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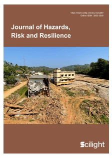

Article

Disaster Impact- and Moderator-Based Empirical Modeling of Disaster Risk Reduction and Management Finance

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How To Cite: Satyal, K.; Bhandary, N.P. Disaster Impact- and Moderator-Based Empirical Modeling of Disaster Risk Reduction and Management Finance. *Journal of Hazards, Risk and Resilience* **2026**, *1*(1), 19. https://doi.org/10.53941/jhrr.2026.100019

Received: 25 March 2026
Revised: 26 June 2026
Accepted: 16 July 2026
Published: 5 August 2026

Abstract: Disasters inflict substantial human suffering and damage physical and financial assets, thereby constraining socioeconomic development. Increasing disaster frequency, intensity, and risk, coupled with constrained financial resources, more prominently in developing countries, underscore the need for evidence-based frameworks to optimize disaster risk reduction and management (DRRM) expenditure. This study examines whether disaster impacts and socioeconomic moderators influence DRRM expenditure allocation in low-income and developing economies, with particular focus in Nepal, where coordination and budgeting challenges remain significant. Using a longitudinal dataset covering 2001–2024, we investigate the relationships between disaster impacts (human losses, affected population, and direct economic losses) and DRRM expenditure while assessing the moderating roles of the Human Development Index (HDI), real GDP, and population. Grounded in a positive economic framework, the analysis employs stationarity tests and robust regression techniques to contribute to the literature on disaster-finance responsiveness in low-income, multi-hazard contexts. Bivariate correlations show negative associations between DRRM budget expenditure and human loss and affected population, but a positive association with direct economic loss. Regression models, in contrast, reveal significant positive associations between DRRM spending and all three disaster impact measures, indicating that spending is predominantly reactive, driven by relief and emergency response following human impacts and by compensation, recovery, and reconstruction following economic loss. Model performance improves when disaster impacts are considered jointly, while HDI, real GDP, and population further enhance explanatory power. These findings indicate that DRRM budgets are shaped by both disaster impacts and socioeconomic conditions, highlighting the need for context-sensitive budgeting frameworks that strengthen ex-ante risk reduction and resilience-building investments alongside post-disaster response and recovery.

Keywords: affected population; DRRM expenditure; economic loss; human loss

1. Introduction

Spending in disaster risk reduction and management (DRRM) is essential to mitigate escalating threats from natural hazards and anthropogenic disasters [1,2]. Disasters affect roughly one-quarter of the world's population each year and cause an estimated economic loss of USD 250–300 billion. They also cause substantial human suffering, socioeconomic disruption, and systemic vulnerability [3–5]. These trends compel governments to invest in disaster management systems, operations, and resilient infrastructure to reduce losses and protect lives [6].

However, low-income countries face severe fiscal constraints that limit investments in DRRM [7], a challenge magnified by systematic undercounting of frequent small-scale disasters in global databases. Such omissions perpetuate a cycle in which recurrent localized events and environmental degradation deepen socioeconomic inequalities and hinder recovery processes [8,9]. In these compounding scenarios, conventional disaster financing remains heavily reactive, with roughly 87% of disaster spending in many countries directed to post-disaster reconstruction rather than proactive risk reduction and financing frameworks [10].

Global data indicate regional and country-level differences in disaster statistics that shape risk exposure and fiscal responses. Between 1900 and 2025, natural disasters accounted for 64.5% while the remaining 35.5% were anthropogenic disasters. Asia suffered the most with 41.26% of global disaster events, 63.6% of casualties, 83.8% of suffering, and 43.7% of economic damage. Among 50 disaster-prone countries, 18 were Asian nations, mostly with developing or least developed economic status. Nepal ranked 28th in disaster event frequency but disproportionately recorded lower human and economic losses. This inconsistency stems from the Emergency Events Database (EM-DAT) threshold of Disasters, which underrepresents small-scale but locally significant disasters [11–13]. Low magnitude events share hazard characteristics and risk mechanisms with larger catastrophes [14]. Socioeconomic conditions and geological factors trigger small-scale hazard exposure and impact in developing and least-developed nations, as evidenced in India, Guatemala, Bangladesh, and Nepal [9,15]. However, DRRM frameworks inadequately address these determinants.

Disaster impacts hinder sustainable development in low-income settings, requiring Disaster Risk Reduction (DRR) investment to meet the Sendai Framework, Sustainable Development Goals (SDGs), and Paris Agreement targets [9]. Reducing systemic damages and losses requires greater attention to slow-onset and small-scale disasters [16] and mainstreaming risk-informed investments that integrate resilient infrastructure, poverty reduction, and climate adaptation [4]. Effective disaster management in low-income countries depends on stronger government leadership and increased financing to coordinate the fragmented implementation efforts of non-governmental actors [17]. Low-income countries experience disproportionate disaster impacts due to the intersection of disasters and socioeconomic vulnerabilities, which inadequate DRR investment fails to address [13,18]. DRRM expenditure allocations remain fragmented across administrative levels in developing countries [19], with overlapping agency activities necessitating standardized investment profiles and databases [20]. Mitigation investment reduces relative disaster impacts and future losses [14], yet developing countries lack reliable investment methodologies. Karim and Noy [21] examined how DRR spending correlates with socioeconomic determinants such as population dynamics and development levels. However, their analysis remained limited in its exploration of relationships between disaster risk reduction budgets and disaster impacts.

Classical economic theory models government investment as risk-neutral, whereas contemporary societies require risk-averse approaches, justifying proactive disaster risk management [22]. Public finance theory conceptualizes government budgeting as empirically observable with scientifically derived allocative norms [23–25]. The optimal-control framework derives expenditure paths from disaster-impact models, generating welfare-maximizing fiscal rules [26–28]. Yet, the practical application remains considerably limited. Empirical evidence suggests that adequate central government DRRM allocations range from 1–2% of national budgets [29]. However, public budgets systematically underfinance mitigation, particularly during non-crisis periods and for smaller disasters, generating predictable recovery costs [21]. Reactive investment intensifies disaster impacts in least developed countries [13], while non-integrated DRR planning accumulates additional risks [30]. Despite rising absolute government DRR investments, a comprehensive understanding of their scale, distribution, and effectiveness remains limited [20]. Investment demand increases with economic development [31], and the frequency of global disasters is accelerating; expanding mitigation infrastructure is essential to meet international targets [4]. Systematic characterization of investment scales and determinants is therefore essential for evidence-based policy optimization [32].

Most existing research either quantifies disaster losses e.g., [33,34] or describes investment barriers e.g., [7,21]. Empirical investigation into whether and how comprehensive disaster impacts, encompassing human loss, affected population, and direct economic loss, influence government's DRRM budget expenditure remains limited. In Nepal's case, the moderating role of socioeconomic factors such as development level, economic capacity, and population size in shaping these budgetary responses has been under-explored. This study attempts to fill this gap by investigating whether Nepal's DRRM budget responds to three disaster impact metrics; human loss, affected population, and direct economic losses, considering them individually as well as jointly. It further tests whether the human development index (HDI), real GDP, and population size moderate the relationship between disaster impacts and DRRM budget. By examining data-constrained, disaster-prone, and low-income countries like Nepal over a span of 24 years, this research work provides evidence-based insights into how various disaster impacts explain financial decisions.

2. Materials and Method

2.1. Data Sources and Preparation

This study adopts a scientific budgeting framework rooted in positive economics, which treats government budgeting as an empirically observable, externally determined process that can be analyzed through quantitative methods [23]. We employed a deductive methodology and a quantitative research design to assess established theoretical frameworks using annual time-series data. To test theoretically derived hypotheses and to examine the relationship between disaster impacts and national DRRM budget allocation, we used statistical analysis methods such as unit-root tests, robust regression, and correlation analysis [35,36]. Based on previous empirical studies, we specify national DRRM expenditure as the dependent variable, with disaster impacts serving as independent variables. Disaster impacts are operationalized through three key indicators: affected population size, direct economic losses, and human loss (deaths and missing persons) [37]. To account for contextual factors that may moderate these relationships, we incorporate three socioeconomic variables as moderators: total population size, real GDP, and HDI, following established empirical evidence [9,38]. This modeling approach enables us to examine both the direct effects of disaster impacts on budget allocation and the conditional effects moderated by country-specific socioeconomic characteristics, thereby investigating relationships and enabling cautious generalization to similar contexts.

In this study, we used three main types of data sets: (1) Federal government disaster risk reduction and management related budget allocation as DRRM expenditure, (2) data on disaster profiles covering number of incidents, human loss (number of death and missing persons), affected population and economic loss (3) data on socioeconomic indicators such as development capacity (HDI), economic scale (real GDP), and demographic scale (total population). The analysis covers whole Nepal data from 2001 to 2024, with one year as the unit of analysis. Aligning with [11,37,39–41], human loss (loss of life), affected population, and economic loss/damage as the major disaster consequences were used as explanatory variables to assess the relationship with DRRM budget expenditure (The original detailed data underlying this analysis are provided in the Supplementary Table: Table S1).

Data collection and preparation were conducted in multiple stages, accounting for inconsistencies in coordination and budgeting codes across federal allocations. First, quantitative data on 74 budget line items for disaster preparedness, relief and recovery, since 2001/02 to 2024/25 AD (2058/59–2081/82 BS) were compiled from official sources (Annual Development Program, Ministry of Finance Red Book, and national archives) and by visiting key DRRM institutions (Ministry of Urban Development, Department of Hydrology and Meteorology, Department of Mines and Geology, National Disaster Risk Reduction and Management Authority) to obtain and cross-check annual allocations. All these expenditures are directly or indirectly targeting the inclusion of DRRM. Second, disaster occurrence and damage records were retrieved from the Nepal Disaster Risk Reduction Portal and the UNDRR Sendai Framework (DesInventar). Incomplete datasets were removed during cleaning, and the validated records were used to construct a national disaster damage profile. Third, socio-economic context data, such as HDI (from UNDP), real gross domestic product (real GDP), and population from the IMF and World Bank, along with other national statistics, were gathered from public sources.

2.2. Statistical Approach and Analysis

First, variable transformations were implemented to enhance reliable outcome and to reduce the risk of multicollinearity [42]. Diagnostic testing indicated that DRRM expenditure was not normally distributed; hence, it was log-transformed. Explanatory and socioeconomic variables were standardized to *z*-scores, calculated as in Equation (1).

$$z = \frac{X-\mu}{\sigma} \tag{1}$$

where X is the observed value, μ is the mean, and σ is the standard deviation.

Second, testing of the stationarity properties of time-series data as a fundamental prerequisite for regression analysis, ensuring that the mean, variance, and covariances are independent of time [43] was conducted. Unit root (non-stationarity) testing is essential to avoid spurious regression results that can occur with non-stationary data [44]. We used Augmented Dickey-Fuller (ADF) unit root tests, which account for serial correlation. The ADF test examines the null hypothesis of a unit root, where rejecting the null indicates that the series is stationary, as represented by Equation (2).

$$\Delta Y_t = \alpha + \varphi t + \Upsilon Y_{t-1} + \sum_{i=1}^{m} \phi \Delta Y_{t-i} + \mu_t \tag{2}$$

where Y is the dependent variable, Δ is differenced form, Y_{t-1} is $t-1$ year value of Y, t is time trend, α is constant/intercept, φ, Y, ϕ are coefficients and μ_t is the error term.

Outliers in the data series were identified using boxplots produced in IBM SPSS Statistics (Version 31) and were deleted only during the correlation analysis following visual inspection. Subsequent Pearson's correlation analyses assessed relationships among independent variables (i.e., human loss, affected population, and direct economic loss), socioeconomic moderators (i.e., HDI, real GDP, and population size), and the dependent variable (i.e., DRRM expenditure), including the number of incidents from 2001 to 2024.

The study also employed robust regression (Huber M-estimation) for parameter estimation, which is identical to ordinary least squares (OLS) to ensure that the coefficients are not biased by outliers in the dataset [45]. This regression model downweights (within the range 0–1) based on their influential behavior and treats data points differently. So, we employed robust regression in Stata, as it treats outliers for reliable coefficients and accounts for violations of normality. Two regression frameworks were then established to test the hypotheses: an OLS model and a moderated multiple regression (MMR) model based on robust regression.

Third, for modeling the effect on DRRM expenditure, Equation (3) was used for OLS, while MMR based on robust regression to test the hypotheses, Equation (4) was used.

$$\Delta^2 Y = \alpha + \beta_1 \Delta X + \varepsilon \tag{3}$$

$$\Delta^2 Y = \alpha + \beta_1 \Delta X + \beta_2 \Delta Z + \beta_3 \Delta(XZ) + \varepsilon \tag{4}$$

where, $\Delta^2 Y$ is second difference of dependent variable, X is independent variable, Z is socioeconomic moderator, XZ is the interaction term of the variables X and Z, and Δ is the first difference form of corresponding variables.

Moderators can strengthen (enhance), weaken (buffer), or reverse (antagonize) the effect of an explanatory variable on an outcome [46,47]. In this study, moderators were introduced because the association between the explanatory variables and the outcomes was weak or inconsistent. Moderators were chosen through testing and retained if their interaction effects were statistically meaningful and aligned with earlier research. Model fitness, statistical significance, and interpretation were used to evaluate and interpret the results.

The size of the moderation effect was evaluated using Equation (5) [46] via MMR to determine the coefficient of determination (R-Square).

$$f^2 = \frac{R_1^2 - R_2^2}{1 - R_1^2} \tag{5}$$

where, f^2 is the size of the moderation effect and represents the coefficient of determination with and without the interaction term, respectively.

The procedure comprised two steps: first, fit a regression model including the explanatory variable, the moderator, and their interaction term (explanatory variable × moderator); second, fit the same model without the interaction term. Based on the studies, the value of f^2 up to 0.02 indicates a small effect, 0.15 indicates a medium effect, and 0.35 indicates a large effect [46,48]. The moderation effect is deemed more substantial when the interaction effect is smaller. Then, the magnitude of the moderation effect was assessed using the R-Square values from each run. Results were interpreted based on the size of the moderation effect [46,49].

Finally, Equation (6) was used to assess the joint effect of direct disaster impacts (human loss, affected population and direct economic loss) on disaster-related financing using OLS (based on robust regression).

$$\Delta^2 Y = \alpha + \beta_1 \Delta X1 + \beta_2 \Delta X2 + \beta_3 \Delta X3 + \varepsilon \tag{6}$$

where, $\Delta^2 Y$ is second difference of dependent variable, $X1$ is human loss, $X2$ is affected population, $X3$ is direct economic loss and Δ is the first difference form of corresponding variables.

3. Results and Discussion

3.1. DRRM Budget and Disaster Impact

Disasters of varying magnitudes and locations destroy capital and suppress new investment, generating pronounced negative effects on economic development that are more severe in low- and middle-income countries than in developed nations [50,51]. The acute concentration of death and destruction in poor households and low-income countries, attributed to limited mitigation capacity, directly impedes achievement of the Sendai Framework and SDG targets [52]. Analysis reveals that government budgeting systems, despite theoretical requirements for transparency and adherence to core principles [53], demonstrate limited adaptability in disaster contexts due to risk-neutral assumptions that neglect inherent uncertainties. This misalignment suggests that enhanced policymaker understanding of disaster impacts and resource allocation drivers enables more optimal resource management through systematic approaches. Optimal control frameworks provide mechanisms for translating objective functions into empirically justified expenditure systems [27,28], supported by recent evidence that damage affects the scale of investment, with investment increasing in proportion to GDP and population growth in flood-related disasters [20].

Investing in resilient infrastructure yields a benefit-cost ratio of about 4:1 in low- and middle-income countries. Targeting these investments to climate-related disaster-exposed areas reduces the scale and cost of subsequent ex-post relief and recovery operations [54]. Figure 1 shows disaster trends and profiles for Nepal from 2001 to 2024, revealing substantial volatility in disaster frequency, human impact, and DRRM budget expenditure. The 2015 Gorkha earthquake, a major disaster, triggered a significant yet delayed surge in DRRM budget expenditures. Subsequently, DRRM expenditure allocations became volatile and occasionally declined, indicating a reactive funding approach and potential underinvestment in sustained disaster risk reduction measures. Empirical evidence demonstrates asymmetric financing patterns characterized by budget surges following major shocks, with predominant reliance on post-disaster (ex-post) allocations rather than anticipatory financing mechanisms [52], aligning with the findings. Developing and low- and middle-income countries experience greater fiscal disruption and more acute human impacts than developed nations [55–57] due to inconsistent and inadequate resource allocation. These findings indicate the need for proactive allocation mechanisms that incorporate risk indicators, rather than reactive responses to disasters.

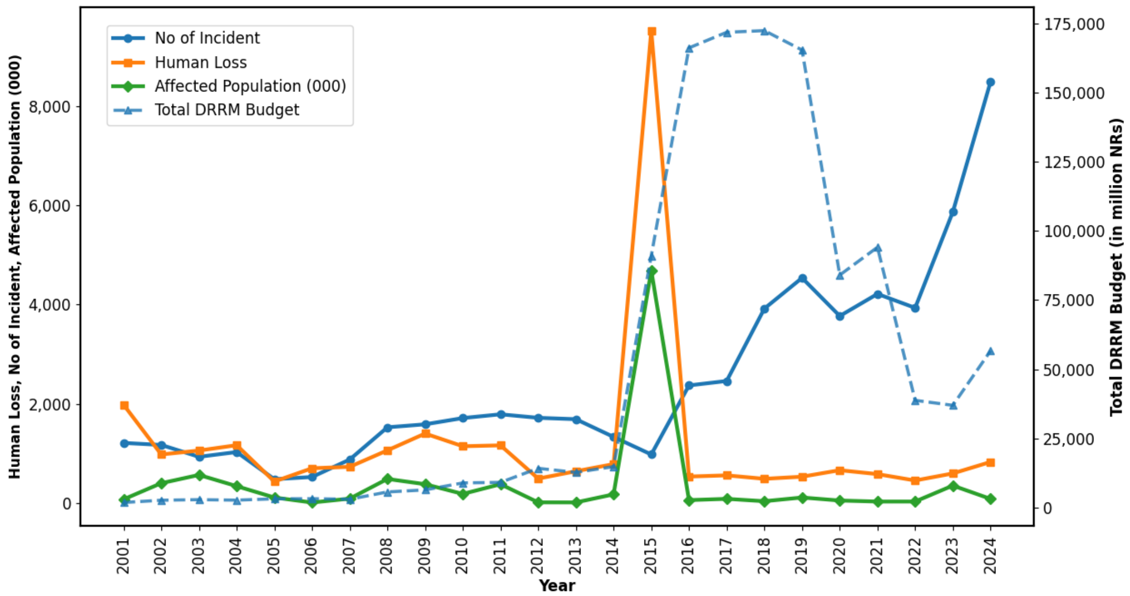

Figure 1. Disaster frequency, disaster impacts, and the Federal DRRM budget of Nepal (in left side axis only Affected population is in thousands, NRs refer to Nepalese Rupee).

3.2. Indicators of the National Economy and Economic Loss

Disasters serve as both indicators and drivers of developmental failures, with escalating frequency, severity, and economic costs that destroy capital and force the reallocation of resources from productive investments toward relief and recovery efforts [23,24]. This reallocation subsequently suppresses new investment, with disproportionately severe effects observed in low- and middle-income countries [15]. These nations experience greater fiscal disruption due to preexisting economic vulnerabilities that amplify disaster impacts [21,22] and allocate resources incrementally and reactively, which is insufficient for ex-ante resilience strategies [2,25]. Resilient investments encompass more than fiscal preparedness and sustainability, which can simultaneously mitigate escalating disaster risks [26] and create new avenues for profitable returns. While disasters and their impacts are difficult to predict, governments in low- and middle-income countries may undermine budget credibility by reducing allocations for disaster response and preparedness. Nevertheless, investment in both hard and soft mitigation strategies remain critical [26,27].

Figure 2 presents real GDP, national budget, and disaster-related direct economic losses (left axis) alongside total DRRM expenditure (right axis) for 2001–2024. The data reveal a consistent upward trajectory in real GDP and the national budget, despite notable fluctuations observed during the 2014–2016 and 2019–2022 periods. In contrast, economic losses remained minimal in most years but were punctuated by significant spikes in 2015 and

2023. DRRM budget expenditure (right axis) remained historically low before 2014 but surged substantially between 2015 and 2019. This also contracted from 2020–2022 and partially rebounded by 2024, consistent with a reactive allocation pattern following large loss events [12,19].

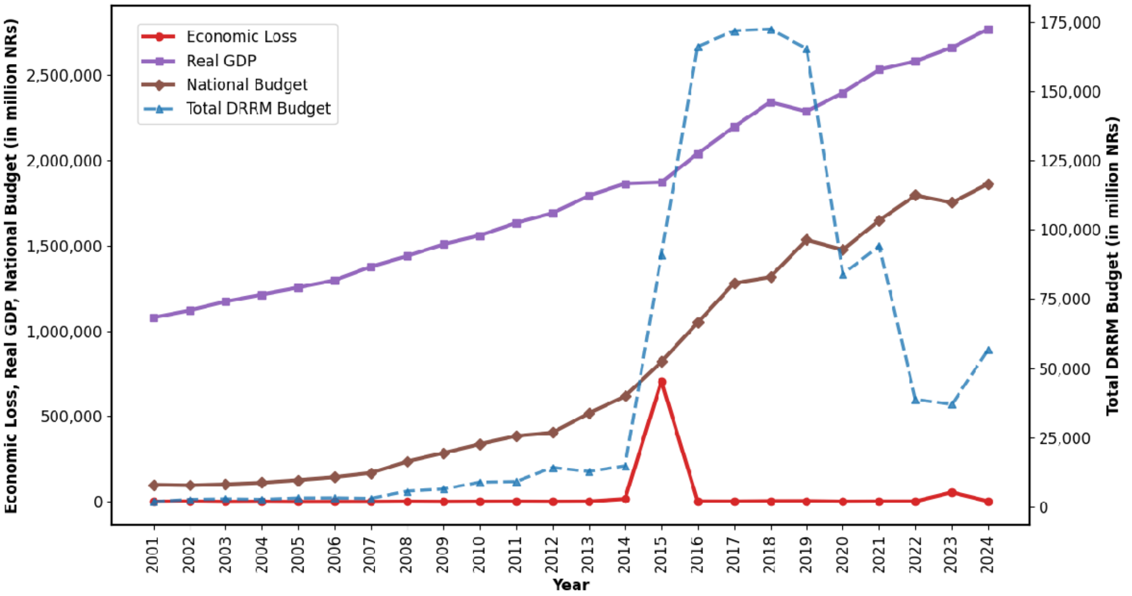

Figure 2. Federal DRRM budget and some economic indicators of Nepal (NRs refers to Nepalese Rupee).

Our analysis suggests that resilient investments extending beyond fiscal preparedness can simultaneously mitigate escalating disaster risks and generate profitable returns [58], challenging the traditional view of DRR as purely cost-bearing activities. This framework supports systematic resource allocation that integrates risk indicators with economic development objectives rather than perpetuating reactive funding patterns.

3.3. Statistical Findings and Discussion

Despite limited direct intervention, the state's roles in allocation, distribution, and stabilization are pivotal. The state should prioritize resilient infrastructure, human capital development, disaster risk reduction and climate adaptation, institutional capacity building, and welfare-preserving policies that mobilize productive private investment. Economic inequality and weak governance systems amplify disaster vulnerability, as natural disasters destroy infrastructure and livelihoods, reducing income and deepening poverty [59]. Low-income, vulnerable populations often inhabit high-risk disaster areas, further compromising their well-being [8]. The Sendai Framework advocates shifting from single-event response to comprehensive, multi-hazard prevention at the local level; investments in ex-ante (prevention) and ex-post (response) measures significantly reduce risk and improve disaster management [60].

Disasters function as indicators of inadequately addressed development issues or developmental failures [13]. Beyond serving as symptoms of poor development, disasters actively impede progress by causing loss of life, weakening social networks, and destroying capital infrastructures. This destruction forces the reallocation of development resources from productive investments toward relief and recovery efforts. In low and middle-income countries, a key challenge is systematic underinvestment in disaster risk management, driven by acute fiscal constraints. Limited revenue bases and competing development priorities create binding budgetary pressures that compel difficult tradeoffs, with development funds frequently reallocated to immediate relief, response, and recovery for disaster-affected populations. The groups most severely affected by direct disaster impacts are those who are socioeconomically and politically marginalized, predominantly from low-income countries [61]. Disaster management requires consideration of economic, social, and humanitarian components during resource allocation [62,63]. Although public funding for DRR has increased, it remains inadequate [21].

Table 1 presents the unit root test results. An ADF test with a trend specification was employed on the annual time series data. All variables exhibited unit roots (non-stationarity) at levels, consistent with [64,65], indicating that the series are not returning to a normal trend due to the major shock. However, DRRM budget expenditure ($DRRM_b$) achieved stationarity at the second difference, while other explanatory variables achieved stationarity at the first difference. These results confirm that the series exhibits time-independent means, variance, and covariances after differencing, allowing for subsequent regression analysis.

Table 1. ADF test results of dependent and primary explanatory variables in trend.

Variable	Values in Level		Values in First Difference		Values in Second Difference	
	Test Statistics	*p*	Test Statistics	*p*	Test Statistics	*p*
$DRRM_b$	−1.649	0.772	−2.748	0.216	−4.661	0.000
Human Loss	−3.366	0.056	−4.919	0.000		
Affected Population	−3.442	0.056	−4.950	0.000		
Economic Loss	−3.260	0.073	−5.022	0.000		

Note: $DRRM_b$ stands for Disaster Risk Reduction and Management Budget expenditure.

The study assessed correlations among disaster impacts (human loss, affected population, and direct economic losses), socioeconomic moderators/determinants (HDI, real GDP, and total population), and annual DRRM budget allocation. The negative correlations between DRRM budget and both human casualties and affected population size are consistent with [18], as sustainable financing prioritizes building resilience, strengthening preparedness, and reducing vulnerability before disasters occur. Higher DRRM allocation is associated with reduced human loss (r = −0.594) and smaller affected populations (r = −0.494). These results align with existing research [18,19,66], which demonstrates that increased DRRM spending mitigates casualties and population exposure in least developed countries by strengthening critical infrastructure, reducing potential fatalities, and mitigating disaster impacts. However, $DRRM_b$ (DRRM budget expenditure) shows a strong positive correlation with recorded economic losses (r = 0.744), consistent with [20]. This seemingly contradictory relationship exists primarily because a substantial portion of DRRM expenditure is allocated to relief, rescue, and emergency management rather than to long-term disaster prevention and mitigation. These findings also support previous research [29,67] linking disaster frequency and impacts to government budget allocation decisions in developing economies. The summary statistics and correlation coefficients are summarized in Table 2.

Table 2. Descriptive statistics and correlation matrix.

Variables	Mean	St Dev.	(A)	(B)	(C)	(D)	(E)	(F)	(G)
(A) $DRRM_b$	48,670.93 (12,656.61)	62,004.50							
(B) Human Loss	1186.54 (370.15)	1813.34	−0.594 **						
(C) Affected Population	363,507.12 (191,176.68)	936,570.65	−0.494 *	0.509 *					
(D) Economic Loss	34,227.17 (29,356.33)	143,816.10	0.744 **	−0.288	−0.219				
(E) Total Population	26,674,668.3 (441,518.81)	2,162,991.6	0.902 **	−0.562 **	−0.515 *	0.640 **			
(F) Real GDP	1,809,177 (106,318.00)	538,607.75	0.901 **	−0.560 **	−0.527 *	0.674 **	0.983 **		
(G) Number of Incident	2421.33 (395.72)	1938.64	0.706 **	−0.296	−0.346	0.678 **	0.833 **	0.879 **	
(H) HDI	0.548 (0.009)	0.047	0.907 **	−0.576 **	−0.534 *	0.647 **	0.986 **	0.967 **	0.817 **

Note: All the results in the above table are obtained after removal of identified outliers; Standard Error of Mean in Parenthesis, $DRRM_b$ is Disaster Risk Reduction and Management Budget expenditure, HDI is Human Development Index, ** $p = 0.01$, * $p = 0.05$.

The moderator variables, such as HDI, population size, and real GDP, are moderately associated with explanatory variables. While $DRRM_b$ shows positive correlations with economic loss and macroeconomic size indicators, it demonstrates inverse relationships with human consequences. DRRM budget expenditure appears concentrated in larger or more affluent economies and is associated with reduced human impacts; however, the effect cannot be inferred from correlations alone. Large standard errors of the mean and standard deviations indicate substantial dispersion and possible skewness in a variable's distribution. Conversely, small values of these statistics suggest low dispersion and an approximately symmetric distribution.

Increasing disaster intensity due to socio-economic and environmental factors requires targeted DRRM funding to address multidimensional vulnerabilities, including livelihood disruption, loss, and weakened self-protection [15,68]. Disasters have a significant negative impact in terms of casualties and lead to more severe indirect economic effects in low-income countries [69]. In disaster economics, human development is crucial for disaster preparedness and financing, as DRRM financing primarily aims to enhance resilience and promote sustainable human development. Individuals with higher levels of human development (e.g., schooling, skills, and health) experience fewer disaster impacts, such as loss of life, compared to those with lower levels of human development. Consequently, public investment in initial human capital stock can accelerate post-disaster recovery [70], thereby improving HDI. Countries with higher income levels and greater educational attainment tend to experience fewer losses [34,69]. Model 1 reveals that human loss significantly increases $DRRM_b$ explaining 33.51 percent of variation. Specifically, a one percent increase in human loss leads to a 28.7 percent increase in $DRRM_b$. This finding supports Kong [71], which indicates that most $DRRM_b$ are allocated to disaster relief rather than prevention. When HDI is introduced as a moderating variable in the relationship between human loss and $DRRM_b$, the explanatory effect increases to 38.50 percent. In Model 2, both human loss and HDI show negative but statistically insignificant association with $DRRM_b$, while the interaction term between human loss and HDI has positive but insignificant effect. Despite these results, HDI appears to play important moderating role in determining the allocation of $DRRM_b$ (DRRM budget expenditure). The regression coefficients for both models are presented in Table 3.

Table 3. Regression models and their statistics.

Model	Variable/Constant	Coefficient Values	St. Error	*t*	*p*-Value	R-Square
1	ΔHuman loss	0.287	0.081	3.54	0.002	0.3351
	Constant	0.007	0.120	0.06	0.951	
2	ΔHuman loss	−0.015	0.356	−0.04	0.966	0.3850
	ΔHDI	−0.273	0.876	−0.31	0.795	
	Δ(Human loss X HDI)	0.675	0.785	0.86	0.401	
	Constant	0.037	0.167	0.22	0.825	

Note: Dependent variable $\Delta^2 DRRM_b$ is second difference of Disaster Risk Reduction and Management Budget expenditure; Human Loss X HDI is interaction term; Δ is first difference of corresponding variables; Model 1 is OLS regression; Model 2 is MMR based on robust regression.

The economy has become much more complex and closely intertwined with human lives, and GDP has shown a significant relationship with disaster-related human suffering. Policymakers strive to increase investment in human development and strengthen national economic capacity [72,73]. The size of the economy can influence the impact of disasters; for instance, Noy [74] found that disaster costs are higher in developing nations than in developed nations. Model 1 (OLS based on robust regression) reveals that the affected population has a significantly positive relationship with $DRRM_b$, with an explanatory power of 40.68 percent. Specifically, a one percent change in the affected population results in a 29.4 percent change in $DRRM_b$. When real GDP is introduced as a moderating variable in the relationship between the affected population and $DRRM_b$, the explanatory power decreases to 37.73 percent. In Model 2, the explanatory continues to show a statistically significant positive association with $DRRM_b$; however, the moderator and the interaction term have insignificant effects on $DRRM_b$. Despite this, the model indicates an antagonistic moderating effect of real GDP and its interaction with the affected population on the relationship between affected population and $DRRM_b$ (DRRM budget expenditure). The regression coefficients for both models are presented in Table 4.

Table 4. Regression models and their statistics.

Model	Variable/Constant	Coefficient Values	St. Error	*t*	*p*-Value	R-Square
1	ΔAffected population	0.294	0.079	3.70	0.001	0.4068
	Constant	0.014	0.118	0.12	0.906	
2	ΔAffected population	0.276	0.114	2.42	0.026	0.3773
	ΔReal GDP	0.223	1.795	0.12	0.903	
	Δ(Affected population X Real GDP)	0.241	0.696	0.35	0.733	
	Constant	−0.010	0.277	−0.04	0.971	

Note: Dependent variable $\Delta^2 DRRM_b$ is second difference of Disaster Risk Reduction and Management Budget expenditure; Affected Population X Real GDP is interaction term; Δ is first difference of corresponding variables; Model 1 is OLS regression; Model 2 is MMR based on robust regression.

Developed countries experience significantly greater direct economic losses from property damage, suggesting that higher levels of development are associated with increased economic losses. In contrast, developing nations bear a disproportionate share of population exposure and disaster risk; however, the allocation of DRRM budget remains misaligned with this reality [69]. Results from Model 1 indicate that direct economic loss has a significant effect on $DRRM_b$ (DRRM budget expenditure), with an explanatory power of 38.78%. The findings further suggest that, in the context of Nepal, a low-income country, DRRMb is significantly associated with economic losses, although this relationship requires further investigation. Specifically, the result also shows that a one percent change in direct economic loss leads to a 29.8 percent change in $DRRM_b$. When population size is introduced as a moderator, the explanatory power of the model increases to 52.07 percent. In Model 2, both economic loss and population size exhibit negative but statistically insignificant association with $DRRM_b$, while the interaction term between economic loss and population size shows a positive but insignificant effect. The regression coefficients for both models are presented in Table 5.

Table 5. Regression models and their statistics.

Model	Variable/Constant	Coefficient Values	St. Error	*t*	*p*-Value	R-Square
1	ΔEconomic loss	0.298	0.083	3.56	0.002	0.3878
	Constant	0.009	0.123	0.08	0.938	
2	ΔEconomic loss	−0.265	5.675	−0.05	0.963	0.5207
	ΔTotal population	−0.529	3.074	−0.17	0.865	
	Δ(Economic loss X Total population)	1.401	14.119	0.10	0.922	
	Constant	0.055	0.153	0.36	0.721	

Note: Dependent variable $\Delta^2 DRRM_b$ is second difference of Disaster Risk Reduction and Management Budget expenditure; Economic loss X Total population is interaction term; Δ is first difference of corresponding variables; Model 1 is OLS regression; Model 2 is MMR based on robust regression.

The moderation effect was evaluated by quantifying the variance uniquely attributable to the interaction term relative to the residual (unexplained) variance in the final model. The moderation effect size of HDI on the human loss—$DRRM_b$ relationship ($f^2 = 0.010$) indicates a small effect. In contrast, the effect of real GDP on the affected population—$DRRM_b$ relationship ($f^2 = -0.037$) reflects a small but negative (antagonistic) effect. Meanwhile, total population on the economic loss—$DRRM_b$ relationship ($f^2 = 0.152$) demonstrates a moderate effect size. Notably, the results suggest that smaller moderation effect sizes are associated with greater statistical significance in the moderation models. The magnitude of these moderation effects is illustrated in Figure 3.

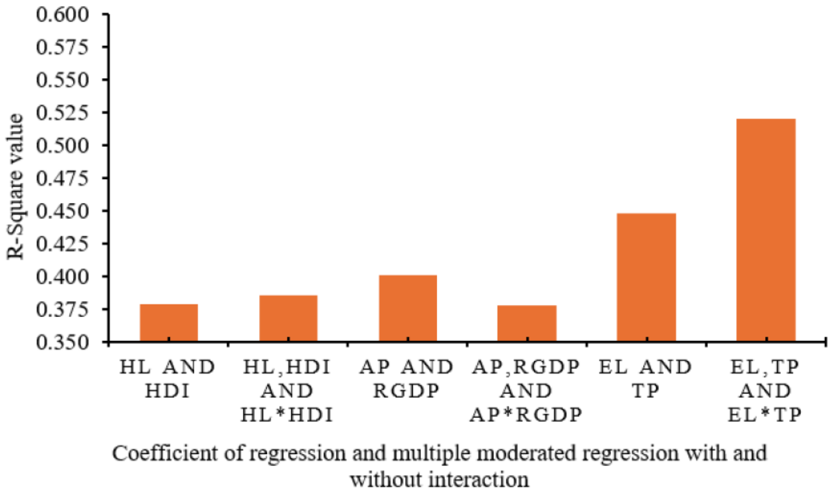

Figure 3. R-square value of moderated multiple regression model with and without interaction term, where $DRRM_b$ is dependent variable, HL is Human loss, HDI is Human Development Index, AP is affected population, RGDP is real gross domestic product, TP is total population and EL is economic loss.

In disaster economics, human loss, direct economic loss, and human suffering are considered as direct damage caused by disasters. This direct damage has a negative impact on the economy [41,75]. This OLS (based on robust regression) model investigates the integrated effect of these direct damages (human loss, affected population and economic loss) on $DRRM_b$ using Equation (6). The results indicate that only human loss is statistically significant and negatively associated with $DRRM_b$, consistent with the findings of [41]. In contrast, the affected population and economic loss show positive but statistically insignificant association with $DRRM_b$. Despite these results, the model explains approximately 55.33 percent of variations in the dependent variable. The regression coefficients of the model are presented in Table 6.

Table 6. Regression models and their statistics.

Model	Variable/Constant	Coefficient Values	St. Error	*t*	*p*-Value	R-Square
1	ΔHuman loss	−1.627	0.695	−2.34	0.031	0.5533
	ΔAffected population	0.670	0.770	0.87	0.396	
	ΔEconomic loss	1.265	0.738	1.71	0.104	
	Constant	−0.028	0.111	−0.26	0.799	

Note: Dependent variable $\Delta^2 DRRM_b$ is second difference of Disaster Risk Reduction and Management Budget expenditure; Δ is first difference form of corresponding independent variables in model 1.

4. Conclusions

Disasters, whether natural or human-induced and regardless of scale (small, moderate, or major), have devastating impacts at local, regional, and global levels. However, developing and low-income countries experience disproportionately severe consequences due to high vulnerability, inadequate investment, socio-economic disparities, and institutional systems that remain reactive rather than proactive. This study analyzed federal DRRM budget allocations in Nepal from 2001 to 2024 to assess how disaster impact dimensions (human loss, affected population, and direct economic loss) determine budget expenditure patterns and which contextual factors enhance these relationships. DRRM expenditures remain fragmented across budget line items, departments, and government levels, lacking standardized definitions. Establishing coherent budget classification frameworks is essential for enhancing transparency and coordination in DRRM, particularly in countries like Nepal. These advancements will facilitate cross-country comparisons and mitigate duplicative agency activities. Establishing a uniform national database that integrates disaster profiles with an optimal DRRM spending framework is essential for informed resource allocation in low-income contexts.

Bivariate correlation analysis indicates a negative association between DRRM budget expenditure ($DRRM_b$) and humanitarian impact (human loss and affected population), suggesting that increased spending is associated with lower human loss and population exposure in least developed countries, alongside a positive correlation between direct economic loss and DRRM spending, consistent with a reactive response to higher-cost property damage. In contrast, individual regression models show significant positive associations between DRRM spending and each disaster impact measure, including human loss, affected population, and direct economic loss, indicating a predominantly reactive spending pattern following disaster impacts. When these impacts are considered jointly, human loss remains the dominant significant explanatory factor for budget expenditure, while affected population and economic loss lose statistical significance, suggesting overlapping explanatory power among these disaster impact measures. Development capacity (HDI), economic scale (real GDP), and demographic scale (population size) serve as key moderators of the relationships between human loss, affected population, and economic loss and budget expenditure. The positive link between direct disaster damage and DRRM expenditure, a pattern commonly observed in developed nations and found to be positive and statistically significant in this study, requires further investigation. Our novel contribution identifies human impacts of disasters and socioeconomic moderators that shape this relationship, offering insights transferable to comparable disaster-prone contexts. These factors are crucial for developing an optimal DRRM budget allocation framework according to positive economic frameworks. This approach provides policymakers with empirical foundations for budget planning, grounded in historical disaster impacts and moving beyond incremental or normative economic approaches. Consequently, risk-based budget allocation strategies facilitate alignment with internationally agreed targets established by the Sendai Framework, Paris Agreement (PA), and SDGs.

This study has some limitations. DRRM budget definitions and line items may differ across countries, and human loss statistics include missing persons. Economic loss data includes only recorded direct losses, not the indirect losses. Affected family population figures were projected based on household size using exponential methods. Additionally, three incomplete event records with missing location and impact data were excluded from a dataset of approximately fifty-eight thousand records, resulting in minimal risk of data uncertainty. Finally, further diagnostic tests could not be performed because the robust regression method treats the outliers, which prevents additional diagnostic testing. However, these results still provide important insights into how disasters affect budget decisions in developing countries. Building on the present finding that human impact and direct economic losses provide a basis for assessing DRRM investment, future work should investigate how DRRM expenditure influences national economic growth, incorporating comprehensive economic impacts (direct, indirect, and induced) to improve the accuracy of DRRM expenditure allocation. Structural break analysis will be another part of further investigation.

Supplementary Materials

The additional data and information can be downloaded at: https://media.sciltp.com/articles/others/2608051505574710/JHRR-26030191-SI.pdf. Table S1: Nepal's DRRM Budget data.

Author Contributions

K.S.: Conceptualization, methodology, data curation, analysis, writing—original draft preparation; N.P.B.: Conceptualization, methodology, resources, supervision, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The datasets used in this study are publicly available from open-source repositories.

Acknowledgments

The authors acknowledge the valuable support and cooperation provided by the Ministry of Home Affairs (MoHA), Ministry of Urban Development (MoUD), Department of Hydrology and Meteorology (DHM), Department of Mines and Geology (DMG), and the National Disaster Risk Reduction and Management Authority, (NDRRMA) Nepal, especially in acquiring the data for this study. They also acknowledge the use of open-source datasets availed by the National Planning Commission, the National Statistics Office, and the Ministry of Finance (Nepal), as well as international databases, including DesInventar, the World Bank, and the International Monetary Fund.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During preparation of the manuscript, the authors used online generative AI-assisted platforms primarily for language editing, including grammatical improvements, sentence clarity, and better readability. The manuscript structure, scientific content, data analysis, result interpretations and discussion, and concluding remarks were entirely developed and written by the authors. After using the AI-assisted tools, the authors reviewed and well edited the manuscript text and take full responsibility for the content of the published article.

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