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ORIGINAL PAPER

The socioeconomic impact of climate-related hazards: flash flood impact assessment in Kuala Lumpur, Malaysia

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Abstract

Small-scale flash flood events are climate-related disasters which can put multiple aspects of the system at risk. The consequences of flash floods in densely populated cities are increasingly becoming problematic around the globe. However, they are largely ignored in disaster impact assessment studies, especially in assessing socioeconomic loss and damage, which can provide a significant insight for disaster risk reduction measures. Using a structured questionnaire survey, this study applied a statistical approach and developed a structural equation model (SEM) for assessing several socioeconomic dimensions including physical impacts, mobility disruption, lifeline facilities, health and income-related impacts. The study reveals that respondents have experienced a stronger impact on direct tangible elements such as household contents and buildings as well as direct intangible elements with β coefficients 0.703, 0.576 and 0.635, respectively, at $p < 0{:}001$ level. The direct intangible impacts affect mobility disruption with β coefficients equal to 0.701 at $p < 0{:}001$ level which then further cause adversity to income-generating activities with β 0.316 at significant $p < 0{:}001$ as well. The overall model fit indices show highly acceptable scores of SRMR 0.068, RMSEA 0.055 and PClose 0.092. Thus, the SEM has successfully incorporated the socioeconomic dimensions of disaster impact and explained the impact phenomena reliably. This modeling approach will allow inclusion of various variables from different disciplines to assess hazard impact, vulnerability and resilience.

Keywords Disaster risk reduction · Disaster impact · Socioeconomic impact · Climate-related disaster · Small-scale hazards · Loss and damage

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1 Introduction

Natural disasters have a wide range of impacts which cover social and economic aspects as well. The same can be applied in terms of flash floods. The socioeconomic aspects of flash flood events have been studied from various disciplinary perspectives. These include social vulnerability to floods and flash floods (Bălteanu et al. 2015); human-related impact factors for dynamic vulnerability factors (Ruin et al. 2008, 2014; Terti et al. 2015a; Aroca-Jimenez et al. 2017; Guillén et al. 2017); structural vulnerability of traditional buildings (Milanesi et al. 2018); and multi-vulnerability assessment considering physical and social factors (Karagiorgos et al. 2016a). Assessment of future risks (Åström et al. 2015; Farhan and Ayed 2017), communication of risks (Lazrus et al. 2016), economic risks (Garrote et al. 2016) and the physical or tangible impact of flash floods is also frequently studied (Basnyat et al. 2017; Pregnolato et al. 2017). There are also studies that focus on flash flood-related impacts in urban areas such as Ellicott City (Basnyat et al. 2017) and Attica, Greece (Papagiannaki et al. 2015, 2017). The socioeconomic aspects of flash flood impacts have been a rising focus in academia as the frequency and impact of climate-related disasters increase (Terti et al. 2017).

Kuala Lumpur has a history of large-scale and small-scale floods. Small-scale floods (often called flash floods, water ponding or street floods in Malaysia) that occur frequently can have an adverse impact on economy and society. A flash flood is defined as a short-term (less than six hours) flood event (Taib et al. 2016; Samsuri et al. 2018). When it comes to the assessment and evaluation of the impact of floods, massive and medium scale floods get more attention, whereas small-scale floods, i.e., flash floods, are largely ignored (Czigány et al. 2010, 2011; Khan and Kelman 2012; Hegedüs et al. 2013; Zaidi 2018). Kuala Lumpur has experienced several major floods in the past. The earliest record started in 1926; since then, there have been several major flood events in 1971, 1982, 1986, 1988, 1993, 1995, 1996, 1997, 2000, 2001, 2001, 2002, 2003, 2007 and 2011 (Lee et al. 2014; Abdullah et al. 2015; Samsuri et al. 2018; Yusof et al. 2018). A study based on newspaper reports identified about 64 flash flood-affected places in Kuala Lumpur from 2011 to 2016 (Bhuiyan et al. 2018). These flash floods are not major events, yet they may be able to adversely affect various aspects of socioeconomic life.

Various structural and non-structural measures were taken in the city after the first massive flood in 1971 to mitigate risks (Abdullah 2004) which included improvement of the river channels, construction of levees, construction of flood by-passes, construction of sediment traps and improvement of hydrological data recording (Hong & Hong, 2016). A key infrastructure project called Stormwater Management and Road Tunnel (SMART) has been carried out to alleviate floods in the city at an estimated cost of RM1,887 million (US$514.6 million). SMART is a multi-purpose project which simultaneously mitigates floods, manages traffic and improves safety by managing stormwater (Lee et al. 2014; Kim-Soon et al. 2016). However, despite the successful implementation of the project in 2007, the city still suffers from a significant number of flash flood events. It is because the SMART covers only part of the city where the flood frequency and severity have been reduced, whereas, in many parts of the city, the flash floods problem remains. As a result, flash floods remain one of the most serious environmental problems of the city (Mahmoud & Alazba 2016).

At the national scale, studies focused on flood characteristics on road networks (Nizam et al. 2019), warning systems and their effectivity (Khalid et al. 2015; Alam et al. 2018), and evaluating the probability of pluvial flash floods caused by heavy rainfall and fluvial flood hazards due to overspill of river banks (Rizeei et al. 2018). The flash floods in Kuala Lumpur are primarily pluvial in origin, and previous studies have focused on an overall review of flash flood scenarios (Samsuri et al. 2018) and forecasting by simple multi-layer perceptron (MLP) neural networks (Hong and Hong 2016). However, studies on the socio-economic impact of flash floods are very limited. Therefore, this study investigates how the socioeconomic state of Kuala Lumpur is affected by flash floods. The social aspects, i.e., human behaviors and perceptions, would provide more in-depth understanding for developing disaster risk reduction (DRR) measures (Špitalar et al. 2014). The incorporation of direct and indirect impacts would provide a comprehensive flash flood impact assessment (Gain and Hoque 2013). Two very relevant questions arise in this context: First are the adaptation and mitigation attempts successful in avoiding the adverse impact of flash floods? Second, if the residual impact remains, how do they relate to the socioeconomic setting in the eyes of those who confront the impact? With these questions in mind, this study aims to assess the socioeconomic impact of flash floods in Kuala Lumpur.

2 Theoretical background and hypotheses

2.1 Theoretical background

The impact of natural disaster has direct vs indirect and tangible vs intangible dimensions. In the first dimension, the impact elements are distinguished according to the occurrence time of loss, contact of the hazard to the damaged or lost elements, and the place (whether in the disaster area or not) of the loss. The other dimension is the tangible vs intangible dimension where tangibility is determined based on whether the impact elements are tradeable in the market and can be priced or monetized (McKenzie et al. 2005; Jonkman et al. 2008; Hochrainer-Stigler 2012). The direct and indirect impacts are divided into tangible and intangible and vice versa.

In this framework, all physical, stock, monetizable and priceable impact elements are denoted as tangible impacts. The non-physical, uncountable, non-market and unmonetizable elements are denoted as intangible impacts. These are further classified as direct and indirect impacts. Direct impacts are the impacts that fulfill any of the following conditions such as impact due to direct contact with flood within the hazard area and impact occurred during the hazard event (EMA 2002; Garcia-Aristizabal & Marzocchi 2012; Hochrainer-Stigler 2012; Mechler et al. 2010; Meyer et al. 2013). The indirect impact elements are the ones that happened as a consequence of the direct impact, which may not necessarily fall within the hazard area, and caused during the time of the hazard. This is one of the basic theories based on which catastrophe simulation models (CATSIM) are developed (Mechler & Hochrainer 2010).

Based on the impact dimension discussed above, this study constructs the following impact categories, such as direct tangible impact, indirect tangible impact, direct intangible impact and indirect intangible impact. To define what item goes in which category, this study adopts the simple guideline from emergency management Australia (EMA 2002) and reviews following studies (EMA 2002; Meyer and Messner 2005; Jonkman et al. 2008; Merz et al. 2010; Meyer et al. 2013; Kousky 2014; Lee et al. 2014). The classification of various impact items is presented below (Table 1).

Based on the impact classification (Table 1) and discussion above, a conceptual framework is developed which describes how each impact category is defined for this study

Table 1 Classification of different impact items

	Direct	Indirect
Tangible	Damage to vehicles, public and private buildings and contents, infrastructure (including riverbank damage), fencing and equipment. Clean-up costs and the decrease in property value	Disruption of transport when roads are cut by disaster events
		Loss of value-added from affected businesses, retail, distribution and services (including networks) and due to manufacturing disruption
		Additional costs of maintaining production or services incurred
		Marginal costs of providing alternative public services
		Disruption to public utility systems outside the hazard-affected area
		Increased travel and congestion costs including food spoilage during transport
		Additional costs of emergency services in a hazard event
		Additional costs borne by volunteer groups
		Loss of tax revenue due to mitigation of the companies in the aftermath of flood
		Temporary housing of evacuees
Intangible	Death and injury	Trauma
	Loss of memorabilia, social contact, working hours, leisure hours	Bereavement
	Disruption to living, including isolation and evacuation	Health effects including respiratory illnesses
	Disruption to education	Long-term depression
	Forced to continue working	Loss of community; access to networks, services and assets including recreation areas
	Lower income earning capacity	Damage to cemeteries
	Reduced land values	Increased demand on existing services
	Increased dependence	Diminished community activity as effort goes to individual recovery
	Near destitute feel trapped	The negative image of the place
	Worry over future hazard events	Damage to cultural and heritage sites
	Temporary loss of utilities	Damage to ecological sites; changed habitats and landscape
		Non-use values of lost heritage and environmental sites
		Changed water regime
		Loss of genetic diversity

Source: EMA (2002), Meyer and Messner (2005), Jonkman et al. (2008), Merz et al. (2010), Meyer et al. (2013), Kousky (2014), Lee et al. (2014)

(Fig. 1). The framework involves economic and non-economic aspects for incorporating physical and non-physical dimensions into the consideration for addressing socioeconomic impact.

In this framework (Fig. 1), damage to buildings/houses, vehicles and household contents are categorized as tangible, which also includes infrastructural elements such as roads, drainage and river. For the houses, roads and drainage-related impact, different land-use classes can be relevant. They may differ in terms of cost of repair, clean-up and price of the property for different areas of residential, public and commercial area. The direct tangible impact includes damage to vehicles such as cars, motorcycles, bicycles, lorries and vans when they are trapped on roads and in parking areas during flash floods events.

The direct intangible impact consists of loss of lives/death, injury, disruption to living, loss of leisure and recreation time and worry of future floods. In a disaster situation, peoples' access to transportation and vehicle often become difficult which causes adversities in many ways to the affected people (Cutter et al. 2008, 2010). A common consequence of flash floods is traffic congestion which delay people going to and coming back from work. These are included as disruption to living. In the following, hypotheses for this study are constructed based on the theoretical background.

2.2 Hypotheses on interrelationship of the impacts

2.2.1 The direct socioeconomic impact

It is widely accepted that natural disasters would have a direct impact on both tangible and intangible items of the affected areas (Rose 2004; Jonkman et al. 2008; Petrucci 2012; Kreibich et al. 2014; Koks et al. 2015b). Therefore, it is assumed that directly affected households will likely have their buildings damaged to a certain extent (Table 2). However, as the flash floods in Kuala Lumpur are generally not as destructive as major floods and inundation level is not too high, this study assumes that building damage will most likely be limited to damage of floors, walls, windows, doors and external wall/fence (Merz et al. 2013; Nafari et al. 2016; Löwe et al. 2017; Allaire 2018; Oddo et al. 2018). As flash floods of Kuala Lumpur mostly occur at the surface level, it is assumed that the flood water will

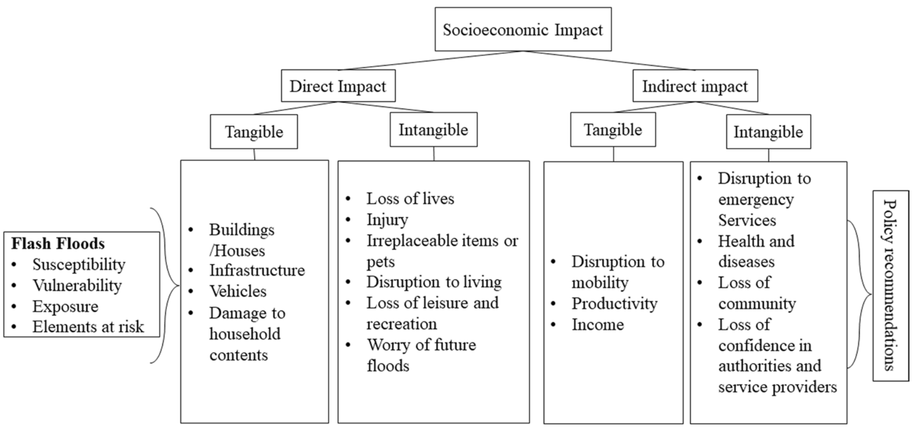

Fig. 1 The conceptual framework for socioeconomic impact assessment

Table 2 Indicators for measuring impact factors

Factors	Attribute/indicators	Sources / references
Direct Tangible Impact	Buildings Household contents	Thieken et al. (2005), Merz et al. (2013), Molinari et al. (2014), Nafari et al. (2016), Rözer et al. (2016), Löwe et al. (2017), Allaire (2018), Oddo et al. (2018)
Indirect Tangible Impact	Mobility Income	Ashley and Ashley (2008), Leenders et al. (2009), Sharif et al. (2012), Terti et al. (2015b), Chamhuri et al. (2016), Nafari et al. (2016), Aroca-Jimenez et al. (2017), Allaire (2018)
Direct Intangible Impact	Loss of lives Injury Disruption to living Loss of leisure and recreation Worry about future floods	EMA (2002), Meyer and Messner (2005), Suarez et al. (2005), Tsuchiya et al. (2007), Ashley and Ashley (2008), Jonkman et al. (2008), Merz et al. (2010); Andreeva et al. (2011), Lumbroso and Tagg (2011), Meyer et al. (2013), Calianno et al. (2013), WMO (2013), Kousky (2014), Lee et al. (2014), Molinari et al. (2014), Moore and Phillips (2014), Romali et al. (2015), Terti et al. (2015a), Himmelfarb (2015), Karagiorgos et al. (2016b), Sene (2016), Chatzivasileiadis et al. (2016), Chhetri et al. (2016), Chu (2016), Papagiannaki et al. (2017), Cumiskey et al. (2018)
Indirect Intangible Impact	Disruption to utility services	Houston et al. (2011), Eleutério et al. (2013), Ishak et al. (2014), Hammond et al. (2015)
	Health and disease	Leenders et al. (2009), Austin and McKinney (2016)
	Loss of community	EMA (2002), Meyer and Messner (2005), Jonkman et al. (2008), Merz et al. (2010), Meyer et al. (2013), Kousky (2014), Lee et al. (2014)
	Loss of confidence in authorities and service providers	Romali et al. (2015)
Household Representative's Profile	Age Marital status Race	Cutter et al. (2003), Kuhlicke et al. (2011), Lujala et al. (2014), Koks et al. (2015a), Karagiorgos et al. (2016a), Shabou et al. (2017), Khajehei (2018)
Household Economy	Household combination Household member Household income Earnings person	Merz et al. (2013), Rufat et al. (2015), Mahmood et al. (2017), Shabou et al. (2017)
Hazard	Flash floods	Thieken et al. (2005), Leenders et al. (2009), Oddo et al. (2018)

mostly get direct contact with household items that are kept at the ground level such as furniture, carpet and other household contents (Thieken et al. 2005; Molinari et al. 2014; Allaire 2018). Based on this theoretical basis, two hypotheses are drawn as listed below:

H1 Flash flood intensity will have a positive relationship with building damage.

H2 Flash flood intensity will have positive relationship with household contents damage.

The direct intangible impacts include loss of lives and injury (Ashley and Ashley 2008; Romali et al. 2015), disruption to living, loss of leisure and recreation (Andreeva et al. 2011; Moore and Phillips 2014; Himmelfarb 2015; Cumiskey et al. 2018) and worry about future floods (Meyer and Messner 2005; Molinari et al. 2014; Sene 2016; Papagiannaki et al. 2017). This also includes loss of memorable items (WMO 2013; Molinari et al. 2014), limited evacuation opportunity (Lumbroso and Tagg 2011; Calianno et al. 2013; Terti et al. 2015a), limited access to transportation, delay to and return from work, roadblocks and children abstaining from school. Whereas indirect intangible impacts include health-related impacts, loss of community, loss of confidence in authority and service providers (EMA 2002; Meyer and Messner 2005; Suarez et al. 2005; Tsuchiya et al. 2007; Jonkman et al. 2008; Merz et al. 2010; Lumbroso and Tagg 2011; Calianno et al. 2013; Meyer et al. 2013; WMO 2013; Kousky 2014; Lee et al. 2014; Molinari et al. 2014; Romali et al. 2015; Terti et al. 2015a; Chatzivasileiadis et al. 2016; Chhetri et al. 2016; Chu 2016). However, disruption to utility services such as food, electricity and water supply loss is often uncountable, especially when temporarily disrupted (Table 1), due to lack of information on duration, degree and nature of disruption/loss. These elements can certainly be considered as tangible when counted as infrastructural elements and the damage happening in physical form (Eleutério et al., 2013 and Hammond et al., 2015). However, in the context of this study, the utility disruptions are relatively temporary, which lacks required information for counting, and therefore, considered as intangible (H3).

H3 Flash flood intensity will also have a direct impact on intangible items.

Floods can affect the income directly or indirectly (Neumayer and Plümper 2007; Aerts et al. 2018; Imran et al. 2019). Income here refers to disruption to the income-generating activities, loss of income opportunity and loss of working hours (Nafari et al. 2016; Allaire 2018). In this study, it is assumed that income opportunities can be directly or indirectly affected by flash floods.

H4 The impact of flash floods on income opportunity can be direct and indirect. Therefore, the proposed model hypothesizes that income would be directly and indirectly affected by flash floods.

2.2.2 The indirect socioeconomic impact

The damage, loss, destruction or adversity caused directly by a natural disaster to the tangible and intangible aspects will cause indirect impact to the society (Paul 2011). Some call it as secondary effect as well (Okuyama 2013). In this study, the indirect socioeconomic impacts have been measured by two latent variables named "Income" and "Mobility." Mobility is measured by the following items: additional travel distance, extra fuel cost, additional travel time and additional fuel consumption. When flash floods affect the road networks, above-mentioned items can result in mobility disruption (Ashley and Ashley 2008; Leenders et al. 2009; Sharif et al. 2012; Terti et al. 2015a; Aroca-Jimenez et al. 2017). Specifically, mobility problems are expected to be caused due to direct intangible impact. Therefore, the indirect impact-related hypothesis can be made as follows:

H5 Direct tangible impact will have a causal relationship with indirect intangible impact.

H6 The direct intangible impact will increase mobility disruption.

H7 The direct intangible impact will increase income opportunity reduction.

H8 The direct intangible impact will increase the indirect intangible impact.

The direct intangible impact would have a causal relationship with the indirect tangible impact by affecting mobility (H6) and income (H7) as well as on the indirect intangible impact (H8) through disruption of emergency services such as electricity and water supply cutoff, or contamination with floodwater, food supply disrupted due to loss of contact with restaurants, food outlets and departmental stores. Floods usually cause waterborne diseases such as diarrhea, dysentery and skin diseases due to poorer water quality caused by floods (Ching et al. 2015). People usually suffer when they lose contact with fellow community members when left isolated during floods. A frequent flood occurrence can also cause loss of confidence and trust in the local authorities. Therefore, all related items are included to measure indirect intangible impact (Fig. 2).

2.2.3 Other indirect impacts

The remaining hypotheses are about the internal relationships between latent variables. Flash floods in Kuala Lumpur largely affect the road network of the city; a network that links other functional factors. Therefore, affected road network leads to additional adversity to other factors (Leavitt and Kiefer 2006) such as mobility and the daily routine of the people (Belmonte et al. 2011). As a consequence of flash floods, working people in the

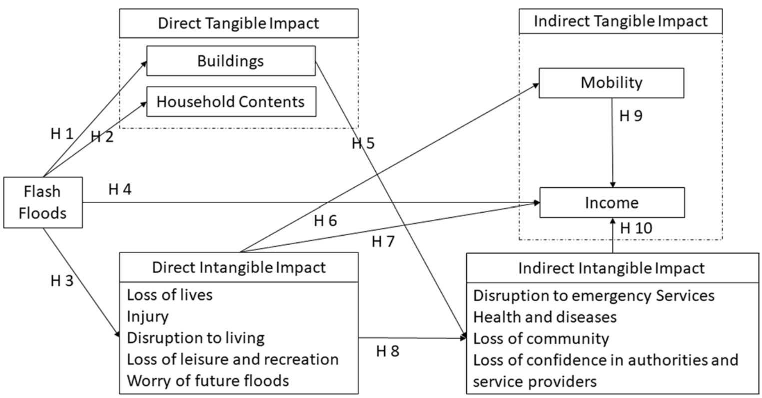

Fig. 2 Proposed socioeconomic model

urban areas have to travel additional distances by using alternative roads, spend extra on fuel cost and additional time in traffic to get to their workplaces (Debionne et al. 2016). Occupational mobility is one of the vulnerable aspects of floods in the Malaysian context (Whittle et al. 2010). When the workforce is delayed going to work, people can be deprived of income opportunities. Therefore, income could be affected directly and indirectly. The indirect impact can be through disruption to mobility and health impacts; anything that causes a person to fail to go to work may result in loss of income, and people may also lose income due to sickness (Chiba and Prabhakar 2017). Therefore, the ninth hypothesis can be set as described below:

H9 Mobility disruption will have an impact on income.

People may become unable to participate in income activities due to an adverse impact on health and utility services (Houston et al. 2011; Eleutério et al. 2013; Ishak et al. 2014; Hammond et al. 2015). The health and diseases variables are measured by three indicators such as skin disease, dysentery and diarrhea (Leenders et al. 2009; Austin and McKinney 2016). Loss of community means that people become socially out of contact and feel helplessness due to the flash floods (EMA 2002; Meyer and Messner 2005; Jonkman et al. 2008; Merz et al. 2010; Meyer et al. 2013; Kousky 2014; Lee et al. 2014). People may lose confidence in the authorities and service providers because they are frequently being affected by floods (Romali et al. 2015). In the indirect intangible impact, disruption to utility services, health problems and loss of community are assumed to reduce the income opportunity of the affected people. It is because, due to the health problems, people may abstain from going to work (Puteh et al. 2018). The loss of community may also result in limiting income opportunity (Haile et al. 2013; Chiba and Prabhakar 2017). Therefore, the 10th hypothesis for this study is provided below:

H10 Income is assumed to be affected by the indirect intangible impact.

A summarized depiction of indicators used for measuring the factors explained in the hypotheses above is supported by previous studies (Table 2). For measuring each indicator in Table 2, further explanatory variables are used from previous studies which are shown in an extended version of this table in the appendix (Table A1).

Based on the literature review and the constructed hypothesis, an SEM model is proposed (Fig. 2). This model has several latent variables with hypothesized impact paths based on the developed hypothesis above. This (flash flood) is the independent variable, and the rest of the latent contracts are the dependent variable in the model.

Based on the problem described above, this study assesses the socioeconomic impact of flash floods in Kuala Lumpur through testing the proposed socioeconomic model (Fig. 2) and its underlying hypotheses.

3 Methodology

3.1 Study area

Kampung Baru (highlighted in green), the area of this study, is situated in the middle of the capital city of Malaysia Kuala Lumpur (Fig. 3); the city is frequently affected by flash

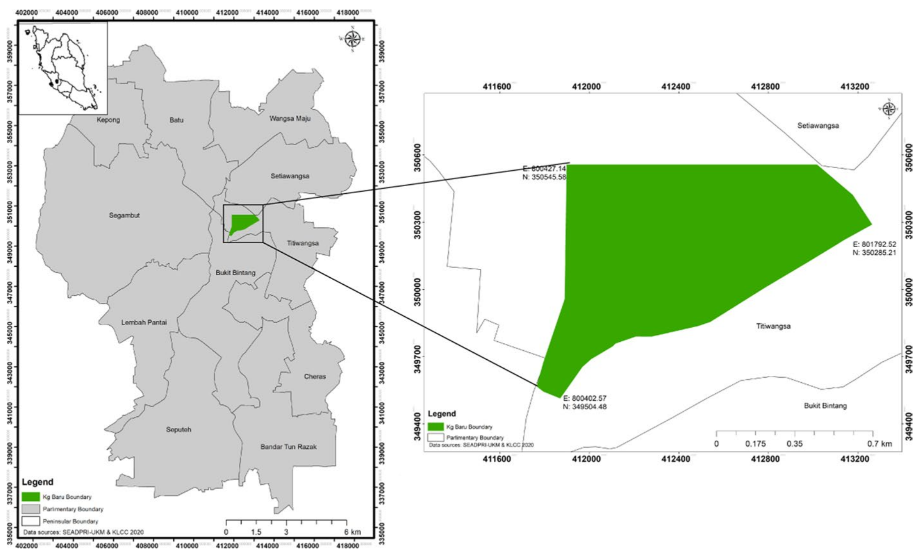

Fig. 3 Location of the study area Kampung Baru in Kuala Lumpur, Malaysia

floods. Based on the documented flood events from 2000 to 2020, the center part of the city has recorded comparatively higher frequency of flash floods (Fig. 4). This area has the conflux of two major rivers named Klang and Gombak river; it is a commercial area and a very busy part of the city. A map with the parliamentary boundary of Kuala Lumpur is overlaid by a flash flood event map of 2000–2020 which shows that the Kampung Baru is situated in a place where flood events are more frequent (Fig. 4). The higher frequency is shown in the surrounding areas as well.

Kampung Baru is a neat layout of traditional Malay villages; it has been relatively less developed even though the surrounding area is highly developed. This city is situated beside the Klang River, one of the two major rivers in the city. The reasons for choosing this village as a study area are: It is a comparatively, less developed area in the middle of Kuala Lumpur; the people who have been residing there for long time have sufficient flood experience; the flood mitigation project SMART has been implemented near this area; however, flash floods are occurring not only within the study area but also in the surroundings. Therefore, this study area will not only help to understand how flash floods affect the socioeconomic state of the community, but also reveal how the flash flood problem is affecting the community despite the implementation of SMART project since 2007.

4 Research design

This study used a quantitative approach to investigate the socioeconomic impact of flash floods. The Likert questions in the questionnaire provide quantitative expression of the qualitative responses. This study used multiple impact dimensions by covering various aspects of socioeconomic impact for ensuring reliability. The hypotheses proposed in the study were tested by adopting the survey method. A questionnaire was prepared based on the loss and damage assessment guidelines prepared by Geest and Schindler (2017) and flood damage assessment guidelines prepared by DID (2003). The questionnaire is

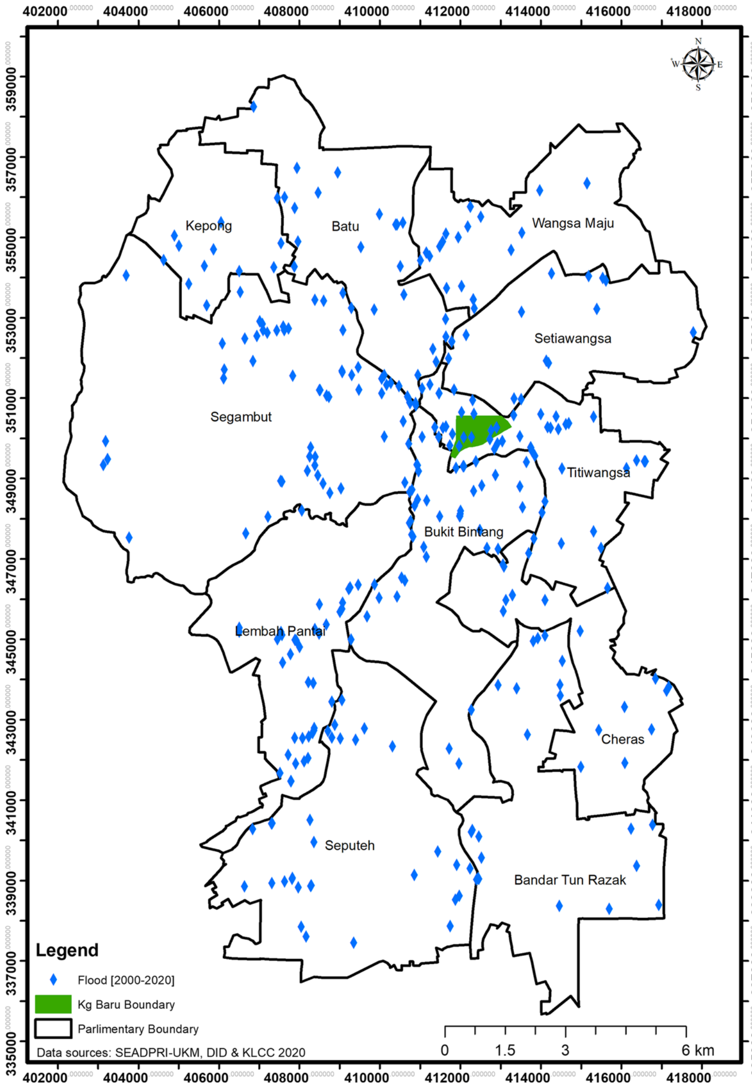

Fig. 4 The documented flood events in Kuala Lumpur

prepared for the household level, aiming to extract detailed information related to tangible and intangible socioeconomic impact.

4.1 Data collection

The survey was conducted over 7 days from August 7 to August 12, 2018, involving 12 trained enumerators. They were briefed about the research and questionnaire. The survey areas were selected based on the flood occurrence data from Kuala Lumpur City Hall (DBKL) and using a flood map from the Department of Irrigation and Drainage (DID).

The sampling scheme consists of 248 randomly distributed households in Kampung Baru (KB). The questionnaire contains four scale Likert questions to avoid neutral response bias (Dolnicar et al. 2011). The households were asked about their socioeconomic status and various direct and indirect socioeconomic impacts of flash floods.

4.2 Data and analysis

This study used SEM for assessing the socioeconomic impact. Although this model has rarely been used in the field of disaster risk reduction (DRR), this model has great potential in assessing disaster impact in the socioeconomic domain. It has been used for assessing socioeconomic vulnerability (Imran et al. 2019) and impact factor of natural hazards (Zou 2012). The SEM approach involves a theory-driven hypothesis-based model specification for linking the variables that are assumed to have an effect on other variables (Diamantopoulos and Siguaw 2000; Kline 2005).

The population of Kampung Baru is about 45,000 (Azid et al. 2015). However, as this study conducts household survey, the total number of households would be the population for this study. According to the Kuala Lumpur development plan 2020 (DBKL 2008), the average member per household in Kuala Lumpur is four persons. Therefore, the total estimated household in the study area is 11,250. This study uses a convenient sampling approach with 95% confidence level and 7% marginal error by using Cochran's sample size formula (Adrian et al. 2003). A higher marginal error was set due to lower response rate. With the stated parameters the study's required sample size is 193 households. The survey collected 248 responses from which 15 cases were excluded due to high rate of missing data, and two more cases were deleted due to inconsistent responses; therefore 231 cases were finally analyzed. The scholars have different opinions on the minimum sample size requirement for SEM. Some opined for the required minimum sample size of 100 to 150 (Tinsley and Tinsley 1987; Anderson and Gerbing 1988; Ding et al. 1995) and some for 200 to 300 (Hoogland and Boomsma 1998; Tabachnick and Fidell 2001; Kline 2005).

The data analysis involves sample demographics, data screening, measurement development and structural model setting. This has been done using data skewness and missing data analysis, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), and finally, structural model setting was performed for testing.

5 Results and discussion

The age of household representatives (HR) of this study is mostly 21 and above (Table 3). The marital status of HR reveals that 22.1% are single, while 70.1% are married. That means 70.1% of the HR is likely to be the head of the household. If the divorced (6.9%), widow/widower (0.4%) and others are included, the 77.9% can be considered as experienced and well informed to give more accurate information as people of these categories are often senior members in the family and play an important part in decision making. In total, 38.5% of the households have a monthly income of less than or equal to RM2000/USD 484, which can be economically vulnerable to floods and flash floods, whereas about 61.5% have more than RM2000/USD 484 monthly income. Among the surveyed households, the 92.2% were Malay (Table 3).

The majority (26.8%) of households comprise four members, whereas 43.7% of the households comprise five to eight members. There are no males in 2.6% of the households

Table 3 Household representative's profile and household income

Age			Marital status			Household income			Race		
Age group	Frequency	Percent	Status	Frequency	Percent	Income range	Frequency	Percent	Race	Frequency	Percent
16–20	13	5.6	Single	51	22.1	No income	14	6.1	Malay	213	92.2
21–40	87	37.7	Divorced	16	6.9	< RM 1000 (USD 242)	16	6.9	China	7	3.0
41–60	97	42	Widow / Widower	1	0.4	RM 1001-RM 2000 (USD 243–484)	59	25.5	India	2	0.9
60 and above	34	14.7	Married	162	70.1	RM 2001-RM 3000 (USD 485- 726)	75	32.5	Others	9	3.9
			Others	1	0.4	RM 3001-RM4000 (USD 727 – 969)	44	19			
						> RM4001 (USD 970)	23	10			
Total	231	100		231	100	Total	231	100	Total	231	100.0

and 4.8% have no females (Table 4). The results represent the distribution of various sizes and types of households from the community.

5.1 Model fit of the measurement model

After data screening and missing data analysis, the data were entered into SPSS 20 software and screened carefully. About 17 out of 248 forms were excluded due to having most of the questions unanswered and unengaged respondent problem. This was followed by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) where the Kaiser–Meyer–Olkin (KMO) and Bartlett's test results show that the grouping and pattern matrix scores are very good with statistically significant p value with 0.00 and KMO adequacy score of 0.907. The communality indicates that the values of all items are considerably higher (mostly higher than 0.40). After performing the EFA, CFA was done. The CFA requires model fit indices to see whether the measurement model is acceptable for the use of SEM. In this study, the chi-square value/degrees of freedom (CMIN/DF), comparative fit index (CFI), standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), and p of close fit (PClose) indices are reported for model fit with each having a specific cutoff criterion to indicate reliability (Table 5).

The EFA determines how factor structures are the best fit to group together in the data set using correlation among the variables which helps to determine problematic variables in the model. CFA is a more powerful and reliable technique that incorporates unidimensionality and evaluates a data set to confirm the underlying structure based on the theories (Mueller 1996). It involves simplifying, modifying and refining the measurement model for testing the theory. The Cronbach's Alpha indicates how well the items are statistically meant to be grouped under each factor. The results of the item under each factor show that the Cronbach's Alpha scores for each group are very good (>0.80) (Table 6). Detailed results that include initial and finals results of EFA and CFA are shown in an extended version of Table 6 in the appendix (see Table A2). The variable named Duration, Depth and Approxim had lower than 0.40 in initial EFA, which were loading under the direct tangible impact factor. This score suggests that they are meant to be predicting something else. This

Table 4 Household profile

	Household member		Gender distribution			
	Frequency	%	Male		Female	
			Frequency	%	Frequency	%
0			6	2.6	11	4.8
1	5	2.2	66	28.6	54	23.4
2	23	10	72	31.2	85	36.8
3	40	17.3	55	23.8	46	19.9
4	62	26.8	24	10.4	22	9.5
5	39	16.9	5	2.2	8	3.5
6	29	12.6	2	0.9	2	0.9
7	22	9.5	1	0.4	2	0.9
8 and above	11	4.7			1	0.4
Total	231	100	231	100	231	100

Table 5 Model fit indices

Measure	Definition	Terrible	Acceptable	Excellent
CMIN/DF	The minimum discrepancy, divided by its degrees of freedom	> 5	> 3	> 1
CFI	Represents the extent to which the model of interest is better than is the independence model	< 0.90	< 0.95	> 0.95
SRMR	The standardized difference between the observed correlation and the predicted correlation	> 0.10	> 0.08	< 0.08
RMSEA	It assesses how far a hypothesized model is from a perfect model	> 0.08	> 0.06	< 0.06
PClose	*p* value testing the null that RMSEA is no greater than .05	< 0.01	< 0.05	> 0.05

Source: (Gaskin and Lim 2016)

is true in the practical sense. These three items construct the independent variables which represent the hazard characteristics and determine the intensity of the hazard. In this study, intensity refers to the severity of the flash flood which is influenced by the depth of the floodwaters, duration of the flood and approximate distance of the house from a stream or riverbank. Therefore, these three items are used for constructing the independent variable. The initial and final CFA results confirm this fact as these three items achieve better loading. As modification indices of the items Duration and Approxim exceeded the threshold of 20, both items were covaried.

The trust and confidence in local authorities' were measured by using three items. Although the EFA results were good enough, there was a case of Heywood (standardized regression weights > 1.00) found in one of the item's regression weights (Table A2). As a result, the entire factor named TrstAuth was deleted to achieve validity and acceptable model fit. The rest of the items of the remaining factors achieved very good score in all cases, and therefore, were kept in the model. In the final model, due to having lower scores, the items Helpless and IsolComm were deleted as they were causing problem to the validity, and overall model fit.

The loading of HmWrkDel exceeds 1.00 in the EFA, however, the initial and final CFA scores show firm loading in the factor. Items MemItm, EvaOpp, RecOpp and AbsSchl have similar scores for EFA and final CFA with the following score, respectively, 0.68, 0.84, 0.72 and 0.60. However, on two occasions, the modification indices exceeded the threshold level 20. That is why the following items were covaried in pairs, RecOpp with LLeisTime and HmWrkDel and WrkDel. The final loadings show improvement for all items. Similarly, ElecSupl, WtrSupl and FoodSup were covaried due to exceeding modification indices threshold. Income is measured by using three items such as Linc, IncOpp and WrkHrs. Finally, since ExtFcost and Fcnsm both indicate the additional fuel used monetarily and quantitatively, the duplication was solved by deleting ExtFcost for more accurate estimation.

The initial model fit measures in Table 7 compares the model fits of initial (unmodified) and final (modified) models. There is a significant improvement as the initial model fit had a lack of enough degrees of freedom due to CFI 0.83 being less than 0.95, the RMSEA 0.095 and PClose score 0.00 were problematic. The deletion of the indicated items (Table 6) and covariation exercises above resulted in a significant improvement in the final model fit (Table 7). Therefore, the modification in the model is justified. The

Table 6 Results of final CFA of all factors

Factors (Cronbach's Alpha)	Item names	Elaboration of the item names	Final loading CFA	Final C.R
Direct intangible impact (.939)	MemItm	Loss of memorable items	0.68	
	AcsTrans	Limited access to Transport	0.88	12.29
	EvaOpp	Limited Evacuation Opportunity	0.84	11.76
	WrkDel	Delay to work	0.85	11.84
	HmWrkDel	Delay to Home from Work	0.82	11.51
	RodBlc	Complete Roadblock	0.75	10.64
	PRodBlc	Partial Roadblock	0.83	11.66
	LLeisTime	Loss of Leisure Time	0.74	10.52
	RecOpp	Loss of Recreation Opportunity	0.72	10.16
	AbsSchl	Children abstain from school	0.6	8.65
InD_Intngbl: indirect intangible impact (.901)	Helpless	People feel helplessness	Deleted	Deleted
	IsolComm	People get Isolated from the community	Deleted	Deleted
	SknDiseas	Suffer from Skin Diseases	0.89	10.95
	Dysentery	Suffer from Dysentery	0.83	10.45
	Diarrhea	Suffer from diarrhea	0.9	11.09
	ElecSupl	Electricity supply loss	0.52	10.63
	WtrSupl	Water supply loss	0.58	11.78
	FoodSup	Food supply loss	0.64	
FF_Intensity: flash flood intensity (.833)	Approxim	Distance of the house from riverbank	0.77	7.823
	Depth	Maximum depth of flood water	0.64	
	Duration	Duration of flood	0.77	8.457
Mobility (.880)	AdTraDis	Additional travel distance	0.89	15.51
	ExtFcost	Extra Fuel cost	Deleted	Deleted
	TrvTime	Additional Travel time	0.88	15.20
	Fcnsm	Additional fuel consumption	0.79	

Table 6 (continued)

Factors (Cronbach's Alpha)	Item names	Elaboration of the item names	Final loading CFA	Final C.R
Incom: Income (.941)	Linc	Loss of income	0.94	26.43
	IncOpp	Loss of income opportunity	0.94	
	WrkHrs	Loss of working hours	0.88	22.05
TrstAuth: trust and confidence in the authorities (.820)	ConfLclGov	Loss of confidence in local govt.	Deleted	Deleted
	EmrgServc	Emergency Service is sufficient	Deleted	Deleted
	CtyConclCns	My city council is concerned	Deleted	Deleted
Building (.930)	Fence	Damage to fence	0.95	16.77
	Doors	Damage to doors	0.91	
HH_Cont: household contents (.833)	Otrs	Damage to other items	0.81	17.37
	Furntr	Damage to furniture	0.93	23.70
	Carpt	Damage to carpet	0.94	

Table 7 Model fit measures

Measure	Threshold	Initial model fit measures		Final model fit measures	
		Estimate	Interpretation	Estimate	Interpretation
CMIN	–	1750.018	–	660.668	–
DF	–	566	–	378	–
CMIN/DF	Between 1 and 3	3.092	Acceptable	1.748	Excellent
CFI	> 0.95	0.83	Need more DF	0.952	Excellent
SRMR	< 0.08	0.084	Acceptable	0.059	Excellent
RMSEA	< 0.06	0.095	Terrible	0.057	Excellent
PClose	> 0.05	0	Terrible	0.056	Excellent

modification process has reduced the χ^2 value by 660.668 (*df* 407, $p < 0.001$) and significantly improved the overall model fit. The CMIN/DF, SRMR, RMSEA PClose and CFI have reached an excellent mark for all.

The model validity measures for the final measurement model indicate that all the dependent factors achieve reliability, convergent validity and discriminant validity (Table 8). However, the convergent validity for FF_Intensity seems problematic because it did not achieve the AVE score equal to or greater than 0.50. However, the good thing is that this variable does achieve convergent validity according to the CR value as it is above 0.70. That means this independent variable achieves convergent validity in a lenient measure but fails in a stricter measure. As this is the only independent variable for the proposed model, we proceed with the model for further analysis on the basis that it achieves the convergent validity according to CR standard. Doing so, the final model fit measures for the final measurement model show that all indices achieved excellent and acceptable scores (Table 7). Therefore, this measurement model is acceptable for moving further for converting into a causal model. Thus, the modified impact model was developed by addressing specific hypothesis within the causal paths (Fig. 5).

After applying all statistically rigorous techniques, the final modified socioeconomic impact model has been achieved where the hypothesized causal relationships are shown. This model will finally be run to test the hypothesis indicated to each path.

The complete SEM model shows the construction of each factor and their item loading weights (Fig. 6). The causal paths are also shown in the model where two control factors were added to see whether any demographic factors, household economic conditions and household representative's profile have any impact on the model.

The control factors have a very minimal impact on building damage (−0.12) which means that a better household economy is likely to have a better quality house that can withstand damaging effects of the hazard (Fig. 6). Therefore, a negative relationship exists between the Household Economy to the building damage. The causal relationship between the profile of the household representative is also shown to have an inverse relationship (−0.14) to mobility which may suggest that the people with the better profile will likely feel less impacted by mobility disruption as they are familiar with the place and may have more alternatives in hand. However, the results show that none of the control variables have statistically significant *p* value, i.e., 0.062 for the household economy and 0.054 for the profile of the household representative (Table 9).

Table 8 Model validity of measurement model

	CR	AVE	MSV	MaxR(H)	Building	Di_Intngbl	Income	Mobility	HH_Cont	InD_Intngbl	FF_Intensity
Building	.93	.87	.31	.937	**.933**						
Di_Intngbl	.938	.605	.456	.947	.395***	**.778**					
Income	.943	.846	.436	.948	.308***	.661***	**.92**				
Mobility	.886	.723	.456	.908	.275***	.675***	.609***	**.85**			
HH_Cont	.921	.797	.438	.938	.557***	.382***	.294***	.133†	**.893**		
InD_Intngbl	.876	.551	.367	.923	.428***	.595***	.661***	.675***	.595***	**.742**	
FF_Intensity	.711	.454	.438	.731	.451***	.625***	.625***	.427***	.662***	.625***	**.674**

Bold indicates the squire roots of AVEs which have to be greater than any correlations of their respective rows

Significance of correlations (2-tailed)

***$p < 0.001$

**$p < 0.050$

†$p < 0.100$

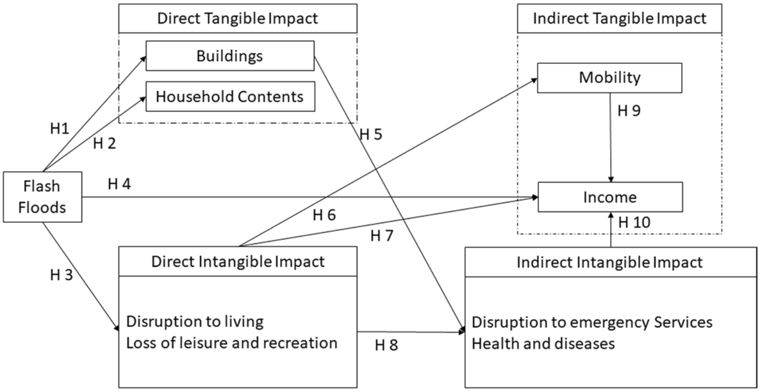

Fig. 5 Modified socioeconomic impact model

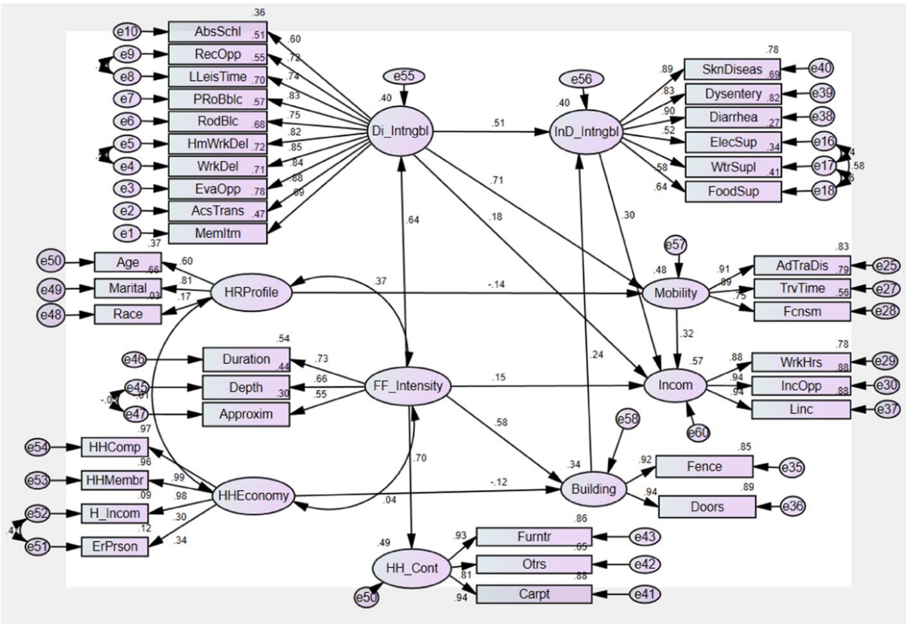

Fig. 6 SEM model of the socioeconomic impact

The SEM outcomes (Table 9) are computed based on the β value of estimated path coefficient. The C.R is the critical ratio which is equivalent to t and p values. The significance of the relationship paths is determined based on the t and p values. The t value must be greater than or equal to 1.96, and the p value must be ≤ 0.05 for a path to be significant (Byrne 2001). Based on these rules, the results of the model are interpreted and discussed below.

Table 9 Overall socioeconomic impact

Endogenous variables	Path	Exogenous Variables	Estimate	S.E	C.R	p	Result
Di_Intngbl	←	FF_Intensity	0.635	0.057	7.13	***	Accepted
Building	←	FF_Intensity	0.576	0.043	7.348	***	Accepted
Building	←	HHEconomy	−0.12	0.079	−1.866	0.062	Rejected
InD_Intngbl	←	Di_Intngbl	0.508	0.066	6.159	***	Accepted
InD_Intngbl	←	Building	0.235	0.061	3.584	***	Accepted
Mobility	←	HRProfile	−0.136	0.036	−1.927	0.054	Rejected
Mobility	←	Di_Intngbl	0.712	0.083	8.198	***	Accepted
HH_Cont	←	FF_Intensity	0.703	0.064	8.861	***	Accepted
Incom	←	InD_Intngbl	0.3	0.112	4.361	***	Accepted
Incom	←	Di_Intngbl	0.177	0.125	1.834	0.067	Rejected
Incom	←	Mobility	0.316	0.1	4.234	***	Accepted
Incom	←	FF_Intensity	0.148	0.062	1.947	0.052	Rejected

Significance of correlations (2-tailed)

***$p < 0.001$

5.2 The direct tangible impacts of flash floods

The direct tangible impact is explained by the impact on Building, HH_Cont and Income. The standardized estimated path coefficient shows that the relationship between income and flash flood intensity is not significant at p value < 0.05 level (Table 9). However, the damage to Building due to flash floods was found positively related with standardized estimated coefficient of 0.576 with significant p value 0.001 and t value of 7.358. This result suggests that one standard deviation increase in flash flood intensity will result in an increase in building damage such as doors and fencing of the houses by 0.576. Physically it is logical as the doors are designed to start from the floor level to a certain level and the fences of houses are usually weaker than walls. As a result, damage to buildings can be realized by walls or fences having defects (Spekkers et al. 2015; Schroeder et al. 2016). Similarly, the damage to household contents such as furniture and carpets and other tangible elements seem to have a significant level of impact by flash floods (Molinari et al. 2014; ten Veldhuis 2011). A positive relation was found at 0.703 standardized path coefficient. This element holds the highest level of impact by flash floods. The result is significant at p value 0.001 significant level (t value 8.863). Usually, flash floods in Kuala Lumpur are short in duration and the water level is not severely high; affecting mostly household contents that are kept at floor level (Mohtar et al. 2020).

5.3 The indirect tangible impacts of flash floods

Flash flood impact on loss of income was not direct. However, the income was affected indirectly through the disruption to mobility, direct and indirect intangible impacts. The direct intangible impacts cause mobility disruption with β 0.71 and this resulted in income to be affected with β 0.32. Both impacts are significant at p value 0.001 with t value of 8.198 and 4.234, respectively. When flash floods hit a particular area, a typical result is that people face problems moving around the city due to roadblocks, traffic congestion and limited access to transportation. These impacts not only influence income-generation of those affected but also limit the option for participating in income-generating activities (Vathana et al. 2015). However, the impact of direct intangible impacts on income was found statistically insignificant (Table 9). Income was also affected by the indirect intangible factors with β of 0.30 at 0.001 significant level with a t value of 4.361; skin diseases, dysentery and diarrhea due to floods limit people to participate in income-generating activities (Chiba and Prabhakar 2017).

5.4 The direct intangible impacts of flash floods

The direct intangible impacts of flash floods are loss of memorable items, limited access to transportation, limiting the evacuation opportunity, delay in getting to and from work, entire roadblocks, partial roadblocks, loss of leisure time, loss of recreation opportunities and children abstaining from school. Altogether, these impacts share the highest β of 0.635 at 0.001 level with a t value of 7.135. These impacts further cause mobility disruption at β of 0.71 which then caused income to be affected at β of 0.32. The reason might be flash flood-related roadblocks, traffic congestion and limited access to transportation (Vathana et al. 2015).

5.5 The indirect intangible impacts of flash floods

The indirect intangible impacts of flash floods include health and service-related indicators. The causal relation between direct intangible impacts and the indirect intangible impacts was positive with β 0.51 at p value 0.001 and t value of 6.16. As the direct intangible impacts caused limited access to transportation and roadblocks, the disruption to the food supply can be affected. The flood water contamination with supplied water may lead to waterborne diseases (ten Veldhuis 2011; ten Veldhuis 2010). The indirect intangible impact is found to be caused by building damage with β 0.235 at p value 0.001 and t value 3. 584. Because, building damage may cause water supply lines to be broken and resulting in flood water contamination in the supply lines (Arnbjerg-Nielsen and Fleischer 2009; Zhou et al. 2012).

Finally, the model fit measures of the model show that the model has an excellent model fit measures in all scales except CFI measure (Table 10). The CMIN of the model is 1024.645 with degrees of freedom at 607. The CMIN/DF scores 1.688, which are within the range. The CFI score is 0.938, though not excellent, but at the acceptable range. The rest of the measures SRMR 0.068, RMSEA 0.055 and PClose 0.092 are all excellent scores. This suggests that the model is reliable and acceptable.

Table 10 Model fit measures for the final SEM model

Measure	Estimate	Threshold	Interpretation
CMIN	1024.645	–	–
DF	607	–	–
CMIN/DF	1.688	Between 1 and 3	Excellent
CFI	0.938	>0.95	Acceptable
SRMR	0.068	<0.08	Excellent
RMSEA	0.055	<0.06	Excellent
PClose	0.092	>0.05	Excellent

6 Conclusion

Assessing the socioeconomic impact of flash floods in Kuala Lumpur was done through a household survey in Kampung Baru, a village right in the middle of the city. The framework, a combination of direct and indirect as well as tangible and intangible impact dimensions, was incorporated into the proposed SEM model underpinned with specific socioeconomic impact-related hypotheses. The study found that the socioeconomic impacts, which mostly involve non-economic aspects, were affecting the people in many ways. The household economy and the profile of the household representatives have a very low level of contribution with β coefficients equal to − 0.12 and − 0.14; respectively, both were statistically nonsignificant with the p value 0.062 and 0.054. However, people have experienced stronger impact on direct tangible indicators, i.e., household contents and buildings, and direct intangible and direct tangible (building) impacts by flash floods with β coefficients equal to 0.703, 0.5760 and, 0.635, respectively, with statistically significant p value 0:001. That means, all kinds of people, regardless of race, marital status and age, are adversely affected by flash floods. Moreover, the indirect impacts are caused due to direct intangible impacts and building damage with β coefficients equal to 0.51, 0.235, respectively, both significant the p value 0:001. The flash flood direct intangible impact also results in mobility disruption with β coefficients equal to 0.701 at significant the p value 0:001. Income is found to be affected by mobility and indirect intangible impact with β coefficients equal to 0.316 and 0.30, respectively, at significant p value 0:001. Overall, the goodness of fit index showed that the CMIN of the model was 1024.645 with degrees of freedom at 607. The CMIN/DF scored 1.688, which was within the range. The CFI scored 0.938, though not excellent, it is within acceptable range. The rest of the measures SRMR 0.068, RMSEA 0.055 and PClose 0.092 were all excellent scores. Therefore, it can be concluded that the SEM successfully incorporated the socioeconomic aspects and explained the impact phenomena reliably.

The results suggest that the socioeconomic impact of flash floods is mostly realized through direct and indirect intangible aspects which then cause further difficulties to mobility and income-generating activities of the masses. In addition, the result also suggests that the income-generating activities can be affected indirectly as a consequence of other direct and indirect impacts such as roadblocks, traffic congestion, limited access to transportation, health conditions and mobility disruption. In terms of affected income-generating activities, the office-going working class might not realize a reduction in income severely; however, in this case, the most vulnerable are the ones who earn on a day-to-day basis, and street shop owners who depend on their daily sales for income.

The results have a great implication to the transportation sector because flash flood impacts primarily evolve around the road networks which are directly affected first, and then other socioeconomic impacts on the people come as a consequence. Therefore, the plan and policy of transportation and related sectors should incorporate related risk reduction strategies to minimize the impact. The urbanization and infrastructural development sectors can apply this result to consider socioeconomic aspects in their planning and operation. As mobility was found to be affected due to multiple direct and indirect impacts which are related to other income-generating activities, the urbanization and infrastructural development sector may use the results of this study to consider how the adverse impact can be reduced so that the daily-earning class and street shop owners can avoid disruption to their income-generating activities.

The use of the SEM model has great potential in disaster risk reduction. It can be applied to other urban settings to understand the socioeconomic impact of flash floods. The outskirts areas of Kuala Lumpur, e.g., Petaling Jaya, Damansara, Ampang Jaya, Cheras, Gombak and Kajang can use this model to assess how socioeconomic aspects are affected by flash floods. In addition, SEM can further be used for assessing the degree of flash flood impact on different vulnerable communities. Although the daily office-going working class may hardly realize the impact on income, the flash flood-related adversity might negatively impact on their performance, which is a further scope of study that can be undertaken in the future. SEM has a great potential of use in emergency services and disaster research which include disaster impact assessment, preparedness, measuring resilience, vulnerability indexing, disaster risk perception as well. The method used in this study can be used for analyzing socioeconomic impact-driven social behavior, disaster recovery and business continuity and other economic impacts. In addition, the method can be more useful for assessing more recent disaster impacts by addressing social, economic and financial issues in the community.

The socioeconomic and demographic indicators alone are not sufficient to comprehend the complete impact phenomena of flash floods. However, this study indicates that despite the smaller scale of the flash floods in Kuala Lumpur, the socioeconomic impact dimension involves complex causal relations. This suggests that further investigations should be done by incorporating more detailed data sets and including a more extensive range of impact aspects. This will not only help in getting a bigger picture but also calculating the cost of the non-economic impact of flash floods. The impact analysis can also be done by including spatial and geographical information, nature of the assets in the affected area and more detailed hazard information in the structural equation model for getting a more accurate assessment.

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Author contributions The contribution of the authors in this paper is described here. Tariqur Rahman Bhuiyan, Er Ah Choy, Nurfashareena Muhamad and Joy Jacqueline Pereira conceived and designed the experiments. Tariqur Rahman Bhuiyan, Er Ah Choy, Nurfashareena Muhamad and Joy Jacqueline Pereira analyzed the data and wrote the paper. Tariqur Rahman Bhuiyan and Nurfashareena Muhamad designed search strategies. Er Ah Choy and Joy Jacqueline Pereira critically reviewed the manuscript for important intellectual content. Tariqur Rahman Bhuiyan, Er Ah Choy, Nurfashareena Muhamad and Joy Jacqueline Pereira read and approved the final version. All authors read and approved the final manuscript.

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Declaration

Conflict of interest There is no conflict of interest between authors.

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