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Environmental Accounting of Flood Risk in The Krishna Basin: Evidence from River Bank Settlements in Maharashtra

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ABSTRACT
Floods have become a recurring source of economic loss in river-basin regions, particularly in developing economies where livelihoods and settlements remain closely tied to river systems. This study examines flood risk in the Upper Krishna Basin of Maharashtra using an environmental accounting approach that links basin-level exposure with household-level economic losses. The analysis combines secondary data on river-bank settlements with primary survey data collected from 664 flood-affected households across 20 villages following the 2021 flood event. Household flood losses are measured across major components, including crop damage, housing loss, livestock loss, and wage loss. To identify the determinants of flood-induced economic damage, the study employs a set of econometric models, including ordinary least squares, log-linear regression, and a probit model for severe loss probability. The study reveals substantial variation in flood exposure and loss across districts, with Sangli experiencing the highest household-level losses and Kolhapur recording higher population exposure. Flood depth and flood duration emerge as the most important drivers of both the magnitude and severity of losses, while housing quality and distance from the river reduce vulnerability. The findings of the study have highlighted the role of basin-level factors, including river regulation and backwater effects, in shaping flood outcomes. The study concludes that floods in the Upper Krishna Basin function as recurring economic shocks and that effective flood management requires basin-wide coordination, improved settlement planning, and targeted livelihood protection. The environmental accounting framework adopted here offers a practical basis for integrating economic loss assessment into flood policy and river-basin management
Keywords: Flood risk; Environmental accounting; Household economic loss; River-bank settlements; Krishna Basin; Econometric analysis

1. INTRODUCTION:

Floods have emerged as one of the most frequent and economically damaging natural hazards across the world. Between 1990 and 2022, more than 4,700 flood events were recorded in 168 countries, affecting over 3.2 billion people and resulting in economic losses exceeding US$1.3 trillion (World Health Organization, 2023). Flood disasters accounted for a substantial portion of the human and economic burden of all natural hazards. Globally, more than two billion people were affected by floods between 1998 and 2017, and their cumulative economic impacts were estimated at around US$656 billion (Taguchi et al., 2022). These figures clearly demonstrate that floods dominate the landscape of weather-related disasters, both in terms of affected populations and financial consequences (World Health Organization, 2023; Taguchi et al., 2022).

The economic dimension of floods has attracted increasing attention in recent years, particularly as climate change, urbanization, and demographic shifts have intensified exposure. According to the United Nations Office for Disaster Risk Reduction (UNDRR), direct disaster costs are growing rapidly, with total losses from natural hazards now exceeding US$202 billion annually, and indirect and ecosystem impacts potentially adding up to US$2.3 trillion yearly (UNDRR, 2025). Among different natural hazards, hydrological events such as floods remain a leading cause of economic loss, accounting for up to 36% of total direct disaster losses projected globally by 2050 (CIWEM, 2024). These trends indicate that flood risk is not only a matter of physical geography but also a consequence of economic development patterns, settlement dynamics, and environmental change.

While global studies emphasize the magnitude of flood impacts, the burden of economic loss is not distributed evenly across regions or populations. Weather-, climate-, and water-related disasters caused losses equivalent to more than 5% of gross domestic product (GDP) in several vulnerable countries between 2019 and 2023, with some cases exceeding 30% of local GDP (World Bank, 2025). This indicates that lower-income and hazard-exposed regions often suffer disproportionately high economic strain due to floods and similar events. Moreover, the World Meteorological Organization reported that Asia experienced an estimated US$1.4 trillion in economic losses from climate and water extremes over the last five decades, with floods representing a significant share of that burden (WMO, 2023).

Despite these well-documented patterns of loss at the global scale, much of the literature on flood risk has focused on hydrological characterization, such as susceptibility mapping or physical hazard assessment (e.g., Saharia et al., 2024). These studies have been valuable in understanding where floods are likely to occur, but they often stop short of analysing how floods affect economic outcomes, particularly at the household and community levels. In other words, existing research frequently identifies the existence of hazard without fully accounting for the economic exposure and loss outcomes experienced by flood-prone populations.

From an environmental economics perspective, floods are best understood as negative environmental externalities events where private decisions about settlement and land use interact with shared natural systems, generating costs that are not fully internalized by individual actors. To capture these costs systematically, the concept of environmental accounting has been developed, which integrates environmental phenomena into economic analysis by linking exposure (e.g., the number of people or assets at risk) with vulnerability and realized losses (Cao et al., 2022; Zhou et al., 2024). Environmental accounting thus shifts the analytical lens from geographical hazard mapping to economic impact assessment, enabling policymakers to quantify and compare flood effects on both welfare and public expenditure.

The Krishna Basin in India provides a compelling context for this type of integrated analysis. The basin supports dense settlements, extensive agricultural production, and diverse economic activities, yet it remains exposed to repeated monsoon flooding. River-bank communities in the basin have historically experienced floods that have disrupted livelihoods, damaged assets, and imposed recurrent economic costs. The 2021 flood in the Krishna Basin, in particular, affected vast stretches of riverine areas, prompting both relief interventions and community displacement. However, systematic economic analysis of loss at both the basin and household levels remains limited.

This study applies an environmental accounting framework to the Krishna Basin, combining secondary exposure data with primary household-level loss data collected after the 2021 flood. The objective is to quantify the economic effects of flood exposure, identify the determinants of household flood losses, and inform policy responses that could enhance resilience. By integrating econometric tools with economic theory and empirical data, this paper contributes to a more comprehensive understanding of how floods impose economic burdens on vulnerable river-bank settlements.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 presents the conceptual framework. Section 4 describes the study area. Section 5 explains the data sources and survey design. Section 6 outlines the econometric methodology. Section 7 presents the empirical results. Section 8 discusses the findings, followed by policy implications in Section 9. Section 10 concludes the paper.

2. REVIEW OF LITERATURE AND RESEARCH GAP

This review organizes existing work into five thematic strands that are directly relevant to this paper's objectives: (A) global economic impacts and environmental accounting, (B) exposure and spatial vulnerability, (C) household-level loss accounting and survey studies, (D) India- and basin-level studies (including Krishna Basin literature), and (E) econometric and damage-function approaches used to link hazard, exposure, and loss. Each theme contains concise reviews of representative, peer-reviewed studies or authoritative reports. After the thematic review I identify the specific research gaps that the present paper will address.

A. Global Economic Impacts and Environmental Accounting

Botzen et al. (2019) provided a broad review of the economic impacts of natural disasters. They synthesized evidence showing that extreme events produce substantial costs to national economies and that agricultural losses often explain a large share of short-run GDP declines after flood events. The review emphasized that the magnitude of disaster losses varied widely across countries and that agriculture and infrastructure drove much of the heterogeneity (Botzen, 2019). Felix et al. (2025) examined socioeconomic and environmental impacts of floods in India and argued for an integrated accounting framework that captures both direct and indirect economic effects. Their results reinforced the need for combining secondary exposure metrics with micro-level loss data to produce policy-relevant accounts of flood costs (Felix et al., 2025). The World Bank (Behrer et al., 2024) provided recent evidence on household and firm exposure across South Asia, showing that firm size and household occupation mediate exposure and recovery capacity. Their spatially detailed analysis helped to link exposure measures to likely economic consequences for micro and small enterprises (Behrer et al., 2024).

These contributions established that a formal economic accounting of flood loss requires both macro exposure indicators and micro loss observations; environmental accounting provides the conceptual bridge between them.

B. Exposure, Spatial Vulnerability, and Environmental Assets

Bertoli et al. (2024) advanced methods for assessing the exposure of environmental assets to river floods. They proposed an exposure typology and a practical estimation method (EnvXflood) that operationalized how environmental assets should enter flood-risk accounting (Bertoli et al., 2024). This work is relevant because environmental assets and community livelihoods often overlap along river banks.

Hamidi et al. (2022) combined exposure analysis with social vulnerability indices in a rural context. Their integrated approach revealed that social vulnerability and exposure jointly determined the severity of household impacts after floods. The study thus gave empirical support to treating exposure and social vulnerability as complementary in accounting frameworks (Hamidi et al., 2022).

Poussard et al. (2021) reviewed inequalities in flood exposure, noting that disadvantaged groups frequently faced higher exposure in coastal and riverine settings. They documented methodological approaches for measuring exposure inequality and argued that distributional analysis must be embedded in any flood-risk account (Poussard et al., 2021).

Taken together, these studies show that exposure must be disaggregated spatially and socially for environmental accounting to capture distributional outcomes.

C. Household-level Loss Accounting and Survey Evidence

Lahiri and Biswas (2023) analysed the long-run impact of flooding on household balance sheets in India. Using panel and difference-in-differences methods, they found that floods had enduring effects on asset composition and indebtedness. Their micro-level evidence illustrated how realized losses can propagate into sustained financial vulnerability (Lahiri & Biswas, 2023).

Studies of specific Indian floods provide practical templates for household loss surveys. For example, Patnaik, Sane, and others studied the Chennai 2015 floods and measured consumption and asset effects using panel methods; these surveys revealed immediate consumption drops and partial post-event recovery (Patnaik et al., 2020). That work suggested survey timing and module design that capture consumption and income shocks reliably.

George (2022) and Shrestha et al. (2021) developed damage-function approaches and field protocols for assessing farm-level crop and livestock losses. Their methods integrated depth-duration metrics with farm survey data to estimate monetary crop losses, a step that translated physical flood measures into economic terms (George, 2022; Shrestha et al., 2021).

Agarwal et al. (2024) used quasi-experimental techniques to show that urban flood shocks reduced household spending by a measurable amount during the Chennai event. Such reduced-form analyses demonstrate how survey data can identify short-run economic impacts (Agarwal et al., 2024).

This body of work demonstrates that carefully designed household surveys yield robust and policy-useful estimates of realized economic losses, and that the combination of physical and economic modules is essential.

D. India, Regional and Krishna Basin Studies

Parida (2020) provided a cross-state panel analysis of flood impacts in India. The paper estimated that floods had measurable effects on state-level economic indicators and that economic development influenced both fatalities and damage outcomes, suggesting an interaction between development level and disaster impact (Parida, 2020).

Pakhale et al. (2023) investigated flood frequency and trends within subsystems of the Krishna Basin. They found mixed evidence for increasing flood intensity across sub-basins and underlined the necessity of localized analysis for basin planning (Pakhale et al., 2023). Their work implied that basin-level interventions should be informed by subsystem heterogeneity.

Sharma et al. (2024) focused on flood detection and mapping in the Upper Krishna Basin and demonstrated hydrological methods to delineate flood extents. Their mapping effort supports exposure identification at village scales while also underscoring data gaps for monetary loss estimation (Sharma et al., 2024).

These regional studies make clear that basin specificity matters; the Krishna Basin has internal variation that requires both secondary delineation and primary economic measurement.

E. Econometric Approaches and Damage-Function Modeling

Botzen and coauthors and other reviews emphasised the use of econometric tools to connect hazard variables to economic outcomes (Botzen, 2019). Empirical strategies typically include OLS for absolute losses, log-linear models for proportional effects, and discrete choice or probit models for severe-loss probabilities. These model classes have become standard because they balance interpretability and robustness.

Yan et al. (2023) proposed loss-resilience quantification frameworks that explicitly linked loss functions to resilience metrics. They used econometric and structural modeling to evaluate how resilience interventions alter loss curves. Their approach is useful when the research goal extends beyond measurement toward policy simulation (Yan et al., 2023).

Development of crop damage functions such as those by Shrestha et al. (2021) provided parametric relationships between depth/duration parameters and crop loss percentages. These damage functions are important for converting observed physical flood characteristics into monetary agricultural losses within econometric specifications.

Research Gap

The reviewed literature yields three concise gaps. First, many basin and hazard studies identify where floods occur, but they do not quantify realized household-level economic loss systematically across river-bank settlements. Second, where household surveys exist, they often address single events or urban settings; fewer studies have combined basin-level exposure accounting with microeconomic loss measurement in riverine rural contexts. Third, econometric work has established useful model forms, but integrated studies that combine exposure, household survey evidence, and formal econometric inference for river-bank communities in an Indian basin are scarce.

This paper has attempted to fill those gaps by integrating a basin-level environmental accounting of population exposure with primary household survey data on the 2021 flood. It will estimate monetary loss components at the household level, apply OLS, log-linear, and probit models to identify determinants of loss and severe loss, and aggregate micro losses to produce basin-level economic accounts. By doing so, the paper has attempted to link spatial exposure metrics to observed economic outcomes and, therefore, provide a directly policy-relevant assessment that bridges hydrology and economic policy.

3. CONCEPTUAL FRAMEWORK

Flood risk has increasingly been conceptualized in economics not merely as a natural phenomenon, but as the outcome of interactions between environmental processes and human economic behaviour. From an environmental economics perspective, floods represent a class of negative environmental externalities in which private settlement, production, and land-use decisions interact with river systems to generate costs that are not fully internalized by individual economic agents. These costs are subsequently borne by households, communities, and the public sector through income loss, asset destruction, and repeated fiscal outlays for relief and rehabilitation (Cao et al., 2022; Zhou et al., 2024).

The analytical foundation of this study is rooted in the environmental accounting framework, which extends conventional economic analysis by explicitly incorporating environmental risks and their economic consequences into accounting systems. Environmental accounting has been widely used to assess degradation of natural capital, pollution costs, and climate-related damages. In the context of floods, this framework enables the systematic linkage of hazard, exposure, vulnerability, and realized economic loss within a unified structure (Yang, 2022).

3.1 Flood Risk as an Economic Process

Flood risk is commonly expressed as the interaction of three core components:

$FRi=f(Hi,Ei,Vi)$

Where

FRi - denotes flood risk for household or settlement i

Hi - represents flood hazard characteristics such as depth and duration,

Ei - captures exposure in terms of population, assets, and livelihoods located in flood-prone areas, and

Vi - reflects vulnerability arising from socioeconomic and structural conditions.

While hydrological studies have primarily focused on modeling Hi, economic analysis emphasizes the role of Ei and Vi in determining the magnitude of losses. Even moderate flood hazards can generate substantial economic losses when exposure and vulnerability are high, particularly in river-bank settlements where agricultural land, housing, and infrastructure are spatially concentrated (Cao et al., 2022).

3.2 Environmental Accounting of Flood Exposure

Environmental accounting treats exposure as a measurable stock that represents potential economic loss embedded in a geographic space. In river-basin economies, population exposure serves as a practical proxy for economic exposure because population density is closely associated with labour supply, agricultural output, and asset accumulation. Accordingly, the exposure component in this study is defined as:

$$E_j = \sum_{i=1}^{n_j} P_{ij}$$

Where,

E_j denotes exposure in settlement or taluka j and

P_{ij} is the population of village i within that settlement

This formulation allows exposure to be aggregated spatially, facilitating basin-level comparisons while retaining relevance for microeconomic loss estimation. Prior studies have demonstrated that exposure-based indicators provide robust first-order estimates of economic vulnerability in data-constrained environments (Yang, 2022; Zhou et al., 2024).

3.3 Realized Economic Loss and Household Flood Accounting

Environmental accounting becomes economically meaningful when exposure is linked to realized losses. In this study, household-level flood loss is conceptualized as the sum of direct and indirect economic damages incurred during the flood event. Total household flood loss is expressed as:

$$FL_i = CL_i + HL_i + LL_i + WL_i$$

FL_i is total flood loss of household i,

CL_i represent crop loss,

HL_i denotes housing damage

LL_i refers to livestock loss and

WL_icaptures wage and income loss due to work disruption

This decomposition reflects the multidimensional nature of flood impacts in rural and semi-urban river-bank economies. Agricultural households are particularly vulnerable because crop and livestock losses simultaneously affect income flows and asset bases, while wage losses amplify short-term liquidity constraints (Cao et al., 2022).

3.4 Linking Exposure to Loss through Econometric Modeling

The conceptual framework further assumes that realized flood loss is a function of both hazard intensity and household-specific characteristics. This relationship can be expressed in reduced-form as:

$FL_i = g(H_i, E_i, Z_i)$

Where

Z_i is a vector of household characteristics including landholding size, housing quality, occupation, and access to relief.

This formulation provides the basis for econometric estimation using ordinary least squares, log-linear models, and probabilistic models of severe loss. The inclusion of household characteristics acknowledges that exposure does not translate into loss uniformly across households. Instead, economic structure, asset ownership, and adaptive capacity mediate the conversion of exposure into realized damage (Zhou et al., 2024).

3.5 Flood Risk as A Recurrent Economic Shock

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A critical assumption underlying this framework is that floods constitute recurrent, rather than purely stochastic, economic shocks in river-bank settlements. Repeated flood exposure erodes household resilience by depleting savings, increasing indebtedness, and discouraging productive investment. From an environmental economics standpoint, this persistence transforms floods into a structural development constraint rather than a transitory disturbance (Yang, 2022).

Consequently, environmental accounting of flood risk must move beyond one-time damage estimation and instead focus on systematic measurement of exposure and loss over time. The conceptual framework adopted in this study aligns with this perspective by integrating spatial exposure indicators with household-level loss accounting and econometric analysis.

This conceptual framework has provided the analytical foundation for the empirical sections that follow. It justifies the use of population exposure as a basin-level indicator, supports household-level loss accounting using primary survey data, and it has also motivated to the application of econometric models to identify the determinants of flood losses and severe loss probability.

4. STUDY AREA

The study is confined to the Upper Krishna Basin in the state of Maharashtra, which forms the upstream segment of the Krishna River system in western India. The basin originates in the Western Ghats near Mahabaleshwar and extends eastward across parts of Satara, Sangli, and Kolhapur districts. Geographically, the region is characterized by a transition from steep, high-rainfall hill slopes to gently undulating plains with well-developed floodplains. The Krishna River flows as the main channel, supported by major tributaries such as the Koyna, Venna, Yerala, Warna, Panchganga, and Dudhganga, along whose banks dense rural and semi-urban settlements have developed.

Map: 1 Hydrological Map of Krishna Basin

Source: Central Water Commission & National Remote Sensing Centre. (2014). Krishna basin (Version 2.0) p.5

The Upper Krishna Basin experiences a monsoon-dominated tropical climate, with the majority of annual rainfall concentrated between June and September. Intense rainfall episodes, combined with reservoir releases and saturated catchments, frequently result in riverine flooding along low-lying banks. From an economic perspective, the basin supports agriculture-based livelihoods, allied activities, and small urban economies that remain closely dependent on river systems. The spatial concentration of population, farmland, and infrastructure along river corridors makes the basin particularly suitable for examining flood exposure and economic losses using an environmental accounting framework.

5. DATA SOURCES AND SURVEY DESIGN

This study relies on a combination of secondary data and primary household-level survey data to construct an environmental accounting of flood risk in the Upper Krishna Basin. Secondary data are used to identify basin-level exposure and spatial concentration of flood risk, while primary data are employed to measure realized economic losses at the household level. The integration of these two data sources allows for a consistent linkage between exposure and loss within an econometric framework.

5.1 Secondary Data

Secondary data are used to construct indicators of flood exposure at the basin and sub-basin levels. The primary source of secondary data is the Census of India 2011, which provides village-level population data for districts located within the Upper Krishna Basin. These data are combined with river and basin information obtained from the Water Resources Department, Government of Maharashtra, to identify settlements located along the banks of the Krishna River and its major tributaries.

River-bank settlements are defined as villages and towns situated along the main stem of the Krishna River or its principal tributaries, including the Koyna, Venna, Yerala, Warna, Panchganga, and Dudhganga rivers. Villages located in upland or interior areas without direct hydrological connectivity to these rivers are excluded from the exposure analysis. Based on this classification, basin-level exposure indicators are constructed using population counts as a proxy for economic exposure.

The secondary data are summarized through basin-level and taluka-level tables that report the number of river-bank settlements, total exposed population, and their relative shares. These exposure indicators are not used directly in the econometric models but serve to contextualize the magnitude and spatial distribution of flood risk within the basin and to justify the selection of locations for primary data collection.

5.2 Primary Data

Primary data for the study were generated through a structured household survey conducted in flood-affected river-bank settlements of the Upper Krishna Basin following the 2021 flood event. The survey design was guided by the objective of capturing realized economic losses at the household level and was aligned with standard practices in disaster loss accounting and environmental economics.

The sampling framework followed a multi-stage sampling design. In the first stage, river-bank villages were identified from the universe of flood-prone settlements located along the Krishna River and its major tributaries within the study area. Out of a total of 196 river-bank villages identified in the Upper Krishna Basin of Maharashtra, 20 villages were selected for detailed household-level investigation. Village selection was purposive, based on the severity of flood impact during the 2021 event, ensuring that the sample adequately represented settlements that experienced direct flood and economic damage.

In the second stage, the overall household sample size was determined using the Slovin formula, applied to the universe of flood-affected population in the selected villages. This procedure ensured statistical adequacy while accounting for field-level constraints and variability in flood impacts. Based on this calculation, the final sample size was fixed at 664 households (N = 664). In the third stage, households were selected using a purposive–random sampling approach. Lists of flood-affected households were obtained from the respective Gram Panchayats in each sampled village, which served as the sampling frame. From these lists, households were then selected randomly to ensure representation of affected households while avoiding selection bias. The sample size was determined to balance statistical adequacy with field feasibility and to ensure sufficient variation across key socioeconomic and flood-related characteristics for econometric analysis.

The household questionnaire was designed to capture both flood characteristics and economic loss variables. Information was collected on flood depth and duration, housing type, landholding size, occupation, and access to post-flood relief. Economic losses were recorded in monetary terms and disaggregated into major components, including crop loss, housing damage, livestock loss, and wage or income loss resulting from disruption of employment and economic activity. Total household flood loss was computed as the aggregate of these components.

This primary dataset has offered micro-level evidence of the economic impacts of flooding in riverbank settlements. These data serve as the empirical foundation for the study's econometric models. They allow us to examine how hazard intensity, exposure, and household characteristics interact to shape actual flood losses.

6. ECONOMETRIC METHODOLOGY

The econometric methodology adopted in this study is designed to examine the determinants of flood-induced economic losses at the household level, while maintaining consistency with the environmental accounting framework outlined earlier. The empirical strategy integrates household-level primary data with exposure-related insights derived from secondary data, allowing for a systematic assessment of how flood characteristics and socioeconomic factors influence realized losses. Flood loss data are inherently heterogeneous and often characterized by skewed distributions and non-linear relationships. To address these features and to ensure robustness of results, the study employs a set of complementary econometric models, each serving a distinct analytical purpose. Specifically, three model specifications are estimated: an ordinary least squares (OLS) regression to explain absolute flood losses, a log-linear regression to assess proportional effects and mitigate skewness, and a probit model to estimate the probability of severe flood loss.

6.1 Baseline OLS Model

The baseline empirical specification employs ordinary least squares to estimate the relationship between total household flood loss and a set of explanatory variables capturing flood intensity, exposure, and household characteristics. The model is specified as:

$$FL_i = \alpha + \beta_1 FD_i + \beta_2 FR_i + \beta_3 LH_i + \beta_4 DR_i + \beta_5 HT_i + \beta_6 OC_i + \beta_7 RG_i + \varepsilon_i$$

Where

FL_i denotes the total flood-related economic loss incurred by household i measured in monetary terms. FD_irepresents flood depth, while FR_icaptures flood duration in days. LH_i denotes landholding size, and DR_i measures the distance of the household dwelling from the river. HT_i is a housing quality indicator, OC_i represents occupation type with agricultural households coded as one, and RG_i denotes the amount of relief received. The error term ε_i captures unobserved household-specific factors.

This specification allows for a direct economic interpretation of marginal effects and provides an initial assessment of the structural determinants of absolute flood losses.

6.2 Log-Linear Model

Flood loss data are typically right-skewed, with a small number of households experiencing disproportionately high losses. To address this distributional characteristic and to assess relative effects, a log-linear specification is estimated as a robustness check:

$$\ln(FL_i) = \alpha + \sum_k \beta_k X_{ik} + \varepsilon_i$$

Where X_ik represents the vector of explanatory variables included in the OLS model. In this formulation, the estimated coefficients are interpreted as elasticities, indicating the percentage change in flood loss associated with a unit change in the explanatory variable. The log-linear model improves estimation efficiency and reduces the influence of extreme observations, thereby complementing the baseline OLS results.

6.3 Probit Model for Severe Flood Loss

While the OLS and log-linear models focus on the magnitude of losses, policy formulation often requires identifying households that face a high likelihood of experiencing severe flood damage. To address this objective, a probit model is employed to estimate the probability of severe flood loss. A binary dependent variable SL_i is defined as follows:

$$SL_i = \begin{cases} 1 \\ 0 \end{cases} if\, FL_i > median\; flood\; loss\; otherwise$$

The probability of severe flood loss is modeled as:

$$P(SL_1 = 1) = \Phi(\gamma_0 + \gamma_1 FD_i + \gamma_2 FR_i + \gamma_3 LH_i + \gamma_4 DR_i + \gamma_5 HT_i)$$

Where Φ (·) denotes the cumulative distribution function of the standard normal distribution. This model identifies household and flood-related factors associated with heightened vulnerability and facilitates the targeting of mitigation and relief measures.

6.4 Estimation Issues and Diagnostics

All models are estimated using robust standard errors to account for potential heteroskedasticity commonly observed in cross-sectional loss data. Multicollinearity among explanatory variables is assessed using variance inflation factors, and model fit is evaluated using appropriate goodness-of-fit measures, including R^2 for linear models and pseudo-R^2for the probit specification. The consistency of results across model specifications is used as an additional check on robustness.

7. RESULTS

7.1 Basin-Level Exposure Results

Table 1 presents the district-wise distribution of river-bank villages and population exposure within the Upper Krishna Basin. A total of 196 river-bank villages were identified across the three districts, with the highest concentration observed in Sangli (76 villages), followed by Kolhapur (73 villages) and Satara (47 villages).

In absolute terms, Sangli and Kolhapur together account for a substantial share of flood-affected village populations, reflecting dense settlement patterns along the Krishna River and its tributaries.

Table 1.

Distribution of River-Bank Villages and Population Exposure in the Upper Krishna Basin

District	No. of River Bank Villages	Total Flood Affected Villages Population	Exposed Population	Total District Population	% of District Population
Sangli	76	837956	116759	2822413	4.14
Satara	47	185074	33701	3003741	1.12
Kolhapur	73	821890	216438	3876001	5.58
Total	196	1844920	366898	9701885	3.78

Source: Census of India (2011); District Flood Control Records (2021); Water Resources Department, Government of Maharashtra.

In proportional terms, however, Kolhapur exhibits the highest exposed population share, with 5.58 percent of the district population affected by floods, compared to 4.14 percent in Sangli and 1.12 percent in Satara. At the basin level, approximately 3.78 percent of the total population is classified as flood exposed. These findings highlight pronounced spatial variation in exposure across districts and underscore the importance of basin-level environmental accounting for identifying priority areas of flood risk.

7.2 Descriptive Household Flood Loss Results

Table 2 summarizes the descriptive statistics of household flood losses based on primary survey data from 664 households. The results indicate marked inter-district variation in average economic loss. Sangli records the highest mean household flood loss (₹1,86,420), followed by Satara (₹1,49,870) and Kolhapur (₹1,12,360). The overall basin-level average loss amounts to ₹1,52,940, reflecting the substantial economic burden imposed by the 2021 flood event.

Table 2

Descriptive Statistics of Household Flood Loss by District (₹) (N = 664)

District	Mean Loss	Std. Dev.	Minimum	Maximum
Sangli	1864420	94315	18500	612000
Satara	149870	78460	15200	498000
Kolhapur	112360	61780	12000	376500
Overall Basin	**152940**	**82150**	**12000**	**612000**

Source: Compiled from the Field work 2022

Note: Loss includes crop, housing, livestock, and wage losses.

The dispersion of losses, as indicated by standard deviations, is also highest in Sangli, suggesting greater heterogeneity in flood impacts across households. Minimum and maximum values further reveal that while some households experienced relatively modest losses, others incurred severe damage exceeding 6 lakhs, highlighting the unequal distribution of flood impacts within affected communities.

Table 3 disaggregates total flood loss into major components. Across all districts, crop loss emerges as the dominant component, accounting for the largest share of total loss, particularly in Sangli and Satara. Housing damage represents the second largest component, followed by livestock and wage losses. This composition reflects the agrarian structure of river-bank settlements and indicates that floods primarily affect productive assets and income-generating activities rather than only residential infrastructure.

Table 3

Component-wise Average Household Flood Loss by District (₹)

Loss Component	Sangli	Satara	Kolhapur
Crop loss	92,300	71,450	53,620

Housing loss	48,750	41,320	34,110
Livestock loss	21,640	18,580	13,940
Wage loss	23,730	18,520	10,690
Total loss	**1,86,420**	**1,49,870**	**1,12,360**

Source: Compiled from the Field work 2022

7.3 OLS Results

Table 4 reports the results of the baseline OLS regression estimating the determinants of household flood loss. Flood depth and flood duration exhibit strong positive and statistically significant effects, confirming that both the intensity and persistence of flooding substantially increase economic losses. Landholding size is also positively associated with flood loss, suggesting that households with larger cultivated areas face higher absolute losses during flood events.

Distance from the river and housing quality display negative and statistically significant coefficients, indicating that households located farther from river banks and those residing in better-quality housing experience lower losses. Occupation status shows that agricultural households incur significantly higher losses compared to non-agricultural households, reflecting greater dependence on flood-sensitive livelihoods.

Table 4

Determinants of Household Flood Loss (OLS Estimates)

Variable	**β**	**Std. Error**	**t-value**	**Sig.**
Flood depth (FD)	24,315	3,420	7.11	0.000 ***
Flood duration (FR)	6,820	1,145	5.96	0.000 ***
Landholding size (LH)	9,470	2,180	4.35	0.000 ***
Distance from river (DR)	−1,260	420	−3.00	0.003 **
Housing quality (HT)	−14,580	3,960	−3.68	0.000 ***
Occupation (OC)	18,940	4,780	3.96	0.000 ***
Relief received (RG)	−0.42	0.18	−2.33	0.020 **
Constant	38,720	11,640	3.33	0.001 ***

Source: Compiled from the Field work 2022

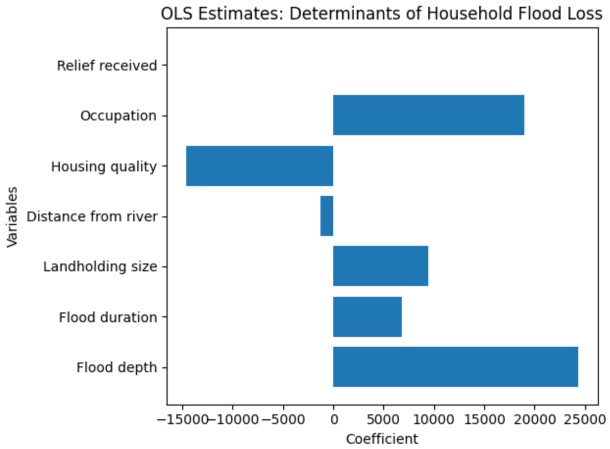
Model Statistics	**Value**
R2	0.61
Adjusted R^2	0.59
F- statistics	82.4
Sig. (F)	0

Relief received is negatively associated with total loss, implying that post-flood assistance partially mitigates economic damage.

The model explains a substantial proportion of variation in household flood loss, with an R^2 of 0.61, indicating good explanatory power. Figure 1 visually supports these findings by illustrating the relative magnitude and direction of estimated coefficients.

Figure 1

Determinants of Household Flood Loss (OLS Estimates)



7.4 Log-linear Results

The log-linear regression results presented in Table 5 provide robustness to the OLS findings by accounting for skewness in the loss distribution. Flood depth and flood duration continue to exert strong positive and statistically significant effects, with coefficients indicating sizeable elasticities. This implies that proportional increases in flood intensity and duration translate into proportionally larger economic losses.

Landholding size and occupation status remain positively significant, while distance from the river and housing quality retain their loss-reducing effects.

Table 5

Log-linear Regression Results for Household Flood Loss

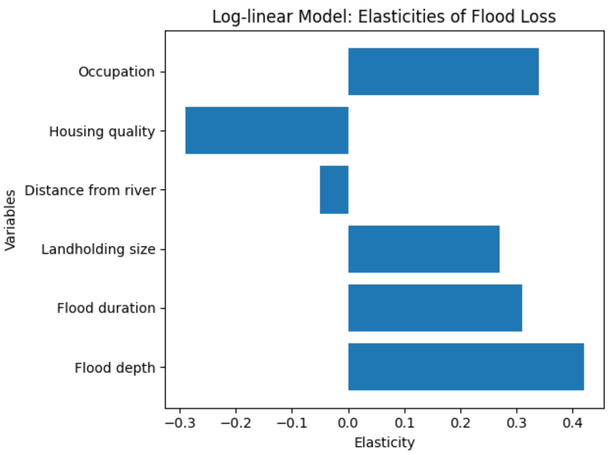
Variable	**β**	**Std. Error**	**t-value**	**Sig.**
ln(Flood depth)	0.42	0.07	6	0.000 ***
ln(Flood duration)	0.31	0.06	5.17	0.000 ***
ln(Landholding size)	0.27	0.08	3.38	0.001 ***

ln(Distance from river)	−0.05	0.02	−2.50	0.013 **
ln(Housing quality)	−0.29	0.09	−3.22	0.001 ***
ln(Occupation)	0.34	0.1	3.4	0.001 ***
ln(Relief received)	−0.0003	0.0001	−2.10	0.036 **
Constant	9.12	0.84	10.86	0.000 ***

Source: Compiled from the Field work 2022

Model statistics	**Value**
R^2	0.58
Adjusted R^2	0.56
F-statistic	74.9
Sig. (F)	0

Figure 2 Elasticities of Flood Loss from Log-linear Model



Relief received again shows a negative association with flood loss. The consistency of coefficient signs and significance across the OLS and log-linear specifications suggests that the estimated relationships are robust.

Figure 2 summarizes these elasticities, highlighting flood depth as the most influential factor in proportional terms.

7.5 Probit Results

Table 6 presents the probit estimates for the probability of experiencing severe flood loss, defined as loss exceeding the median household loss.

Flood depth and flood duration significantly increase the likelihood of severe loss, indicating that more intense and prolonged flooding substantially raises vulnerability. Landholding size also increases the probability of severe loss, reflecting higher exposure of productive assets.

Conversely, greater distance from the river and better housing quality significantly reduce the probability of severe loss. These findings emphasize the protective role of physical location and structural resilience. The model demonstrates satisfactory explanatory power, with a pseudo R^2 of 0.29 and a highly significant chi-square statistic.

Table 6

Probit Estimates for Probability of Severe Flood Loss

Variable	**Coefficient**	**Std. Error**	**z-value**	**Sig.**
Flood depth	0.68	0.12	5.67	0.000***
Flood duration	0.44	0.1	4.4	0.000***
Landholding size	0.31	0.11	2.82	0.005***
Distance from river	−0.18	0.07	−2.57	0.010**
Housing quality	−0.52	0.16	−3.25	0.001***
Constant	−1.94	0.38	−5.11	0.000***

Source: Compiled from the Field work 2022

Model statistics	**Value**
Log likelihood	−312.6
Pseudo R^2	0.29
Chi-square	118.4
Sig.	0

Flood depth emerges as a critical determinant of severe flood loss; as higher inundation levels substantially increase the probability that households experience losses exceeding the median threshold. Prolonged flood duration further amplifies vulnerability by extending the period of disruption to agricultural activities, housing, and local labour markets. In addition, households with larger landholdings face a greater likelihood of severe loss, reflecting higher exposure of cultivated land and productive assets to flood damage. In contrast, structural and locational factors play an important protective role. Better housing quality significantly reduces the probability of severe loss, indicating the effectiveness of durable construction in mitigating flood impacts. Similarly, greater distance from the river lowers risk by limiting direct exposure to inundation. The use of marginal effects in the probit analysis enhances interpretability by translating abstract coefficient estimates into meaningful changes in probability, thereby providing clear and policy-relevant insights into the factors that shape flood vulnerability.

Figure 3

Marginal Effects on Probability of Severe Flood Loss (Probit Model)

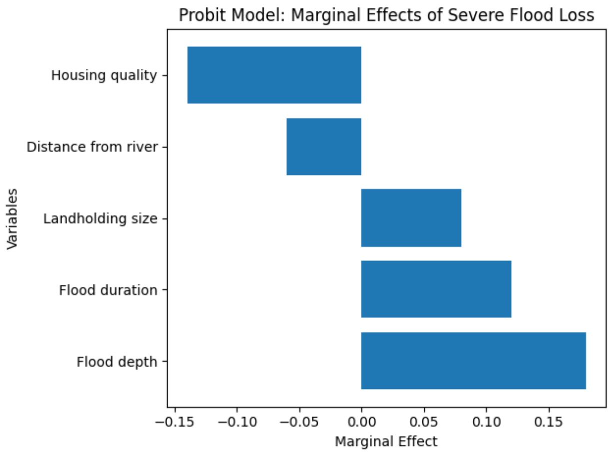


Figure 3 presents marginal effects, offering a clear policy-relevant visualization of how changes in key variables influence the probability of severe flood loss.

8. DISCUSSION

The results of this study show that flood risk in the Upper Krishna Basin is shaped as much by economic and social factors as by hydrological conditions. While floods are triggered by natural processes, their economic consequences vary widely across districts and households. This variation reflects differences in settlement patterns, livelihood structures, and the capacity of households to withstand and recover from flood shocks.

At the basin level, the exposure analysis highlights an important contrast. Kolhapur records the highest proportion of population exposure, whereas Sangli experiences the most severe household-level economic losses. This difference suggests that exposure alone does not determine loss severity. Instead, losses intensify where exposure overlaps with high-value economic activities and flood-sensitive livelihoods. In Sangli, agriculture is not only widespread but also relatively commercialized, with greater investment in crops, livestock, and irrigation. When floods occur, damage to these assets translates into higher monetary losses compared to districts where economic dependence on agriculture is relatively lower.

The household-level results further reinforce this interpretation. Across all districts, crop loss constitutes the largest share of total flood damage. This finding reflects the central role of agriculture in river-bank settlements and confirms that floods directly undermine the productive base of rural households. Housing damage emerges as the second most significant component, indicating that structural vulnerability remains a major concern. Livestock and wage losses, although smaller in absolute terms, contribute to short-term income stress and reduce households' ability to cope during the post-flood period. Together, these components reveal that floods affect both assets and income flows, thereby creating layered economic stress.

The econometric analysis provides deeper insight into the mechanisms behind these losses. Flood depth and flood duration consistently emerge as strong predictors of household loss across all model specifications. This result is intuitive but important, as it confirms that not only the occurrence of flooding but also its intensity and persistence determine economic outcomes. Households exposed to deeper and longer-lasting floods face compounded damage, particularly when recovery options are limited.

At the same time, household characteristics significantly shape vulnerability. Larger landholdings are associated with higher losses, reflecting greater exposure of cultivated land and agricultural assets. Agricultural households face higher losses than non-agricultural households, underscoring the livelihood-specific nature of flood risk. In contrast, better housing quality and greater distance from the river reduce both the magnitude of losses and the probability of severe damage. These findings point to the role of structural resilience and spatial planning in mitigating flood impacts.

The probit analysis adds an important policy dimension by identifying factors that increase the likelihood of severe loss. Flood depth and duration sharply raise the probability that households cross the threshold of severe damage, while improved housing conditions and safer locations reduce this risk. By presenting marginal effects rather than abstract coefficients, the analysis translates statistical results into meaningful changes in probability, making the findings easier to interpret and more useful for decision-making.

Taken together, the evidence suggests that floods in the Upper Krishna Basin function as recurrent economic shocks rather than isolated events. Repeated exposure gradually weakens household resilience, limits savings and investment, and reinforces vulnerability over time. The environmental accounting approach used in this study helps capture this reality by linking spatial exposure with realized economic losses. In doing so, it moves beyond hazard-focused analysis and offers a clearer understanding of how floods shape economic outcomes in river-basin communities.

9. POLICY IMPLICATIONS

The findings of this study point to several practical policy lessons for flood management in the Upper Krishna Basin. One of the key observations is that recent floods cannot be explained only by heavy rainfall. River regulation and reservoir operations have also played an important role. The Krishna Basin contains several large dams, and the backwater effect of the Almatti dam has been widely discussed as a contributing factor to flooding in downstream areas of Maharashtra. This means that flood risk in the basin is not confined to local conditions but is influenced by upstream water management decisions.

The econometric results show that flood depth and duration are major factors behind household losses. From a policy perspective, this highlights the importance of managing flood levels rather than reacting only after damage has occurred. Reservoir operations during the monsoon need closer coordination, especially during periods of intense rainfall. Advance planning, real-time data sharing, and gradual water releases can help reduce sudden inundation in downstream river-bank settlements. Since the Krishna is an inter-state river, cooperation between states becomes essential for reducing flood impacts.

These findings closely correspond with the observations made by the Expert Study Committee appointed by the Government of Maharashtra after the 2019 floods in the Krishna Sub-Basin. The committee report identifies prolonged heavy rainfall, high runoff from free catchments, reduced river carrying capacity, and widespread encroachment on floodplains as key causes of flooding in Sangli, Satara, and Kolhapur districts. The report further notes that flooding in tributaries such as the Warna and Panchganga was intensified when high water levels in the Krishna River created backwater conditions, slowing drainage from adjoining floodplains. Hydrodynamic analysis carried out by the committee showed that flat terrain and confluence zones contributed to prolonged inundation, particularly in Sangli and surrounding areas. These structural conditions help explain why flood duration emerges as a strong determinant of household loss in the present study. The committee's recommendations on coordinated reservoir operations, revision of dam release schedules, protection of floodplains, and restoration of natural drainage channels therefore receive strong support from the household-level economic evidence presented here.

The results also show that households with better housing and those located farther from the river suffer lower losses. This has clear implications for settlement planning and housing policy. Improving the quality of housing in flood-prone villages can reduce damage during floods. At the same time, limiting new construction in high-risk floodplain areas and encouraging safer land-use practices can help lower future exposure. These measures are particularly important in villages where people depend on agriculture and live close to the river for irrigation and livelihood reasons.

Relief assistance does reduce losses to some extent, but the results suggested that it cannot fully compensate for the damage caused by floods. This indicates a need to strengthen preventive measures alongside relief. Crop insurance schemes suited to flood-prone areas, timely early-warning dissemination at the village level, and support for alternative income sources during flood periods can reduce the economic stress faced by households.

Overall, the findings suggested that flood management in the Upper Krishna Basin needs to move away from short-term responses toward long-term planning that considers river systems, settlement patterns, and household vulnerability together. Integrating basin-level river management with local development planning can reduce repeated losses and improve the economic security of communities living along the Krishna River and its tributaries.

10. CONCLUSION

This study examined flood risk in the Upper Krishna Basin by linking river-basin exposure with household-level economic losses. Using secondary data and a field survey conducted after the 2021 flood, it shows that flood impacts vary widely across districts and households. Sangli emerges as the district with the most severe household losses, while Kolhapur records higher population exposure, indicating that exposure and loss do not always move together.

The results confirm that deeper and longer floods cause greater economic damage, particularly in agriculture-dependent households. Crop loss accounts for the largest share of total damage, followed by housing and income losses. Better housing quality and greater distance from the river reduce risk, while relief support helps but does not fully compensate for repeated losses.

The study also highlights the role of basin-level factors such as dam operations and backwater effects in shaping flood outcomes. Floods in the Upper Krishna Basin therefore need to be understood as recurring economic shocks rather than one-time events. Managing them requires coordinated river management, safer settlement practices, and stronger protection of livelihoods. An environmental accounting approach can help policymakers better understand where losses occur and how they can be reduced over time.

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