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ORIGINAL ARTICLE

Modeling the association between socioeconomic features and risk of flood damage: A local-scale case study in Sri Lanka

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Abstract

Floods cause severe damage to people as well as to properties. The same flood can cause different levels of damage to different households, but investigations into floods tend to be conducted on regional and national scales, thereby missing these local variations. It is therefore necessary to understand individual experiences of flood damage to implement effective flood management strategies on a local scale. The main objectives of this study were to develop a model that represents the relationship between socioeconomic conditions and flood damage at a local scale, and to understand the socioeconomic factors most closely tied to flood damage. The analysis is novel in that it considers not only the impact of flood characteristics, but also the impact of social, economic, and geographic factors on flood damage. This analysis derives from a quantitative modeling approach based on community responses, with the responses obtained through questionnaire surveys that consider four consecutive floods of differing severity. Path analysis was used to develop a model to represent the relationships between these factors. A randomly selected sample of 150 data points was used for model development, and nine random samples of 150 data points were used to validate the model. Results suggest that poor households, located in vulnerable, low-lying areas near rivers, suffer the most from being exposed to frequent, severe floods. Further, the results show that the socioeconomic factors with the most significant bearing on flood damage are per capita income and geographic location of the household. The results can be represented as a cycle, showing that social, economic, geographic, and flood characteristics are interrelated in ways that influence flood damage. This empirical analysis highlights a need for local-scale flood damage assessments, as offered in this article but seldom seen in other relevant literature. Our assessment was achieved by analyzing the impact of socioeconomic and geographic conditions and considering the relationship between flood characteristics and flood damage.

KEYWORDS
flood damage, inter-relationship, local scale, model development, path analysis, socioeconomic features

1 | INTRODUCTION

1.1 | General background

Disaster occurs when a vulnerable person or people experience a hazard and suffer severe damage and/or disruption to their livelihoods, in such a way that recovery is unlikely without external aid (Wisner et al., 2003). De Silva and Kawasaki (2018) discussed the impact of livelihood patterns on financial loss due to flood and drought disasters and identified that agriculture-based livelihoods are the most vulnerable. This finding is consistent with other literature (Chau et al., 2013; De Silva & Kawasaki, 2018; Lehner et al., 2006; Yaro, 2004). In turn, agricultural economies, environments, and societies are negatively affected by floods and droughts (Barelli et al., 2016; Naveen, 2014).

Ward et al. (2017) developed a framework for urban areas, on a global scale, which can be used to identify regions where river flood protection investments should be prioritized, or where other risk reducing strategies should be emphasized.

However, the use of local scale analysis to understand socioeconomic influences on flood damage is limited in past literature (Kawasaki et al., 2020). There is a need for more of this household level analysis so that we can understand better the interrelationships between flood characteristics and social, economic, and geographic conditions. The challenge is that conducting such analysis can be made difficult by poor accessibility of remote riverine areas and difficulties in collecting data from residents. Still, it is worth persisting. Examining climate change impacts from the bottom up—that is, looking first at households and then aggregating data at the macrolevel—offers a new and important perspective on climate change (Hallegatte & Rozenberg, 2017).

This article focuses on the following research question: "what socioeconomic features have the strongest effect on flood impact on a local-scale?" This question was evaluated through the hypothesis: "in addition to flood characteristics, socioeconomic conditions have a significant impact on flood damage." This might be a general concept familiar to many, but no research has been done to demonstrate the hypothesis quantitatively. The main objective of this article is to use community observations collected through questionnaires to develop a model to represent the relationships between socioeconomic conditions and flood vulnerability on a local scale. In this case, four floods of differing severity were considered using path analysis, with a model then quantitatively developed to assess those interactions. This type of quantitative modeling approach is capable of developing a web of relationships between exogenous and endogenous variables. Further, this type of approach is not commonly found in the literature. The approach and the associated findings are novel.

1.2 | Literature review

According to EM-DAT statistics, floods are identified as the most common natural hazard affecting large numbers of people, and causing great damage to the economy (Wahlstrom & Guha-Sapir, 2015). Moreover, floods are likely to be more severe and more frequent in the future as a result of climate change (IPCC, 2012). For decisionmakers, flood damage and socioeconomic factors are becoming important components of the new paradigm in flood risk management (Ho et al., 2008). The level of flood damage is associated with several factors. Water level, flood duration, and contamination are the most influential factors concerning building and contents damage. Building characteristics also have an impact on flood damage (Thieken et al., 2005).

Past literature has suggested that people who make their living through agriculture are highly vulnerable to flood risk (Borgomeo et al., 2017; Brouwer et al., 2007; De Silva & Kawasaki, 2020; Hallegatte, et al., 2010; Henry et al., 2015; Patnaik & Narayanan, 2010; Tahira & Kawasaki, 2017). This applies to developing countries especially, where more people are engaged in agricultural work (Kawasaki & Rhyner, 2018; Pelling & Garschagen, 2019; Sirimanne et al., 2015). However, these studies have limitations. Most consider only a single flood event at the local scale and do not account for flood frequency, while the studies that consider multiple floods use national statistics. Other studies have widened the focus beyond livelihoods and investigated the vulnerability of different economic groups to certain disasters, and their responses to those disasters (Brouwer et al., 2007; Glave et al., 2008; Lopez-Calva & Ortiz-Juarez, 2009; Masozera et al., 2007; Rodriguez-Oreggia et al., 2013). These studies have confirmed that floods have a significant, adverse effect on poverty and human development. However, it remains rare for scholars to study the relationship between risk of flood damage and socioeconomic conditions at the household level by considering the whole community as a single unit, while also taking account of multiple floods, their frequency, and the reactions of affected rural communities. Further, even though the previous study by De Silva and Kawasaki (2020) has adopted a similar methodology, it differs from this study in that it considers different community groups seperately.

1.3 | Study area

This case study was carried out in Sri Lanka, a disaster-prone, developing country. While several studies have investigated the poverty–disaster relationship in Sri Lanka (Hallegatte et al., 2010; Piratheeparajah, 2014; Wickramasinghe, 2014), the concept of socioeconomic vulnerability has not been investigated at the household level. Further, there is evidence that extreme rainfall and floods in Sri Lanka are becoming more frequent and hazardous (Alahacoon et al., 2018; De Silva et al., 2012; Herath & Rathnayake, 2004; Rathnayake & Herath, 2005). It is worth investigating the relationship between floods and poverty.

Sri Lanka is a tropical island located between latitude 6°–10° north and longitude 80°–82° east. The country, near the southern tip of India, covers 65,610 km^2. Its topography varies from mountainous in the central part, to plains in the coastal region. Rainfall patterns in Sri Lanka are affected by extreme low-pressure developments in the Bay of Bengal. There are two distinct monsoons: northeast (December–March), and southwest (May–September). The country is divided into three agroecological zones based on monsoon rainfall patterns; the wet zone, intermediate zone, and dry zone. The average mean temperatures of the wet, intermediate, and dry zones are about 24°C, from 24–26°C, and about 28°C, respectively. The annual average rainfall in these zones is more than 2500 mm, from 1750–2500 mm, and less than 1750 mm, respectively.

The study area, Ratnapura, is highly prone to flood, with an annual rainfall of 4000–5000 mm. Most of this rain falls during the southwest monsoon. While floods affect the area every year, in some years they are critical, with the Irrigation Department defining "critical" as those floods that exceed 24.4 m MSL at Rathnapura stream flow measuring gauge. There were critical floods in 1913, 1940, 1941, 1947, 2003, and 2017. Table 1 shows annual flood damage in Rathnapura district. It indicates that every year the area experiences floods and, as a result, significant financial losses are incurred. The annual average mean temperature of the area is

TABLE 1 Annual flood damage in the Kalu River basin, 1984–2003

Year	Annual flood damage in million rupees	Year	Annual flood damage in million rupees
1984	0.37	1994	3.01
1985	0.22	1995	5.64
1986	1.10	1996	NA
1987	0.05	1997	2.18
1988	0.23	1998	0.46
1989	3.94	1999	7.69
1990	3.11	2000	2.72
1991	6.34	2001	0.08
1992	12.42	2002	0.25
1993	2.41	2003	50.60

approximately 27°C, with temperatures varying from 23 to 32°C (Rathnaweera et al., 2012).

The Rathnapura district, which covers approximately 3275 km^2, is about 100 km from Sri Lanka's commercial capital, Colombo. Ratnapura and its adjoining area are biophysically diverse—mountain areas with steep slopes, river valleys, lowlands, and plains together form a highly complex natural environment.

Within the study area are various ethnic communities, but the predominant ethnic group is Sinhala–Buddhist. Around 70% of the working force is in the 18–60 age group, though there is an increase in school drop-out rates after 11 years of schooling and the completion of G.C.E. O/L examinations. According to the 2016 census a total of 49,083 people were employed in eight major economic sectors. More than 30% were government employees, while half the working population was employed in the private sector, or self-employed in agriculture or the gem industry (Urban Development Authority, 2019). Eight percent of Sri Lanka's mines are located in Rathnapura (Priyanath, 2002). Due to its geological and geographical features, approximately 90% of the region has underground gem deposits. According to the latest Central Bank statistics, the gem industry is Sri Lanka's fifth-largest export economy, accounting for 3% of the national economy (Urban Development Authority, 2019).

Land cover in this area is mostly green vegetation; there is little urbanization outside the main city of Rathnapura. The average temperature varies from 23 to 32°C, and being a tropical area there is high humidity. Poverty levels in Rathnapura are high, with the district home to the largest poor population in Sri Lanka. Figure 1 shows the study area.

2 | METHODOLOGY

2.1 | Data and analysis methods

Path analysis (in IBM SPSS Amos) was used to understand the web of relationships among measured variables, by applying the maximum likelihood estimation method. This was done because regression analysis allows only for discussion of direct relationships, without considering causal effects or indirect relationships.

Path analysis, developed by Sewall Wright (1918, 1934), is capable of addressing both direct and indirect effects between variables hypothesized as causes, as well as variables treated as effects. However, as a method, path analysis determines the tenability of causal models and is not capable of determining causes and effects. As such, researchers need to formulate causal models based on knowledge and theoretical considerations. Path analysis involves two types of variables, namely exogenous and endogenous variables. A variable whose variation is assumed to be governed by causes outside the hypothesized model is considered as an exogenous variable. In contrast, a variable whose variation is explained with the help of exogenous or other endogenous variables within the model is called an endogenous variable (Pedhazur, 1997).

Rufat et al. (2015) suggest that socioeconomic conditions, land tenure, demographics, health, coping capacity, neighborhood characteristics, and risk perception are highly influential factors in flood damage. In this study, social factors (educational level), asset ownership (vehicle and amount of land), house type, income, livelihood type (dummy variable) were considered as variables, along with geographical factors (elevation of house location, distance from the river to house), flood characteristics (inundation depth and duration), and financial loss due to floods. Relative losses due to floods were considered as the main target parameter.

The average cost of the damage due to a particular flood is defined as the absolute loss, whereas the absolute loss for average annual income is the relative loss (Equation 1). Relative loss is a measure used to indicate the level of damage that a household can sustain. Relative loss can be high even if the absolute loss is not large. If the same loss occurred in a high-income household and a low-income household, the relative loss would be higher for the low-income household. In this study, the term "flood damage" is used to interpret the relative loss.

$$\text{Relative flood loss} = \frac{\text{Flood loss}}{\text{Annual average income}} \times 100. \quad (1)$$

2.2 | Questionnaire survey

Survey data were used for the analysis and obtained through questionnaires conducted with 275 randomly selected households in Ratnapura district, Sri Lanka, in September 2017. However, due to incomplete answers, a final sample of 231 was selected for analysis. The four main flood events that occurred between 1997 and 2017 (2003, 2008, 2016, 2017) were analyzed. Irrigation department records indicate that the 2003 and 2017 floods resulted in the water level at Rathnapura gauging station reaching 23.9 m and 24.4 m above MSL, respectively. The highest water levels during the 2008 and 2016 floods were, 20.9 m and 20.1 m above MSL respectively. Hence, according to the classification used by the

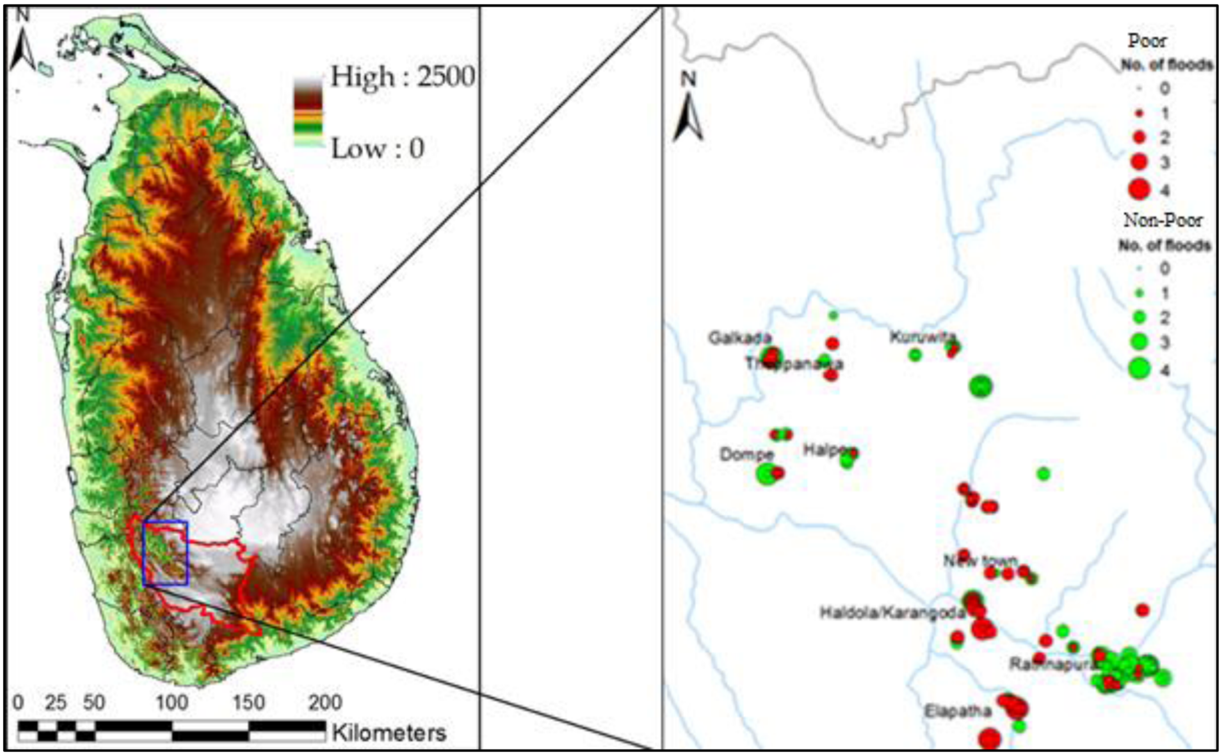

FIGURE 1 Sri Lanka/study area for questionnaire survey

irrigation department, the 2003 and 2017 floods were critical floods, and the 2008 and 2016 floods were major and minor floods respectively. Interviews were conducted in the local Sinhala language. Probability sampling method (Denscombe, 2010) was used to check the sample size validity. Crandall and Crandall (2008) suggest that a confidence level of 80%–99% is suitable whereas Cochran (1997) notes that an error limit of 4%–6% is appropriate for sample size determination. The optimized combination to achieve the best sized sample is a 99% confidence interval and an error percentage of 1% or less. However, this study considers a 90% confidence level with 5.5% error percentage, obeying the limitations introduced by previous researchers. Accordingly, the minimum valid sample size calculated for the population of 1,088,007 (2011 census data), was 224 households. Hence, the sample of 231 households was sufficient.

The questionnaire included two main sections: general household demographics and flood characteristics. Factors such as the number of household members, age of household head, income and expenditure of household members, education levels and occupations, and house type, were discussed under household demographics. In order to understand flood impacts, household members were questioned about inundation depth, duration of inundation, direct financial damage, the period they were unable to attend work and the corresponding losses, status of insurance coverage, donations received and other recovery procedures. The net financial damage was then calculated as the sum of all damages minus recoveries.

The analysis, drawing on the data collected from the questionnaire surveys conducted in Rathnapura district, was used to test the hypothesis that: "in addition to flood characteristics, socioeconomic conditions have a significant impact on flood damage." Four main flood events were considered for the analysis. The Sri Lankan Irrigation Department classifies the 2003 and 2017 floods as critical, the 2008 flood as major, and the 2016 flood as minor. However, Disaster Management Center (DMC) records show that the damage from the 2003 and 2017 floods was similar, and so too for the 2008 and 2016 floods. According to the survey data, average absolute losses were 128,000 LKR, 20,000 LKR, 34,000 LKR, and 96,000 LKR (2003, 2008, 2016 and 2017 floods, respectively). For further analysis, the 2008 and 2016 floods were considered minor, and the 2003 and 2017 floods severe.

The selected effective sample of 231 data points was used in the path analysis model to understand the general characteristics of households in a flood prone area. Development (calibration) and validation of the model are the main challenges associated with using a limited number of data points. Hence, random sampling was used to segment the sample into ten and so remove the sample bias, with each of the ten samples including 150 data points (randomly selected). One of these randomly selected samples was used to develop the model. The relationships found in the original model were then applied, for validation, to the other nine random samples. Validation was carried out by checking the model fit parameters (probability level, root mean square error approximation [RMSEA], goodness of fit index [GFI], adjusted

TABLE 2 Socioeconomic characteristics of the household sample

Household Characteristics	Value
Average household income (LKR/month) (SD)	55,000 (32,000)
Average per capita income (LKR/month) (SD.)	14,250 (7600)
Percentage of households under the poverty threshold (approximately US$2/day) (%)	35
Income inequity (GINI coefficient)	0.291
Percentage of houses built with bricks (%)	54
Percentage of houses built with concrete blocks (%)	45
Average land size owned by households (Perch)	38
Percentage of households affected by at least one selected flood (%)	99
Average financial loss due to a typical floods (LKR) (SD)	93,400 (106,300)
Average annual financial loss due to floods as a percentage of annual household income (%)	14 $\left[\frac{93{,}400}{55{,}000\times 12}\right]$

goodness of fit index [AGFI], comparative fit index [CFI], normed fit index [NFI], Tucker–Lewis coefficient [TLI], minimum discrepancy, and Akaike information criterion [AIC]), by comparing the factor loadings with the original values and through *T*-tests. The degree of poverty was also assessed using the Poverty Head Count Ratio (PHCR), Poverty Gap Index (PGI), Squared Poverty Gap Index (SPGI), and the GINI coefficient (World Bank, 2008).

2.3 | Characteristics of survey data

Initially, the characteristics of the data series were studied, and possible relationships were examined by applying cross-tabulation. Next came the quantitative investigation of those associations.

Demographic data shows that 96% of households are headed by a male, aged around 50 years. He is the income-earner and generally takes care of about three dependents. More than 80% of households consist of members educated beyond primary level. Approximately 35% of the sample relies on farming, mining, or laboring for their livelihood. Households are randomly scattered through Rathnapura district, and most respondents live in their own houses, located, on average, on approximately 40 perch of land. Further information about household socioeconomic characteristics considered in the questionnaire survey is shown in Table 2. The questionnaire survey results shown in Table 2 indicate that the monthly average per capita income of a person in the study area is approximately 14,250 LKR. This questionnaire survey was conducted near to the Rathnapura city area where it is highly exposed to frequent floods. However, according to the household income and expenditure survey 2016 (DCS, 2018), the per capita income of a person living in Rathnapura district is 12,724 LKR. The household income and expenditure survey covers the whole Rathnapura district. This insignificant difference can be due to the difference in selected area and the year of data collection. Hence, the sample can be considered as a representative sample for further analysis. Almost all households in the sample were affected by at least one of the selected flood events.

3 | RESULTS

3.1 | Model development

All four flood events, occurring between 1997 and 2017, were analyzed to understand the general characteristics and factors that lead to floods causing financial damage at a household level. Analysis of the sample suggests that the average absolute loss due to a typical flood is about 93,400 LKR, whereas the relative loss is 14% of the average annual per capita income. The average financial damage is approximately 90,000 LKR for severe floods and 20,000 LKR for minor floods.

The relationships among the variables affecting relative flood damage were then developed for a randomly selected subsample. The relationships among all variables, with coefficients, are shown in Figure 2, with a more detailed tabular representation provided in Table 3. The strength of the correlation between two variables is given by the estimate, and the significance level is shown by the *p*-value. Influencing variables were selected in such a way that the standardized estimate is greater than 0.10. Table 3 illustrates the correlation between each variable and its significance level.

The relationship shown in Figure 2 indicates that living conditions are closely connected to livelihood patterns. For example, people with a certain level of education tend not to depend on natural resources and laboring for their livelihood. In turn, they are more likely to have a vehicle and a well built, high-quality house. There is a positive correlation between per capita income and living conditions. Relative flood loss is directly influenced by flood characteristics, geographic location of the house, and per capita income.

The correlations presented in Figure 2 can be explained as equations. Derived from consideration of the whole sample,

TABLE 3 Influencing variables for average flood damage

Variable 1	Variable 2	Estimate (Standardized)	*p*-Value
Livelihood not dependent on natural resources/laboring	Highest education level (year)	0.11 (0.51)	***
House type	Livelihood not dependent on natural resources/laboring	0.15 (0.17)	0.018
	Per capita income in 10,000s	0.07 (0.12)	0.092
Distance from river (km)	House type	−0.31 (−0.20)	0.002
Vehicle ownership	Livelihood not dependent on natural resources/labouring	0.39 (0.37)	***
	Highest education level (year)	0.03 (0.14)	0.044
No. of severe floods	Distance from river (km)	−0.14 (−0.18)	0.006
Per capita income in 10,000s	Highest education level (year)	0.10 (0.30)	***
	Vehicle ownership	0.56 (0.36)	***
	Livelihood not dependent on natural resources/laboring	0.17 (0.11)	0.095
	Home land area (Perch)	0.001 (0.14)	0.008
Flood duration (days)	No. of severe floods	0.72 (0.24)	***
Inundation height (ft)	Flood duration (days)	1.39 (0.48)	***
	Geographic elevation (m MSL)	0.03 (0.10)	0.091
	Distance from river (km)	−1.68 (−0.25)	***
No. of minor floods	Livelihood not dependent on natural resources/laboring	0.26 (0.18)	0.009
	Distance from river (km)	−0.20 (−0.19)	0.004
	Per capita income in 10,000s	0.18 (0.20)	0.003
	Geographic elevation (m MSL)	0.01 (0.15)	0.017
	Inundation height (ft)	−0.02 (−0.14)	0.031
	House type	−0.20 (−0.12)	0.055
Relative flood loss (%)	Inundation height (ft)	0.01 (0.11)	0.121
	Distance from river (km)	−0.05 (−0.18)	0.006
	Flood duration (days)	0.02 (0.22)	0.002
	Per capita income in 10,000s	−0.02 (−0.10)	0.122
	No. of minor floods	−0.03 (−0.11)	0.091
	Geographic elevation (m MSL)	−0.002 (−0.11)	0.062

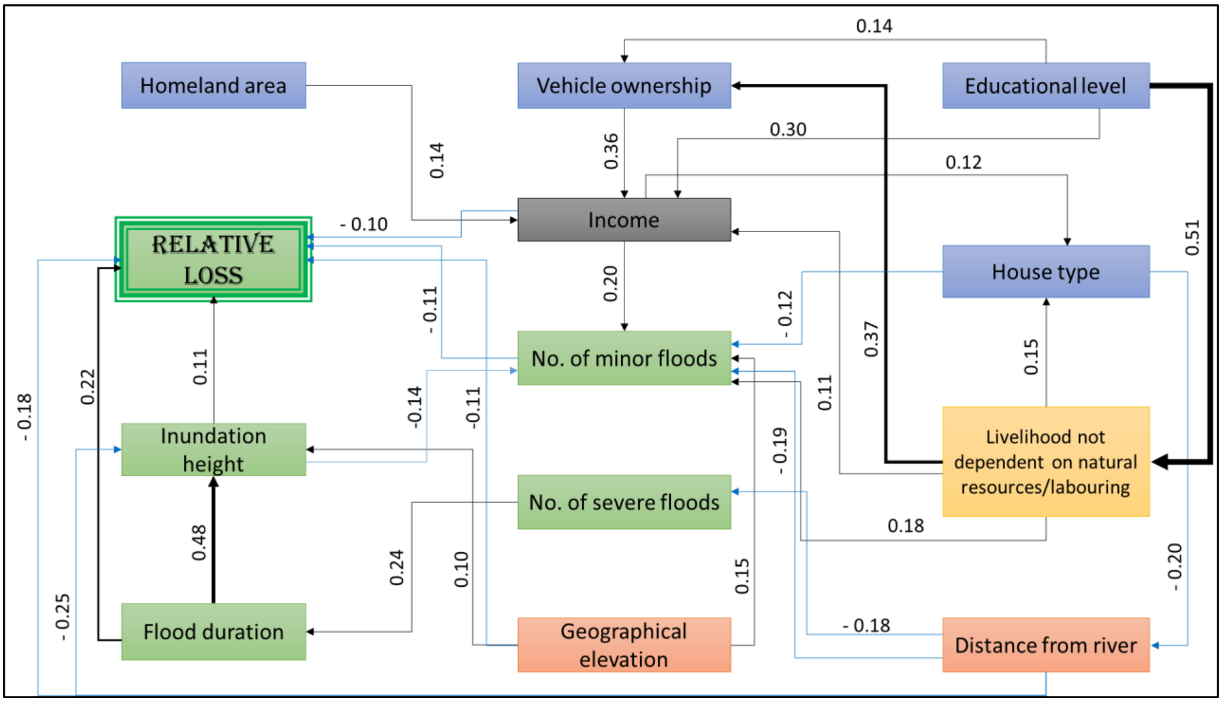

FIGURE 2 Factors affecting average flood damage (all selected floods). Blue boxes represent household living conditions. The ash box and yellow box represent financial status and livelihood conditions respectively. Orange boxes represent geographic conditions, green boxes flood impacts and characteristics. The black arrows indicate positive correlations; negative relationships are indicated by blue arrows. Arrow thickness represents the strength of the correlation

the following equations show how each factor relates to flood damage and the other endogenous variables.

$$\mathrm{RL} = 0.004 \times \mathrm{IH}_{\mathrm{Avg}} + 0.02 \times \mathrm{FD}_{\mathrm{Avg}} - 0.02 \times \mathrm{Inc} - 0.002 \times \mathrm{GE} - 0.03 \times \mathrm{MF} - 0.05 \times \mathrm{Dist} + 0.02, \quad (2)$$

$$\mathrm{IH}_{\mathrm{Avg}} = 1.39 \times \mathrm{FD}_{\mathrm{Avg}} - 1.68 \times \mathrm{Dist} + 0.03 \times \mathrm{GE} + 13.20, \quad (3)$$

$$\mathrm{FD}_{\mathrm{Avg}} = 0.72 \times \mathrm{SF} + 0.25, \quad (4)$$

$$\mathrm{Inc} = 0.56 \times \mathrm{Dummy}_{\mathrm{Vehicle}} + 0.10 \times \mathrm{Edu} + 0.17 \times \mathrm{Dummy}_{\mathrm{Livelihood}} + 0.001 \times \mathrm{Dummy}_{\mathrm{Homeland}} + 0.36, \quad (5)$$

$$\mathrm{MF} = 0.18 \times \mathrm{Inc} - 0.2 \times \mathrm{Dist} + 0.26 \times \mathrm{Dummy}_{\mathrm{Livelihood}} - 0.02 \times \mathrm{IH}_{\mathrm{Avg}} + 0.01 \times \mathrm{GE} - 0.2 \times \mathrm{Dummy}_{\mathrm{HT}} + 0.40, \quad (6)$$

$$\mathrm{Dist} = -0.31 \times \mathrm{Dummy}_{\mathrm{HT}} + 0.39. \quad (7)$$

TABLE 4 Model fit parameters (calibration)

	Value	Acceptable range
Probability level	0.000	Closer to "0"
RMSEA	0.074	Closer to "0"
GFI	0.932	Closer to "1"
AGFI	0.879	Closer to "1"
CFI	0.863	Closer to "1"
NFI	0.790	Closer to "1"
TLI	0.790	Closer to "1"
CMIN/DF	2.274	Less than "5"
AIC	195.96	Lower is better

Table 3 illustrates the strength and significance of the correlations between different variables. Higher standardized estimates, associated with higher significance levels, indicate a better correlation between two variables.

The most significant relationships in the model are those between education level and livelihood; livelihood and vehicle ownership; education level and per capita income; vehicle ownership and per capita income; number of severe floods and average flood duration; average flood duration and inundation height; and distance from river and inundation height.

The model fit was checked by considering the probability level, RMSEA, GFI, AGFI, CFI, NFI, the TLI, minimum discrepancy, and the AIC. See Table 4.

Table 4 indicates that the model fitting values are reasonable as they lie within the acceptable range. The summation

TABLE 5 Total effect due to influencing variables

Factors influence to relative flood loss	Total effect (Standardized)
Geographic elevation (m MSL)	0.001 (−0.11)
Livelihood not dependent on natural resources/laboring	−0.01 (−0.06)
Homeland area	0.00 (−0.04)
House type	0.02 (0.06)
Distance from river (km)	−0.05 (−0.20)
No. of severe floods	0.02 (0.07)
Vehicle ownership	−0.01 (−0.04)
Highest education level (year)	0.00 (−0.06)
Flood duration (days)	0.03 (0.28)
Per capita income in 10,000s	−0.03 (−0.11)
No. of minor floods	−0.01 (−0.13)
Inundation height (ft)	0.03 (0.11)

of direct and indirect effects, known as "total effect" on relative flood loss, is shown in Table 5. As expected, flood characteristics, geographic location, and income level have the greatest effect on flood damage (Table 5). Moreover, the results of Tables 3 and 5 suggest that households that include members with advanced education levels, and where living conditions are better, suffer lower losses than socioeconomically poor households. It is these poor households that suffer most when exposed to frequent floods.

As expected, flood severity strongly affects flood damage; with increased inundation height and flood duration increasing flood damage. Geographic location is negatively correlated with flood damage, suggesting that households located far from the river and at higher elevations suffer less damage due to floods. Across the community, the effect of floods is significantly affected by livelihood type, even though it has no direct impact. People that depend on agriculture, natural resources or laboring for their livelihood suffer the most from being exposed to floods. Average relative loss becomes lower when their exposure to minor floods is high.

3.2 | Model validation

Validation of the model was carried out by using the data of other nine random samples. Reliability checks of this validation process are based on model fit parameters, T-test results and through comparisons of factor loadings with the values of the original model. Table 6 shows the model fit parameters for validation, while Table 7 shows the T-test results. In Table 6 the abbreviation "S" stands for sample (e.g., S 1 means sample 1). Model fit parameters for the validation lie within a reasonable range, meaning the results can be accepted. Each relationship was evaluated through a T-test, carried out by considering the parameters of all 10 samples together and creating two subgroups of five samples each. T-test results, shown in Table 7, indicate that all T-values are less than the critical T value (2.78 and 2.13 for two-tailed tests with 0.05 probability and degree of freedom equal to 4 and 9, respectively; the degree of freedom is equal to sample size minus one). This means that the null hypothesis (no significant difference between calibration and validation parameters) cannot be rejected. Further, the percentage change in standardized factor loading concerning the original model is shown in Table 8, where the term sample is abbreviated as "S" (e.g., S 1 means sample 1). The results indicate that all the percentage changes in standardized factor loadings are less than ± 30% for all variables and are not biased to either side (plus or minus). This evidence confirms that the model parameters are stable and have a reproducible capacity.

This study develops a model to represent the relationship between socioeconomic conditions, flood characteristics, and flood damage on a local scale, by considering four main floods during a 20 year period in a highly flood prone area of Sri Lanka. The results suggest that households located near the river, at lower elevations, and with less income, suffer the most from being exposed to frequent floods (higher inundation depth and longer duration). The analysis shows that flood damage is determined not only by flood characteristics but also by socioeconomic conditions. The results confirm that income and geographic location are the socioeconomic factors that bear most heavily on flood damage.

4 | DISCUSSION

This analysis was based on cross-sectional data. Thus, the development of a vicious cycle is still challenging when these results are used for the analysis. Edmundson and Sukhatme (1990), Vorster (2010), Shiferaw (2002), and Eneh and Eneh (2014) have proposed a vicious cycle for poverty, in terms of capital, education, livelihood, health, and technology, without integrating disasters. However, the results can be simplified into the following cycle as socioeconomic factors and flood characteristics are interrelated, and influence flood damage.

The analysis results shown in Figure 3 reveal that *low-income* households have *poor living conditions* and, hence, *lower education* levels. De Gregorio and Lee (2002) and Ferguson et al. (2007) have shown that there is a direct relationship between education, income, and wellbeing. Because of *lower education*, households struggle to find higher paying occupations, meaning that *livelihoods depend on natural resources*, which are highly vulnerable to climate shocks

TABLE 6 Model fit parameters of model validation

Parameter	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S 10	Acceptable range
Probability level	0.000	0.007	0.000	0.001	0.001	0.002	0.005	0.000	0.006	0.004	Closer to “0”
RMSEA	0.089	0.061	0.084	0.070	0.071	0.060	0.083	0.074	0.090	0.086	Closer to “0”
GFI	0.905	0.929	0.911	0.920	0.924	0.900	0.944	0.905	0.896	0.915	Closer to “1”
AGFI	0.831	0.873	0.840	0.857	0.865	0.870	0.825	0.886	0.836	0.874	Closer to “1”
CFI	0.791	0.900	0.859	0.872	0.882	0.898	0.782	0.879	0.891	0.827	Closer to “1”
NFI	0.700	0.779	0.771	0.762	0.778	0.782	0.810	0.798	0.789	0.777	Closer to “1”
TLI	0.681	0.846	0.784	0.804	0.820	0.784	0.795	0.867	0.700	0.853	Closer to “1”
CMIN/DF	2.17	1.55	2.05	1.74	1.75	1.84	2.05	1.97	1.87	1.64	Less than “5”
AIC	190.8	159.2	184.5	168.6	169.1	188.5	195.3	179.2	187.8	178.8	Lower is better

TABLE 7 *T*-test for model validation compared to the calibration

Variable 1	Variable 2	*T*-value		
		First 5 samples	Second 5 samples	All 10 samples
Livelihood not dependent on natural resources/laboring	Highest education level (years)	0.45	0.07	0.11
House type	Livelihood not dependent on natural resources/laboring	0.09	0.51	0.19
	Per capita income in 10,000s	0.42	0.11	0.26
Distance from river (km)	House type	0.27	0.31	0.32
Vehicle ownership	Livelihood not dependent on natural resources/laboring	1.30	0.66	1.00
	Highest education level (year)	0.21	0.44	0.33
No. of severe floods	Distance from the river (km)	0.39	0.38	0.43
Per capita income in 10,000s	Highest education level (year)	0.55	0.25	0.44
	Vehicle ownership	0.19	0.02	0.14
	Livelihood not dependent on natural resources/laboring	0.47	0.39	0.21
	Home land area (Perch)	0.06	0.04	0.03
Flood duration (days)	No. of severe floods	0.31	0.12	0.11
Inundation height (ft)	Flood duration (days)	0.36	0.32	0.04
	Geographic elevation (m MSL)	0.45	0.52	0.13
	Distance from river (km)	0.37	0.23	0.32
No. of minor floods	Livelihood not dependent on natural resources/laboring	0.60	0.46	0.16
	Distance from the river (km)	1.40	1.06	0.01
	Per capita income in 10,000s	0.47	1.28	0.44
	Geographic elevation (m MSL)	0.03	0.79	0.44
	Inundation height (ft)	1.08	0.13	0.45
	House type	0.86	0.41	0.67
Relative flood loss (%)	Inundation height (ft)	0.07	0.42	0.14
	Distance from the river (km)	1.20	0.58	0.22
	Flood duration (days)	1.61	0.75	0.10
	Per capita income in 10,000s	0.35	0.11	0.27
	No. of minor floods	0.48	0.71	0.01
	Geographic elevation (m MSL)	0.15	0.10	0.01

TABLE 8 Comparison of factor loadings between the model development and validation

Variable 1	Variable 2	Percentage change in standardized factor loading with reference to the original model									
		S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S 10
Livelihood not dependent on natural resources/laboring	Highest education level (year)	−1.6	4.5	1.4	−0.8	12.6	−8.2	6.8	15.3	−9.7	−8.6
House type	Livelihood not dependent on natural resources/laboring	−14.2	−26.6	−14.2	12.6	−0.5	1.5	9.2	−1.8	−2.4	10.6
	Per capita income in 10,000s	−13.9	16.1	−7.3	16.1	−19.0	6.4	−5.7	−14.6	20.1	1.9
No. of severe floods	Distance from river (km)	−13.9	22.6	−27.0	2.2	19.7	1.5	−12.8	−21.6	11.8	−0.5
Distance from river (km)	House type	11.5	12.2	19.9	19.9	−14.2	−11.8	5.9	−17.9	−14.5	1.1
Vehicle ownership	Livelihood not dependent on natural resources/laboring	−13.5	−12.6	25.0	0.3	12.6	2.1	−1.8	−22.5	−9.5	5.2
	Highest education level (year)	−24.3	−12.1	−5.6	−19.6	25.2	2.8	24.8	4.8	−7.9	0.7
Per capita income in 10,000s	Highest education level (year)	7.2	−24.6	29.9	7.8	−1.2	−2.7	15.8	−12.9	1.8	14.5
	Vehicle ownership	16.0	−2.5	−6.7	10.9	8.4	5.9	−15.5	1.2	0.9	8.6
	Livelihood not dependent on natural resources/laboring	1.0	−5.0	−25.7	8.4	−2.5	−5.6	7.9	12.6	−1.9	2.7
	Homeland area (Perch)	−2.8	−2.8	25.8	2.2	8.4	14.7	−5.9	−14.8	1.9	6.7
Flood duration (days)	No. of severe floods	−3.7	26.4	21.5	−7.9	−10.7	5.8	−13.8	1.9	−22.7	18.4
Inundation height (ft)	Flood duration (days)	−8.1	13.8	6.0	2.5	1.5	−14.3	−1.8	2.9	10.4	−17.5
	Geographic elevation (m MSL)	14.3	−3.7	−12.7	−13.5	2.4	1.5	16.3	−4.8	3.1	5.9
	Distance from river (km)	11.8	−17.2	−21.5	4.3	17.2	−22.6	18.1	1.9	−7.4	−8.8
No. of minor floods	Livelihood not dependent on natural resources/laboring	30.5	10.2	27.7	9.0	−12.4	−1.9	5.4	−20.4	−13.7	2.8
	Distance from river (km)	−1.6	−15.1	-4.3	−17.3	−27.0	24.9	28.1	−4.9	15.6	11.7
	Per capita income in 10,000s	−9.0	−20.0	−10.5	15.0	−9.0	18.6	12.3	−1.6	9.8	17.5
	Geographic elevation (m MSL)	14.7	1.5	25.0	6.6	2.2	−8.5	2.8	−22.8	−18.4	−0.8
	Inundation height (ft)	2.5	13.1	−21.3	−18.0	6.6	12.7	−1.5	−16.2	10.9	2.1
	House type	−6.9	−20.0	−2.1	9.0	−13.8	5.9	19.8	−8.7	22.7	−7.2

(Continues)

TABLE 8 (Continued)

Variable 1	Variable 2	Percentage change in standardized factor loading with reference to the original model									
		S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S 10
Relative flood loss (%)	Inundation height (ft)	−16.8	−11.5	6.2	−11.5	15.0	18.4	−5.3	10.2	2.9	−3.7
	Distance from river (km)	16.0	25.7	1.1	16.0	13.1	−15.9	1.8	−6.7	−12.8	4.9
	Flood duration (days)	−9.2	−21.7	−11.5	−1.4	−14.3	27.5	13.2	−5.9	4.9	10.2
	Per capita income in 10,000s	−3.1	23.7	28.9	28.9	−20.6	17.8	−1.5	−11.7	2.9	−1.1
	No. of minor floods	−8.3	25.0	−25.0	−13.0	−21.3	21.5	13.8	−4.6	2.7	5.9
	Geographic elevation (m MSL)	−19.3	14.0	−20.2	7.0	−12.3	2.9	−11.8	12.5	3.1	−1.7

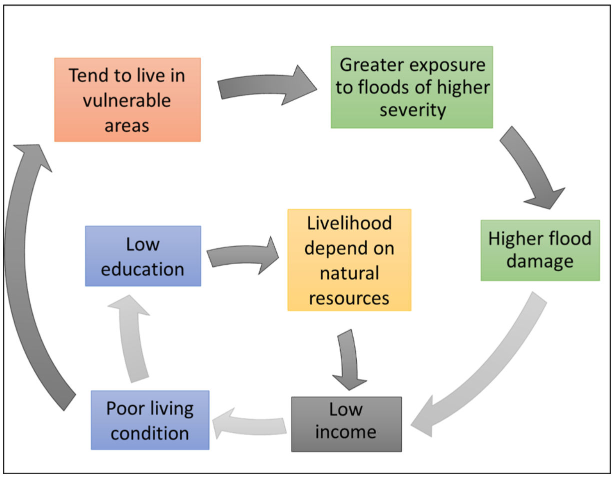

FIGURE 3 Interrelationship between socioeconomic conditions and flood vulnerability on a local scale. Blue boxes represent the living conditions of households. The ash and yellow boxes represent financial status and livelihood conditions respectively. Orange boxes represent geographic conditions, green boxes flood impacts and characteristics. The dark color arrows represent relationships directly obtained from the developed path model. Light color arrows represent relationships not directly from the path model but experienced on the ground

(Berg, 2010; Kamanga et al., 2009). Consequently, they will receive *lower income* and experience *poor living conditions*. Therefore, they *tend to live in vulnerable areas*, low lying and near the river. This is common in many places of the world (Colten, 2006; Jenkins, 2003). Hence, they experience *greater exposure to severe floods* and suffer *greater loss/damage*. These *losses*, in turn, affect their *income* and wellbeing. These processes are interconnected and continue as a cycle (refer to Figure 3).

This cycle can be disrupted by improving socioeconomic conditions. One way to do this is to provide better education for the next generation. Livelihood diversification is another possibility. If people can pursue a good education, and so increase their earning potential, the possibility arises of living in areas where flood exposure, and thus the threat of flood damage, is less.

However, these results were obtained and validated from randomly selected samples of 150 data points. Even though this sample size is quite small, the results are still reliable as the validation considers 10 sets of randomly selected samples, and the percentage changes in standardized factor loadings for those 10 samples are less than ±30% for all variables, and are not biased to either side (plus or minus), meaning the results can still be considered sufficiently reliable for reuse. Nevertheless, the reliability of the results would certainly increase with an increase in sample size, and future researchers would be encouraged to implement the analysis with larger samples. Moreover, the focus of this study is limited to selected socioeconomic and geometric characteristics. Here we considered only education level and not the area of educational specialization, nor the status of disaster education. Another limitation of this study is that the only geographic characteristic considered is the distance of the household from the river. Elevation of the household would also be worthy of consideration in future studies. This concept can be further developed by considering additional socioeconomic and geographic characteristics, along with intangible and indirect losses, and additional recovery options.

5 | CONCLUSIONS

A sample of 150 households was randomly selected from the overall sample, then path analysis with maximum likelihood estimation method was used to develop a model. The aim was to understand the factors that most influence flood damage on a local scale. Flood characteristics were considered, as well as socioeconomic and geographic conditions. *Socioeconomic factors, geographic conditions, livelihood patterns, and flood characteristics* were selected to develop the model, along with the main target parameter, *relative flood related loss*. Finally, the model was developed to examine the relationships between *education level, asset ownership (vehicle and amount of land), income, livelihood type (dummy), elevation of house location, distance from the river, flood loss, inundation depth, and duration*. The model was then validated based on model fit parameters, *T*-test results, and by comparing factor loadings with the original model.

The results show that flood severity (*inundation depth and duration*) has the highest impact on *flood damage*, with households located *near the river* and at *lower elevations* the most at risk of damage. Households where people's *livelihood depends on agriculture, and other natural resources, or laboring*, suffer higher losses from being exposed to floods, even though livelihood type has no direct effect on flood damage. Further, results show that households with better socioeconomic conditions experience lower losses when exposed to frequent floods.

This study concludes that flood damage is not only a function of flood characteristics but also the result of a household's socioeconomic and geographical characteristics. *Income* and *geographic location* of the household are the socioeconomic and geographical characteristics that have the highest impact on flood damage. Thus, this study encourages policymakers to think about the socioeconomic conditions of communities when addressing flood damage and its associated impacts. The results of this study suggest that policymakers should develop policies for educational improvements and livelihood diversification as a means of reduce the losses caused by floods. These measures should be considered alongside risk transfer and risk sharing mechanisms; the development of control processes for construction in hazard prone areas; the development of proper land use practices for hazard prone areas, including the relocation of vulnerable communities; the updating of multihazard profiles; regular assessments of vulnerability and risk; the promotion and use of advanced technologies for risk assessments; the development of hazard maps; and by encouraging research activities on disaster management and climate change adaptation as mitigation measures for disaster risk reduction (Ministry of Disaster Management, 2013). As this model is quantitative, it addressed only the number of years in school. However, policymakers could consider the number of school years, as well as the quality of education in such areas as disaster management, preparedness, and recovery. The current policy (Ministry of Disaster Management, 2013) considers only how to recover from the disruption that floods cause to livelihoods, whereas it might also encourage people to change livelihood, where that is possible. Further, proper land use management practices can be introduced through government involvement.

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