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Examining direct and indirect flood damages in residential and business sectors through an empirical lens

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ABSTRACT

Investment to reduce flood risk for social and economic wellbeing requires quantitative evidence to guide decisions. Direct and indirect flood damages at individual household and business building levels were assessed in this study using multivariate analysis with three groups of flood damage attributes, i.e., flood characteristics, socioeconomic conditions, and building types. A total of 172 and 45 respondents from residential and commercial buildings were gathered through door-to-door interviews at areas in Peninsular Malaysia that were pre-identified to have frequently flooded. Two main findings can be drawn from this study. First, flood damage is greatly contributed by high-income households and businesses, despite them being less exposed to floods than low-income earners. This supports the current use of mean economic damage in engineering-based flood intervention analysis. Second, indirect damages increase with the increase in family size, indicating the importance of strengthening preparedness and social support to those with great social responsibility. Overall, the study highlights the importance of holistic flood management accounting for both direct and indirect losses.

Key words: building characteristics, flood damage, indirect damage, multivariate analysis, socioeconomic characteristics

HIGHLIGHTS

- National flood damage is greatly contributed by high-income households and businesses, despite them being less exposed to floods than low-income earners, suggesting that the least mean economic damage is used in engineering-based flood intervention analysis.
- Indirect damages increase with the increase in family size, thus requiring a greater investment for the socially vulnerable group.

1. INTRODUCTION

Flood damage assessment is a crucial risk assessment step that quantifies economic flood losses. In flood risk analysis, the flood damage model has been one of the governing components that represent the degree of susceptibility of receptors to flood damage. For example, countries such as the UK, Germany, the USA, Japan, and Australia have adopted various standard damage models to assist flood risk analysis (Paulik *et al.* 2022). A myriad of social and physical variables theoretically are associated with flood damage (Svenningsen *et al.* 2020), but a model's complexity could jeopardize the usability of such a model in flood risk assessment (Olsen *et al.* 2015). Nevertheless, flood damage assessment with consideration of multiple variables offers evidence for non-engineering measures related decisions (Gissing & Blong 2004). Certain parts of the society that are vulnerable to floods can be targeted for more effective interventions at the local level through multivariate analysis.

Many studies have investigated multiple factors associated with flood damage on a larger spatial domain and fewer have concentrated on individual household or building-level assessment. Although the larger spatial scale approach has its own advantages and usefulness, it may need to be verified with more specific and accurate information at the household or building level. Dealing with survey-based assessment at the building- or household-level entails laborious work on door-to-door interviews that are time consuming and resource-expensive, which could lead to insufficient information in the end.

Furthermore, past studies that might have collected building-level information of flood damage may not be accessible to enhance the analysis. Despite the challenges, the survey-based assessment is preferred because it focuses on local information and personal information. This will lead to more precise information for damage prediction (Merz *et al.* 2013; Amadio *et al.* 2018).

There are only limited studies that have considered combining flood characteristics, physical building characteristics, and socioeconomic variables to predict flood damage for residential and commercial buildings (Merz *et al.* 2004; Kreibich *et al.* 2009; Dawson *et al.* 2011; Merz *et al.* 2013; Van Ootegem *et al.* 2015; Wijayanti *et al.* 2017; Svenningsen *et al.* 2020). A combination of information at the household or building level offers an added value to how flood risk can be managed, for example, by non-structural and socially centered interventions.

The feasibility of using the combination of information based on household-level surveys is conducted in the present study through a methodology that consists of a sequential analysis of damage and factors associated with it. A set of questions was dedicated to flood losses experienced by the respondents, while questions related to socioeconomic, physical, and flood characteristics were considered for the independent variable. This study addresses two research questions: what are the estimated tangible flood damages, and how these are associated with flood characteristics, physical building's type, and socioeconomic variables? Areas that are often flooded in Peninsular Malaysia were chosen for data collection.

2. MATERIALS AND METHODS

2.1. Survey and study area

Surveys using a structured questionnaire and interviews were conducted to gather first-hand information on flood damage and the associated variables. The study focuses on collecting flood damage-related samples from residential and commercial locations within Peninsular Malaysia that are known to be experiencing damaging floods. The locations for the surveys were identified based on a rigorous search of authorized documents and reports, for example, published by the Department of Irrigation and Drainage (2012), Kuala Lumpur City Hall (2015), and the National Statistics Department. Grey literature and open-source websites were also searched to assist and verify the case study areas. According to the Department of Irrigation and Drainage Report (2012), the flood-prone area in Malaysia is approximately 33,298 km^2. About 14.7% of the flood-affected areas located in Peninsular Malaysia include 738.8 and 43.5 km^2 of residential and commercial areas, respectively (Malaysian Department of Irrigation and Drainage 2012). There is no information on the direct and indirect damages of past events. Descriptions of the potential location's population density, land uses, flooded experiences, and development were studied before the final selection of locations.

The final chosen locations for the field survey are Kuala Lumpur (one of the Federal Territory in Malaysia), Selangor (a state southwest of Peninsular Malaysia), and Kelantan (a state northwest of Peninsular Malaysia). In Kuala Lumpur, the specific area is in the Segambut suburban city located in proximity to the Toba River with frequent floods reported over the past ten years (Fatdillah *et al.* 2022) and a total of 2,000 residents once evacuated in 2013 (Khairi *et al.* 2013). Locations in Selangor are within the Kajang and Dengkil cities, located in proximity to the Langat River. According to reports, around 200 people were once evacuated in Kajang in the 2020 flood event. Meanwhile, in Dengkil, almost 500 people were evacuated to public shelters from different flooded sites. Meanwhile, samples in Kelantan were collected from Kota Bharu city, where a total of 319,156 people were evacuated and nine people were killed in a flood event from December 2014 to January 2015 in various districts of the states (Malaysian Department of Irrigation and Drainage 2017).

Figure 1 shows the states and cities where the survey and interviews were undertaken. Respondents were approached on a one-to-one basis at their houses or business premises. This allows discretization of the respondents, where only those who have been living in the area and have experienced floods within the recent 10 years (between 2010 and 2020 when the survey was conducted) are approached.

The survey questionnaire includes sets of important parameters that are commonly included in flood damage analysis (e.g., Merz *et al.* 2013; Van Ootegem *et al.* 2015; Amadio *et al.* 2018, 2019): (1) flood characteristics, (2) building characteristics, (3) socioeconomic characteristics, and (4) monetary losses of possessions. The latter governs the estimates of direct and indirect flood monetary damage at the building level. For residential buildings, the types of buildings considered are bungalows, terraced, and low-cost types, with the latter including village houses. For business premises, business unit sizes are classified as either micro or small-medium business units according to the number of employees (SME Corporation Malaysia 2022). A micro-size business has less than five permanent full-time employees, while a small-medium business has 5–30 or above full-time employees working permanently.

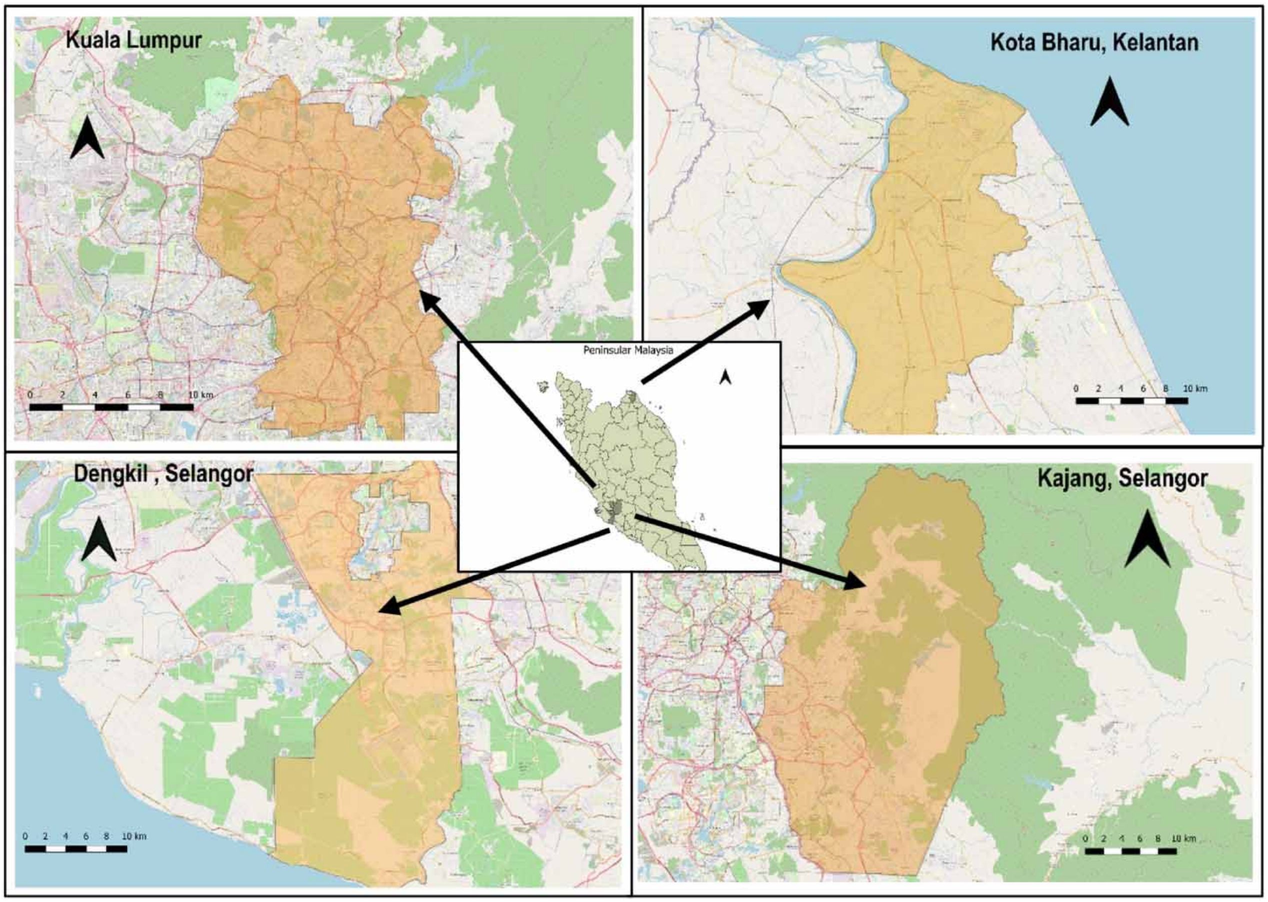

Figure 1 | Areas where surveys were conducted are enlarged and arrows indicate their locations in Peninsular Malaysia. Top left: Kuala Lumpur Federal Territory; Top right: Kota Bharu district, Kelantan; Bottom left: Dengkil, Sepang district; Bottom right: Kajang, Hulu Langat district. Except for Kota Bharu, the other locations are in the southwest of Peninsular Malaysia.

A total of 380 residential and business units were approached for interviews, but only 217 responses with sufficient information for the analysis, i.e., at a 57% return rate, were obtained. From the 217 responses, 79.3% (172) are from residential buildings, and the remaining 20.7% (45) are from commercial buildings. The small number of respondents from the commercial buildings was influenced by the fewer commercial activities as compared to the residential buildings. Furthermore, business owners and workers are less attentive. Most respondents were from Kota Bharu, whose worst flood experience was in 2014. In Segambut, the respondents of the residential buildings were mainly from low-cost building residences and low-income people, unlike Kota Bharu and Dengkil, which had a fair mix of residential building types and income levels. Only 16% of the respondents from household interviews are government employees, and the rest are from the private sector. The limited number of respondents of T20 was due to the lack of higher-income group people living in the area. Moreover, some of the T20 households were not keen to be interviewed. In terms of their capacity to adapt to floods, 20% of the respondents indicated a positive response, for example, by self-efforts to install measures or raising walls on their properties. Moreover, 70% of the respondents took shelter actions during floods, for example, moving to a safer place such as relative houses or public buildings (e.g., mosques, schools, or community shelters). Respondents from the commercial buildings from all surveyed locations are mainly from the micro-size business type (i.e., 75% of the respondents) and the remaining are from small and medium businesses. Small and medium businesses are very limited in the study area and it was challenging to find such businesses in the targeted flood-prone area. Supplementary material, Appendix A summarizes the categorical data of respondents according to the types of residential buildings and the business size from all locations.

2.2. Processing empirical flood damage

Table 1 lists the items considered for direct and indirect damage computations. Some are directly obtained from the survey, and others use proxies to derive the monetary damage. The present study considers direct damage to residential buildings as the sum of the structure's damage, damaged items inside and outside the building (e.g., garage or workshop, storage, garden, fence, etc.), and cleaning-up costs. These are direct damages, such as the impacts are directly during floods.

Similar to the direct damage to a residential building, the direct damage to a business premise is indicated by the damage to assets and equipment in the premise and its compound. Meanwhile, indirect tangible damages here are related to the indirect adverse consequences of floods, which use proxies as an indication. These are the evacuation costs that the victims have to spend for and during the evacuation, and wages or profit loss due to the days of out-of-work, including days of business interruption. It is assumed that the profit loss due to the days of business interruption is double the time it was closed. From the responses, less than 5% of the respondents reported their vehicle damages that caused a high variance in flood damage aggregation. Thus, vehicle damage was discarded from computations. Further preparation for the damaged data includes removing absurd data indicated by skewness and three standard deviations cutoff point. The tangible damage computation approaches were found to be varied between studies owing to different assumptions (Supplementary material, Appendix A).

The computed damage eventually was converted to the same reference year using the Malaysian inflation calculator (Malaysia CPI Inflation Calculator 2021; AR2007 - Audited Financial Statements for the Year Ended 30 June 2007 n.d.) with consideration of their depreciation and market values, as well as the inflation rate.

2.3. Regression analysis

Figure 2 shows the variables considered in this study. The variables of flood characteristics are the flood depth in buildings from the ground and the duration that the building is inundated by water. The building characteristics consist of the type of building and its location from the river. Meanwhile, the socioeconomic characteristics are the household size, having children and/or elderly, household or business income/profit per month, property ownership, and years of living in the properties or operating the business premises.

An analysis of flood damage was first made by simple charts and visualization with consideration of the income levels of residents (or profit of business premises) and a building's distance from the river. These two variables were chosen (1) to verify the greater exposure of low-income households and small businesses to floods and (2) to examine the monetary damages endured by the different economic levels of society. The income categories were distinguished into three classes (Department of Statistics Malaysia 2020): (1) People with less income and within the bottom 40% of the average national income range (B40). People in this category are assumed to have less than MYR4,850 per month; (2) People with income in the middle 40%, who earn between MYR4,850 and MYR10,959 per month (M40); (3) People with income in the top 20%, which is more than MYR10,959 earnings per month (T20), and henceforth, referred to as B40, M40, and T40, respectively. The classifications that are being used to distinguish the different socioeconomic conditions of people are subjective in nature and depend on revisions from time to time. Some studies have used smaller divisions to class the poorer segment, for example, low-income, median, and very poor household groups (e.g., Wijayanti *et al.* 2017; UNESCAP 2019). However, the three classes adopted in this study are deemed sufficient, given the range size of the samples. Business premises, in general, are classified by Kreibich *et al.* (2009) into micro, small-medium, and large business sizes. In Malaysia, service and other

Table 1 | Direct and indirect damage computations for residential and commercial buildings with equations the damages are estimated

Residential		**Business**	
Direct	**Indirect**	**Direct**	**Indirect**
Building structure (S_r) Inside of building/Assets (A_r) Outside of the building (O_r) Cleaning (C_r)	Evacuation cost (E_r) Wages loss (Salary per day) (W_r)	Building structures (S_c) Contents/Assets (A_c) Cleaning (C_c)	Evacuation cost (E_c) Business interruption (Income loss for days of close operation) (B_c)
Total direct damage for a residential building $= S_r + A_r + O_r + C_r$	Total indirect damage for a building $= E_r + W_r$	Total direct damage for a commercial building $= S_c + A_c + C_c$	Total indirect damage for a commercial building $= E_c + B_c$

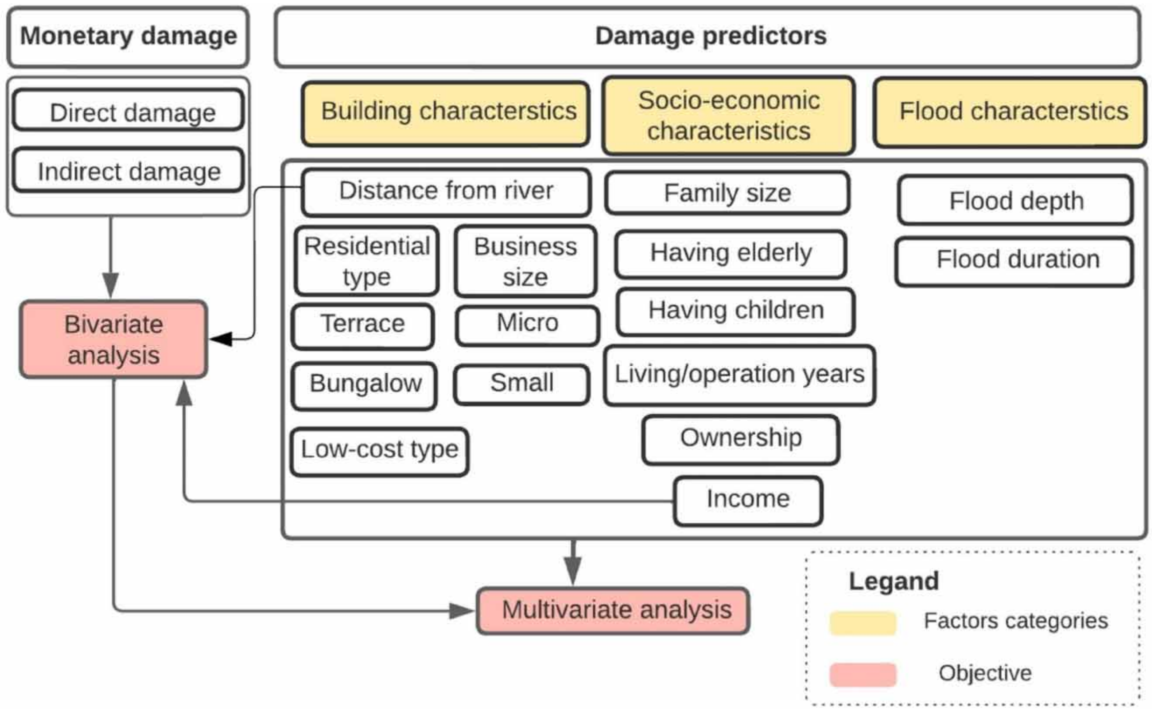

Figure 2 | Initial factors considered for the analysis. Boxes fall under either one of the considered main components in yellow boxes. These are used as input to objectives within the overall methodological framework highlighted in pink boxes.

businesses are categorized into micro, small-medium, and large sizes of less than five employees, between 5 and 29 employees, and more than 30 employees, respectively (SME Corporation Malaysia 2022).

The analysis then proceeded to multivariate analysis, where the multiple regression model was adopted. Direct and indirect flood damages individually are the dependent variables, while the independent variables are the flood characteristics, building (or business) type, and socioeconomic variables (Table 2). A total of 10 independent variables and 7 independent variables were used as input variables for residential and business premises analysis, respectively. A preliminary investigation of the datasets was conducted, and preparation was undertaken as needed prior to the model fit. This includes log–log and log-linear transformations (e.g., Lee 2020, Svenningsen *et al.* 2020) to accommodate non-Gaussian variables in their original form. For residential buildings, the datasets are log–log transformed except for the categorical type of independent variables, such as building type, having elderly, having children, and ownership. For commercial buildings, the datasets are not transformed except for the income data, where it is transformed into logarithmic values because the other datasets fulfill the Gaussian distribution criteria. To ensure that there is no data outside the acceptable range, they were further cleaned based on the Mahalanobis distance method. The multivariate regression models are shown in Equations (1) and (2) for residential and business premises, respectively, where β_0 is a constant, and beta (β_n) are regression coefficients of damage predictors, and $\boldsymbol{\varepsilon}$ is an error. Both equations represent generic equations; therefore, all variables are included in these equations.

$$\begin{aligned} Log\ (Flood\ damage) = {} & \beta_0 + \beta_1 log\ (Flood\ Depth) + \beta_2 log\ (Flood\ Duration) + \beta_3\ Building\ Type \\ & + \beta_4 log\ (Distance\ from\ River\ ) + \beta_5 log\ (Family\ Size\ ) + \beta_6\ Childern\ \ + \beta_7\ Elderly + \beta_8 log\ (Income) + \beta_9\ Ownership \\ & + \beta_{10}\ log\ (Living\ Duration) + \varepsilon \end{aligned} \tag{1}$$

$$\begin{aligned} Log\ (Flood\ damage) = {} & \beta_0 + \beta_1\ Flood\ Depth + \beta_2\ Flood\ Duration + \beta_3\ Business\ Size \\ & + \beta_4\ Distance + \beta_5 log\ (Income) + \beta_6\ Ownership \\ & + \beta_7\ Business\ premises\ Duration + \varepsilon \end{aligned} \tag{2}$$

Table 2 | Descriptions of explanatory variables used in the multivariate analysis and their used in the regression analysis

Explanatory variables	Description	Multivariate analysis
Flood characteristics		
Flood depth	Water depth inside the building from the ground floor, range residential (0.3–2 m), business (0.3–1.6 m)	Continuous variable
Flood duration	Water duration stays around the house during the day, ranging (1–14 days)	Continuous variable
Building or business characteristics		
Building type (low-cost type, Terrace, Bungalow)	Low-cost, terrace or bungalow	Dummy variable (Low-cost house = 0, Terrace & bungalow = 1)
Business size	The micro or small-medium business premise	Dummy variable (Micro = 0, Small to medium = 1)
Distance from River	Distance of building from the fluvial flood stream, residential (10–1,320 m) and business (5–1,250 m)	Continuous variable (meter)
Socioeconomic conditions		
Family size	Number of members in the household or family (1–12 persons)	Continuous variable
Ownership	Tenant or owner	Dummy variable (Tenant = 0, Owner = 1)
Income (family/business)	Average monthly income per household or revenue per premise of residential (MYR500–10,000) and commercial (MYR500-20,000)	Continuous variable
Living duration or premise operation years	Number of years the respondent lives in the area or operated a business in the area (1–64 years).	Continuous variable
Having children	With children or not.	Dummy variable (Without children under 14 years old = 0, with = 1)
Having elderlies	Household with elderlies.	Dummy variable (Without elderly above 65 years old = 0, with = 1)

3. RESULTS AND DISCUSSION

3.1. Flood damages versus income and distance from river

Tabulation of flood damages against the income categories and distance from rivers (Figure 3) obtained from the survey verifies that the majority of respondents exposed to flood damage are from the lower-income group who mostly resided near rivers. This is similar to what was found in studies in other countries (e.g., de Silva & Kawasaki 2020). Families with higher earnings (i.e., M40 and T20) resided within the 1 km distance is much smaller in numbers as compared to the lower income people (i.e., B40) with only 15% of the total samples. Greater exposure indicates that the less fortunate segment of the society moved to a higher residence despite the known exposure of an area to fluvial floods. The B40 group also has the largest share of the total flood damage despite the lower average flood damage per individual building. This provides evidence that despite the expected lower possessions from the lower-income group, community-wide flood damage is expected to be dominated by the aggregated losses of individual residences of lower-income people.

With regard to the business premises, results show that micro-sized businesses have a greater total damage at each respective distance interval from the river, compared to small-medium-sized businesses (Figure 4). This is despite the smaller average damages at individual building levels due to possessions, again highlighting the greater influence of aggregated losses of low-income people. A higher proportion of the micro-sized business type residing near to the river as compared to the small-medium-sized business type is also evident from the results.

The average damage of a residential building falls within the range of MYR 3,000–8,000 for direct damage and MYR 530–2,000 for indirect damage. Meanwhile, the average damage of both business sizes falls between MYR 7,000 and 12,000 for direct damage and MYR 1,400 and 2,000 for indirect damage. The values highlight that a commercial building yields a greater building-level average damage due to its greater assets and equipment. However, the residential buildings in aggregate contribute a larger portion to the total damage obtained from the survey, which is similar to what was found from the 2022

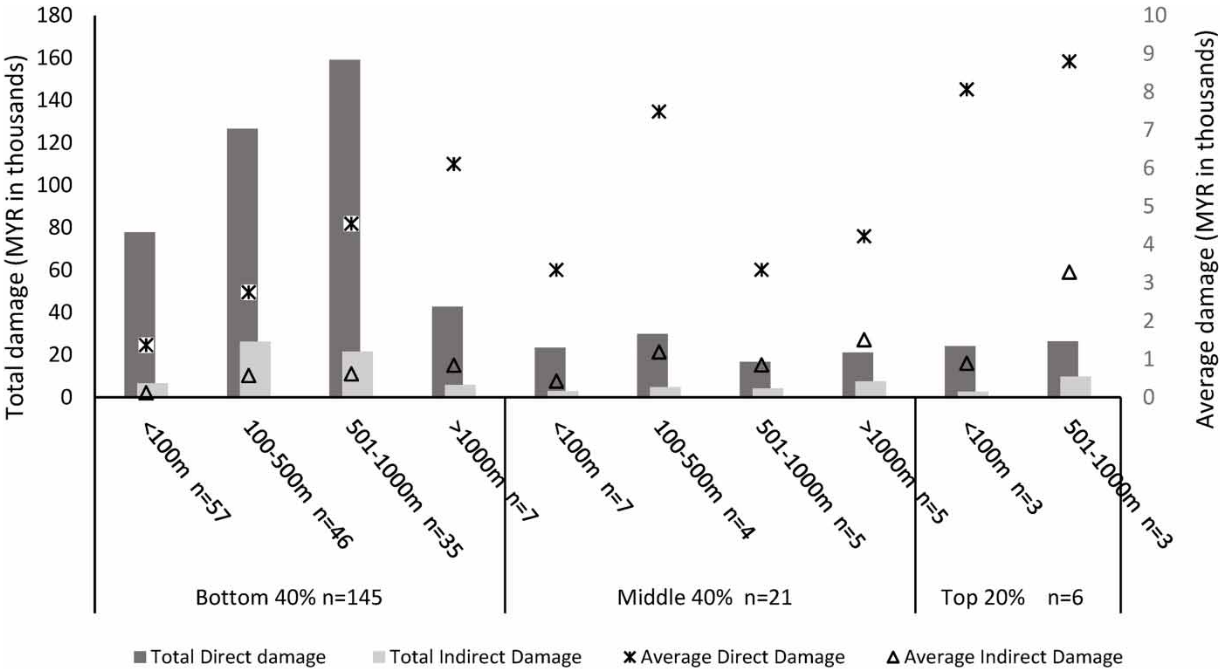

Figure 3 | Tabulation of the total and average flood damage of residential buildings considering income categories, distance from river, and the number of samples, *n*.

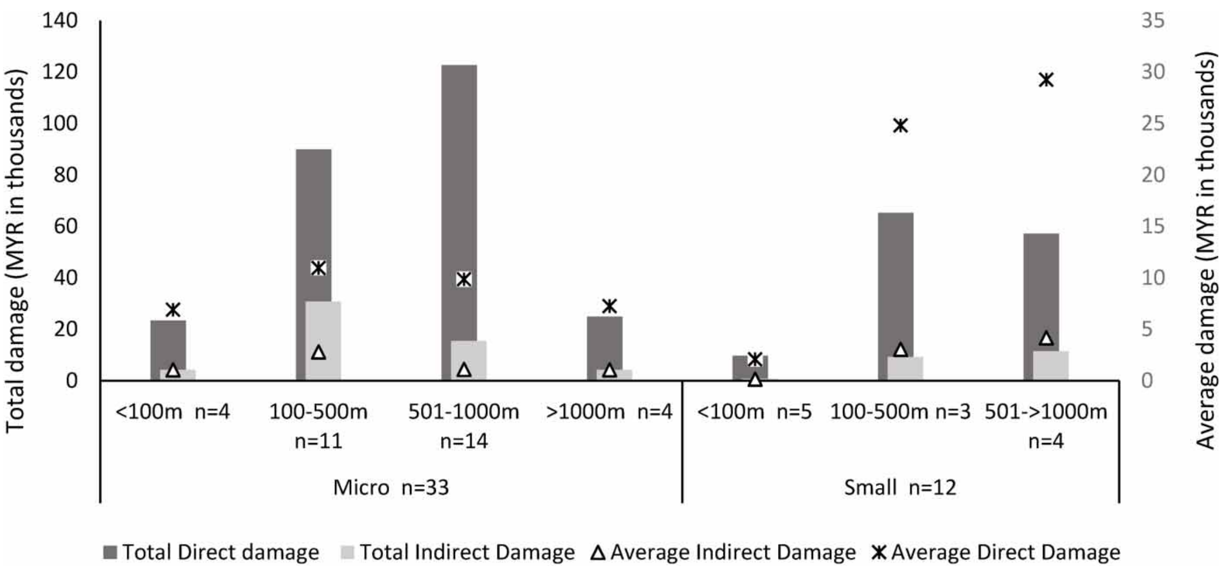

Figure 4 | Tabulation of the total and average flood damage of commercial buildings considering income categories, distance from river, and the number of samples, *n*.

nationwide flood in Peninsular Malaysia (Prime Minister Department 2022). The greater damage is due to the large number of residential buildings as compared to commercial buildings impacted by floods.

Indirect damage poses a smaller portion of monetary losses as compared to direct damage, which is 15–25% for residential buildings and 15–21% for commercial buildings. The fractions are similar to the study by Hammond *et al.* (2013), which suggested a 21% indirect damage from the total damage. The Department of Irrigation and Drainage (DID) reported in 2012 that indirect damage is 30% of the direct damage in Malaysia (Department of Irrigation & Drainage 2012). The

2012 study, however, did not consider disrupted working days accounting wages or business interruption costs for the indirect damage calculation.

It is worth pointing out that the highest flood depths on residential properties and business premises found from the survey were around 2 and 1.8 m from the ground. Many respondents experienced shallow flood depths of 1.2 m or less. Only two residential properties experienced flood depths greater than 2 m high, and none of the business premises surveyed experienced flood depths greater than 1.8 m high. A large number of samples for shallow flood depths and vice versa is aligned with the fact that floods of greater magnitudes are rare. Malaysia Department of Irrigation and Drainage (DID) suggested four categories of flood level for flood hazards: less <0.5 shallow, 0.5–1.2 moderate, 1.2–2.5 high, and the last category is very high flood which is more than 2.5 m flood level (Malaysian Department of Irrigation and Drainage 2017).

3.2. Multivariate analysis for residential building

Table 3 shows the correlation matrix between flood damages and the considered independent variables when they are individually correlated. For residential buildings, six variables (i.e., flood depth, flood duration, type of building, distance from river, having elderly, and income) are correlated to direct damage with a significance level of 1 or 5%. All six variables that are statistically significant for direct flood damage are also correlated to indirect damage in between 1 and 10% statistically significant levels. In addition, living duration is another variable that is correlated to indirect damage at a 5% statistically significant level.

Although the correlation coefficient is generally weak, only two variables pose greater than 0.5; the results, henceforth, are discussed in terms of the positive or negative correlation to the flood damage. The positive correlation of flood depth and flood duration to direct damage indicates the reality of the increase in damage with the increase in the physical flood indicator. On the other hand, the distance from the river shows a positive correlation to direct damage. This is not intuitive since in simple theory, the farther a building is from a river, the safer it is from direct damage. The explanation for this lies in the fact that those living farther from the river are mostly the higher-income groups who have more possessions.

Table 3 | Correlation matrix of damage predictors with direct and indirect flood damages of residential buildings and business premises

	Residential building			Business premises	
Variables	Direct damage	Indirect damage	Variables	Direct damage	Indirect damage
Log (Direct damage)	1		Log (Direct damage)	1	
Log (Indirect damage)	0.364***	1	Log (Indirect damage)	0.693***	1
Characteristics of flood					
Log (Flood depth)	0.326***	0.145*	Flood depth	0.089	0.165
Log (Flood duration)	0.270***	0.536***	Flood duration[a]	0.158	0.244
Characteristics of Building					
Building type (Low-cost = 0, Terraced & Bangalow = 1)	0.274***	0.282***	Business size (Micro = 0, Small-medium = 1)	−0.021	−0.165
Log (Distance from river)[a]	0.392***	0.645***	Distance from river	0.287*	0.256*
Socioeconomic characteristics					
Having Children	0.054	−0.068	Ownership	0.046	−0.025
Having Elderly	0.156**	0.152**	Premises operation (year)	0.135	0.274*
Ownership	−0.004	−0.027	Log (Income)	0.468***	0.718***
Log (Family size)	0.052	0.119			
Log (Income)	0.242***	0.398***			
Log (Living duration)	.078	−0.172**			

[a]Variable removed due to multi-collinearity between independent variables.
*Significant at 0.1 level.
**Significant at 0.05 level.
***Significant at 0.01 level.

When considering individual building-level damage, greater direct-flood damage can be expected for those who live a bit farther from the river. On the contrary, the lower-income group who lives nearer to the river has less possession, thus less direct damage has been experienced at individual building level despite their greater exposure. The counter effects are aligned with what was found in Section 3.1.

Living duration has a negative correlation with indirect damage indicating that people living longer in a flood-prone area are less prone to indirect damage due to their greater resilience to flooding. This may also be contributed by their familiarity to the place that enabled them to evacuate more effectively. From the correlation analysis, it was found that the flood duration and a building's distance from the river endure multi-collinearity in the case of direct damage, leading to the removal of the building's distance from the river before multiple regressions.

The relative contribution of variables to flood damage is next explored from the multiple linear regression by OLS. Five out of 10 variables are statistically significant at 0.1 *p-value* to predict direct damage, and three variables to indirect damage at the same *p*-value threshold (Table 4). The regression's goodness-of-fit shows that the *R*-squared (R^2) value is approximately 0.3 for direct damage and 0.5 for indirect damage. The R^2 value determined the variance in damage, which can be predicted by multiple independent variables. A higher R^2 value for indirect damage indicates that the independent variables used can explain the variation of indirect damage better, as compared to direct damage. The values are acceptable although a stronger value is typically sought (Evans 2012). Some studies have even found smaller R^2, for example, around 0.25 by Wijayanti *et al.* (2017) and Svenningsen *et al.* (2020) despite the larger sample size used in their study.

The five variables that are statistically significant to predict direct flood damage are flood depth, building type, distance from river, income, and living duration, while the three variables for indirect damage are distance from river, income, and

Table 4 | Multiple regression results for flood damage of residential and commercial buildings

Residential building

	Direct damage ($R^2 = 0.289$)				**Indirect Damage ($R^2 = 0.538$)**			
Explanatory variables	**Unstandardized Coefficient B**	**Standard Error**	***p*-value**	**Standardized Coefficient *β***	**Unstandardized Coefficient B**	**Standard Error**	***p*-value**	**Standardized Coefficient *β***
Flood characteristics								
Log (Flood depth) (m)	1.491	0.354	0.000	0.288	n.s.			
Building characteristic								
Building type (low-cost = 0 Terrace or Bungalow = 1)	0.156	0.74	0.037	0.151	n.s.			
Log (Distance from river) (m)	0.231	0.056	0.000	0.300	0.469	0.045	0.000	0.609
Socioeconomic characteristics								
Log (Income) (MYR)	0.420	0.120	0.001	0.243	0.607	0.096	0.000	0.351
Log (Living duration) (year)	0.271	0.095	0.005	0.213		n.s.		
Log (Family size)	n.s.				0.376	0.147	0.012	0.153

Commercial building

	Direct damage ($R^2 = 0.302$)				**Indirect Damage ($R^2 = 0.692$)**			
Explanatory variables	**Unstandardized coefficient *B***	**Standard error**	***p*-value**	**Standardized coefficient *β***	**Unstandardized coefficient *B***	**Standard error**	***p*-value**	**Standardized coefficient *β***
Socioeconomic characteristics								
Log (Income) (MYR)	0.593	0.173	0.001	0.476	0.968	0.115	0.000	0.780
Business premises operation (year)		n.s			0.008	0.003	0.014	0.270

n.s., not significant.
Variables that are not significant at 10% level for both direct and indirect damages are excluded.

family size. The smaller number of predictors for indirect damage highlights the inherent challenge of linking the factors contributing to it. It is interesting to find that while the predictor of direct damage includes flood depth as one of the indicators, it is not the case for indirect damage. Furthermore, the inclusion of family size as a predictor of indirect damage while not that of direct damage highlights the greater burden endured by households with a larger family size during evacuation, more than it affects the direct damage of flooding.

By deducing the relationship of variables for direct damage[1], it is found that a 1% increase in flood depth, distance from river, and income increases 1.5, 0.23, and 0.42% direct damage. The positive and significant increase in direct damage due to flood depth supports the use of flood depth as the main flood indicator in quantitative flood risk analysis to reflect the physical consequences of flood inundation. Meanwhile, the influence of building types on flood damage shows that bungalows or terraced buildings yield 16.81% more total damage compared to the referenced low-cost buildings[2]. Greater values reflect the huge amount of internal assets of the former compared to the latter. A similar study has shown that a terraced building can receive less damage than detached houses from ground flooding (Van Ootegem *et al.* 2015).

In the case of indirect damage, a 1% increase in the building's distance from the river and a 1% increase in income lead to a rise of 0.47 and 0.61% of indirect damage. As found from the empirical data, higher-income people live farther from the river and this coincides with the multivariate regression that they receive greater indirect damage as compared to lower-income people who live nearer to the river (e.g., Win *et al.* 2018). One percent increase in family size increases 0.38% of indirect damage. Therefore, the addition of one member to a family can increase indirect damage by 3.17%. Larger family sizes received higher indirect damage due to higher evacuation costs.

3.3. Multivariate analysis for business premises

Similar to the residential case, the correlation of variables with direct and indirect flood damages for the business premise shows that only distance from river and income are the most statistically significant to direct damage at a p-value of 0.1 (Table 3). Meanwhile, the two variables are also statistically significant to indirect damage with the addition of premise operation years.

The variables that are statistically significant yield positive correlation values for both direct and indirect damages. The micro businesses that live near rivers have fewer assets; therefore, they are less affected even though they are exposed more to flooding. The result is supported by the analysis of exposure in Section 3.1. The positive correlation of indirect damage with business premises operation is intuitive because of the greater accumulation of assets and possessions over the years that result in a greater loss when the business is not operated due to floods.

The interrelationship of independent variables demonstrates collinearity between flood duration and business premise operation years. Therefore, flood duration was removed from the independent variables in multiple regressions. From the regression analysis, the R^2 values for direct and indirect damage regression of commercial buildings are greater than 0.37, which is similar to residential buildings. The higher R^2 value for indirect damage model prediction than the direct damage model means that the independent variables used for the indirect damage model have a greater ability to explain the variation of the indirect damage, as compared to the latter.

The regression results (Table 4) indicate that only the income variable is statistically significant at 0.1 p-value to direct and indirect damage predictions. In addition, business premises operation years are statistically significant predictors for indirect damage. The remaining independent variables are found to be statistically insignificant predictors. A 1% increment in income raises the direct damage by 0.59%, similar to a study by Van Ootegem *et al.* (2015). A 1% increase in income increases 0.97% of indirect damage. In addition, business premises operation years as a predictor for indirect damage shows that a year increase in the operation year increases the indirect damage by 0.0125%. This means that 10 years of business premises operation years can increase the indirect damage by 0.125%.

4. DISCUSSION

The study highlights valuable insights related to efforts in reducing flood risk in a fluvial flood-prone area. In terms of analysis of flood risk reduction measures, the results have verified that flood depth is one of the physical factors that provide a good

[1] The log–log transformation is the logarithmic transformation of the dependent (Y) and independent variables (X) and was recalculated by following the formula: • Multiplying X by 10 will multiply the expected value of Y by 10β. • To have changes in Y due to a percentage (p) increase in the X value, $a = \log((100 + p)/100)$ and take $10^{a\beta}$. β = regression coefficient, a = determinant (Benoit, 2011).

[2] The dummy variable effect uses the equation by Svenningsen *et al.* (2020); $100^{*}(10^{(\beta_x - 0.5\beta^2_{Std\ Err})} - 1)$.

indication of direct flood damage and verified the use of it in quantitative flood risk analysis that has been widely practiced (e.g., Olesen *et al.* 2017; Rehan 2018; Shrestha *et al.* 2021; Fatdillah *et al.* 2022; Rehan & Yiwen 2023).

Social factors are not pronounced in the assessment of economic damage, hence proving that flood mitigation interventions are challenging to be justified for the vulnerable group of people, for example via benefit–cost analysis. Nevertheless, the present study shows that there is a positive relation between family size and indirect damage. To address the indirect flood damage that greatly affect people with greater responsibility (i.e., larger family size), non-structural measures should be advocated (Van Duivendijk 2006; Sun *et al.* 2012). Efforts should aim to increase preparedness and offer better post-flood recovery actions that are tailored to or prioritized for the targeted vulnerable households. Enhancing risk communication would improve their ability to respond to flood effectively (Dawson *et al.* 2011; Koks *et al.* 2015), and adopt appropriate self-precautionary measures to enhance understanding of flood risk. The inclusion of measures that target vulnerable people would pave the way for a more holistic approach of flood management planning (Molinari *et al.* 2013).

The present study reveals that at the building level, damages are more pronounced for the higher-income households despite them being less exposed to flooding. Nonetheless, the low-income households outnumbered the high-income households when it came to the portion of samples collected. The variation highlights the importance of overlaid information on residential building locations and flood areas that ultimately determine the total flood losses of the community (Van Ootegem *et al.* 2015; Lechowska 2018) for engineering-based flood project assessment. The spatial discrepancies and socioeconomic inherent disparity indicate the need to include, to some degree and practicality, heterogenous information of the flooded area, which are either averaged or discretely included in the index or risk analysis. Some studies have used a larger area or aggregation to address the heterogeneity, for example, the use of GDP (Taguchi 2022) and census data (Sayers *et al.* 2018). Alternatively, median household damage can be used for large-scale analysis of aggregated damage and risk.

Flood damage variables for commercial buildings are more difficult to discern as compared to residential buildings. The multivariate regression model shows that only income can be used for the prediction of direct and indirect damages, and in addition, business operating years for indirect damage. The limited predictability of other variables may be due to insufficient information from the survey, or simply, the inherent complexity of the predictor variables (e.g., Hammond *et al.* 2013). It is widely acknowledged that for robustness, a sufficiently large dataset is required (Merz *et al.* 2013), but it comes with extra expenses (Shiker 2012; Van Ootegem *et al.* 2015). There is a need for collaborative efforts and coordination to ensure that flood damage information is properly documented and comprehendible for reanalysis.

Similarly, indirect damage information is scarce and far more less than knowledge on direct damage (Merz *et al.* 2010; Jongman *et al.* 2012). Regarded as a secondary effect of a subsequent action, a simplified assumption is often used to account for indirect damages (Penning-Rowsell & Parker 1987;Merz *et al.* 2010; Hammond *et al.* 2013). The assumption is that indirect flood damages are comparatively small compared to direct damages. A small portion is actually verified in studies that undertook surveys for flood damage assessment, such as that found in the present study. Ward *et al.* (2011) also show that indirect damage is slightly above 15% as compared to direct damage in business sectors. Another study by Jongman *et al.* (2012) shows 40% for industrial direct damages. The uncertain percentage of damage has led to the simplification of analysis when the focus is on a large area impacted by floods (Nga *et al.* 2018).

5. CONCLUSION

Evidence of the relationship between exogenous non-physical factors and flood damage is part of the needed information to support flood damage reduction actions. Such information can be translated into the nation's investment portfolios to help reduce the risk of floods by considering suitable structural and non-structural measures. The study has successfully undertaken a comprehensive interview and survey of residential and business sectors at the building level across states in Malaysia to assess their correlation and collective contributions to direct and indirect damages. It is among the few published empirical-based studies in this region.

Two main findings from multivariate analyses are that (1) damages are more pronounced for the higher-income households despite them being less exposed to floods, and (2) there is a positive relation between family size and indirect damage, indicating the greater effect of indirect damage to people with greater responsibility. The former supports the use of least mean damage in decision analysis of engineering-based flood interventions, and the latter emphasizes the need to strengthen preparedness and social responsibility, such as proper planning on post-flood recovery actions for the most socially vulnerable group. Overall, the study highlights the importance of holistic flood management to account for the different characteristics of flood receptors.

Future studies can evaluate intangible flood damage, such as health impact, including stress, anxiety, and trauma, to address the wider impacts flood can bring to human wellbeing. Integrating both the tangible and intangible damages would improve decision-making in flood mitigation efforts.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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