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A local-scale analysis to understand differences in socioeconomic factors affecting economic loss due to floods among different communities

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ABSTRACT

Investigation of the relationships between socioeconomic factors and water-related disasters, such as floods, is rather complex. The general practice is to undertake a qualitative analysis of the impact of socioeconomic factors on economic loss in disasters, while climate and structural impacts are investigated quantitatively. As such, an integrated approach is timely for understanding socioeconomic influences on economic loss due to floods. This paper is an attempt to understand the influence of different factors on economic loss, in different types of floods, among different economic groups, using a quantitative approach. Data was collected using a questionnaire survey delivered to randomly selected households in Rathnapura, Sri Lanka, in September 2017. Path analysis was used to analyze the influence of socioeconomic status on economic loss due to floods, using an effective sample of 231 households after subdividing the sample into poor and non-poor subcategories, based on socio-economic condition. The results suggest that flood characteristics and household income level have a direct impact on economic loss in severe floods for both economic groups, with more significant impacts among poor households. Even for minor floods, inundation depth is the most significant factor affecting relative loss, irrespective of the economic group. Further, the absolute loss difference between poor and non-poor households is 48% of the loss experienced by non-poor households in severe floods, and 10% of the loss due to minor floods. These results indicate that severe floods increase the economic gap between the poor and non-poor cohorts. Through this analysis, it is concluded that floods exacerbate the economic gap between poor and non-poor communities, while the factors affecting economic loss due to floods differ among the different economic groups.

1. Introduction

The effects of disasters on economic growth are still unclear, as some studies have reported negative effects, and others have revealed no effects, or even positive ones. Sometimes people may be willing to live in hazard-prone areas and accept high levels of risk to have access to opportunities [1]. For example, people live in areas at risk of flood because of agricultural benefits or for close access to river fisheries. These opportunities may result in all people, rich and poor, being exposed to hazards [2]. Floods are one of the most common natural hazards, and they affect people worldwide. Floods can cause the deterioration of people's social and economic lives, and harm the national economy [3]. Crops, livestock, and poultry; households; transportation and communication systems; educational, institutional and service buildings; and social facilities, can all be affected by floods, causing considerable losses [4]. However, poor people are more likely to live in areas, often rural, that are highly vulnerable to disasters [5,6], because they lack the means to live in less vulnerable locations [7–9].

Further, the economies of developing countries are more sensitive to disasters caused by natural hazards than those of developed countries, with more sectors affected and the effects larger [1]. Statistical relationships between national-level economic indicators and disaster losses on a global-scale have been investigated in the past by researchers to determine whether developing countries are more vulnerable to natural hazards than developed countries [10–13]. These studies have discussed the relationship between average income and disaster impact, but have not investigated the spatial or socioeconomic distribution of losses within countries, or the impacts on different economic groups on a regional or local-scale.

The vulnerability of different communities to certain disasters, and community responses to those disasters, have been examined by considering the impact of either floods [14–20], droughts [21–25],

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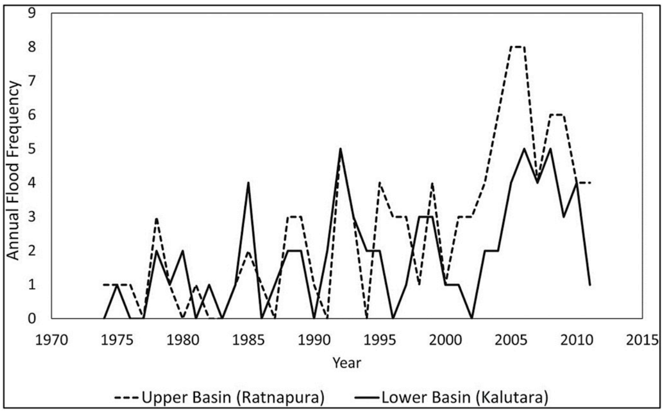

Fig. 1. Flood frequency in the upper and lower basins, 1974 to 2011. Data from http://www.desinventar.lk/Source [38]:.

hurricanes [26–30]; or various disaster types [31,32]. In addition, several qualitative studies have investigated the relationship between disasters and poverty [33–35]. Many of those studies confirmed significant adverse effects of disasters on poverty, and human and economic development.

Floods are one of the most common hazardous, natural events affecting people worldwide. Floods can cause the deterioration of people's social and economic lives, and harm the national economy [3]. Crops, livestock, and poultry; households; transportation and communication systems; educational, institutional and service buildings; and social facilities, can all be affected by floods, causing considerable losses [4]. According to past literature, the main drivers for social vulnerability to floods are socioeconomic conditions, land tenure, demographics, health, coping capacity, neighbourhood characteristics, and risk perception [36]. Further, the relationship between poverty and flood vulnerability may go in both directions. First, poor people may be more likely to settle in flood-prone areas where land prices are more affordable. Second, those poor households affected by floods have a higher risk of falling into poverty or being trapped in poverty as they face greater challenges in recovering from damage: recouping properties and assets is more difficult from a position of financial hardship [2].

This study considers Rathnapura, Sri Lanka, as the study area. The paper addresses issues relating to economic loss due to floods in terms of socioeconomic conditions, demographics, and flood characteristics.

The area receives frequent heavy rainfall and is subjected to floods. From 1883 to 2017, high rainfall (above 3000 mm) caused major floods and landslides. The highest rainfall in this district was monsoonal and was recorded from April–June (493 mm) and October–December (625 mm) [37]. In the devastating floods of 1992, 2003 and 2017, flood losses were approximately 12 Million, 50 Million and 45 Million, respectively (http://www.desinventar.lk/). Fig. 1, based on Disaster Management Centre (DMC) statistics [38], shows how frequently the area is flooded. In Rathnapura (upper basin), annual flood frequency is increasing, and there is a pressing need to understand the impact caused by more frequent floods. To investigate the causes of flood damage on a local scale (household level), it helps to consider socioeconomic and demographic characteristics, along with flood characteristics for different economic groups. Loss and damage differs from one individual to another, even in the same flood.

The main objective of this study is to understand the direct economic impact of different types of floods on different communities by analyzing the factors influencing economic loss. A previous study [39] explored the effects of floods and droughts on livelihoods. This paper differs in that it discusses the impact of floods on a local economy. Studies that consider the number of flood events experienced by different economic groups – to understand the relationship between local poverty (at a household level) and floods – are limited in past literature.

This article analyzes the main research question, "which group of people suffers more from being exposed to frequent floods?" through the hypotheses, "the factors affecting economic loss due to floods for each economic group are specific while the effects differ from one group to other". The hypothesis is based on the PAR (Pressure and release) model and Access model theories. The basis for the PAR idea is that a disaster is the intersection of two opposing forces: those processes generating vulnerability on one side and the natural hazard event on the other, while the 'release' idea is incorporated to conceptualize the reduction of disaster to relieve the pressure. However, the PAR model does not provide a detailed and theoretically informed analysis of the precise interactions of environment and society at the 'pressure point', the point at which the disaster starts to unfold. Any analysis of a disaster must explain differential vulnerability to, and the impacts of, a disaster – why wealthier people often suffer less, and why women and children may face different (and sometimes more damaging) outcomes than men and adults. Particular groups, defined by ethnicity, class, occupation, location of work or domicile may suffer differentially from others. In these senses, the Access model focuses on the precise detail of what happens at the pressure point between the natural event and longer-term social processes, and, to signify this in visual terms, a magnifying glass is drawn on the PAR model [40]. Based on the aforementioned PAR and Access model approaches, a path analysis technique was used to investigate how the socioeconomic and geographic factors and flood characteristics affect economic loss due to floods for each subgroup.

Path analysis is a subset of structural equation modelling (SEM), which was developed by Sewall Wright [41,42] as a method to study direct and indirect effects between variables hypothesized as causes and variables treated as effects. Researchers have adopted these methods in analyzing questionnaire survey data. Partial Least Squares Structural Equation Modelling (PLS-SEM) has been used to understand the direct influence of demographic characteristics on flood exposure [43], and to construct a social vulnerability index in Indonesia [44]. Liu et al. [45]; Kantamaneni [46]; and Greene et al. [47] are others who have applied SEM in data analysis. Even though most of those studies harness SEM in discussing disasters, none has examined disaster impact, characteristics or exposure by considering the number of consecutive flood events. Moreover, those studies did not divide the sample into sub-groups by considering socioeconomic conditions, or conduct separate analysis for each group. This study quantitatively analyzes and compares the factors affecting economic loss for different economic groups, by considering a series of flood events from a selected period, at a local household level.

2. Study area

Sri Lanka, an island in southern Asia, lies on the Indian plate near the southern tip of India, between north latitude of 6° – 10° and east longitude 80° – 82°. It covers 65,610 km^2. The island's centre is mountainous, with plains extending towards the coast. Because of the topographical features and monsoon rainfall patterns, the country is divided into three agro-ecological zones; wet, dry and intermediate [48].

The study area, Ratnapura, is situated in the wet zone where higher rainfall has resulted in rich vegetation and an environment of greenery interspersed with streams and waterfalls. The climate of Ratnapura is classified as tropical and the area receives rainfall mainly from the southwestern monsoons. Outside of the monsoons, the area receives a considerable amount of rain due to convective precipitation. The average annual rainfall is about 4000–5000 mm, while the average temperature varies from 24 to 35 °C with high humidity levels [49]. Ratnapura is highly vulnerable to frequent river floods. Located approximately 100 km from Colombo, the total area of the district is approximately 3275 km^2. More than a million people (2011 census data), most of whom rely on the gem industry for their livelihood, live in this area. Approximately 85% of Sri Lanka's gems are found in Ratnapura district, where 80% of the country's mines are located [50]. This

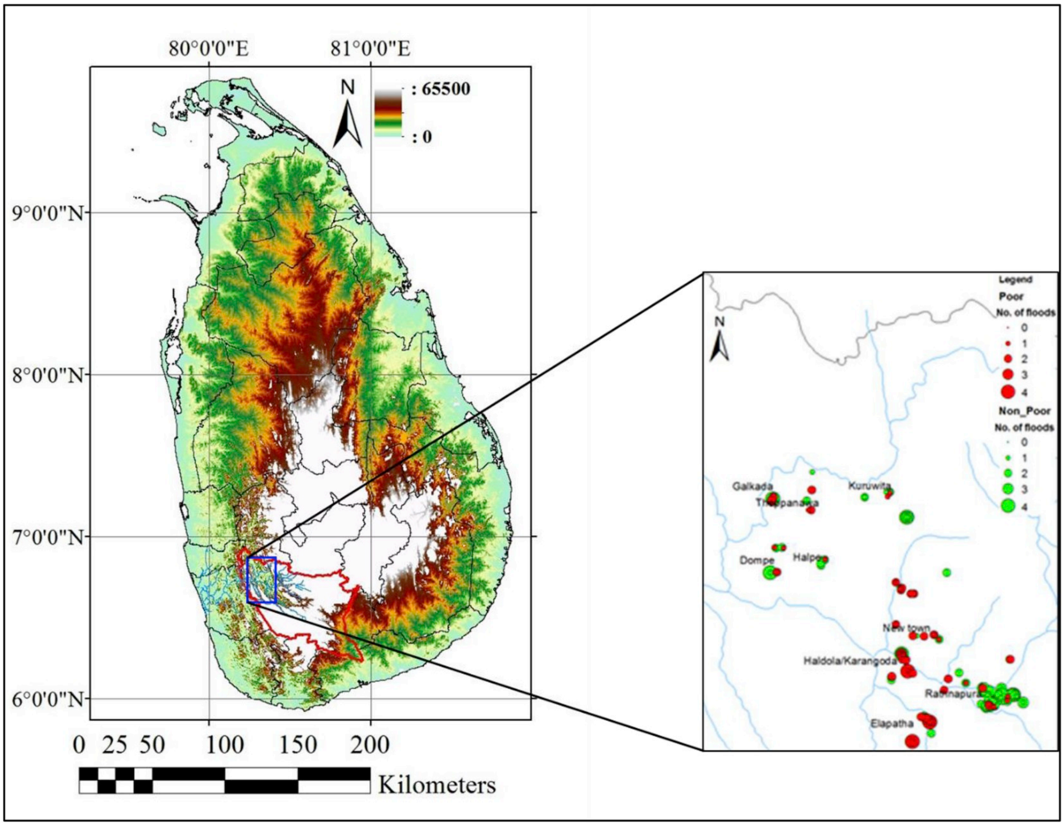

Fig. 2. Sri Lanka and study area for the questionnaire survey. Source: (based on SRTM DEM and coordinates measured during the survey).

district also contains the largest poor population in Sri Lanka. Fig. 2 shows a topographic map of Sri Lanka with the boundary of Ratnapura district and the area selected for the survey, along with the locations of households surveyed.

3. Methodology

This section describes the data collection and associated methods, and sampling and analyzing techniques, used in this study.

3.1. Data collection (questionnaire survey) and characteristics

The analysis is based on questionnaire survey data. As this study focused on the local, household level, and relevant household level data were not available for past floods, we used questionnaires as a data collection tool. The survey was conducted on September 2017 in Ratnapura district in Sri Lanka with randomly selected households. Random sampling procedure involves numbering and listing households, then running an "R" code to randomly select the households. The survey considered the 20 year period from 1997 to 2017. Four main flood events occurred during the selected period (2003, 2008, 2016, and 2017). The questionnaire survey was based on face-to-face interviews conducted by local interviewers (hired university students) in Sinhalese, the national language. 275 households were interviewed, though as some answers were incomplete, the sample selected for analysis was 231.2011 Census and Statistics Department data were used to check the sample size validity. The sample size validity was calculated using a probability sampling method [51]. Crandall and Crandall [52], suggested that a confidence level of 80–99% is suitable; Cochran [53] recommended an error limit of 4–6%. The minimum valid sample size, calculated for the population of 1,088,007 (2011 census data), was 224 for a 90% confidence level, 5.5% error. Hence, the sample of 231 households can be considered sufficient. Interviewees were asked about

Table 1
Sample distribution according to economic status (N = 231).

	Poor	Non-poor
No. of households	81 (35%)	150 (65%)

Source: (questionnaire survey data)

their livelihood and socioeconomic conditions, their exposure to selected floods, and the way those floods have affected them. The sample was subdivided into two main groups – poor and non-poor – based on monthly per capita income. Among the sample of 231 households, 81 (35%) received per capita income of less than 10,000LKR per month, which is equivalent to the absolute poverty line (US$1.9 per day) as defined by the World Bank [54]. Table 1 shows the distribution of the sample according to economic status. Here economic status is classified according to monthly per capita income.

The questionnaire included two sections. The first section related to general demographic data, including the age of the household head; the number of household members and their income-expenditure; education levels, and occupations; and whether the house was single or two-story. The second section concerned the household's experience of the identified floods. Inundation duration, inundation depth, economic damage, and recovery procedures were considered under this section. General household demographics and socioeconomic characteristics of the sample (231 households) are summarized in Table 2.

Among the selected households, 96% were headed by men, 4% by women. The average age of a household head was 49 years, with more than 50% of household heads between 35 and 55 years old. Only 11% of those interviewed were educated to tertiary level. Primary education was considered to be less than or equal to 5 years of schooling, with secondary education being 5–11 years of schooling, and tertiary more than 11 years of schooling. The average household consisted of four people, generally with dependents. One person, usually male, earned the

Table 2
Summary statistics: household demographics, socioeconomic characteristics (N = 231).

Household Characteristics	Value
Percentage of households with a male as the head (%)	96
The average age of household head (yrs)	49
Age of household head (%)	
Young adults (age below 30 years)	07
Middle-aged adults (age between 30 and 55 years)	57
Old adults (age above 55 years)	36
The education level of household members (%)	
Illiterate/primary education	18
Secondary education	71
Tertiary education	11
Household occupation (%)	
Farming, mining or labouring	35
Occupation other than farming mining or labouring	65
Average family size (min - max)	4.0 (1–11)
Average no. of old adults whose age is over 60 years (min-max)	0.5 (0–3)
Average no. of children (min - max)	0.3 (0–4)
Average household income (LKR/month) (St. dev.)	55,000 (32,000)
Average per capita income (LKR/month) (St. dev.)	14,250 (7600)
Percentage of households under the poverty threshold (approximately US$1.9/day) (%)	35
Income inequity (GINI coefficient)	0.291
Percentage of houses built with bricks (%)	54
Percentage of houses built with concrete blocks (%)	45
The average size of homeland owned by households (Perch)	38
Percentage of households affected by at least one selected flood (%)	99
Average annual economic loss due to floods (LKR) (St. dev.)	93,400 (106,300)
Average annual economic loss due to floods as a percentage of annual household income (%)	14

Source: (questionnaire survey data)

Table 3
Number of households affected by floods.

	2003 flood	2008 flood	2016 flood	2017 flood
Poor (n = 81)	46 (57%)	7 (9%)	6 (7%)	80 (99%)
Non-poor (n = 150)	93 (62%)	31 (21%)	38 (25%)	147 (98%)
Grand total	139 (60%)	38 (16%)	44 (19%)	227 (99%)

Source: (questionnaire survey data)

household income. The standard deviation and sample GINI coefficient (in Table 2) suggest a large variation in annual household income. Thirty-five per cent of the population included in the sample had an income under 10,000 LKR/month per person; about US$ 1.9 per day (poor), which is the absolute poverty line according to the World Bank. Absolute poverty lines indicate the minimum amount of money required to allow a household to purchase the goods and services required to support life [55]. Only 35% of the sample wholly depend on natural resources (mainly agriculture, mining and labouring) for their income. All households are connected to electricity and have good sanitary facilities, with easy access to pure drinking water.

3.2. *Targeted 4 flood events*

The main floods of the past two decades were considered. Of these flood events, four were devastating.

Table 3 shows the distribution of flood-affected populations among subgroups. It shows that 227 households (99% of the total sample) were affected by at least one flood during the period under consideration.

The analysis was done against the main hypothesis that 'the factors affecting economic loss due to floods for each economic group is specific while the effects differ from one group to other'. Poverty was defined according to binary categories – poor and non-poor – based on monthly per capita income. Households with monthly per capita income under 10,000LKR (near the $1.9 per day limit) were considered poor, while households earning more than this were considered non-poor.

Based on questionnaire survey data, a higher number of households were affected by the 2003 and 2017 floods (139 and 227 households respectively) than the 2008 and 2016 floods (38 and 44 households respectively). According to Irrigation Department categorizations, the 2003 and 2017 floods were considered critical floods, while the 2008 flood was classified as major, and the 2016 flood as minor. Table 4 shows the status of flood events according to Irrigation Department records. Flood severity is categorized according to the water level at Rathnapura water level gauging station.

Further, the number of families affected, the number of houses damaged, and the number of deaths that occurred during each event (Source: DMC, SL), were examined (Fig. 3).

The data indicate that nearly equal numbers of families were affected during the 2003 and 2017 floods. Further, the number of deaths and

Table 4
Flood inundation, and severity classification proposed by the Irrigation Department.

Event	Rainfall	Water level	Flood severity
2003	260 mm/6 h	23.9 m MSL	Critical
2008	473 mm/3 days	20.9 m MSL	Major
2016	355 mm/day	20.1 m MSL	Minor
2017	553 mm/day	24.4 m MSL	Critical

Source: (Irrigation Department)

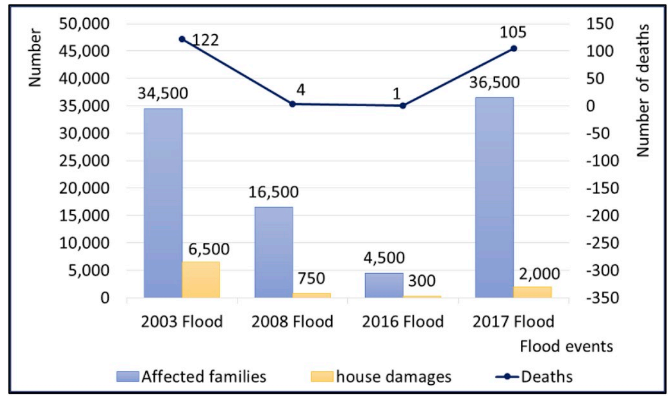

Fig. 3. Impact due to considered floods. Source: (DMC, SL data).

Table 5
Depth and duration of selected floods and the effect on economic loss among poor and non-poor communities.

	Flood event	Poor	Non-poor
Inundation depth (m)	2003	9	10
	2008	0	3
	2016	5	4
	2017	8	9
Duration of inundation (days)	2003	5	5
	2008	0	2
	2016	3	3
	2017	4	4
Average economic loss due to floods in LKR (relative economic loss due to floods %)	2003	88,000 (104)	153,000 (71)
	2008	43,000 (56)	29,500 (13)
	2016	21,600 (32)	44,000 (18)
	2017	60,300 (72)	120,000 (55)

Source: (based on questionnaire survey data)

Table 6
Flood impact on different economic groups (N = 231)[a].

	Number of households affected (%)	Average economic loss due to floods in LKR (relative loss %)	No. of households suffering low loss (%)	No. of households suffering medium loss (%)	No. of households suffering high loss (%)
Non-poor	149 (99)	111,000 (51)	128 (77)	26 (15)	11 (5)
Poor	80 (99)	60,800 (73)	71 (63)	23 (26)	14 (10)

[a] Low loss – 0–20% of relative loss; medium loss – >20–50% of relative loss; higher loss – >50% relative loss.
Source: (based on questionnaire survey data)

number of damaged houses were approximately equal during the 2003 and 2017 floods, whereas those values were relatively lower for the 2008 and 2016 floods. Hence, it is suggested that the 2003 and 2017 floods had similar impacts, while the impacts of the 2008 and 2016 floods also were rather similar. Next, the flood impact and loss statistics were calculated for each economic group in each flood event (Table 5).

Table 5 indicates that inundation depth and duration were nearly equal for the 2003 and 2017 floods, and similar for the 2008 and 2016 floods. (The 2008 and 2016 floods were shallower and shorter than the 2003 and 2017 floods.) These patterns around inundation depth and duration are echoed in the economic losses incurred during each pair of floods. Hence, it can be established that the impacts of the 2003 and 2017 floods were similar, as were the impacts of the 2008 and 2016 floods. This result aligns with Irrigation Department and DMC records. Hence, in further analysis the 2003 and 2017 floods will be considered "severe" (highly damaging with high economic loss), and the 2008 and 2016 floods "minor" (moderately damaging with low economic loss).

3.3. Path analysis

Initially, the data series was checked for possible relationships through cross-tabulation and the characteristics of data. Thereafter, path analysis technique (in IBM SPSS Amos), with maximum likelihood estimation method, was used. This evaluated the hypothesis by examining the web of relationships among measured variables, as regression only allows the evaluation of the direct relationship and is not capable of handling causal effects or indirect relationships. The path analysis technique involves two types of variables, namely exogenous and endogenous variables, and was developed by Sewall Wright [41,42] as a method to study direct and indirect effects between variables hypothesized as causes, and variables treated as effects.

This path analysis model was developed by considering variables such as education level, asset ownership (vehicles and land), income, livelihood type (dummy), elevation of house, distance from river to house, economic loss due to floods, and inundation depth and duration. These variables were used after identifying the most significant factors among the influencing variables (socioeconomic conditions, land tenure, demographics, health, coping capacity, neighbourhood characteristics, and risk perception) as suggested by past studies [36]. Relative losses due to floods were considered the main target parameter.

The absolute loss means the average cost of damage due to a particular flood. The relative loss is the financial loss suffered, with regard to average annual income (Equation (1)). This measure indicates the level of loss a household can sustain; the higher the relative loss the higher the impact, even in cases where the absolute loss is not large. If a rich household and a poor household suffer equal loss in a disaster, the relative loss will be higher for the poor household as their income is lower.

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

The analysis was done by considering severe floods and minor floods separately, as people's behaviour and responses, and flood impacts, differ with the severity of the flood. Hence, the analysis was carried out by dividing the sample into four different communities: (1) poor subjected to severe floods, (2) non-poor subjected to severe floods, (3) poor subjected to minor floods, and (4) non-poor subjected to minor floods. For severe floods, 2017 flood data were used to develop the model, which was validated using 2003 flood data. For minor floods, 2016 flood data were used to develop the model, with the model validated using 2008 flood data. The same relationships were applied and factor loadings were compared with the original model (2017 for severe floods and 2016 for minor floods). Model fit parameters – probability level, Root Mean Square Error Approximation (RMSEA), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Tucker-Lewis Coefficient (TLI), minimum discrepancy, and Akaike Information Criterion (AIC) – were also checked for further evidence. In addition, the degree of poverty for each sub-group exposed to floods was assessed using the Poverty Head Count Ratio (*PHCR*), Poverty Gap Index (*PGI*), Squared Poverty Gap Index (*SPGI*), and the GINI coefficient [56].

Table 7
Relationships between economic loss due to severe floods and poverty in different economic groups.

		Number of households affected			
		2003		2017	
		Non-poor	Poor	Non-poor	Poor
Absolute loss	Low	22 (24%)	21 (46%)	49 (34%)	46 (57%)
	Medium	24 (26%)	13 (28%)	51 (35%)	24 (30%)
	High	46 (50%)	12 (26%)	44 (31%)	10 (13%)
Relative loss	Low	15 (16%)	4 (9%)	32 (22%)	11 (14%)
	Medium	28 (31%)	9 (19%)	69 (48%)	28 (35%)
	High	49 (53%)	33 (72%)	43 (30%)	41 (51%)

Source: (based on questionnaire survey data)

4. Results

Table 6 details the average impact of floods on each economic group.

Approximately 99% of households were exposed to at least one of the floods under consideration. Average loss was about 93,500LKR per household, which is almost 55% of average annual household income. Losses were due mainly to household damage, with 15% stemming from losses relevant to the occupation of household members. Cross-tabulation results and analysis show that the average economic loss due to floods, and relative economic loss due to floods (percentage of average economic loss due to floods to annual average income ratio), is 60,800LKR and 73% respectively for poor households and approximately 111,000LKR and 51% for non-poor households. The percentage of households who suffer higher losses is larger among poor households than non-poor.

4.1. Comparison between poor and non-poor for severe floods

Among the four selected floods, two (2003 and 2017) were considered severe.

4.1.1. Absolute loss and relative loss

Cross-tabulation results suggest that the majority of poor households

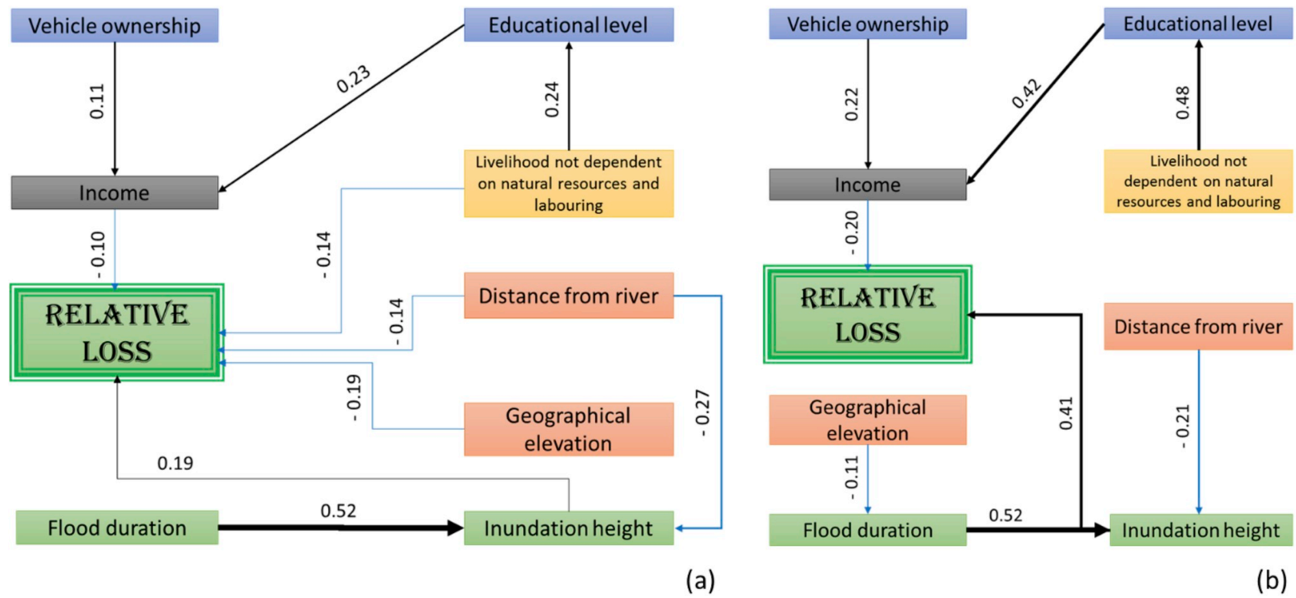

Fig. 4. Factors influencing household economic loss from severe flooding (a) for non-poor (b) for poor. Source: (based on questionnaire survey data).

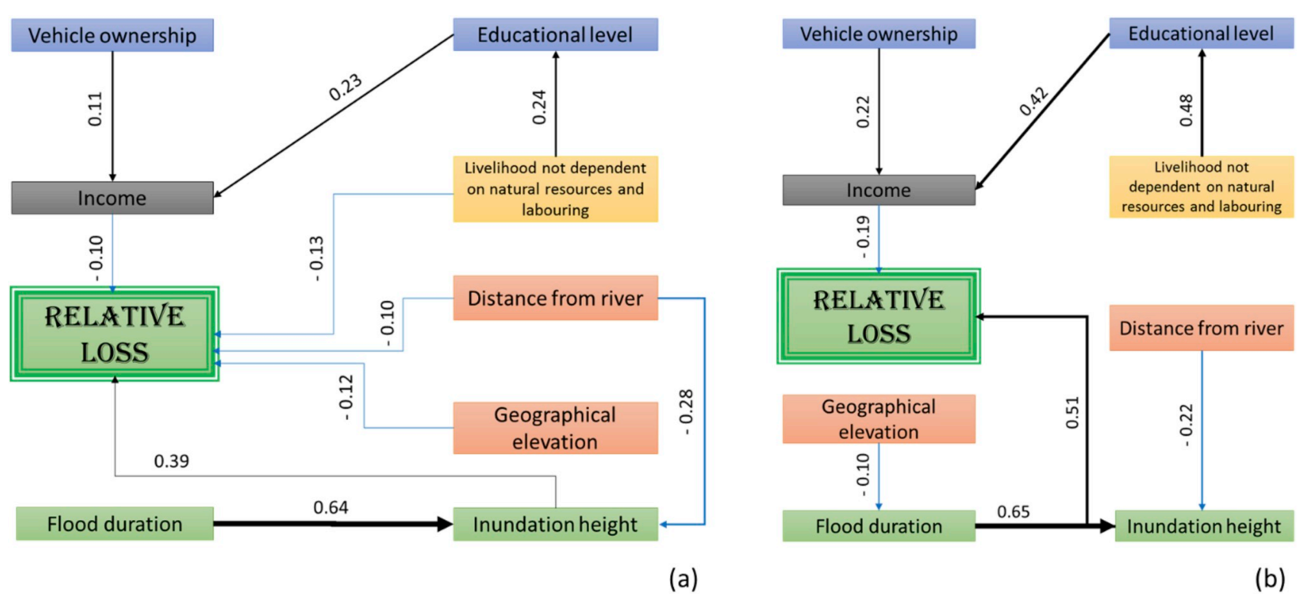

Fig. 5. Validation of path model for severe floods using 2003 flood data (a) for non-poor households and (b) for poor households. Source: (based on questionnaire survey data).

suffer a higher relative loss when exposed to severe floods. Non-poor households suffer a greater absolute loss due to severe floods as they have better living conditions and more assets than the poor (refer to Table 7).

In absolute terms, losses less than 50,000, from 50,000–100,000, and higher than 100,000LKR, are defined as "Low", "Medium" and "High" respectively. Similarly, relative loss percentages under 20%, from 20 to 50%, and more than 50%, are considered "Low", "Medium" and "High" respectively.

The average absolute loss due to severe floods among non-poor households is about 94,000LKR, and 50,000LKR among poor households. However, the relative loss due to the 2003 flood is 43% of the annual average income among non-poor households, whereas this figure is 60% among the poor. For the 2017 flood, the absolute losses are about 117,000LKR among non-poor households and 59,500LKR among poor households, with relative losses of 53% and 72% of annual average income for non-poor and poor households respectively. This means that poor households suffer more due to floods.

In the path analysis model, relative economic loss due to floods, rather than absolute loss, was selected as the damage indicator as it represents the actual suffering experienced by the household.

4.1.2. *Results of path analysis*

Data collected for the 2017 flood was analyzed in a path analysis framework to understand the factors affecting damage from severe floods. The models developed (using 2017 flood data) to determine the factors affecting economic loss due to floods is shown in Fig. 4 for both non-poor and poor groups.

In these path analysis Figs. (4)–(6), (8), blue boxes represent the living conditions of the households, while ash and yellow boxes represent financial status and livelihood conditions respectively. Orange boxes represent geographic conditions, green boxes flood impacts and

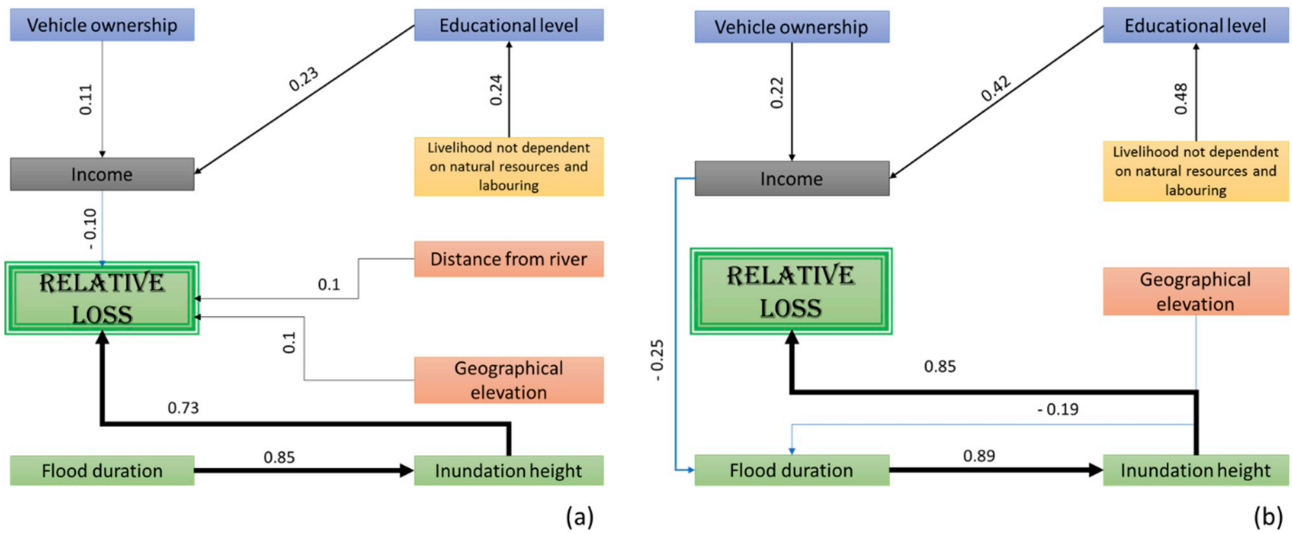

Fig. 6. Factors affecting economic loss due to minor floods (a) for non-poor households and (b) for poor households. Source: (based on questionnaire survey data).

Table 8
Model fit parameters of the path analysis model for severe floods.

	Model development 2017		Validation 2003		Acceptable range
	Non-poor	Poor	Non-poor	Poor	
Probability level	0.09	0.15	0.12	0.41	Closer to "0"
RMSEA	0.05	0.05	0.05	0.02	Closer to "0"
GFI	0.95	0.92	0.95	0.93	Closer to "1"
AGFI	0.92	0.87	0.92	0.88	Closer to "1"
CFI	0.89	0.95	0.97	0.99	Closer to "1"
NFI	0.73	0.75	0.90	0.88	Closer to "1"
TLI	0.85	0.94	0.96	0.99	Closer to "1"
CMIN/DF	1.39	1.17	1.33	1.04	Less than "5"
AIC	74.08	66.83	72.56	63.07	Lower is better

Source: (based on questionnaire survey data)

characteristics. The black arrows indicate positive correlations, blue arrows negative relations. Arrow thickness represents the strength of the correlation.

Table 8 indicates that all the fit values for model development (2017 flood) and validation (2003 flood) show reasonable results as they lie within the acceptable range.

The strength of the correlation between two variables is given by the estimate. 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 9 illustrates the correlation between each variable and its significance level.

Results of the analysis suggest that relative economic loss due to floods was directly affected by inundation depth (positively) and per capita income (negatively) for both economic groups. However, this impact was more significant among poor households than non-poor households. Further, inundation depth was the most significant factor affecting relative economic loss due to floods (for poor and non-poor households).

Economic loss due to floods for non-poor households was directly affected by inundation depth (positively), as well as by per capita income, elevation, and distance from river (negatively). Livelihood type also directly influenced economic loss due to floods. The relative economic loss due to floods was greater for households in which people's livelihoods depended solely on agriculture, mining, or labouring, than it was for those whose inhabitants did not rely on natural resources for their livelihoods.

There are some factors that showed an indirect effect on relative economic loss due to floods. This indirect effect can be understood by calculating the total effect, which shows that the factors negatively affecting economic loss due to severe floods, on poor households, have a negative impact on non-poor households as well. Table 10 demonstrates the total effect of each variable on relative economic loss due to floods.

Poor or non-poor households located far from the river and at higher elevations, with higher per capita incomes, better living conditions; and occupants who were better educated and employed in industries that did not depend on natural resources and labouring, suffered less impact due to severe floods than households located nearer the river and at lower elevations, with lower per capita income, poor living conditions, and

Table 9
Influencing variables for economic loss due to severe floods.

Variable 1	Variable 2	Non-poor household		Poor households	
		Estimate (standardized)	P value	Estimate (standardized)	P value
Highest education level (yrs)	Livelihood not dependent on natural resources and labouring	1.24 (0.24)	0.003	2.36 (0.48)	***
Per capita income in 10,000s	Highest education level (yrs)	0.08 (0.23)	0.003	0.03 (0.42)	***
	Vehicle ownership	0.17 (0.11)	0.172	0.13 (0.22)	0.026
Inundation duration (days)	Elevation (m MSL)			−0.05 (−0.11)	0.312
Inundation depth (ft)	Inundation duration (days)	1.44 (0.52)	***	1.37 (0.52)	***
	Distance from river (km)	−2.14 (−0.27)	***	−1.49 (−0.21)	0.021
Relative economic loss (%)	Inundation depth (ft)	2.28 (0.19)	0.017	6.30 (0.41)	***
	Elevation (m MSL)	−1.04 (−0.19)	0.014		
	Livelihood not dependent on natural resources and labouring	−23.57 (−0.14)	0.061		
	Per capita income in 10,000s	−7.23 (−0.1)	0.296	−76.80 (−0.20)	0.045
	Distance from river (km)	−14.00 (−0.15)	0.068		

Source: (based on questionnaire survey data)

Table 10
Total effect due to influencing variables for severe floods.

	Total effect (standardized)	
	Non-poor households	Poor households
Livelihood not dependent on natural resources and labouring	−24.30 (−0.14)	−6.19 (−0.04)
Elevation (m MSL)	−1.04 (−0.19)	−0.40 (−0.09)
Inundation duration (days)	3.29 (0.10)	8.63 (0.22)
Vehicle ownership	−1.22 (−0.01)	−10.30 (−0.04)
Distance from river (km)	−18.87 (−0.20)	−9.38 (−0.09)
Highest education level (yrs)	−0.59 (−0.02)	−2.62 (−0.08)
Inundation depth (ft)	2.28 (0.19)	6.30 (0.42)
Per capita income in 10,000s	−7.23 (−0.10)	−76.79 (−0.20)

Source: (based on questionnaire survey data)

occupants who had less education and depended on natural resources and labouring for their livelihoods.

The path models developed using the 2017 flood for both poor and non-poor groups, and validated with 2003 flood data, are shown in Fig. 4. The model developed for the 2017 flood was applied to the 2003 flood and the respective factor loadings for validation were compared with the factor loadings of the 2017 flood model, to check its stability. Colours and arrows in Figs. 5, 6 and 8 represent the same as in Fig. 4.

Table 11 shows the comparison of factor loadings between calibration and validation for non-poor and poor households. Those results, along with the results shown in Table 10, indicate a reasonable fit of the model for validation, suggesting that the models can be applied to any other severe flood to determine the economic loss.

4.2. Comparison between poor and non-poor for minor floods

Among the four selected floods, two (2008 and 2016) were considered minor.

4.2.1. Absolute loss and relative loss

Cross-tabulation results suggest that only 9% of poor households and 21% of non-poor households were affected by the 2008 flood. For the 2016 flood, the figures are 7% and 25% respectively. The percentage of households affected by a minor flood was less than 20% of the total population (refer Table 3).

The average absolute loss due to the 2008 flood among non-poor households was about 18,000LKR, and 31,000LKR among poor households. The relative loss among non-poor households was 1%, a figure that rose to 6% among poor households for the same flood. For the 2016 flood, absolute loss was about 37,000LKR and 18,000LKR among non-poor and poor households respectively, whereas relative losses were 1% and 3% respectively. Even though losses due to minor floods are relatively small, these findings support the conclusion that poor households suffer more from floods.

4.2.2. Results of path analysis

To understand the factors affecting the economic loss due to minor floods, data collected for the 2016 flood was analyzed in a path analysis framework. Here, also, the damage indicator is relative economic loss due to floods. The model developed using 2016 flood data to examine the factors affecting economic loss is shown in Fig. 6.

As in section 4.1, the model fit was checked by considering GFI,

Table 11
Comparison of factor loadings between model development and validation for severe floods for non-poor and poor households.

Variable 1	Variable 2	Non-poor					Poor				
		Model development		Model validation		% difference reference to 2017 model	Model development		Model validation		% difference reference to 2017 model
		Estimate (standardized)	P value	Estimate (standardized)	P value		Estimate (standardized)	P value	Estimate (standardized)	P value	
Highest education level (yrs)	Livelihood not dependent on natural resources and labouring	1.24 (0.24)	0.003	1.24 (0.24)	0.003	0	2.36 (0.48)	***	2.36 (0.48)	***	0
Per capita income in 10,000s	Highest education level (yrs)	0.08 (0.23)	0.003	0.08 (0.23)	0.003	0	0.03 (0.42)	***	0.03 (0.42)	***	0
	Vehicle ownership	0.17 (0.11)	0.172	0.17 (0.11)	0.172	0	0.13 (0.22)	0.026	0.13 (0.22)	0.026	0
Inundation depth (ft)	Inundation duration (days)	1.44 (0.52)	***	1.92 (0.64)	***	33	1.37 (0.52)	***	1.57 (0.65)	***	15
	Distance from river (km)	−2.14 (−0.27)	***	−1.89 (−0.28)	***	12	−1.49 (−0.21)	0.021	−1.16 (−0.22)	0.126	22
Inundation duration (days)	Elevation (m MSL)						−0.04 (−0.19)	0.068	−0.05 (−0.10)	0.068	25
Relative economic loss due to floods (%)	Inundation depth (ft)	2.28 (0.19)	0.017	3.31 (0.39)	***	45	6.30 (0.41)	***	7.65 (0.51)	***	21
	Elevation (m MSL)	−1.04 (−0.19)	0.014	−0.93 (−0.12)	0.106	10					
	Livelihood not dpendent on natural resources and labouring	−23.57 (−0.14)	0.061	−20.98 (−0.13)	0.041	11					
	Per capita income in 10,000s	−7.23 (−0.1)	0.296	−6.40 (−0.1)	0.472	11	−76.79 (−0.20)	0.045	−64.81 (−0.19)	0.126	15
	Distance from river (km)	−14.00 (−0.15)	0.068	−12.67 (−0.1)	0.176	9					

Source: (based on questionnaire survey data)

Table 12
Model fit parameters of the path analysis model for minor floods.

	Model development 2016		Validation 2008		Acceptable range
	Non-poor	Poor	Non-poor	Poor	
Probability level	0.01	0.02	0.19	The sample includes only 7 poor households exposed to the 2008 flood, which is less than 10% of the sample. Hence, validation cannot be performed due to insufficient sample size.	Closer to "0"
RMSEA	0.07	0.09	0.04		Closer to "0"
GFI	0.93	0.91	0.95		Closer to "1"
AGFI	0.89	0.84	0.92		Closer to "1"
CFI	0.94	0.95	0.98		Closer to "1"
NFI	0.87	0.89	0.91		Closer to "1"
TLI	0.92	0.93	0.98		Closer to "1 the "
CMIN/DF	1.73	1.69	1.22		Less than "5"
AIC	82.55	65.43	68.19		Lower is better

Source: (based on questionnaire survey data)

AGFI, TLI, NFI, CFI, RMSEA, AIC, probability level and minimum discrepancy. Table 12 indicates that all the fit values for the model show reasonable results as they lie within the acceptable range.

Table 13 illustrates the correlation between each variable and its significance level for the minor floods. Results of the analysis suggest that the relative economic loss due to floods was directly and positively affected by inundation depth, irrespective of economic conditions. However, this relationship is a little stronger among poor households than non-poor households. Even for minor floods, inundation depth is the most significant factor affecting relative loss, irrespective of income level. Economic loss due to floods for non-poor households was directly and negatively affected by per capita income, and positively affected by inundation depth, elevation, and distance from the river. The positive impacts of elevation and distance from the river contradict the hypothesis.

It seems that households located far from the river and at higher elevations had better living conditions, with inhabitants having

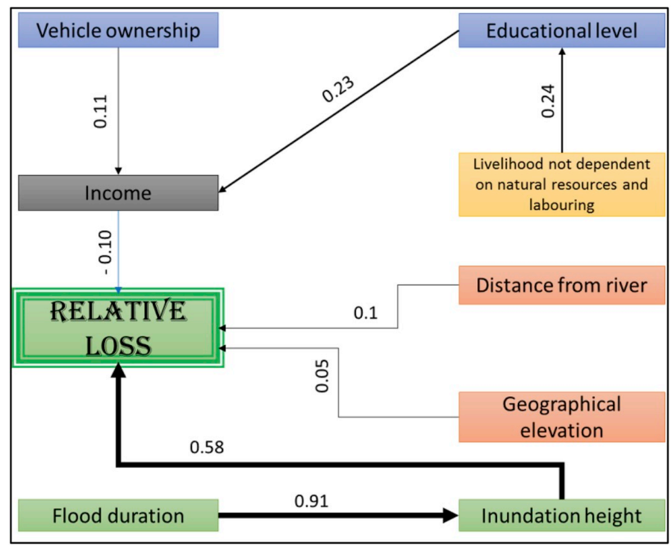

Fig. 8. Validation of the path model for minor floods using 2008 flood data for non-poor households. Source: (based on questionnaire survey data).

Table 13
Influencing variables for economic loss due to minor floods.

Variable 1	Variable 2	Non-poor households		Poor households	
		Estimate (standardized)	P value	Estimate (standardized)	P value
Highest education level (yrs)	Livelihood not dependent on natural resources and labouring	1.24 (0.24)	0.003	2.36 (0.48)	***
Per capita income in 10,000s	Highest education level (yrs)	0.08 (0.23)	0.003	0.03 (0.42)	***
	Vehicle ownership	0.17 (0.11)	0.172	0.13 (0.22)	0.026
Inundation depth (ft)	Inundation duration (days)	1.34 (0.85)	***	1.52 (0.89)	***
Inundation duration (days)	Elevation (m MSL)			−0.04 (−0.19)	0.068
	Per capita income in 10,000s			−1.20 (−0.25)	0.019
Relative economic loss due to floods (%)	Inundation depth (ft)	5.79 (0.73)	***	4.80 (0.85)	***
	Elevation (m MSL)	0.13 (0.10)	0.132		
	Per capita income in 10,000s	−2.44 (0.10)	0.083		
	Distance from river (km)	2.04 (0.10)	0.176		

Source: (based on questionnaire survey data)

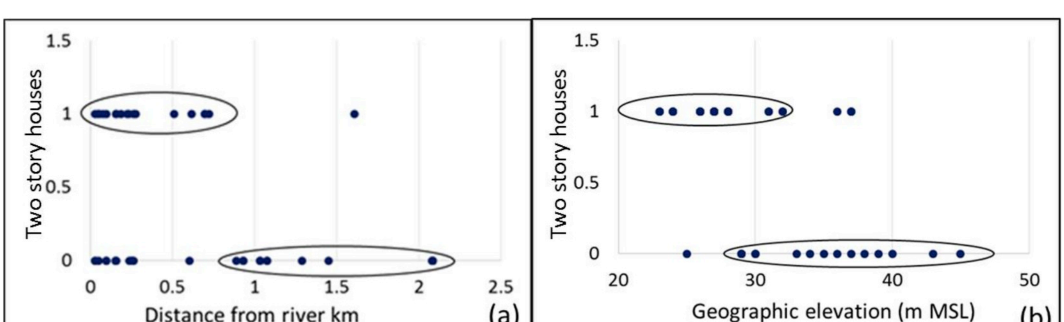

Fig. 7. Relationship between house type with (a) distance to the river and (b) elevation. Source: (based on questionnaire survey data).

Table 14
Total effect due to influencing variables for minor floods.

	Total effect (standardized)	
	Non-poor households	Poor households
Livelihood not dependent on natural resources and labouring	−0.25 (−0.01)	−0.71 (−0.04)
Elevation (m MSL)	0.13 (0.10)	−0.29 (−0.14)
Inundation duration (days)	7.78 (0.63)	7.30 (0.75)
Vehicle ownership	−0.41 (−0.01)	−1.18 (−0.04)
Distance from river (km)	2.04 (0.10)	
Highest education level (yrs)	−0.20 (−0.02)	−0.30 (−0.08)
Inundation depth (ft)	5.79 (0.73)	4.80 (0.85)
Per capita income in 10,000s	−2.44 (−0.10)	−8.76 (−0.19)

Source: (based on questionnaire survey data)

reasonably good incomes and lower expectations of floods. Because of this, they suffer more from minor flooding than people who live near the river and are prepared for minor floods. Fig. 7 shows the scattered variation between house-types, with distance to the river and elevation.

As shown in Fig. 7, when distance from the river and elevations are greater, people tend to live in single-story houses. This suggests they do not expect frequent floods as they live in safer places. However, being non-poor, their belongings have a higher value, and when exposed to minor floods their loss becomes higher compared with those who live nearer the river and who have better adaptive capacity.

There are some factors that show an indirect impact on relative economic loss due to floods. The total effect shows that these factors negatively affect economic loss due to floods, for minor floods on non-poor households, and also have a negative impact on poor households. However, distance from the river has no significant impact on economic loss due to floods for poor households, while in the case of minor floods greater losses occur among non-poor households located far from the river and at higher elevations. Table 14 demonstrates the total effect of each variable on relative economic loss due to floods.

Validation could only be performed for the non-poor group (Fig. 8) as the number of poor households exposed to the 2008 flood was very small (7 only) and insufficient for statistical analysis.

Fig. 8, Tables 12 and 15 suggest that the path model developed for investigating the impact of minor floods on non-poor households shows reasonable reproducibility.

5. Discussion

The results suggest that households that are located near the river at low elevations, have low per capita income and poor living conditions, and whose inhabitants have relatively little education and work in industries that depend on natural resources and labouring, suffer the most from severe floods. Anh et al. [43] have confirmed that households with lower income, poor living conditions, and a lower education level are highly exposed to floods. The absolute loss difference between poor and non-poor for severe and minor floods is about 48% and 10% respectively. These results It suggests that severe floods cause an increased economic gap between the poor and non-poor. In addition, Bui, et al. [57]; Krause and Reeves [58] have shown that natural disasters significantly exacerbate poverty and inequality. Hence, the policies relevant to severe flood management should better consider poor households to indirectly reduce inequality in society. These findings are based on a poverty threshold of 10,000 LKR per month (nearly $1.9 per day) The sensitivity of these results to the poverty threshold can be assessed by doing the analysis for probable changes in the poverty threshold.

In Ratnapura, households are scattered everywhere and the district lacks proper city planning. Most land is privately owned and people choose where they live based on the affordability of land. Hence, the poor tend to live in more vulnerable, lower-cost areas such as low-lying land near river banks, where homes and properties are more exposed to damage from frequent floods. Kawasaki et al. [59], Hoeven et al. [60], and Shepherd et al. [61] have also shown that poor households are often located in low lying areas where they are exposed to frequent floods. As a result, the economic gap between poor and non-poor populations may increase, leading to higher inequality.

Further, Households nearer the river suffer lower economic losses than single-story houses further from the river. Moreover, the impact of livelihood type on flood loss is significant only with regard to non-poor households exposed to severe floods: in the three other cases, that relationship is not significant. This indicates that livelihood diversification may not be a good solution for flood management in Ratnapura. Management of the floodplain, by restricting the construction of settlements in the reservation area, might be a better option for reducing the economic losses caused by floods, and thus inequality. Authorities might also consider encouraging settlement at higher elevations. This could be done by providing poor households with the financial means to move away from the river, perhaps through the provision of concessionary rates or by allowing payments to be made in installments.

6. Conclusions

In this study, floods were categorized, based on their severity, into two groups – severe and minor. Factors affecting economic losses caused by severe floods and minor floods were analyzed separately for different economic groups. Accordingly, the sample was subdivided into four subcategories with each analyzed separately to understand the factors that influence flood damage. The relationships between socioeconomic conditions, flood characteristics, and the losses caused by each flood category were analyzed in a path analysis framework. There appears to be a significant correlation between "relative economic loss due to floods" and inundation, which suggests that households that are inundated to a higher level are highly vulnerable to economic loss. However, inundation depth and inundation duration have a more significant impact on losses from minor floods than they do for severe floods.

Table 15
Comparison of factor loadings between model development and validation for minor floods for non-poor households.

Variable 1	Variable 2	Model development		Model validation		
		Estimate (standardized)	P value	Estimate (standardized)	P value	% difference relative to 2016 model
Highest education level (yrs)	Livelihood not dependent on natural resources and labouring	1.24 (0.24)	0.003	1.24 (0.24)	0.003	0
Per capita income in 10,000s	Highest education level (yrs)	0.08 (0.23)	0.003	0.08 (0.23)	0.003	0
	Vehicle ownership	0.17 (0.11)	0.172	0.17 (0.11)	0.172	0
Inundation depth (ft)	Inundation duration (days)	1.34 (0.85)	***	1.19 (0.91)	***	11
Relative economic loss due to floods (%)	Inundation depth (ft)	5.79 (0.73)	***	4.66 (0.58)	***	19
	Elevation (m MSL)	0.13 (0.10)	0.132	0.17 (0.05)	0.262	30
	Per capita income in 10,000s	−2.44 (−0.10)	0.083	−2.52 (−0.10)	0.147	3
	Distance from river (km)	2.04 (0.10)	0.176	1.69 (0.10)	0.204	17

Source: (based on questionnaire survey data)

Interestingly, geographic location has a positive impact on loss with regard to minor floods among the non-poor, suggesting that non-poor households located far from the river and at higher elevations suffer greater losses due to minor floods. It appears that this is because two-story houses located nearer the river suffer lower economic losses than single-story houses further from the river.

Absolute losses are lower, while among poor and non-poor for minor floods they are near parity, with the loss difference between these groups being about 10% (of non-poor loss). In the case of severe floods, absolute loss difference between poor and non-poor is 48% relative to the loss on non-poor. This suggests that severe floods widen the economic gap between poor and non-poor. The results indicate that the factors affecting economic loss due to floods differ between economic groups, while flood impact helps determine the gap between poor and non-poor communities. The approach and outcomes elucidated in this paper will benefit policymakers for they will be able to address each economic group separately, while implementing policies for flood management and inequity reduction.

Declaration of competing interest

All the authors have declared that they have no conflicts of interest relevant to this article.

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Appendix A. Supplementary data

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References

[1] N.V. Loayza, E. Olaberría, J. Rigolini, L. Christiaensen, Natural disasters and growth: going beyond the averages, World Dev. 40 (7) (2012) 1317–1336.
[2] H.C. Winsemius, B. Jongman, T.I.E. Veldkamp, S. Hallegatte, M. Bangalore, P. J. Ward, Disaster risk, climate change, and poverty: assessing the global exposure of poor people to floods and droughts, Environ. Dev. Econ. 23 (3) (2018) 328–348.
[3] A. Kawasaki, J. Rhyner, Investing in disaster risk reduction for resilience: roles of science, technology, and education, J. Disaster Res. 13 (7) (2018) 1181–1186.
[4] G.A. Parvin, A.C. Shimi, R. Shaw, C. Biswas, Flood in a changing climate: the impact on livelihood and how the rural poor cope in Bangladesh, Climate 4 (4) (2016) 1–15.
[5] I.O. Adelekan, Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria, Environ. Urbanization 22 (2) (2010) 433–450.
[6] J. Askman, O. Nilsson, P. Becker, Why people live in flood-prone areas in akuressa, Sri Lanka, Int. J. Disas. Risk Sci. 9 (2) (2018) 143–156.
[7] N.W. Chan, Choice and constraints in floodplain occupation: the influence of structural factors on residential location in Peninsular Malaysia, Disasters 19 (4) (1995) 287–307.
[8] J.Y. Kim, Rich and Poor: Opportunities and Challenges in an Age of Disruption, The World Bank, 2018.
[9] S. Fankhauser, R. Leemans, L. Erda, L. Ogallo, B. Pittock, R. Richels, C. Rosenzweig, U. Safriel, R.S.J. Tol, J. Weyant, G. Yohe, Vulnerability to Climate Change and Reasons for Concern: A Synthesis, IPCC, 2001.
[10] M.E. Kahn, The death toll from natural disasters: the role of income, geography, and institutions, Rev. Econ. Stat. 87 (2) (2005) 271–284.
[11] H. Toya, M. Skidmore, Economic development and the impacts of natural disasters, Econ. Lett. 94 (1) (2007) 20–25.
[12] S. Ferreira, K. Hamilton, J.R. Vincent, Nature, Socioeconomics and Adaptation to Natural Disasters: New Evidence from Floods, World Bank, 2011.
[13] B. Jongman, H.C. Winsemius, J.C.J.H. Aerts, E. Coughlan de Perez, M.K. van Aalst, W. Kron, P.J. Ward, Declining vulnerability to river floods and the global benefits of adaptation, Proc. Natl. Acad. Sci. U. S. A. 112 (18) (2015) E2271–E2280.
[14] R. Brouwer, S. Akter, L. Brander, E. Haque, Socioeconomic vulnerability and adaptation to environmental risk: a case study of climate change and flooding in Bangladesh, Risk Anal. 27 (2) (2007) 313–326.
[15] U. Patnaik, K. Narayanan, Vulnerability and Coping to Disasters: A Study of Household Behaviour in Flood Prone Region of India, Munich Personal RePEc Archive, 2010.
[16] M. Henry, A. Kawasaki, I. Takigawa, K. Meguro, The impact of income disparity on vulnerability and information collection: an analysis of the 2011 Thai Flood, Flood Risk Manag. 10 (2015) 339–348.
[17] Y. Tahira, A. Kawasaki, The impact of the Thai flood of 2011 on the rural poor population living on the flood plain, J. Disaster Res. 12 (1) (2017) 147–157.
[18] E. Borgomeo, J.W. Hall, M. Salehin, Avoiding the water-poverty trap: insights from a conceptual human-water dynamical model for coastal Bangladesh, Int. J. Water Resour. Dev. 34 (6) (2017) 900–922.
[19] R. Few, Flooding, vulnerability and coping strategies: local responses to a global threat, Prog. Dev. Stud. 3 (1) (2003) 43–58.
[20] J. Buckland, M. Rahman, Community-based disaster management duringthe1997 red river flood in Canada, Disasters 23 (2) (1999) 174–191.
[21] T. Reardon, J.E. Taylor, Agroclimatic shock, income inequality, and poverty: evidence from Burkina Faso, World Dev. 24 (5) (1996) 901–914.
[22] J. Hoddinott, Shocks and their consequences across and within households in rural Zimbabwe, J. Dev. Stud. 42 (2) (2006) 301–321.
[23] P.D. Little, M.P. Stone, T. Mogues, A.P. Castro, W. Negatu, 'Moving in place': drought and poverty dynamics in south Wollo, Ethiopia, J. Dev. Stud. 42 (2) (2006) 200–225.
[24] T.A. Smucker, B. Wisner, Changing household responses to drought in Tharaka, Kenya: vulnerability, persistence and challenge, Disasters 32 (2) (2008) 190–215.
[25] S. Eriksen, J.A. Silva, The vulnerability context of a savanna area in Mozambique: household drought coping strategies and responses to economic change, Environ. Sci. Pol. 12 (1) (2009) 33–52.
[26] S.S. Morris, O. Neidecker-Gonzales, C. Carletto, M. Munguía, Q. Wodon, Hurricane Mitch and the Livelihoods of the Rural Poor in Honduras, 2006 (Washington DC).
[27] M. Van Den Berg, Household income strategies and natural disasters: dynamic livelihoods in rural Nicaragua, Ecol. Econ. 69 (2010) 592–602.
[28] M. Masozera, M. Bailey, C. Kerchner, Distribution of impacts of natural disasters across income groups: a case study of New Orleans, Ecol. Econ. 63 (2–3) (2007) 299–306.
[29] D.P. Eisenman, K.M. Cordasco, S. Asch, J.F. Golden, D. Glik, Disaster planning and risk communication with vulnerable communities: lessons from hurricane katrina, Am. J. Publ. Health 97 (S1) (2007) S109–S115.
[30] S. Laska, B.H. Morrow, Social vulnerabilities and hurricane katrina: an unnatural disaster in new orleans, Mar. Technol. Soc. J. 40 (4) (2006) 16–26.
[31] E.D. Tesliuc, K. Lindert, Vulnerability: A Quantitative and Qualitative Assessment, *Guatemala Poverty Assessment Program*, 2002.
[32] J. Foltz, J. Gars, M. Özdoğan, B. Simane, B. Zaitchik, Weather and Welfare in Ethiopia, 2013 (Washington, DC).
[33] E. Dube, O. Mtapuri, J. Matunhu, Flooding and poverty: two interrelated social problems impacting rural development in Tsholotsho district of Matabeleland North province in Zimbabwe, J. Disas. Risk Stud. 10 (1) (2018) 455.
[34] M.T.G. Tuason, C.D. Güss, L. Carrioll, The disaster continues: a qualitative study on the experiences of displaced Hurricane Katrina survivors, Prof. Psychol. Res. Pract. 43 (4) (2012) 288–297.
[35] A.C.K. Lee, Barriers to evidence-based disaster management in Nepal: a qualitative study, Publ. Health 133 (2016) 99–106.
[36] S. Rufat, E. Tate, C. Burton, A. Maroof, Social vulnerability to floods: review of case studies and implications for measurement, Int. J. Disas. Risk Reduct. 14 (2015), 470-186.
[37] H.W.Y.J. Hettiwaththa, R.A.B. Abeygunawardana, Measuring Flood Risk in Ratnapura Town Area in Sri Lanka, TIIKM publishers, 2018, pp. 31–41.
[38] N. Eriyagama, M. Thilakarathne, P. Tharuka, T. Munaweera, L. Muthuwatta, V. Smakhtin, W.W. Premachandra, D. Pindeniya, N.S. Wijayarathne, L. Udamulla, Actual and perceived causes of flood risk: climate versus anthropogenic effects in a wet zone catchment in Sri Lanka, Water Int. 42 (7) (2017) 874–892.
[39] M.M.G.T. De Silva, A. Kawasaki, Socioeconomic vulnerability to disaster risk: a case study of flood and drought impact in a rural Sri Lankan community, Ecol. Econ. 152 (2018) 131–140.
[40] B. Wisner, P. Blaikie, T. Cannon, I. Davis, At Risk: Natural Hazards, People's Vulnerability and Disasters, second, ., 2003.
[41] S. Wright, On the nature of size factors, Genetics 3 (1918) 367–374.
[42] S. Wright, The method of path coefficients, Ann. Math. Stat. 5 (1934) 161–215.
[43] H.H. Anh, T.M.D. Hanh, N.T.T. Vi, Y. Shunbo, Examining the interaction of flood vulnerability determinants in Cambodia and Vietnam using partial least squares structural equation modeling, Water Pol. 20 (6) (2018) 1256–1278.
[44] R. Kurniawan, T.H. Siagian, B. Yuniarto, B.I. Nasution, R.E. Caraka, Construction of social vulnerability index in Indonesia using partial least squares structural equation, Int. J. Eng. Technol. 7 (4) (2018) 6131–6136.
[45] D. Liu, Y. Li, S. Fang, Y. Zhang, Influencing factors for emergency evacuation capability of rural households to flood hazards in western mountainous regions of Henan province, China, Int. J. Disas. Risk Reduct. 21 (2017) 187–195.
[46] K. Kantamaneni, Counting the cost of coastal vulnerability, Ocean Coast Manag. 132 (2016) 155–169.
[47] G. Greene, S. Paranjothy, S.R. Palmer, Resilience and vulnerability to the psychological harm from flooding: the role of social cohesion, Am. J. Publ. Health 105 (9) (2015) 1792–1795.
[48] Government of Sri Lanka, Framework Development and Infrastructure Financing to Support Public Private Partnerships, Ministry of Finance, Colombo, 2018.
[49] K. Goto, B. Kumarendran, S. Mettananda, D. Gunasekara, Y. Fujii, S. Kaneko, Analysis of effects of meteorological factors on dengue incidence in Sri Lanka using time series data, PloS One 8 (5) (2013).

[50] H.M.S. Priyanath, Socio-Economic and Environmental impact of gem mining industry in Sri Lanka: a case study of Hunuwala village in Ratnapura district, Sabaragamuwa Univ. J. 2 (1) (2002) 101–109.
[51] M. Denscombe, The Good Research Guide, fourth ed., Mc Graw Hill Open University press, Berkshire, England, 2010.
[52] J.S. Crandall, C.R. Crandall, Computer Systems and Methods for Surveying a Population, *United States Patent Application Publication*, 2008.
[53] W.G. Cochran, Sampling Techniques, 3th Edition, John Wiley & Sons, 1997.
[54] D. Jolliffe, E.B. Prydz, Societal Poverty A Relative and Relevant Measure, World Bank, 2017.
[55] J. Falkingham, C. Namazie, Measuring Health and Poverty: a Review of Approaches to Identifying the Poor, DFID Health Systems Resource Centre, London, 2002.
[56] World Bank, Measuring Poverty; Defining Welfare Measures [Online], 2008. Available at: http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTPOVERTY/EXTPA/0. (Accessed 19 July 2017). contentMDK:20242876~isCURL:Y~menuPK:492130~pagePK:148956~piPK:216618~theSitePK:430367,00.html.
[57] A.T. Bui, M. Dungey, C.V. Nguyen, T.P. Pham, The impact of natural disasters on household income, expenditure, poverty, and inequality: evidence from Vietnam, Appl. Econ. 46 (15) (2014) 1751–1766.
[58] E. Krause, R.V. Reeves, Hurricanes Hit the Poor the Hardest, Social Mobility Memos, 2017.
[59] A. Kawasaki, G. Kawamura, W.W. Zin, *A local level relationship between floods and poverty: a case in Myanmar*, Int. J. Disaster Risk Reduct. (2019).
[60] A.V. Hoeven, H. Benn, M.M. Brown, T. Chino, D.J. Johnston, O. Kabbaj, P. Nielson, K. Töpfer, H. Wieczorek-Zeul, S. Zhang, S. Zhang, Poverty and Climate Change; Reducing the Vulnerability of the Poor through Adaptation, 2015.
[61] A. Shepherd, T. Mitchell, K. Lewis, A. Lenhardt, L. Jones, L. Scott, R. Muir-Wood, The Geography of Poverty, Disasters, and Climate Extremes in 2030, 2013.