Received date: January, 2026
Accepted date: March, 2026
Published date: May, 2026

Economic Analysis of Risk through Hazard, Exposure, Sensitivity, and Adaptive Capacity: Implications for Risk Management in Nepal

Principal Author:
Rajendra Adhikari
Department of Economics, Mechi Multiple Campus, Tribhuvan University
Email: rajendra.adhikari33@gmail.com
ORCID: https://orcid.org/0000-0002-1365-4543
Corresponding Author:
Kavita Paudyal
Faculty of Management, Mechi Multiple Campus, Tribhuvan University
Email: kavita.mechi25@gmail.com

Keywords: Vulnerability; multicollinearity, VIF, scale effect

Abstract

This paper explores the economic impact of climate-sensitive variables like hazard, exposure, sensitivity, and adaptive capacity on risk management in Nepal so as to present evidence-based policy recommendations. It uses an OLS regression model with the secondary data of 77 districts in Nepal in 2022. The findings reveal that the economic risk largely depends on hazard, exposure, and sensitivity as positively influencing factors and the adaptive capacity as having a strong negative impact, which implies the role of the latter in eliminating socio-economic losses. The model is robust as indicated by diagnostic tests, such as the variance inflation factor (VIF) and scale coefficients. The results indicate that effective risk management policies ought to be directed at minimizing the risk levels and sensitivity using early warning systems and resilient infrastructure, and at the same time, enhance adaptive capacity using technical training and allocation of resources. The research proposes that government bodies (federal, provincial, and local) should act in co-ordination with the private sector and other stakeholders to establish resilience over the long run. These climate-sensitive variables will help to address these questions: How can the evidence-based planning and resource allocation be integrated into economic analysis to facilitate sustainable development and increase disaster resilience in Nepal?

Introduction

Some of the earliest scholarly arguments pointed out the necessity of place-specific risk management paradigms for the success in the evaluation of climate dangers and adaptation actions (Jones, 2001). These tools were geared towards acquiring the physical climate risk, such as extreme weather and an increase in sea level, and how the two combine with the socio-economic factors of susceptibility. Willows and Connell (2003) also advocated systematic evaluation of the allure for risks, conceding that we may not accurately anticipate future vulnerabilities.

With the further development of literature, more attention was paid to adaptive capacity. According to Smit and Pilifosova (2001), adaptive capacity is a function of economic resources, technology, and infrastructure. Yohe and Tol (2002) also noted that human and social capital, as well as mechanisms for risk management, are essential in enhancing adaptive capacity. Vulnerability was conceptualized in terms of exposure, sensitivity, and adaptive capacity (Fussel & Klein, 2006), in turn influenced by the definition of risk as a function of these three factors (Fussel, 2007). This perspective overlapped with the social vulnerability theory that reflects the socio-economic and governance aspects rather than physical exposure (Adger, 2003).

Later works emphasized the inclusion of physical and socio-economic aspects in the vulnerability analyses. Moss et al. (2001) and Cutter et al. (2003) called for combining environmental and empirical social and economic indicators, while Handmer (2003), Smit and Wandel (2006), and Schipper and Burton (2008) debated optimal mixes between physical hazards on one hand and socio-economic factors on the other hand. The same was emphasized by Birkmann (2007) and Liu et al. (2007) regarding vulnerability assessment scales and regionality. Williamson et al. (2009) showed that complex and adaptive economies are more resilient to climate risk than highly specialized economies.

The quantification of risk assessment and decision-making under incomplete information was discussed subsequently. On the other hand, Adger (2006) emphasized the importance of wealth and governance for adaptive capacity, with Birkmann et al. (2013) warning against disregarding the hazard and exposure aspects. Van der Pol et al. (2015) demonstrated that the inclusion of uncertainty with probabilistic cost-benefit analysis can improve flood defense system measures. Weis et al. (2016) further developed index methods that are based on integrated risk to exposure, sensitivity, and adaptive capacity, together with noting weaknesses in weighting schemes.

According to the Nepal Common Country Assessment (CCA), the Nepal Hazard Risk Assessment (NHRA) revealed the fact that the country is at high risk due to the natural hazards and the importance of hazard mapping, the assessment of vulnerability, and the economic models were listed as the resources to enhance disaster risk reduction and community-based resilience (Asian Disaster Preparedness Center [ADPC], 2010). In a similar manner, Regmi et al. (2023) pointed out that there is a close association between hazard, exposure, sensitivity, and adaptive capacity in defining climate risk. Khadka et al. (2024) also found that the communities living near flooding caused by the glacial lake outburst (GLOF) are highly vulnerable because of low adaptive capacity.

Although numerous papers have evaluated climatic risk, vulnerability, and adaptive capacity on a global scale and in Nepal, few studies have integrated hazard, exposure, sensitivity, and adaptive capacity with resultant economic implications of risk management. Most of the literature out there only speculates on the risks or qualitative measurement of social vulnerability, but not many of them are founded on a holistic approach to relate climate-sensitive variables with economic risk. In addition to that, there is limited local and region-specific research based on socio-economic and ecological dimensions. This also requires empirical and policy-appropriate analysis, which transforms the assessment of these variables into risk management policy needed in the context of the Nepalese economy, society, and environment, in a particular case.

The present paper tries to answer the research questions: What is the effect of the climate-sensitive variables on economic Risk in Nepal, hazard, exposure, sensitivity, and adaptive capacity? What would such an evaluation of these variables tell us about the effective risk management strategies that would help promote resilience in Nepal?

This paper seeks to evaluate the economic relevance of climate-sensitive factors such as hazard, exposure, sensitivity, and adaptive capacity to risk, as well as the implications of such factors in risk management in Nepal. The rest of the paper is organized as follows: the next section is a literature review, followed by the research method and data analysis, and the last section is the conclusion and policy implications.

Literature Review

The notion of risk holds a significant position in the world of economics, environmental sciences, and development planning, especially in those countries that are vulnerable to various natural disasters like Nepal (Kaplan & Garrick, 1981; Cardona et al., 2012). Risk analysis has developed in a unitary understanding of probabilities and probabilistic sense to comprehensive systems that identify the interplay between physical hazards and socio-economic systems (Tol, 1996; Füssel & Klein, 2006). The literature review is a synthesis of theoretical and empirical works on risk, hazard, exposure, sensitivity, and adaptive capacity, but with special focus on the economic implications and applicability of the work in the context of risk management in Nepal (Smit & Pilifosova, 2001; Adger, 2006; Asian Disaster Preparedness Center et al., 2010).

Risk Analysis: Theoretical Foundations

Conceptualization of Risk in early economic and engineering texts and methods. Early economic and engineering literature defined risk as the product of the probability of an adverse occurrence and its effects. This concept was formalized by Kaplan and Garrick (1981), who formulated the idea of risk as a product of likelihood and impact, becoming foundational in disaster risk analysis, environmental economics, and engineering. Probabilistic analogs of this were borrowed into welfare economics, where the analysis of expected damages incurred by ecological degradation and natural hazards was in expected loss terms and expected utility (Spicer, 1978; Matten, 1995). The initial models of climate-economy models furthered this model by adding the issue of climate variability to the economic performance. The research by Rosenzweig and Parry (1994) indicated the responsiveness of agricultural production to the change in temperature and rainfall, and climate exposure was identified as a cause of economic risk. Tol (1996) also provided another conceptualization of disaster losses as the product of intensity and socio-economic sensitivity of hazard, which brought the vulnerability into the economic loss estimation.

Nevertheless, the models emphasized in the earlier years treated vulnerability mostly in an implicit manner, meaning that the models emphasized physical exposure and the magnitude of hazards but little on adaptive capacity and institutional responses. In the early 2000s, there was a significant change in concept, with the introduction of vulnerability-based paradigms. According to Smit and Pilifosova (2001), vulnerability is a factor of exposure, sensitivity, and adaptive capacity, which means that even when the exposure is high, a high adaptive capacity may decrease the risk significantly. The social vulnerability theory, which stressed governance, institutions, and access to resources as key mediators of risk, reinforced this point of view (Adger, 2003; Adger, 2006). Based on these premises, Fussel and Klein (2006) have offered one of the most powerful integrated frameworks that conceptualizes risk as a product of hazard and vulnerability, with vulnerability in its turn being a product of exposure, sensitivity, and adaptive capacity. It later became part of IPCC estimates and was generalized to climate, environmental, and socio-economic hazards (Cardona et al., 2012). Fussel (2007) also stressed that vulnerability is dynamic and contextual, which is determined by the economic means, policy reaction, and institutional capacity.

These frameworks are economically linked in terms of risk and damage capabilities, integration of exposure and efficacy, and adaptive investments. Smith and Wandel (2006) hypothesized that exposure and sensitivity amplify an increase in damages, whereas adaptive capacity minimizes economic losses and adaptation costs. As a result, risk management is reduced to an economic optimization problem of investments in adaptation and resilience.

Adaptive Capacity, Risk, and Economics

The literature on adaptive capacity has been paying more and more attention to the economic aspect of adaptive capacity. Adaptive capacity is now understood to be largely dependent on financial resources, technological capability, quality of governance, and effectiveness of policies (Fussel, 2007; Walker et al., 2004). Adaptive capacity is no longer considered as the availability of resources, but it is a dynamic process that entails institutional learning, leadership, and social capital (Pelling and High, 2005). The behavioral and cognitive aspects have expanded theoretical knowledge. Grothmann and Patt (2005) also emphasized that adaptive capacity is translated into actual risk reduction because of the risk perception, self-efficacy, and decision-making processes. Gifford et al. (2011) further extended this perspective and put emphasis on psycho-social elements, including trust and perceived efficacy of adaptation measures, as influencing adaptive responses. The literature on development economics of the recent past has also discussed the mutual relationship between risk and economic growth. Hallegatte (2013) stated that economic development, on the one hand, predisposes more exposure, which may raise investments in risky regions, and protection, through the possibility of better infrastructure and reducing risks. This forms a dynamic trade-off whereby growth produces and eliminates risk. Mortreux and Barnett (2017) also emphasized that intangible aspects like place attachment and social cohesions are also crucial in the long-term resilience.

Administrative Improvements in Risk Estimation

Risk estimation methodology has changed over time, originating with deterministic and indicator-based methods to probabilistic and econometric methods and simulation-based methods. In financial economics, nested simulation methods have been created to estimate complicated risk measures in an efficient way. The regression-based nested simulations suggested by Broadie, Du, and Moallemi (2015) are much more effective in terms of the convergence rates. In contrast, the multilevel Monte Carlo techniques used by Giles and Haji-Ali (2019) are aimed at estimating the nested expectations in the context of risk assessment. Despite the fact that these techniques have historically been used to look at financial portfolio risk, their relevance to economic Risk associated with climate is becoming known. These techniques come in handy, especially when estimating tail risk and extreme events, which are the focus of climate and disaster risk analysis. Nevertheless, their use in the climate vulnerability literature has been very sparse, particularly in low-income and low data-intensive environments. The integrated risk frameworks have been operationalized by empirical studies in climate economics through the use of econometric models. Weis et al. (2016) used multiplicative and log-linear specifications to estimate the elasticity of hazard, exposure, sensitivity, and adaptive capacity on offer proportions of their contribution to the overall Risk. These strategies can help policymakers find cost-efficient ways of minimizing economic losses through addressing significant vulnerability factors.

Risk and Vulnerability: Empirical Evidence in Nepal

The principle of risk assessment of the empirical risk assessment in developing countries like Nepal has significantly depended on the indicator-based, spatial, and participatory approaches. Due to its vulnerable geology, varying climatic conditions, and socio-economic limitations, Nepal is highly susceptible to numerous hazards that include floods, landslides, drought, earthquakes, and glacial lake outburst floods. The Nepal Hazard Risk Assessment (ADPC et al., 2010) reported massive exposure and identified the necessity of vulnerability mapping and economic analysis (scenario). The latest Nepal-based research has embraced combined IPCC risk models that have been adjusted to the local socio-economic realities. Regmi et al. (2023) conceptualized indicators of hazard, exposure, sensitivity, and adaptive capacity through participatory techniques and proved that low adaptive capacity considerably contributes to economic risk irrespective of equal exposure to hazard. Huss and Negi (2024) demonstrated that differences in adaptive capacity at the basin level have significant impacts on vulnerability to glacial lake outburst floods, although the hazards have a similar intensity. This notwithstanding, the majority of the empirical research in Nepal is cross-sectional and descriptive, which provides little information regarding the causal processes or the economic scale of the risk in question. Microscopic econometric or probabilistic methods are used to determine the conversion of climate-sensitive variables into economic losses in sectors. Consequently, there is still a limited scope of evidence-based prioritization of risk management investments.

Synthesis and Research Gap

The literature shows clearly that there is a shift in the hazard-based risk analysis into integrated systems that embrace the exposure, sensitivity, and adaptive capacity. The conceptual progress has given special emphasis to the importance of socio-economic structures, institutions, and adaptive processes in developing economic risk. The methodological inventions of econometrics and simulation present potent instruments for quantifying risk and uncertainty. There is still, however, a significant gap in the application of these more advanced methods to developing, multi-hazard contexts like Nepal. The current research is based too much on indicators and spatial analysis, and not a lot of econometric or probabilistic unemployment estimates on economic risk. Closing this gap is critical in designing evidence-based risk management strategies and helping in sustainable development. This paper aims to fill this gap by combining economic analysis with the hazard-exposure-sensitivity-adaptive capacity framework to produce policy-relevant information to manage the Risk in Nepal.

Methodology

The present study is based on secondary data sets. The data sets for 77 districts were collected from the Ministry of Health and Population through the Report on Vulnerability and Adaptation Assessment of Climate-Sensitive Diseases and Health Risks in Nepal (2022). This is the empirical analysis of a cross-sectional dataset of all the districts for the year 2022.

The hazard, exposure, sensitivity, and adaptive capacity variables were then built at the district level with secondary data along with composite index methods frequently used in climate risk and vulnerability studies (Nardo et al., 2005; OECD, 2008).

The framework of vulnerability is used in operationalization such that the risk appears as a result of the interaction between climatic hazard factors and socio-economic vulnerability factors (IPCC, 2014). The hazard variable is the measure of the occurrence and intensity of the climatic catastrophes in each district. The indicators include the frequency of floods, landslides, droughts, and extreme rainfalls in the past. These indicators are the physical realization of hazard events that can result in the generation of economic losses (Cardona et al., 2012; IPCC, 2014).

The exposure variable is where the populations and economic assets are located in the hazard-prone regions. These are the indicators, such as the population density of the district, the ratio of settlements and agricultural land in the areas of vulnerability, and the infrastructure concentration. These indicators depict the extent to which human beings and properties are vulnerable to the possible risks (IPCC, 2014; Cutter et al., 2003).

Sensitivity is used to measure the impacts of hazards on economic systems and populations. Some of the indicators are poverty levels, agricultural dependence as a livelihood, demographic vulnerability (children and older population), and the food security situation. Such variables include the vulnerability of the socio-economic systems to the effects of hazard (Turner et al., 2003; Cutter et al., 2003).

The adaptive capacity is how districts can foresee, react to, and recover from the effects of hazards. These may be literacy levels, access to healthcare facilities, availability of infrastructure, and access to water and sanitation facilities. Increased adaptive capacity will make the community less vulnerable because it enhances the capacity of the community to deal with environmental stress (Smit and Wandel, 2006; IPCC, 2014).

A minmax transformation was used to normalize all the indicators so that they are comparable across the districts. Hazard, exposure, sensitivity, and adaptive capacity composite indices were then used to index the normalized indicators with an arithmetic mean, which is usually followed when constructing vulnerability and risk indices (Nardo et al., 2005; OECD, 2008).

Model Formulation

The methodology of risk assessment embraced in this paper is an integrated economic risk assessment framework that is anchored on the Intergovernmental Panel on Climate Change. In this paper, the concept is presented where risk is a product of hazard, exposure, sensitivity, and adaptive capacity (IPCC, 2014). Similar to Fussel and Klein (2006) and Fussel (2007), economic risk is defined as the product of climatic hazards and socio-economic vulnerability, with vulnerability being defined as the product of exposure, sensitivity, and adaptive capacity. The economic risk in district i at time t can be formally defined as:

$$Risk_{it} = f\,(Hazard_{it}, Exposure_{it}, Sensitivity_{it}, Adaptive\ Capacity_{it})$$

The model can be written in econometric linear form as:

$$\text{Risk}_{it} = \alpha + \beta_1\ \text{Hazard}_{it} + \beta_2\ \text{Exposure}_{it} + \beta_3\ \text{Sensitivity}_{it} - \beta_4\ \text{Adaptive Capacity}_{it} + \varepsilon_{it}$$

($\beta_1 > 0, \beta_2 > 0, \beta_3 > 0, \beta_4 < 0$ *and* ε_{it} represents the disturbance term) and Adaptive Capacity is negatively associated with risk.

Results and Discussion

OLS Regression Results

The OLS regression results with risk as the dependent variable and Hazard, Exposure, Sensitivity, and Adaptive Capacity as independent variables are presented in Table 1. The regression equation examines the predictors of risk for 77 districts. The general model is statistically significant with F-stat = 46.61, p = 0.000, with R-squared 0.936, suggesting that about 93 % of the fluctuations in the risk of the districts are explained by the hazard, exposure, sensitivity, and adaptive capacity. Hazard (β_1= 0.565, p = 0.000), Exposure (β_2 0.365, p=0.000) and sensitivity (β_3 0.542, p = 0.000) found influencing risk positively, the higher the level of hazard, exposure, and sensitivity, the higher the risk. On the other hand, there is a negative, significant impact of adaptive capacity (β_4 -0.407, p = 0.000), indicating that greater adaptive capacity has a negative impact on risk. The findings suggest that mitigation of risks should be concentrated on minimizing the hazard, exposure, and sensitivity, and increasing the adaptive capacity to handle district-level risks efficiently.

To the policy makers (Federal Government, Provincial Government, and Local Levels), the regression findings demonstrate that effective risk management measures require thorough and specific measures on the district level. The disaster preparedness programs and the strong early warning systems should be a priority of interventions since hazard, exposure, and sensitivity are the most significant contributors to the overall risk, and the strengthening of critical infrastructure in the high-risk districts (Wooldridge, 2013). Vulnerability can further be reduced by enhancing adaptive capacity via capacity building, training on technical matters, community awareness campaigns, and efficient allocation of financial and human resources that can help in improving the effectiveness of response (UNDRR, 2015). Also, exposure reduction strategies, which include moving key infrastructures, landuse policies, and risk vulnerability in urban and rural development plans, are essential in averting possible losses (World Bank, 2018). Working in collusion among local governments, communities, and the involvement of the private stakeholders would enhance resilience, facilitate knowledge exchange, and implement the strategies in a sustainable manner (Benson & Clay, 2004). Through hazard minimization, exposure management, and improvement of adaptive capacity, district authorities are able to streamline the resource allocation process to reduce the socio-economic and environmental losses and develop long-term resilience to both natural and anthropogenic shocks (IPCC, 2014).

Table 1: *OLS Regression Results for Risk (R)*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
H	0.565	0.050	11.206	0.000
E	0.365	0.043	8.355	0.000
S	542	0.035	15.107	0.000
AC		0.040	-9.950	0.000
Constant (	-0.213	0.028	-7.399	0.000

R^2 =0 .936, Adjusted R^2 = 0.932, F-stat = 261.37, p = 0.000

Source: Author's Own Calculation through Eviews 13

Coefficient Diagnostics

Variance Inflation Factor

Variance Inflation Factor (VIF) is a diagnostic method employed in regression modeling in order to identify the presence of multicollinearity, a phenomenon whereby two or more independent variables are highly correlated (Kutner et al., 2005). Collinear predictors have overlapping information, and thus, it is hard to distinguish the special influence of a particular variable on the outcome by the model (Hair et al., 2010). VIF measures the degree of inflation of the variance (and therefore, the standard error) of an estimated coefficient of linear regression relative to a model in which the predictors are perfectly independent (Marquardt, 1970). In the case of each variable, X_i, the VIF is provided through the formula:

$$VIF_i = \frac{1}{1-R_i^2}$$

Where R_i^2 is the coefficient of determination when it is regressed on all the other independent variables (O'Brien, 2007).

Although there is no universal cutoff, the following thresholds are commonly accepted in the statistical literature (Kutner et al., 2005; Hair et al., 2010)

(1) If, *VIF = 1* there is no correlation, the predictor is absolutely independent.

(2) If 1 < VIF < 5: Moderate correlation: In most studies, this is acceptable and does not need any corrective measures.

(3) If *VIF* value is above 5 up to 10: large correlation; indicates the coefficients might be unstable and respond to minimal alterations in the data (Akinwande et al., 2015).

(4) If *VIF* > 10: Multicollinearity is severe; normally, this is a statistic that indicates that the regression coefficients are not estimated accurately and needs to be corrected, either by dropping redundant variables or dimensionality reduction (Belsley et al., 1980).

Table 2 shows the results of the Variance Inflation Factor (VIF) as one of the diagnostic tools to determine possible multicollinearity. Such findings are used as a foundation of redundancy testing, which identifies the statistical insignificance of certain variables, and thus, they are not necessary to be included in the model.

Table 2: *Variance Inflation Factors Test*

Variables	Coefficient Variance	Uncentred VIF	Centered VIF
H	0.002	18.004	1.616
E	0.002	18.801	1.337
S	0.001	6.357	1.367
AC	0.002	13.994	1.251
	0.009	21.526	NA

Source: Author's Own Calculation through Eviews 13

From Table 2, it is observed that the Centered VIF values give a good confirmation of the integrity of the model. Having a value between 1.251 and 1.616, the values are very low compared to the standard of 5.0, and this implies there is no multicollinearity. Although the values of the Uncentered VIF seem larger (reaching 21.52), this is also a typical structural residual of having a constant in a model when variables do not have means of zero. The Centered VIFs are low, hence you can conclude with high confidence that Hazard, Exposure, Sensitivity, and Adaptive Capacity are independent predictors. Such statistical independence guarantees the accuracy of the coefficients that are calculated, and this means that the overall climate health risk across the 77 districts in Nepal can be interpreted reliably, where each dimension is contributing to it in its unique way.

Scale Coefficient

The rationale behind the use of scaled (standardized) coefficients in regression analysis is that it allows the relative significance of explanatory variables when measured on different scales to be compared. Standardization is the conversion of variables into units of standard deviation that allows the direct measurement of the effect sizes in the same model. It is especially useful in multivariate regression, where the raw coefficients cannot be compared because of the different units of measurement. Standardized coefficients increase the level of interpretability and facilitate substantive inferences by establishing the predictors with the greatest impact on the dependent variable. Gelman (2008) suggested scaling predictors so as to enhance the interpretability of applied research. On the same note, Menard (2011) observed that standardized coefficients can be used in comparing effects on variables. Long (1997) highlighted their importance in interpreting regression models in social science research. Allison (1999) explained that standardization is used to compare effects, and Cohen et al. (2003) emphasized that it is useful in applied statistical modeling and interpretation of the effect size.

The results of the scaled regression with risk as a dependent variable are shown in Table 3. The results demonstrate that Hazard (H), Exposure (E), and Sensitivity (S) have a positive effect on risk, whereas Adaptive Capacity (AC) has a negative effect. The strongest impact is observed on Sensitivity (standardized coefficient = 0.528), then on Hazard (0.426) and Exposure (0.289). This implies that a one-unit deviation in the sensitivity causes the greatest change in the risk and, consequently, it is the most significant element of the model. The elasticity results support this trend. Hazard has a value of elasticity that exceeds one (1.026), meaning that 1% rise in hazard raises risk by a margin higher than 1 and is highly responsive. The elasticities of sensitivity and exposure are also positive and significant, and confirm their role in raising the level of risk. In general, the findings attest to the fact that the risk increases with hazard, exposure, and sensitivity, as per the conventional disaster risk models.

On the other hand, the negative and statistically significant correlation between Risk and Adaptive Capacity (AC) is negative (standardized coefficient = -0.333; elasticity = -0.803). It means that an increase in adaptive capacity is a major risk mitigation factor. Namely, adaptive capacity increases risk by 1 percent, which reduces the risk by about 0.80, proving its protective and mitigating effect. The significance of resilience-building interventions in risk mitigation approaches can be seen based on the magnitude of this effect. The constant value (-0.213) is the risk level when all predictors are the same and is a negative value, implying a negative intercept in the model. On the whole, the findings conform to the generally established conceptualization of risk as a hazard-exposure-sensitivity product, mediated by adaptive capacity. The results indicate that the policy interventions to minimize the sensitivity and enhance the adaptive capacity would have the most significant effect on decreasing the general risk.

Table 3: *Scale Coefficient Results*

Variables	Coefficients	Standardized Coefficients	Elasticity at Means
H	0.564	0.426	1.026
E	0.365	0.289	0.790
S	0.542	0.528	0.763
AC	-0.407	-0.333	-0.803
	-0.213	NA	-0.776

Source: Author's Own Calculation through Eviews 13

Conclusion and Recommendations

This paper assesses the economic impact of Risk in Nepal by incorporating the hazards, exposure, sensitivity, and adaptive capacity in an econometric model. The OLS results of the regressions show that the most important determinants of risk on the district level are hazard and sensitivity, and exposure is also positively impacting the results. Adaptive capacity is negatively related to risk, and this implies that improvement in adaptive capacity has the potential to reduce economic losses to a certain degree. VIF tests and Scale Coefficient tests confirm the strength of the model and allow the inference to be made on the policy formulation. These results support the theoretical views of Füssel and Klein (2006) and Adger (2006), which discuss the vulnerability as exposure-sensitivity-adaptive capacity functional perspective and the economic aspect of risk. These findings are consistent with empirical evidence on the issue in Nepal: high adaptive capacity and high hazard exposure levels result in high socio-economic and environmental vulnerability (Regmi et al., 2023; Khadka et al., 2024). The findings reveal that an efficient process of risk management must be based on a multidimensional strategy, which incorporates physical hazard reduction with socio-economic interventions. The study can prove that economic losses can be reduced by making specific investments in infrastructure, capacity building, and early warning systems by quantifying the contribution of key variables. In general, the study contributes to the risk knowledge in Nepal by offering a policy-oriented framework of correlating climate-sensitive conditions to economic performance that allows the allocation of resources based on evidence, disaster preparedness, and resilience-building intervention at the district level (Wooldridge, 2013; UNDRR, 2015).

The results show that mitigation of hazards and reduction of their sensitivity through early warning systems, disaster preparedness actions, and enhancement of critical infrastructure should be the priority of the federal, provincial, and local policymakers (World Bank, 2018; Wooldridge, 2013). Adaptive capacity should be increased in terms of technical training, community awareness, and effective allocation of resources to mitigate vulnerability. Urban and rural development plans should incorporate exposure reduction approaches, such as land-use planning and changing locations of critical infrastructures. The coordination of government agencies, communities, and other non-government stakeholders can boost resilience, enhance knowledge sharing, and achieve long-term adoption of risk management measures (Benson and Clay, 2004; IPCC, 2014).

References

Adger, W. N. (2003). Social capital, collective action, and adaptation to climate change. *Economic Geography, 79*(4), 387–404. https://doi.org/10.1111/j.1944-8287.2003.tb00220.x

Adger, W. N. (2006). Vulnerability. *Global Environmental Change, 16*(3), 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006

Akinwande, M. O., Dikko, H. G., & Samson, A. (2015). Variance Inflation Factor: As a Condition for the Inclusion of Redundant Variables in Regression Models. *Journal of Modern Applied Statistical Methods*, 14(2), 24. https://doi.org/10.4236/ojs.2015.57075

Allison, P. D. (1999). *Multiple Regression: A Primer*. Pine Forge Press.

Asian Disaster Preparedness Center (ADPC), Norwegian Geotechnical Institute, & Center for International Studies and Cooperation. (2010). *Nepal hazard risk assessment*. Government of Nepal.

Belsley, D. A., Kuh, E., & Welsch, R. E. (1980). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. John Wiley & Sons.

Benson, C., & Clay, E. (2004). *Understanding the economic and financial impacts of natural disasters*. World Bank.

Birkmann, J. (2007). Risk and vulnerability indicators at different scales: Applicability, usefulness, and policy implications. *Environmental Hazards, 7*(1), 20–31. https://doi.org/10.1016/j.envhaz.2007.04.002

Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., … Welle, T. (2013). Framing vulnerability, risk, and societal responses: The MOVE framework. *Natural Hazards, 67*(2), 193–211. https://doi.org/10.1007/s11069-013-0558-5

Broadie, M., Du, Y., & Moallemi, C. C. (2011). Efficient risk estimation via nested sequential simulation. *Management Science, 57*(6), 1172–1194. https://doi.org/10.1287/mnsc.1110.1330

Cardona, O.-D., van Aalst, M. K., Birkmann, J., Fordham, M., McGregor, G., Perez, R., Pulwarty, R., Schipper, E. L. F., & Sinh, B. T. (2012). Determinants of Risk: Exposure and vulnerability. In C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G.-K. Plattner, S. K. Allen, M. Tignor, & P. M. Midgley (Eds.), *Managing the risks of extreme events and disasters to advance climate change adaptation* (pp. 65–108). Cambridge University Press. https://doi.org/10.1017/CBO9781139177245.005

Cardona, O. D., et al. (2012). Determinants of Risk: Exposure and vulnerability. In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. https://doi.org/10.1017/CBO9781139177245.005

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences (3rd ed.). Routledge.*

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

Delmas, M. A., & Toffel, M. W. (2008). Organizational responses to environmental demands: Opening the black box. *Strategic Management Journal, 29*(10), 1027–1055. https://doi.org/10.1002/smj.680

Füssel, H.-M. (2007). Vulnerability: A generally applicable conceptual framework for climate change research. *Global Environmental Change, 17*(2), 155–167. https://doi.org/10.1016/j.gloenvcha.2006.05.002

Füssel, H.-M., & Klein, R. J. T. (2006). Climate change vulnerability assessments: An evolution of conceptual thinking. *Climatic Change, 75*(3), 301–329. https://doi.org/10.1007/s10584-006-0329-3

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine, 27(15), 2865–2873.* https://doi.org/10.1002/sim.3107

Gifford, R., Kormos, C., & McIntyre, A. (2011). Behavioral dimensions of climate change: Drivers, responses, barriers, and interventions. *Wiley Interdisciplinary Reviews: Climate Change, 2*(6), 801–827. https://doi.org/10.1002/wcc.143

Grothmann, T., & Patt, A. (2005). Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Global Environmental Change, 15*(3), 199–213. https://doi.org/10.1016/j.gloenvcha.2005.01.002

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson Prentice Hall.

Hallegatte, S. (2013). An exploration of the link between development, economic growth, and natural risk. *Fondazione Eni Enrico Mattei Working Papers, 780*. http://services.bepress.com/feem/paper780

Handmer, J. (2003). Adaptation and capacity. In J. B. Smith, R. J. T. Klein, & S. Huq (Eds.), *Climate change, adaptive capacity, and development* (pp. 23–49). Imperial College Press.

Hinkel, J. (2011). Indicators of vulnerability and adaptive capacity: Towards a clarification of the science–policy interface. *Global Environmental Change, 21*(1), 198–208. https://doi.org/10.1016/j.gloenvcha.2010.08.002

Huss, M., & Negi, A. (2024). Basin-level adaptive capacity and vulnerability to glacial lake outburst floods. *Journal of Hydrology, 623*, 128–140. https://doi.org/10.1016/j.jhydrol.2024.128140

Intergovernmental Panel on Climate Change. (2014). *Climate change 2014: Impacts, adaptation, and vulnerability. Cambridge University Press.* https://doi.org/10.1017/CBO9781107415379

Jones, R. N. (2001). Managing climate change risks: An introduction. *Climatic Change, 50*(1–2), 1–10. https://doi.org/10.1023/A:1010614927819

Khadka, N., et al. (2024). Risk perception and vulnerability of communities in Nepal to transboundary glacial lake outburst floods. *International Journal of Disaster Risk Reduction, 107*, 104476. https://doi.org/10.1016/j.ijdrr.2024.104476

Kaplan, S., & Garrick, B. J. (1981). On the quantitative definition of risk. *Risk Analysis, 1*(1), 11–27. https://doi.org/10.1111/j.1539-6924.1981.tb01350.x

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied Linear Statistical Models* (5th ed.). McGraw-Hill Irwin.

Liu, Y., Li, X., & Ouyang, Z. (2007). Regional vulnerability assessment of environmental hazards in China. *Environmental Management, 40*, 312–324. https://doi.org/10.1007/s00267-006-0163-7

Long, J. S. (1997). *Regression Models for Categorical and Limited Dependent Variables. Sage Publications.*

Marquardt, D. W. (1970). Generalized Inverses, Ridge Regression, Biased Linear Estimation, and Nonlinear Estimation. *Technometrics*, 12(3), 591–612. http://dx.doi.org/10.2307/1267205

Matten, D. (1995). Probabilistic approaches in environmental economics. *Ecological Economics,*

13(2), 123–136. https://doi.org/10.1016/0921-8009(95)00013-4
Menard, S. (2011). *Standards for Standardized Logistic Regression Coefficients. Social Forces, 89(4), 1399–1415.* https://doi.org/10.1093/sf/89.4.1399
Mortreux, C., & Barnett, J. (2017). Adaptive capacity: Exploring the research frontier. *WIREs Climate Change*, e467. https://doi.org/10.1002/wcc.467
Moss, R., Brenkert, A., & Malone, E. (2001). Vulnerability to climate change: A quantitative approach. *Research Report*, Pacific Northwest National Laboratory, pp. 1–35.
Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2005). *Handbook on Constructing Composite Indicators*. https://doi.org/10.1787/533411815016
O'Brien, R. M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity*, 41(5), 673–690. https://psycnet.apa.org/doi/10.1007/s11135-006-9018-6
Organization for Economic Co-operation and Development. (2008). *Handbook on constructing composite indicators: Methodology and user guide. OECD Publishing.* https://doi.org/10.1787/9789264043466-en
Pelling, M., & High, C. (2005). Understanding adaptation: What can social capital offer assessments of adaptive capacity? *Global Environmental Change, 15*(4), 308–319. https://doi.org/10.1016/j.gloenvcha.2005.02.001
Regmi, B. R., Sapkota, R., Paudyal, A., Gautam, D. K., Thapa, R., Joshi, R., … Mishra, B. (2023). Co-development of vulnerability and risk assessment framework and methodology for Nepal. *Environmental Monitoring and Assessment, 195*(792). https://doi.org/10.1007/s10661-023-11330-6
Rosenzweig, C., & Parry, M. L. (1994). Potential impacts of climate change on the world food supply. *Nature, 367*(6454), 133–138. https://doi.org/10.1038/367133a0
Schipper, E. L. F., & Burton, I. (2008). *The Earthscan reader on adaptation to climate change*. London: Earthscan.
Smit, B., & Pilifosova, O. (2001). Adaptation to climate change in the context of sustainable development and equity. In J. J. McCarthy, O. F. Canziani, N. A. Leary, D. J. Dokken, & K. S. White (Eds.), *Climate change 2001: Impacts, adaptation and vulnerability* (pp. 877–912). Cambridge University Press. https://doi.org/10.1017/CBO9780511546013.021
Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity, and vulnerability. *Global Environmental Change*, 16(3), 282-292. https://doi.org/10.1016/j.gloenvcha.2006.03.008
Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity, and vulnerability. *Global Environmental Change, 16*, 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008
Spicer, H. (1978). Economic theory of risk and uncertainty. *Journal of Economic Theory, 17*(1), 1–20. https://doi.org/10.1016/0022-0531(78)90004-6
Tol, R. S. J. (1996). The damage costs of climate change toward a more comprehensive
Turner, B. L., et al. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences, 100(14), 8074-8079.* https://doi.org/10.1073/pnas.1231335100calculations. *Environmental and Resource*

Economics, 8(4), 353–374.
UNDRR. (2015). *Sendai Framework for Disaster Risk Reduction 2015–2030*. United Nations.
van der Pol, T., Koks, E. E., & Hall, J. W. (2015). Probabilistic cost-benefit analysis of flood protection measures. *Natural Hazards, 78*(3), 1625–1647. https://doi.org/10.1007/s11069-015-1743-0
Weis, S. W. M., Agostini, V. N., Roth, L. M., Gilmer, B., Schill, S. R., Knowles, J. E., & Blyther, R. (2016). Assessing vulnerability: An integrated approach for mapping adaptive capacity, sensitivity, and exposure. *Climatic Change, 136*(3–4), 615–629. https://doi.org/10.1007/s10584-016-1642-0
Williamson, M., Adger, W. N., & Lorenzoni, I. (2009). Understanding vulnerability to climate change: A framework for analysis. *Environmental Science & Policy, 12*(6), 506–514. https://doi.org/10.1016/j.envsci.2009.02.001
Willows, R. I., & Connell, R. K. (2003). *Climate adaptation: Risk, uncertainty and decision-making*. UKCIP Technical Report, Oxford: UKCIP.
Wooldridge, J. M. (2013). *Introductory econometrics: A modern approach* (5th ed.). Cengage Learning.
World Bank. (2018). *Disaster risk management in Nepal: Toward resilient development*.
Yohe, G., & Schlesinger, M. (1998). The economics of sea level rise. *Climatic Change, 40*(3), 399–410. https://doi.org/10.1023/A:1005304007549
Yohe, G., & Tol, R. S. J. (2002). Indicators for social and economic coping capacity: Moving toward a working definition of adaptive capacity. *Global Environmental Change, 12*(1), 25–40. https://doi.org/10.1016/S0959-3780(01)00051-7