficacy, although collective efficacy itself was not directly
341 measured in this survey and remains a proposed mechanism (Zhang et al., 2023),
342 enabling farmers to maintain production confidence even in the face of recent flood
343 damage. When farmers believe that neighbours, village leaders, and local irrigation
344 networks can respond collectively, they can reduce uncertainty about how to continue
345 farming under mixed drought-flood conditions, strengthen informal risk-sharing
346 arrangements (Fafchamps & Lund, 2003), and facilitate the sharing of specific local
347 adaptation knowledge, such as drainage routing, waterlogging-tolerant varieties, and
348 field repair methods ² (Tai et al., 2020; Tozier De La Poterie et al., 2018). In that sense,

² These specific knowledge-transfer practices are plausible mediating channels suggested by the existing literature;

349 community communication supports recovery and continuity.

350 Media-based disaster comparison reveals a third mechanism. Farmers who
351 perceived disasters seen on social media and television as more severe than their own
352 experience reported higher perceived future drought loss ($\beta = 0.177$, $p < 0.001$), but the
353 same variable is not significant for future flood loss. It suggests that mediated disaster
354 signals do not operate uniformly across hazards. They matter most when local first-
355 hand memory is comparatively weaker or less dominant. The amplification mechanism
356 for drought perception operates through vicarious exposure (Holman et al., 2014).
357 Social media platforms deliver visually intense disaster content from other regions that
358 triggers emotional responses even without local equivalents (Houston et al., 2015; Joffe,
359 2008). By translating geographically distant hazards into proximal, concrete exemplars,
360 mediated signals can reduce the psychological distance of climate risks and elevate both
361 societal and personal risk judgments (Spence et al., 2012; Van Der Linden, 2015).

362 For flood perception, recent lived experience already provides a strong and locally
363 anchored signal (Lechowska, 2018). Additional media exposure may add less when the
364 hazard has already been made salient by recent firsthand experience (Xu et al., 2020).
365 Drought perception, by contrast, remains more open to amplification through cross-
366 regional comparison. In practice, farmers may see drought devastation elsewhere and
367 incorporate those images into their own expectations even if recent local experience is
368 dominated by flooding (Rosenthal, 2022). This finding helps explain why digital media
369 can expand the hazard imagination beyond what is immediately experienced on the
370 ground. In Hetao, historically, local knowledge, infrastructure, and policy attention
371 have emphasized the management of water scarcity. Recent flood shocks have not

they were not directly measured in our survey, and future research should test them with targeted items on drainage practice, varietal choice, and repair-cooperation behaviour

372 erased that history, but they have overlaid it with new memories of excess water,
373 drainage failure, and sudden loss. As a result, farmers' perceptions now reflect a mixed-
374 risk environment. First-hand flood experience anchors local judgment, while second-
375 hand media exposure continues to shape concern about other possible hazards. This
376 selective amplification matters because digital communication redistributes attention
377 across hazards. Risk communication strategies therefore need to be hazard-specific and
378 locally grounded rather than assuming that all disaster information has the same
379 behavioral effect.

380 The asymmetry in model fit reinforces this interpretation. The marginal R^2 for
381 future flood loss perception is 0.318, while the marginal R^2 for future drought loss
382 perception is only 0.103. The three information channels we measure (personal
383 experience, community communication, and media-based comparison) jointly capture
384 much more of the variance in flood-loss perception because in the current Hetao context
385 flood-loss perception is being actively reshaped by a recent, unfamiliar, and locally
386 concentrated experience that the three channels are well-suited to register. Drought-loss
387 perception, by contrast, sits within a long-standing, broadly shared, and culturally
388 familiar hazard schema that varies less sharply with recent first-hand experience and is
389 may shaped by additional factors, including inherited family narratives and farm-level
390 adaptation history.

391

392 **3.1 Policy Implications**

393 Based on these findings, agricultural risk management policies for the Hetao
394 Irrigation District and comparable ecologically fragile regions should adopt channel-
395 differentiated intervention strategies. First, personal disaster experience appears to have
396 a lasting restrictive effect on production expectations. Farmers with stronger first-hand

397 experience of the currently salient hazard are more likely to anticipate higher future
398 losses and to plan production contraction, suggesting that simple disaster relief
399 payments may be insufficient to restore production confidence. Targeted, multi-year
400 recovery instruments, such as subsidized stress-tolerant seed packages and policy
401 guidance for moderate production recovery, may help prevent severe loss experience
402 from becoming a persistent cycle of risk avoidance and production contraction. Second,
403 community communication should be treated as a core resource for local risk
404 management (Adger, 2003; Yijia et al., 2022). Its positive association with willingness
405 to expand indicates that village-level discussion networks can strengthen production
406 confidence and support adaptive decision-making. Local extension services and
407 irrigation-district administrators could therefore organise structured community fora
408 that link experienced farmers with technical staff, combining peer learning with formal
409 agronomic, hydrological, and insurance-related advice. Third, media-based disaster
410 comparison should be used more selectively. Because mediated disaster content
411 increases concern about historically familiar risks but not necessarily about the
412 currently unfolding local risk, generic media warnings may misallocate attention or
413 amplify anxiety without producing adaptive action. Meteorological and agricultural
414 departments should make fuller but more targeted use of communication platforms:
415 messages about past, well-known threats should be paired with concrete, locally tested
416 adaptation options to translate vigilance into action, while communication about
417 present risks should rely more heavily on local evidence, field-level cues, and practical
418 response guidance rather than stylised warning narratives (Witte, 1992). More broadly,
419 comparable regions facing mixed hydroclimatic transitions may apply the same
420 channel-differentiated approach, while calibrating interventions to local crop structures,
421 market conditions, and social institutions. As anthropogenic warming is expected to

422 increase the likelihood of compound hydroclimatic extremes and rapid transitions
423 between different forms of water-related stress in the twenty-first century, calibrated
424 interventions that align personal experience, community communication, and media-
425 based risk comparison are likely to become increasingly important for sustaining
426 agricultural resilience (H. Wang et al., 2024; Zscheischler et al., 2018).

427 The findings also speak to broader work on socio-hydrology and collective
428 memory. Recent flood events can rapidly shift the reference hazard in local decision-
429 making, even where long-term water institutions were built around another problem.
430 For comparable river basins and irrigated floodplains, resilience planning should
431 therefore pay closer attention to how new flood memories are incorporated into
432 advisory systems, infrastructure management, and community coordination. Future
433 research can extend this analysis by tracking whether the influence of recent flood
434 experience persists over time and whether anticipated planting adjustments translate
435 into observed changes in crop choice, land area, or household preparedness.

436 **4. Conclusion**

437 This study examined how personal disaster experience, community
438 communication, and media-based disaster comparison shape farmers' risk perception
439 and planting intentions in the Hetao Irrigation District. The main finding is that recent
440 flood experience now dominates local risk cognition in a historically drought-oriented
441 irrigation system. Farmers who reported stronger disaster experience perceived higher
442 future flood loss and were more likely to plan production contraction. By contrast,
443 community communication was associated with greater willingness to expand,
444 suggesting that local discussion networks support coordination and confidence rather
445 than simply amplifying fear.

446 Media-based disaster comparison heightened drought risk perception but had no

447 significant effect on future flood loss perception. This indicates that second-hand
448 information is most influential where local first-hand memory is less dominant, whereas
449 recent flood shocks provide a sufficiently strong signal on their own. For flood risk
450 management, the implication is that communication strategies should distinguish
451 between hazards anchored in lived experience and hazards circulating primarily
452 through mediated comparison. For the Hetao Irrigation District and comparable
453 agricultural regions, strengthening flood resilience requires more than reinforcing flood
454 warnings. It requires reconnecting risk communication with the specific flood
455 characteristics of the local water system. In systems shaped by long-term human-water
456 interactions, recent flood memories can become a powerful basis for adaptive change.

457

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