Integrating Socio-Economic Variables in Urban Flood Damage Assessments: A Case Study of Bengaluru, India

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Abstract

Urban flooding, a result of precipitation surpassing the drainage capacity of a metropolitan area, has notable consequences on the economic and social facets of the community. Understanding and mitigating the potential impacts of flooding necessitates completing a comprehensive flood risk assessment. This research evaluates flood damage in flood-prone areas of the Koramangala-Challaghatta Valley (KC Valley) in Bengaluru, India. The study surveyed flood-prone areas to gather data on the population's characteristics, demographics and economic status, property specifics, and repair costs for residential and commercial properties. By employing Random Forest and multivariate regression analyses, the study pinpointed the primary variables influencing flood damage, which were then utilised to create flood damage functions for the residential and commercial sectors. The results reveal that economic variables play a vital role in determining the degree of safeguarding and capacity for resilience against the repercussions of flood-induced impacts within commercial environments. It was observed that regions with higher commercial property valuations are more inclined to allocate resources towards enhanced flood mitigation strategies and possess more robust infrastructural frameworks, resulting in diminished susceptibility to potential damages. This study's findings have significant practical implications for policymakers and urban planners, empowering them to make informed decisions that underscore the significance of economic resilience in regions susceptible to flooding and the potential for these insights to shape future flood risk management strategies.

Keywords: Urban flooding, flood damage assessment, flood depth-damage curves, survey, multivariate regression, Bengaluru, India.

1. Introduction

Urban flooding, a pressing global issue, has seen a rise in frequency and severity in an era of increased extreme weather events. In rapidly urbanising cities like Bengaluru, India, vulnerability to flooding has surged, causing disruptions in daily life, infrastructure damage, and hindrances to economic progress (Hammod et al., 2015). While previous research has advanced our understanding of the patterns of urban floods and their predictions (Shivamurthy, 2017; Mujumdar et al., 2021), there has been a noticeable lack of focus on assessing vulnerability to floods and the economic damage they cause in Bengaluru (Prasad et al., 2016; Narayan, 2023). It is crucial to have a thorough understanding of flood damage and vulnerability to flooding, especially given the growing global problem of urban flooding (Zeleňáková et al., 2020). It is imperative to include socioeconomic factors such as poverty rates, insurance coverage, and infrastructure quality in the assessment to develop more effective strategies for mitigating the risk of flooding.

Empirical damage models aim to quantify the relationship between flood characteristics, i.e., the intensity and duration of a flood event, building specifics, and the resulting damage to buildings. These models are based on observed data and use statistical techniques to develop relationships that can help predict the extent of damage under different conditions. In addition to the characteristics of a flood and building specifics, other components typically considered in empirical damage models for floods include repair costs and financial implications (Jonkmanet al., 2008; Messner et al.,2007; Aribisala et al., 2022). The former refers to the costs of repairing structural damage and replacing damaged contents, while the latter consists of economic losses to individuals and communities and insurance-related considerations. Aribisala et al. (2022), Zhai et al. (2005), and Fatemi et al. (2020) demonstrated the efficacy of empirical damage models to estimate flood damage in Nigeria, China, and Iran, respectively.

Choi et al. (2017) underscored the significance of employing a multidimensional approach to flood damage assessment to gain comprehensive insights into the effects on building structures and contents. They noted that structural damage is associated with the depth of flooding, while the duration of flooding affects content damage. Integrating flood depth into regression models for forecasting flood damage has proven effective. Nadal et al. (2010) developed an empirical damage model using data from 15 flood events in Spain, incorporating flood depth, duration, and infrastructure attributes. Rehan et al. (2021) employed an expert-based model in Pakistan, considering building age, material, and location as variables and achieved commendable predictive accuracy. Sulong and Romali (2022) used a hybrid model in Malaysia, combining empirical and expert-based data to predict flood damage accurately using flood depth, duration, infrastructure type, and building age as variables.

Site-specific depth-damage functions (SDDFs) are tools used in flood risk management. These functions estimate the potential damage caused by a flood at a specific location based on the relationship between the floodwater depth and the resulting damage to assets at a given location. SDDFs are tailored to specific asset categories, such as residential buildings, commercial structures, and industrial facilities, with their accuracy contingent upon how well the characteristics of the assessed assets match those used to develop the functions. In a study conducted by Shrestha et al. (2021), the effectiveness of SDDFs in estimating flood-induced damage across various building types in Nepal was demonstrated, achieving a 10% accuracy. Similarly, Nofal et al. (2020) showcased the skill of SDDFs in assessing the impacts of flooding on diverse infrastructure in Egypt, achieving a 15% accuracy.

Penning-Rowsell and Chatterton (1977) emphasised the importance of integrating socioeconomic factors in flood damage assessment to understand floods' impact on communities comprehensively. They highlighted the significant influence of affluence and insurance on the extent of harm and the recovery of communities. Similarly, Romali and Yusop (2021) highlighted the role of economic status and insurance access in influencing flood damage and the recovery of affected communities. These factors play a crucial role in understanding and mitigating the impact of urban flooding, and their consideration is paramount in any comprehensive flood damage assessment.

Evaluating flood damage requires considering several factors to comprehend the scope and consequences of flooding. These factors include flood depth, flow velocity, building characteristics (construction materials, design, elevation, foundation type), and socioeconomic aspects such as population density, income levels, and infrastructure quality. A comprehensive flood damage assessment integrates these factors to provide information on the impact of flooding on a community's physical and social aspects. This study aims to enhance our understanding of flood damage assessment by creating Depth-Damage curves for the study area. The study adopts a systematic approach to assess flood damage severity by identifying key variables that influence it, using them to build regression models for predicting flood damage, and creating SDDFs.

2. Materials and Methodology

2.1 Description of the study area

Bengaluru's urban expanse spans 709 km^2, administered by Bruhat Bengaluru Mahanagara Palike (BBMP) within Bangalore Development Authority's (BDA) 1245 km^2 jurisdiction. The city features three key valleys 900 meters (m) above sea level: Hebbal, Vrishabhavathi, and Koramangala-Challaghatta (KC), with interconnected lakes. Urbanisation and encroachments have degraded the water bodies of these valleys, reducing their storage capacity. The percentage of imperviousness in central Bengaluru has significantly increased over the past few decades. A study by the Indian Institute of Science found that over 93 % of Bengaluru has turned into a concrete jungle, drastically altering the natural landscape and increasing impervious surfaces (Ramachandra and Aithal 2017), causing high surface runoff during heavy rains.

This study focuses on the KC Valley (Figure 1), which has a catchment area of 289.68 km^2 and is one of the major valleys in Bengaluru (Pavithra et al. 2021). The KC Valley is distinctive due to its crucial role in the city's drainage system and its susceptibility to flooding, influenced by extensive urbanisation and critical infrastructure (Avinash et al 2019). The KC Valley watershed, which encompasses 35.5% of the BBMP area, receives an annual rainfall of 750-850 mm and hosts a population of 3.96 million. It is renowned for its interconnected lake system, hosting approximately 85 lakes, which is vital in managing runoff. The water bodies in the valley have undergone significant changes over the years due to the ongoing drying of lakes caused by urbanisation. The low-lying areas and susceptibility to flooding create urban challenges (Avinash et al., 2019), making this valley an ideal case study site.

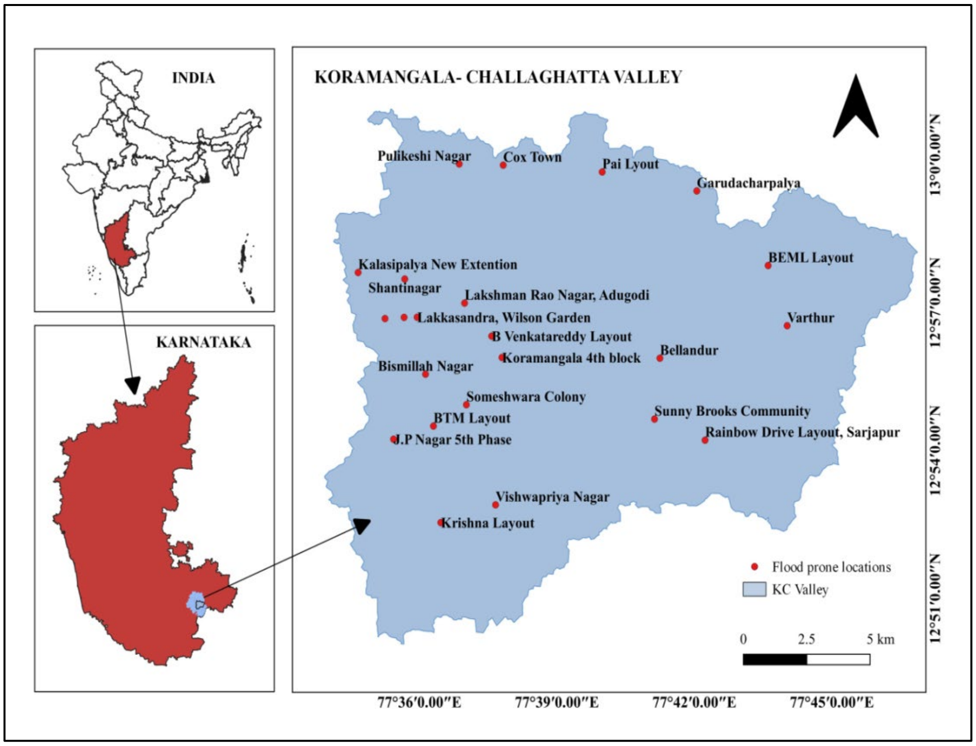


Figure 1. Location of the study area.

2.2 Methodological Framework

A Site-Specific Damage Curve (SSDC) visually illustrates the correlation between flood intensity and the consequent damage in a particular area. Evaluating the area's susceptibility to flooding is crucial, although most research focuses on direct damage, such as structural damage to buildings. However, this approach falls short in addressing indirect tangible losses, including income loss and business disruptions, as well as intangible losses, such as loss of life and psychological distress.

Different regression techniques were assessed in the development of the SSDC, encompassing the evaluation of linear, polynomial, and logarithmic regressions. The logarithmic regression model was ultimately selected as the most appropriate due to its effective capture of the non-linear relationship between flood depth and damage, commonly observed in flood impact data (Pistrika et al., 2014; Romali & Yusop, 2021). The selection process involved a thorough assessment of key performance metrics, such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Logarithmic regression achieved the lowest RMSE and MAE values and the highest R^2, indicating superior predictive accuracy. The model's robustness and reliability were further validated using training and testing datasets (Amadio et al., 2016; Zeleňáková et al., 2020).

The overall methodology is illustrated in Figure 2. Flood parameters were selected based on data availability and their prevalent use in existing literature. A comprehensive questionnaire developed from an extensive literature review was used to gather relevant data. On-site surveys provided essential physical and economic data critical for assessing flood-related damages. These data were then analysed to calculate damage estimates, expressed as percentages.

A Random Forest (RF) analysis was also performed to identify the most influential factors contributing to flooding vulnerability. Demographic factors like annual income, property price, asset value, and family size were integrated into the RF model as independent variables alongside flood parameters (e.g., depth and duration). These variables were used to predict the damage factor, representing the percentage of replacement costs due to flooding. The RF model evaluated the importance and interactions of these variables, ensuring accurate capture of their relationships. This approach helps avoid overprediction, which might occur if multiple dependent factors were considered independent. The outputs of the RF model were then used to construct depth-damage curves, which illustrate the relationship between flood intensity and resulting damage, differentiated by demographic characteristics.

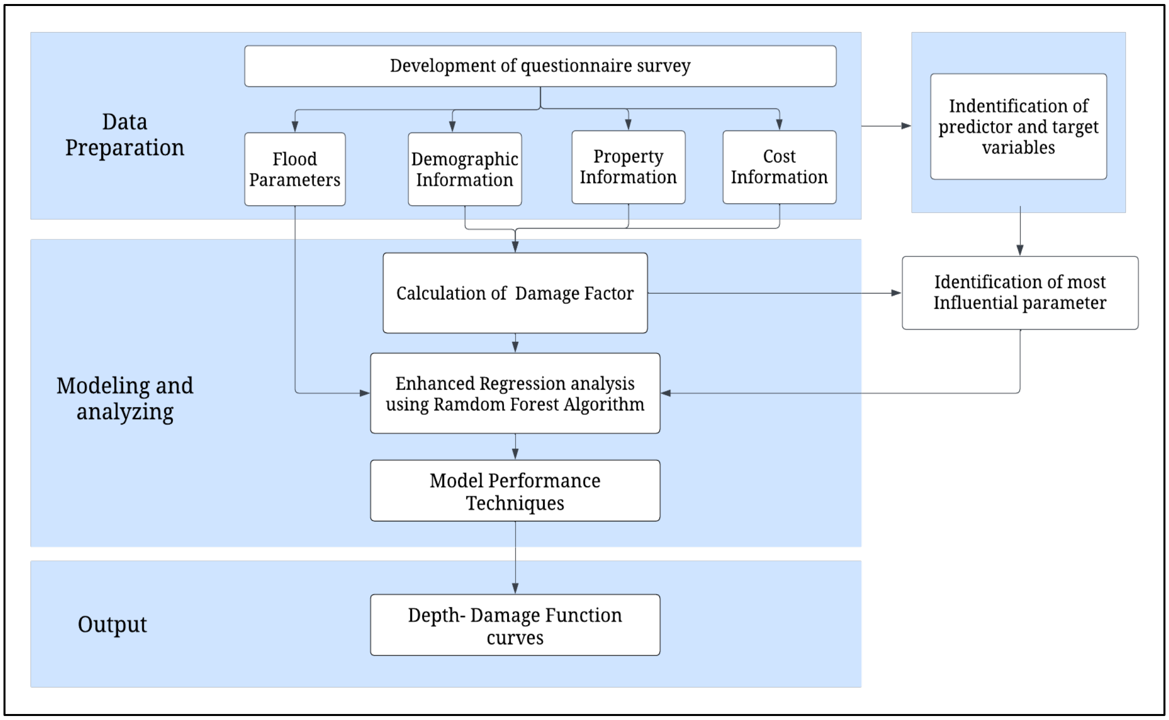


Figure 2. Flowchart of the methodology used in the study to develop the flood depth-damage curves.

2.3 Data Collection

A comprehensive methodology that combined insights from various information sources significantly improved the analysis of flood-prone areas within the KC Valley. This study used data from news reports, articles, and media accounts of past flood events. In addition, it was supported by detailed assessments of flood-prone regions from BBMP reports. The BBMP, as a key authority in urban planning and infrastructure, provides comprehensive assessments of flood-prone areas.

The study also conducted a thorough survey focusing in areas directly affected by the 2022 flood event. During this event, Bengaluru experienced an unprecedented 1709 mm of rainfall, flooding 75 areas. The survey systematically collected data on flooding incidents in residential and commercial sectors. This comprehensive approach contributed to a detailed and holistic understanding of flood impacts.

2.3.1 Survey Outline

The study used probability sampling to ascertain appropriate sample sizes for assessing residential and commercial damage (Liang et al., 2012). Employing a stratified random sampling approach, the study divided the sampling frame into residential and commercial categories, creating subsets within flood-prone areas. The minimum required sample size was determined by population size, confidence level, margin of error, and proportion. With a confidence level of 98%, the margin of error less than 6%, and accounting for a 50% response rate, the study established a target minimum sample size of 369. Specialised questionnaires were utilised to study the 2022 flood extensively to gather data from 411 residential homes and 97 commercial businesses. This extensive survey was conducted over two months, specifically during June and July 2023. Data were collected from flood-prone locations across diverse areas, including Shantinagar, Bismillah Nagar, J P Nagar 5th Phase, Koramangala 4th Block, BEML Layout, Pulikeshinagar, Garudacharpalya, Lakshman Rao Nagar, Adugodi, Pai Layout, Bellandur, B Venkatareddy Layout, BTM Layout, Lakkasandra, Wilson Garden, Cox Town, Rainbow Drive Layout, Varthur, 2nd Block Jayanagar East, Vishwapriya Nagar, Krishna Layout, Someshwara Colony, and Kalasipalya New Extension.

The structured questionnaire consisted of four main sections. These sections covered aspects related to flooding, socio-economic dynamics, property attributes, and the extent of incurred damages. The survey delved into flooding specifics, including causes, challenges, flood depth, water stagnation duration, and the extent of residence inundation. The socio-economic portion collected details such as family size, income, employment, occupation, and ownership status. Comprehensive data on property damage and recovery costs were also gathered, including daily wage losses and repair expenses during the flooding. These inquiries aimed to facilitate a thorough evaluation of flood-induced damages.

Figure 3 illustrates the severity of flooding in a specific area, juxtaposing images captured during the flooding event and post-flooding.

(a) (b)

Figure 3. Image of the same location at the entrance of Rainbow Drive after (left) and before (right) a recent flood (source: https://images.hindustantimes.com).

2.3.2 Damage assessment

This study assessed tangible direct damages in residential and commercial sectors. Two categories of damage were examined for the residential flood damage assessment: (1) structural damage and (2) content damage. Structural damage encompassed expenses related to repairing or reconstructing damaged or destroyed buildings. It also included the cost of constructing new houses to replace completely lost houses and repairing external household structures affected by the flood. Content damage encompassed costs associated with harm or loss of belongings such as furniture, clothing, appliances, kitchen utensils, and other household items.

In conjunction with evaluating damages, households were queried regarding the inundation depth experienced during the 2022 flood event. Respondents were solicited to estimate their residential properties' aggregate value, their in-house belongings' valuation, and their annual household income. These collected data were then utilised to compute the damage rate for each household, derived as the ratio of the damage value to the overall household value. Additionally, as part of the field investigations, the plinth level (floor height above the ground) of each dwelling was measured. In instances where houses were destroyed, the plinth levels were approximated through interviews with homeowners.

Our field investigations were thorough, leading to the meticulous classification of residential buildings into three categories based on their property prices: low-price, medium-price, and high-price. This comprehensive approach, which is crucial in enhancing our understanding of flood-related impacts (Sulong and Romali, 2022), recognizes property values as pivotal economic resilience and investment potential indicators. The segmentation, comprising Low-priced houses (below INR 25 lakh), Medium-priced houses (INR 25 lakh–INR 69 lakh), and High-priced houses (above INR 69 lakh), employs quadrant values for a structured and data-informed classification. This balanced approach prevents skewed categorization and facilitates meaningful comparisons across property categories (de Vries and van Kempen, 2009; Cuadrado-Roura and Coy, 2011), thereby enabling comprehensive insights (Hairet al., 2014; Agresti and Finlay, 1997).

Two distinct damage types were considered to assess commercial flood damage: (1) structural damage and (2) content damage. Structural damage encompasses the expenses related to repairing or reconstructing damaged or destroyed buildings. Additionally, it includes the costs associated with damage to building materials and inventories that were adversely affected by the flood event. On the other hand, content damage pertains to the financial implications stemming from harm to equipment and stocks, including the costs linked to their damage or loss.

2.3.3 Development of Depth-Damage Function Curves

We checked the survey data before making the depth-damage function curves to ensure they followed a normal distribution. We found that the damage variables did not follow the expected distribution pattern. Hence, we decided to transform the Damage Factor (DF) variables into log-normal distributions.

The calculation of the DF adhered to the definition by Pistrika et al. (2014), Romali and Yusop (2021), Win et al. (2018) and Sulong and Romali (2022), wherein the structural damage ratio of buildings is given by Equation 1 while the building contents damage ratio is given by Equation 2:

$$DF\ (\%) = \frac{Overall\ Replacement\ Cost}{Price\ of\ Property} \times 100 \quad (1)$$

$$DF\ (\%) = \frac{Overall\ Replacement\ Cost/\ Repair\ Cost}{Value\ of\ Damaged\ Assets} \times 100 \quad (2)$$

The overall replacement signifies the expenditures borne by flood-affected individuals for repairing their properties after a flood, either through self-financed, government, or insurance compensation.

The study aimed to develop flood depth-damage curves with interior flood depth as the primary parameter. Previous research (Nafari et al. 2016; Frongia et al. 2017; Amadio et al. 2016) emphasised the importance of flood depth in evaluating physical damage. Parametric functions established the relationship between flood depth and damage percentage. An R code was employed for curve fitting, utilising logarithmic functions to forecast flood damage as a function of depth. The selection of curves was guided by correlation coefficients, with R-squared values exceeding 0.8 indicating a strong explanation of variance in the model (Pistrika et al. 2014; Win et al. 2018; Romali and Yusop 2020; Amadio et al. 2016; Zeleňáková et al.2020).

2.4 Influential Factors Affecting Damage

The damage factors can be classified into flood-related actions and building resistance parameters. The resistance parameters encompass building attributes, private precautions, flood experience, and socioeconomic status (Gissing and Blong, 2004). The research utilises RF to identify key parameters that influence predictive outcomes. RF makes predictions using decision trees and diverse data subsets, improving accuracy while reducing the risk of overfitting (Strobl et al., 2008).

The investigation was conducted with a comprehensive approach, systematically examining flood depth and duration, annual income, asset value, building age, property story count and price, and employee count. These factors were analyzed using the calculated DF as the target variable (Hasanzadeh et al., 2016; Thieken et al., 2005). RF models were used to assess the significance of these variables in residential and commercial sectors, as demonstrated through a correlation matrix. With notable correlation coefficients, this matrix highlights key variables that significantly influence flood extent. The DF, as a predictive metric for damage extent, enhances data-driven predictive flood damage insights (Kelman and Spence, 2004; Merz et al., 2013).

2.5 Introducing Enhanced Regression Analysis with RF Algorithm

This section introduces an innovative methodology that effectively leverages the capabilities inherent in the RF algorithm to enhance the reliability and precision of regression analysis. This forward-looking approach is guided by influential works such as Cutler et al. (2007) and Chen and Ishwaran (2012), culminating in crafting a distinctive and original analytical framework.

2.5.1. Data Preparation

Empirical data related to damage factors were sourced from pertinent references and compiled into an Excel file. Subsequently, the dataset was imported into the R environment, facilitating streamlined data manipulation and analysis. A preliminary assessment of the dataset's structure, composition, and attributes was conducted to comprehend its characteristics.

The dataset was partitioned into distinct training and testing subsets to evaluate the model's performance robustly. This division was accomplished using the `createDataPartition` function from the "caret" library, which generates indices for the training data. The chosen partition ratio, set at 80%, ensured the allocation of the remaining data points for testing.

2.5.2 Enhancing Predictor-Response Relationships and Regression Model Construction

The process of refining input variables to enhance their effectiveness in explaining or forecasting desired outcomes, as well as comprehending the underlying relationships between predictors and the target variable to extract more pertinent information from existing data, involved the utilisation of the RF algorithm, which yielded correlation coefficients that highlighted the parameter with the highest correlation to the most influential factor contributing to damage.

A regression model was constructed using a set of predictor variables, including flood depth, flood duration, building age, household asset value, household income, family size, property price, and number of stories. The foundational stage of this model development involved utilising a training dataset comprising pertinent features. Subsequently, a specific regression function aligned with the chosen approach was employed to establish the intricate relationship between the response variable and the predictors.

2.5.3 Prediction and Performance Evaluation

The trained regression model is used to predict outcomes on the testing dataset. The predicted outcomes are compared with the actual values present in the testing data. A range of performance metrics, including RMSE, MAE, Mean Bias Error (MBE), Coefficient of Variation (CV), and R-squared, were computed to assess the model's predictive accuracy and explanatory strength. These metrics offer measurable indications of the model's predictive accuracy, its ability to capture variability, and its explanatory capability.

Integrating data partitioning, feature enhancement, regression modelling, prediction, and performance assessment forms a cohesive and systematic approach to predicting damage factors using regression methods. The following section unveils the exposition and discussion of the results, focusing on the model's effectiveness and contextual importance aligned with the study's objectives.

3. Results and discussions

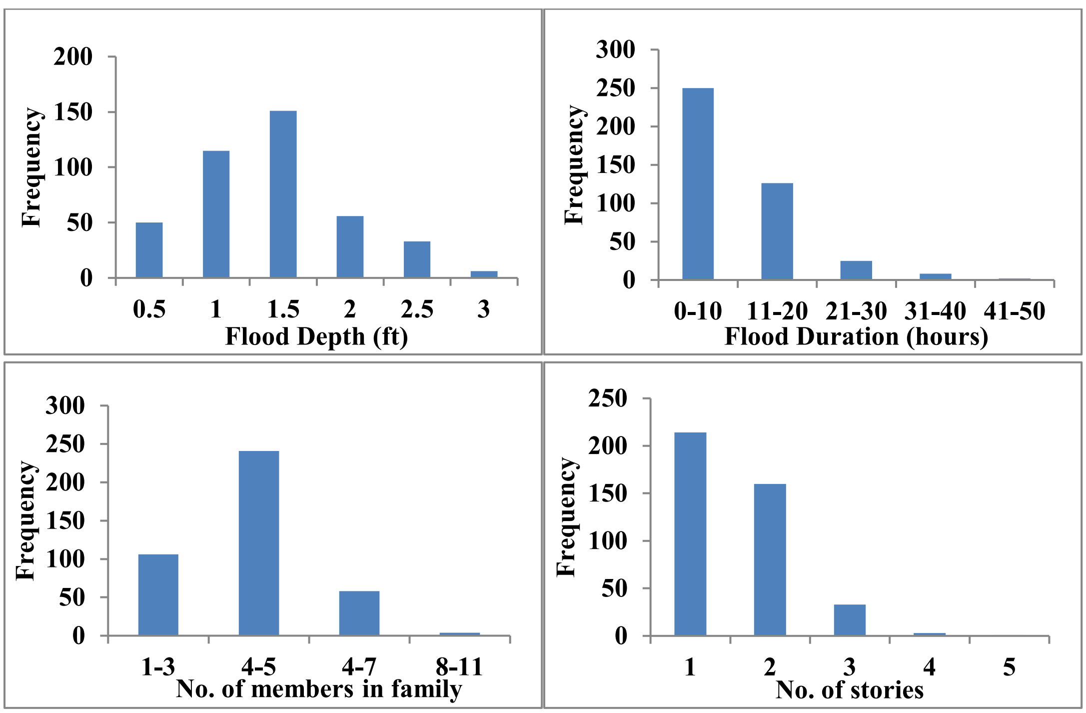
3.1 Description of damage dataset

The study examines flood damage-influencing variables in the residential and commercial sectors to construct a flood loss model. Table 1 shows the predictor variables and their classification and range. Figures 4 and 5 illustrate the frequency distributions of flood damage factors in the residential and commercial sectors.

Table 1. Comparison of the variables used in flood-related damage assessment for the residential and commercial sectors.

Categories	Variables	Residential sector	Commercial sector
Flood Characteristics	Flood depth	0.2-2.8 ft above floor level	0.3-3.5 ft above floor level
	Flood duration	4-48 hours	6-48 hours
Demographic and socio-economic characteristics	No. of family members	1-11	-
	Household/business income	INR 30 thousand-INR 24 thousand	INR 2 lakh -INR 82 lakh

	No. of employees	-	1-21
	Occupation	Salaried/ Business	-
	Ownership status	Own/Rent	Own/Rent
Property characteristics	Age of building	5-28 years	8-40 years
	Price of property	INR 4.8 lakh-INR 3.6 crore	INR 1.4 lakh -INR 4.2 crore
	No. of floor	0-5	0-6
	Value of assets	INR 5 thousand-INR 1.5 lakh	INR 10 thousand-INR 1.1 crore



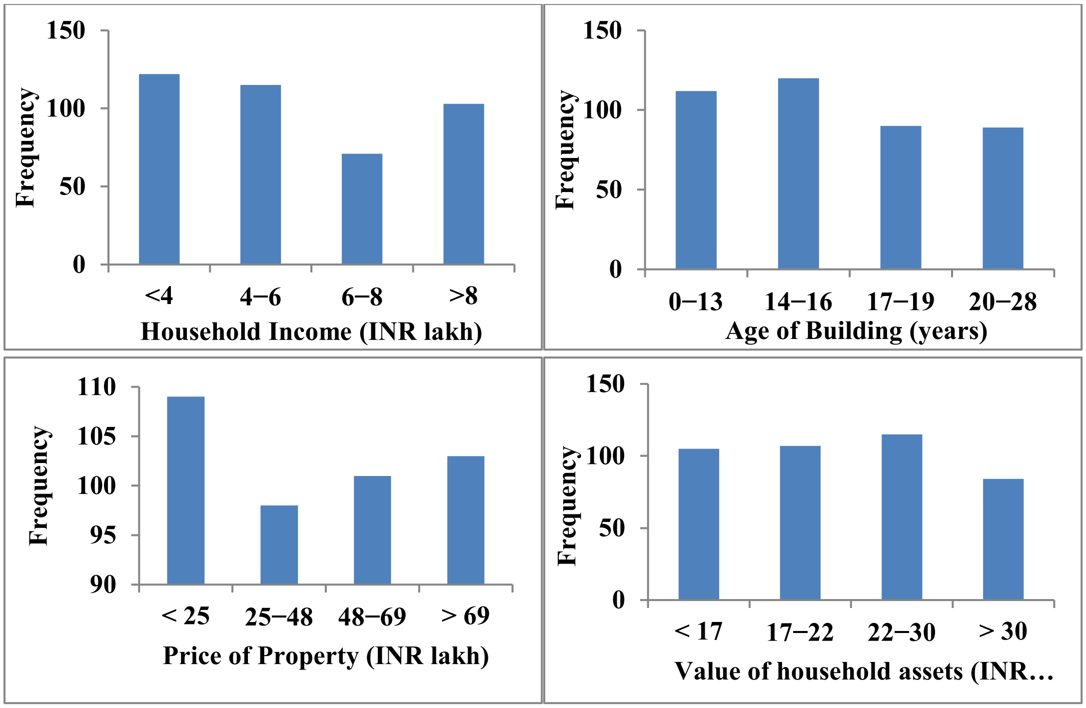


Figure 4. Frequency distribution of different variables for the residential sector

The histograms for the residential sector depict flood depths of 0.2 to 2.8 feet, with 10% experiencing day-long flooding and 90% around 20 hours (Figure 4). The graphical representation discloses urban family size distribution. Predominantly, families of 4 or 5 members prevail (~300 and ~250). Another cluster includes around 200 families, with 4 to 7 members. A subset exhibits larger sizes: five families with 8 to 11 members and one with 12 or more members. This highlights diversity in urban family composition. Constructing attributes highlight buildings with fewer than two floors in 90% of cases, accentuating the prevalence of low-rise designs. The age of these structures spans from 5 to 28 years, with the majority (90%) falling within the 15 to 25-year range, while a minority (10%) are under 15. The classification process involved organising the criteria according to household income brackets (ranging from INR 30,000 to INR 24 lakh), segmenting them further based on occupation as either salaried or business-related. Additionally, consideration was given to property ownership status. Residential structures were grouped into Low, Medium, and High Price Houses (INR 4.8 lakh to INR 3.6 crore), yielding 27%, 48%, and 25%, respectively. The graph reflects property price ranges, with an increase of 25-48 lakhs. Household assets range from INR 5,000 to INR 1.5 lakh.

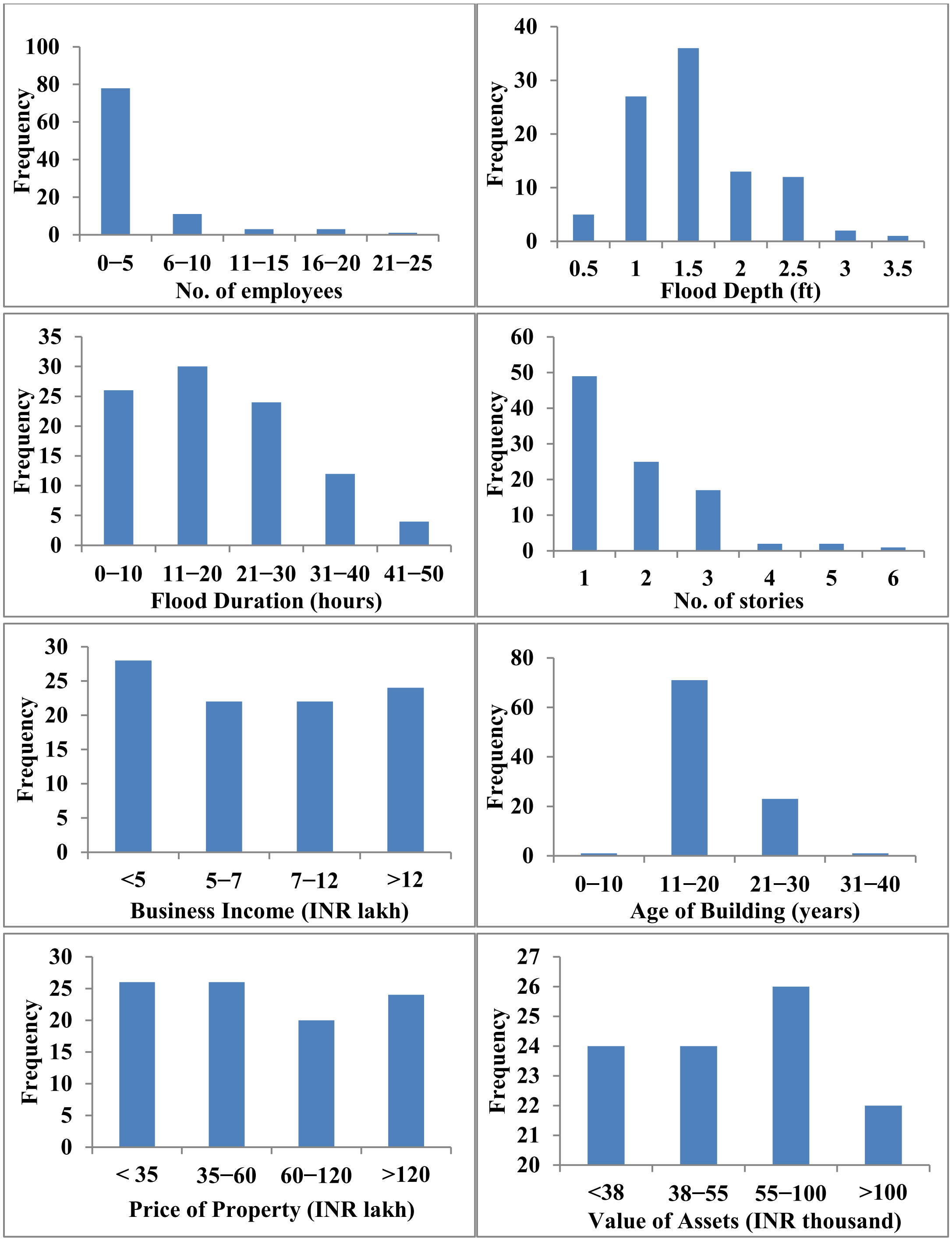


Figure 5. Frequency distribution of different variables for the commercial sector

Flood depths ranged from 0.3 to 3.5 feet above floor level for commercial areas, segmented in 0.5 ft intervals. Around 70% experienced depths up to 1.5 feet, while 30% faced deeper floods. Flood durations were divided into 10-hour intervals. Only 15% encountered flooding over a day, and

85% suffered about 20 hours. The commercial business income range was INR 2 lakh to INR 82 lakh, classified into four quadrants. 52% operated micro/small-sized businesses, 23% medium-sized, and 25% large-sized. Building ages ranged from 8−40 years, 74% aged 11−20, and 26% above 20 years. Commercial buildings mainly had up to 6 stories (95%). Assets ranged from INR 10 thousand to INR 110 thousand.

3.2 Significant flood damage influencing parameters

Identifying significant flood damage influencing parameters using the RF algorithm begins with compiling a comprehensive dataset, encompassing various factors potentially linked to flood damage. This dataset then trains an ensemble of decision trees, each considering different data subsets and features. Through iterative processes, the algorithm refines its predictions, leveraging the collective wisdom of these trees. Subsequently, the algorithm quantifies the importance of each parameter by evaluating how much shuffling them affects prediction accuracy. The significant, influential factors from the analysis are presented for each sector, considering their correlation coefficients.

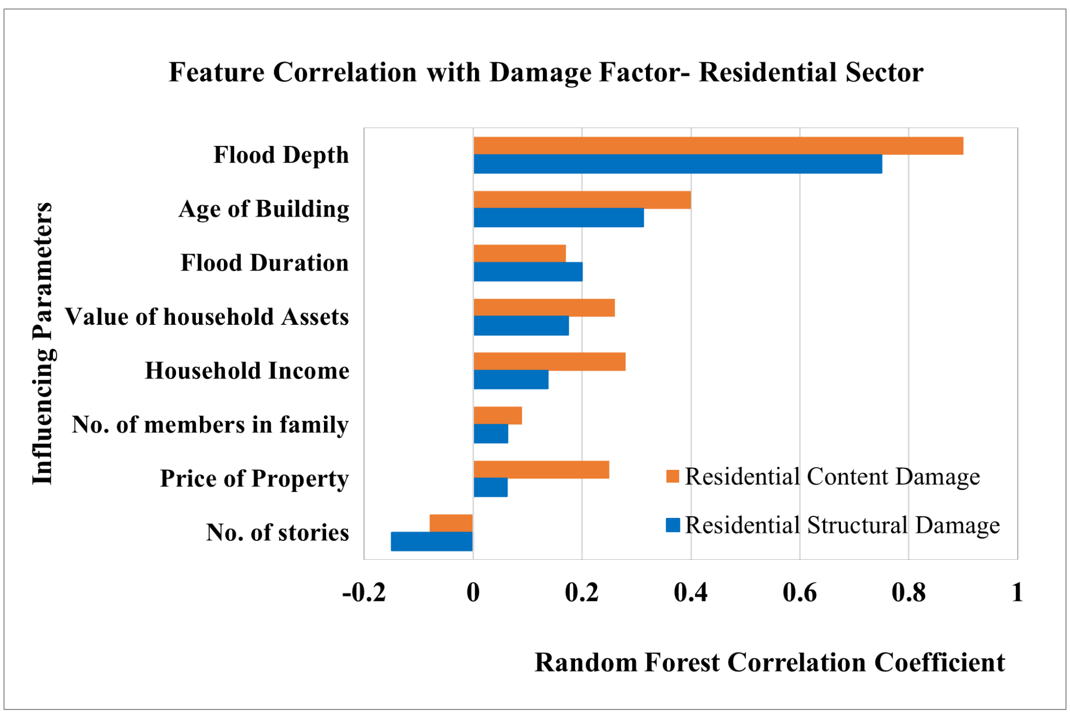


Figure 6. Parameters influencing flood damage in the residential sector.

The study revealed numerous variables related to floods, property characteristics, and socio-economic factors that significantly influenced the extent of structural and content damage in residential areas. These variables encompass flood depth, duration, building age, household asset value, and income.

The correlation coefficients of 0.75 for structural damage and 0.9 for content damage affirm a strong link with flood depth. The higher coefficient for content damage (0.9) indicates a notably stronger connection than for structural damage (0.75). Figure 6 underscores that as flood depth increases, content damage risk intensifies, with a robust correlation coefficient of 0.9, surpassing its impact on structural damage. Regarding building age, in both cases, content and structural damage moderately correlate with older buildings. Yet, building age is just one factor. Construction quality and maintenance are essential in comprehensive risk assessment and mitigation. The slightly higher correlation coefficient for structural damage (0.2) compared to content damage (0.17) in relation to flood duration may be due to the physical vulnerability of buildings to prolonged flooding. Structural elements can weaken over time with exposure to water, potentially resulting in more significant structural damage.

Additionally, variations in building design, construction materials, and data variability could contribute to this difference. The correlation coefficient of 0.26 for content damage suggests that valuable household assets, including electronics and furnishings susceptible to water damage, increase the likelihood of content damage during flooding events. The correlation coefficient of 0.28, signifying a positive association between higher household income and heightened content damage during flood events, can be elucidated by the presence of more valuable content possessions and potentially flood-prone geographic locations for affluent households. Conversely, the coefficient of 0.14, indicating a less pronounced link between higher income and diminished structural damage, can be attributed to wealthy households' propensity to invest in structural fortifications and expedited recovery measures.

The observed negative correlation coefficients (-0.15 for structural damage and -0.08 for content damage) suggest that buildings with more stories exhibit a lower susceptibility to damage during flooding events. This phenomenon may be attributed to enhanced construction quality, adherence to building codes, or the inherent elevation of multi-story structures, which reduces their exposure to floodwaters. It is crucial to note that while these correlations hint at protective advantages for taller buildings, they remain relatively weak, emphasising the multifaceted nature of flood-related damage, which is influenced by numerous factors beyond building height.

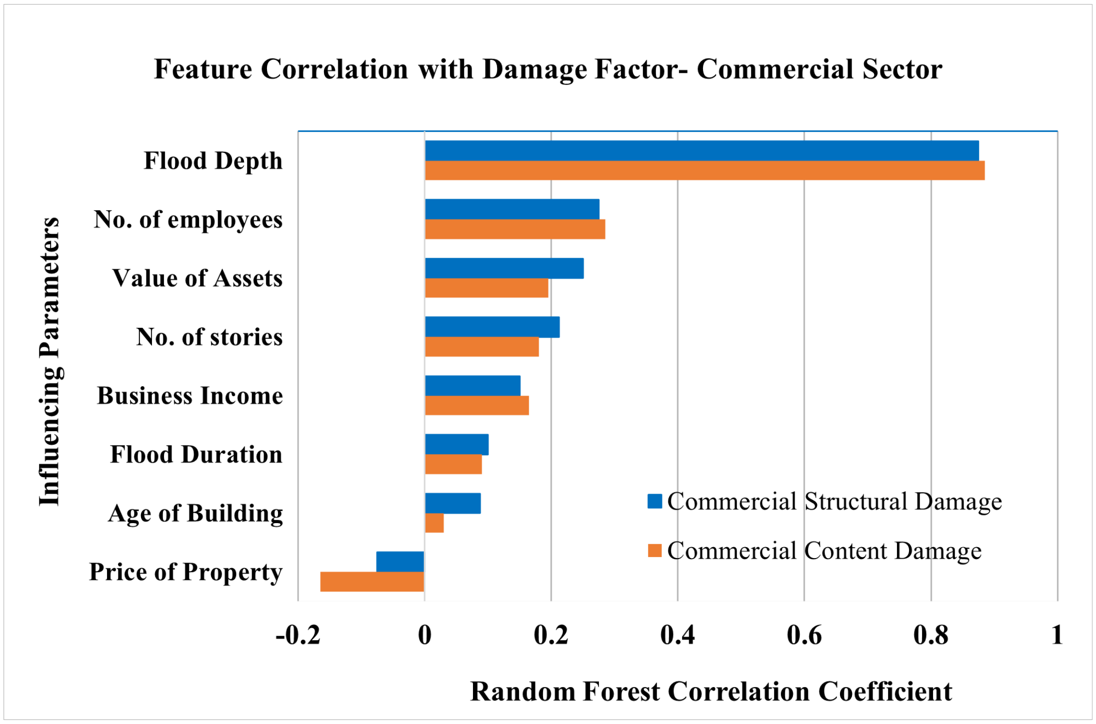


Figure 7. Parameters influencing flood damage in the commercial sector.

According to the research findings, flood depth, employee count, asset valuation, business income, and building height were recognised as substantial factors contributing to damage to commercial properties (Figure 7). Flood depth, employee count, asset value, and business income in the commercial sector impacted company inventory and merchandise. These connections are rooted in flood vulnerabilities: deeper floods heighten water exposure, affecting inventory and merchandise; employee count influences evacuation and asset protection. Higher asset value and business income are associated with greater financial exposure and potential losses. A negative correlation between property prices and flood damage suggests that higher-value areas may experience less harm due to superior mitigation and infrastructure. In brief, economic factors play a pivotal role in bolstering commercial resilience against flood impacts.

3.3 Exploring Flood Damage Factors: Comparative Study of Multivariate Regression Approaches

The multivariate regression analyses were conducted in residential and commercial domains to determine the best-fitting model among linear, logarithmic, and polynomial regressions. This assessment involved comparing how well each regression type captured the relationships between the independent variables and flood damage, ultimately aiding in selecting the most effective modelling approach for accurately predicting and understanding flood damage outcomes in residential and commercial settings.

Table 2. Validation of regression models for predicting structural damage during a flood

Regression Models	**Classification of property**	**Metrics**				
		RMSE	**MAE**	**MBE**	**CV**	**R^2**
Linear	Low Price House	0.16	0.14	0.06	0.28	0.9
	Medium Price House	0.19	0.16	-0.02	0.3	0.86
	High Price House	0.15	0.1	-0.01	0.3	0.87
	Commercial	0.24	0.21	-0.03	0.16	0.79
Logarithmic	Low Price House	0.16	0.14	0.05	0.25	0.54
	Medium Price House	0.19	0.15	-0.01	0.29	0.25
	High Price House	0.19	0.15	0	0.29	0.29
	Commercial	0.18	0.15	-0.07	0.23	0.46
Polynomial	Low Price House	0.17	0.14	0.06	0.27	0.93
	Medium Price House	0.18	0.15	0	0.35	0.87
	High Price House	0.17	0.14	0.01	0.3	0.89
	Commercial	0.16	0.13	-0.02	0.21	0.86

The regression models for predicting structural damage across property classifications are shown in Table 2. Linear regression demonstrates favourable performance with low RMSE and MAE values and high R^2 values. However, it struggles with medium to high-priced houses and commercial properties, revealing limitations in complex scenarios.

Logarithmic regression excels for low-priced houses but falters for others, notably in MAE classification and R^2 values. It struggles with medium-to-high-priced houses and commercial properties, reducing predictive accuracy.

Polynomial regression consistently performs well across all property categories, achieving low RMSE and MAE values. This is driven by strong explanatory power (high R^2). Its ability to capture non-linear relationships makes it effective for diverse property types.

In summary, polynomial regression stands out among the evaluated models, excelling in predictive accuracy due to its proficiency in handling non-linear associations.

Table 3.Validation of regression models for predicting content damage during a flood.

Regression Models	**Classification of property**	**Metrics**				
		RMSE	**MAE**	**MBE**	**CV**	**R^2**
Linear	Low Price House	2.37	2.03	-1.06	0.21	0.92
	Medium Price House	4.10	3.38	0.19	0.21	0.79
	High Price House	2.92	2.44	-0.40	0.17	0.74
	Commercial	3.93	3.16	0.25	0.11	0.80
Logarithmic	Low Price House	2.52	2.09	-0.20	0.19	0.49
	Medium Price House	2.67	2.08	0.02	0.232	0.68
	High Price House	2.67	2.08	0.02	0.23	0.68
	Commercial	2.88	2.22	0.19	0.11	0.29
Polynomial	Low Price House	2.08	1.71	-0.75	0.22	0.93
	Medium Price House	3.37	2.49	-0.21	0.23	0.92
	High Price House	2.21	1.94	0.06	0.16	-0.04
	Commercial	4.70	3.08	-0.73	0.11	0.87

The findings from a range of regression models employed to anticipate content damage across property classifications are outlined in Table 3. Linear regression demonstrates robust predictive accuracy, with minimised RMSE and MAE values across properties and commendable R^2 values. However, challenges arise in the MAE classification and CV metrics for medium to high-priced houses and commercial properties, potentially limiting its efficacy in cases of complexity. The logarithmic model exhibits varying performance, characterised by comparatively higher RMSE and MAE values, particularly for high-priced houses and commercial properties. Polynomial regression yields mixed outcomes, excelling for some property types while struggling with predictive accuracy for high-priced houses.

In summary, model effectiveness in content damage prediction varies across property types. Linear regression offers reliable accuracy, while the logarithmic model's limitations are pronounced in specific scenarios. Polynomial regression is effective in some cases but not in high-priced houses. Model selection should weigh predictive power against different property categories' unique attributes and complexities.

3.4 Development of Depth-Damage Function Curves

Recognising the paramount importance of flood depth, a direct correlation between flood depth and resultant damage is established, aligning with the fundamental methodology for assessing flood damage. Logarithmic functions were utilised to create depth-damage curves, plotting Damage Factor (%) against Flood Depth (ft) for valuable insights**.** The logarithmic model was chosen due to its ability to capture the diminishing returns behaviour observed in the data effectively and showed acceptable results for other performance indicators (RMSE, MAE and MBE). In many natural and engineered systems, the initial increases in input result in rapid changes in the output, which gradually slow down. This characteristic aligns with the logarithmic function, making it an appropriate choice for modelling the relationship. Logarithmic models are known for their simplicity and ease of interpretation, further supporting their selection in this context.

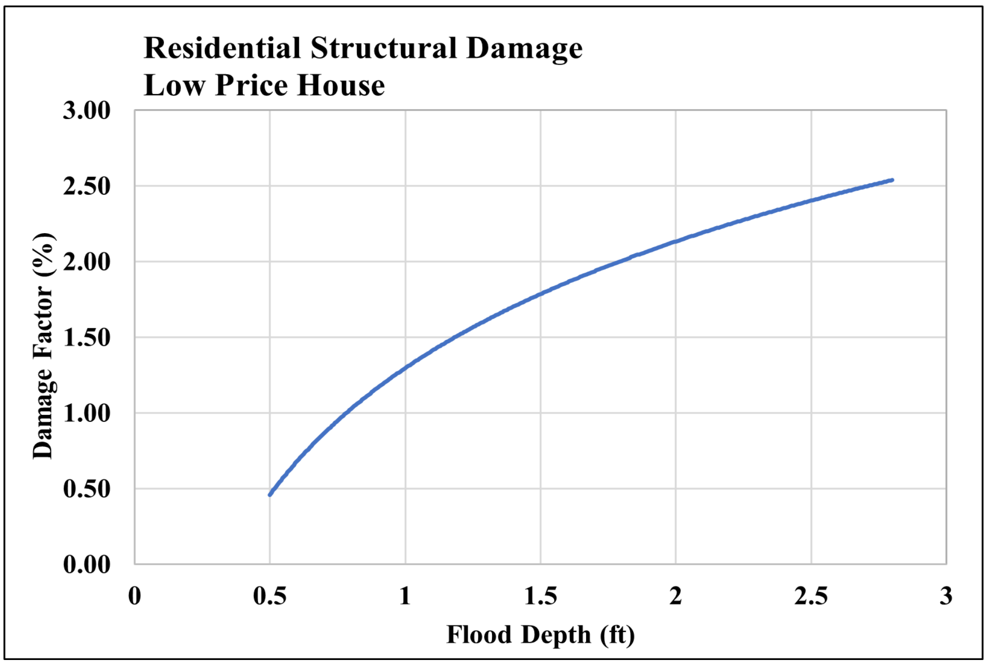
3.4.1 Residential Category Depth-Damage Function Development

Table 4.Flood Depth-Damage Functions for the residential sector for the residential sector

Category	Depth-Damage Functions	R^2
Residential Structural Damage (LPH)	$y = 1.2071\ln(x) + 1.2974$	0.87
Residential Structural Damage (MPH)	$y = 0.9432\ln(x) + 1.4604$	0.82
Residential Structural Damage (HPH)	$y = 1.0967\ln(x) + 1.3894$	0.85
Residential Content Damage (LPH)	$y = 25.337\ln(x) + 28.757$	0.89
Residential Content Damage (MPH)	$y = 18.969\ln(x) + 38.753$	0.91

Residential Content Damage (HPH)	y = 16.293ln(x) + 40.061	0.84

The depth-damage functions specifically designed for the residential sector are outlined in Table 4, classifying them by price of property levels as Low Price House (LPH), Medium Price House (MPH), and High Price House (HPH). These functions are mathematical models for estimating structural and content damages based on varying flood depths. Notably, each function is accompanied by an R-squared value, ranging from 0.82 to 0.91, indicating the model's goodness of fit.



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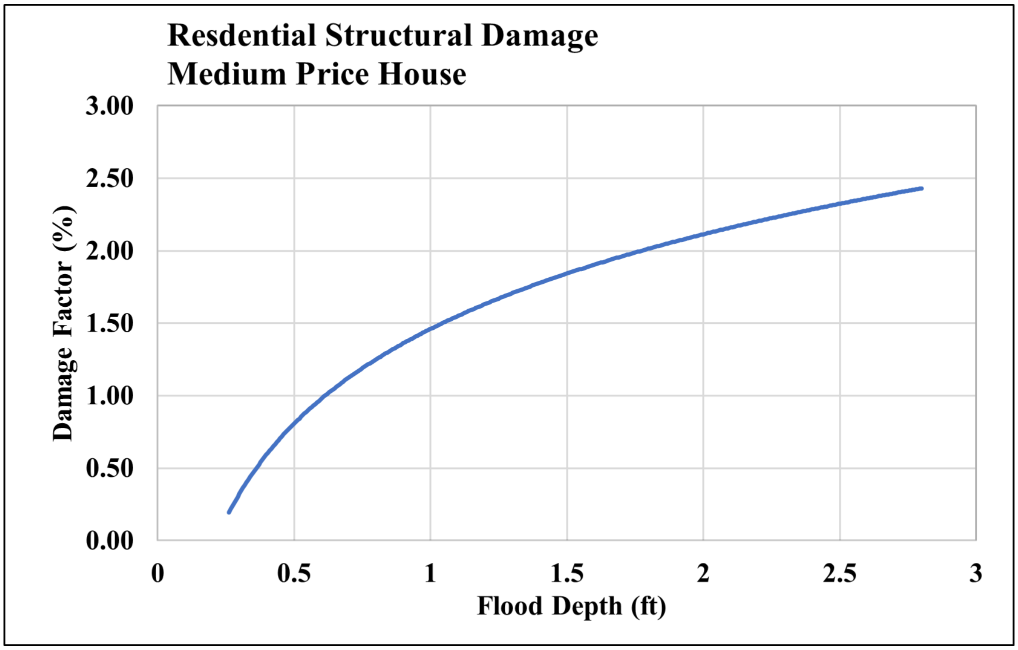

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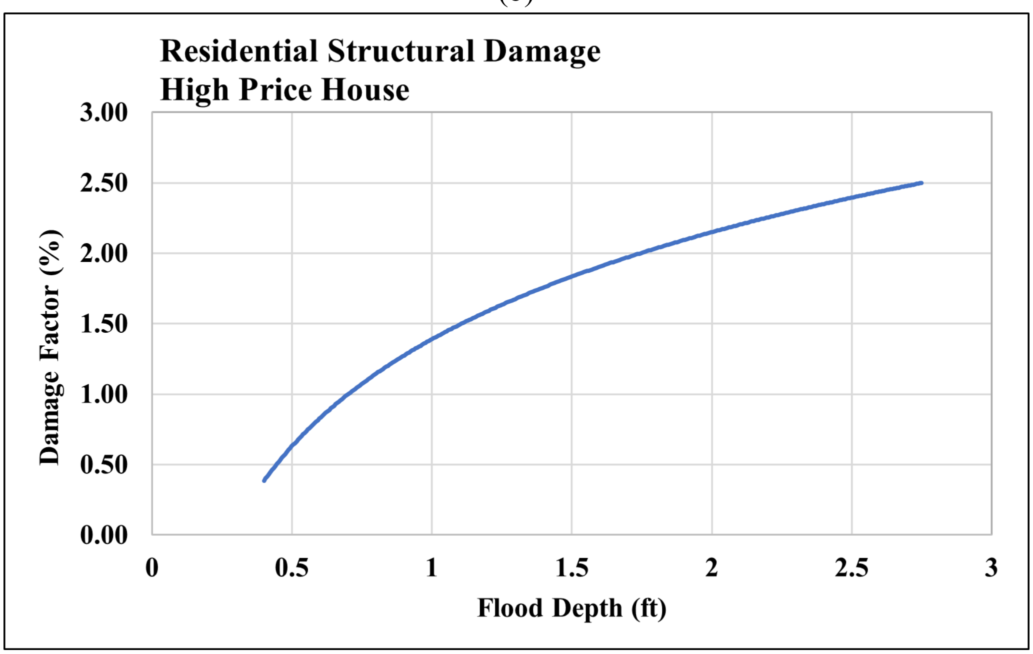
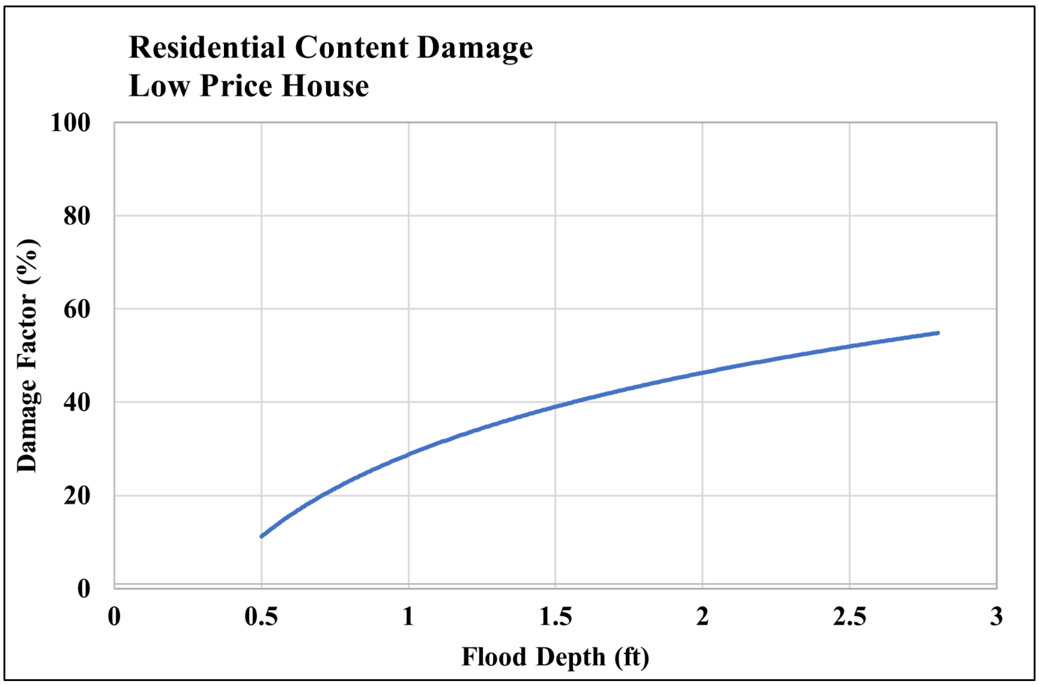


(c)

Figure 8. Flood depth-damage curves for structural damage to (a) Low-Price House, (b) Medium-Price House, (c) High-Price House

Depth-damage curves were developed for the residential category, explicitly focusing on low-price house (LPH), medium-price house (MPH), and high-price house (HPH) values, depicted in Figure 8. These curves highlight a strong correlation, indicating a significant rise in building structure damage percentages as flood depths increase. The achieved R^2 values exceed 0.80, aligning with prior research (Sulong and Romali 2022). The LPH curve demonstrates an R^2 of 0.87, while the MPH and HPH curves show R^2 values of 0.82 and 0.85, respectively, consistent with residential zone outcomes reported by Win et al. (2018).

A strong, consistent positive correlation emerges between flood depth and residential structural damage, consistent across all curve categories. A distinct non-linear pattern becomes evident, underscoring uneven damage progression with increasing flood depth. This non-linearity intensifies damage within specific depth intervals, suggesting potential thresholds denoting structural vulnerability.



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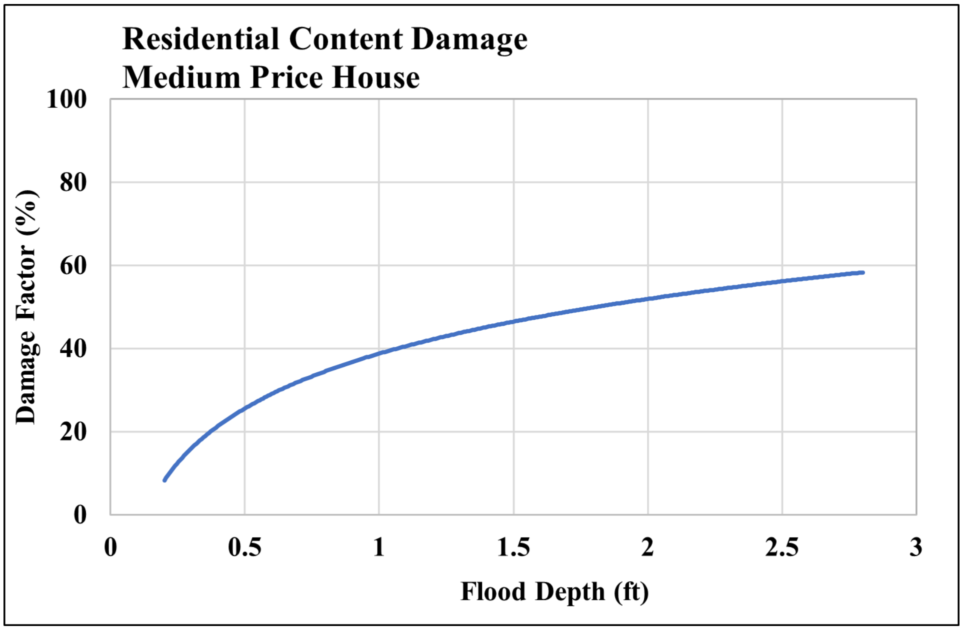

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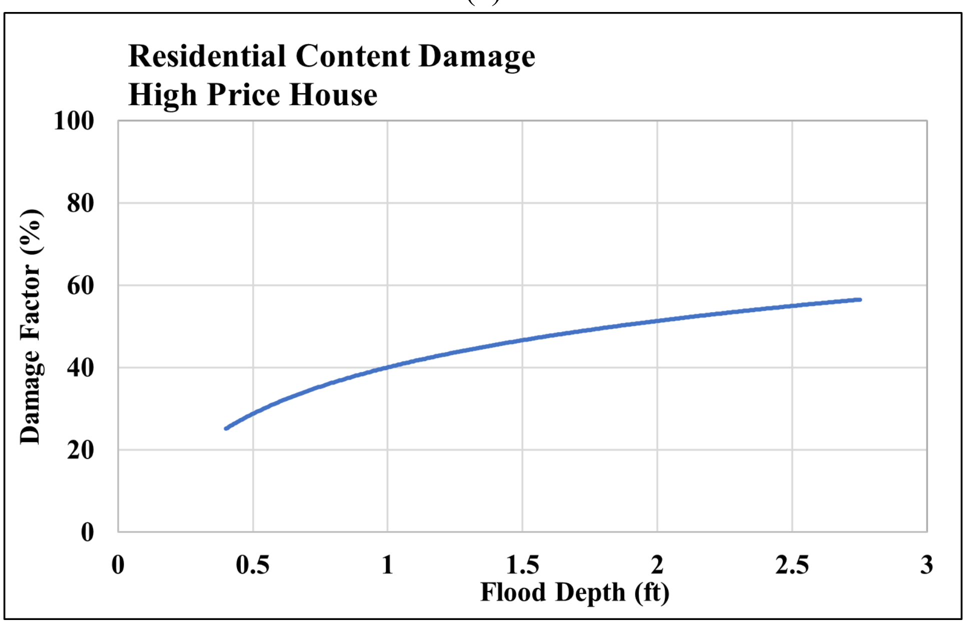


(c)

Figure 9. Flood depth-damage curves for content damage to (a) Low-Price House, (b) Medium-Price House, (c) High-Price House

The empirical flood depth-damage curve proposed for the residential-content damage category is presented in Figure 9. The R^2 value for the LPH curve is 0.89, while the MPH and HPH curves show R^2 values of 0.91 and 0.84, respectively. These findings indicate a robust relationship between flood depth and damage percentages across property value segments. Higher R^2 values for MPH and LPH curves suggest enhanced predictive accuracy and better fit to observed data.

Collectively analysing LPH, MPH, and HPH curves reveal a clear correlation between increased flood depths and amplified damage to house contents, with a notable 15% average damage observed at 1.5 feet. Notably, the non-linear pattern, particularly the intensified damage escalation between 1 and 1.5 feet compared to 1.5 and 2 feet, underscores the heightened susceptibility of submerged contents.

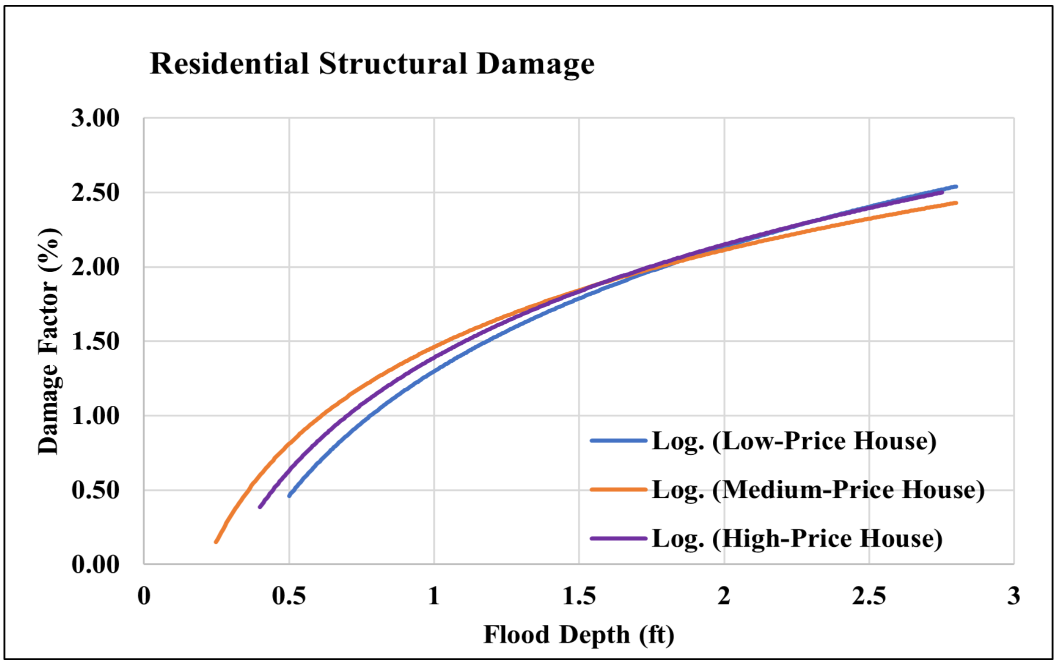


Figure 10. Comparison of the curves for the residential structural damage category

The structural damage analysis based on property price categorisation is presented, with graphical results in Figure 10. Notably, at a flood depth of 2.8 feet, the LPH category witnessed the highest structural damage at 2.52%, followed by HPH at 2.5%, and the MPH curve displayed the lowest structural damage at 2.4%. Relative to MPH, elevated damage in LPH and HPH categories may arise from construction material quality, building design, or structural reinforcement variations. Geographic location and proximity to flood-prone areas could contribute to heightened damage in HPH structures. A distinct damage surge around a 1-foot flood depth indicates the initiation of structural vulnerabilities, persisting until around 2.5 feet, where damage stabilises due to substantial structural compromise. Upscale residences' heightened damage percentages may result from susceptible, costly construction materials. While insightful, the graph doesn't encompass all factors influencing damage outcomes.

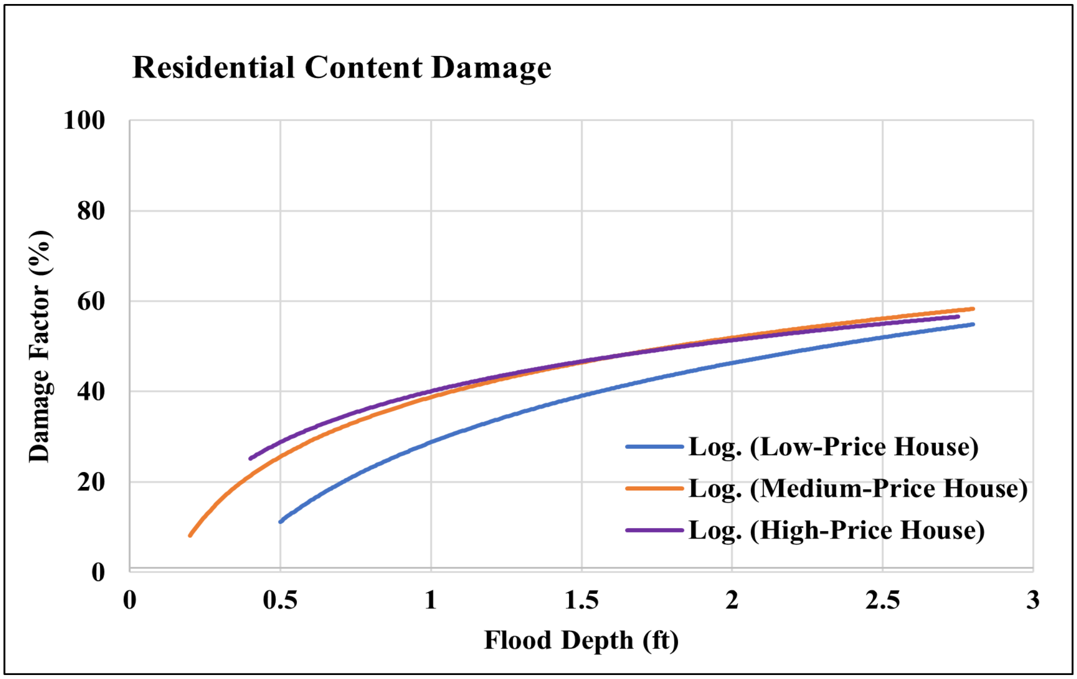


Figure 11. Comparison of the curves for the residential content damage category

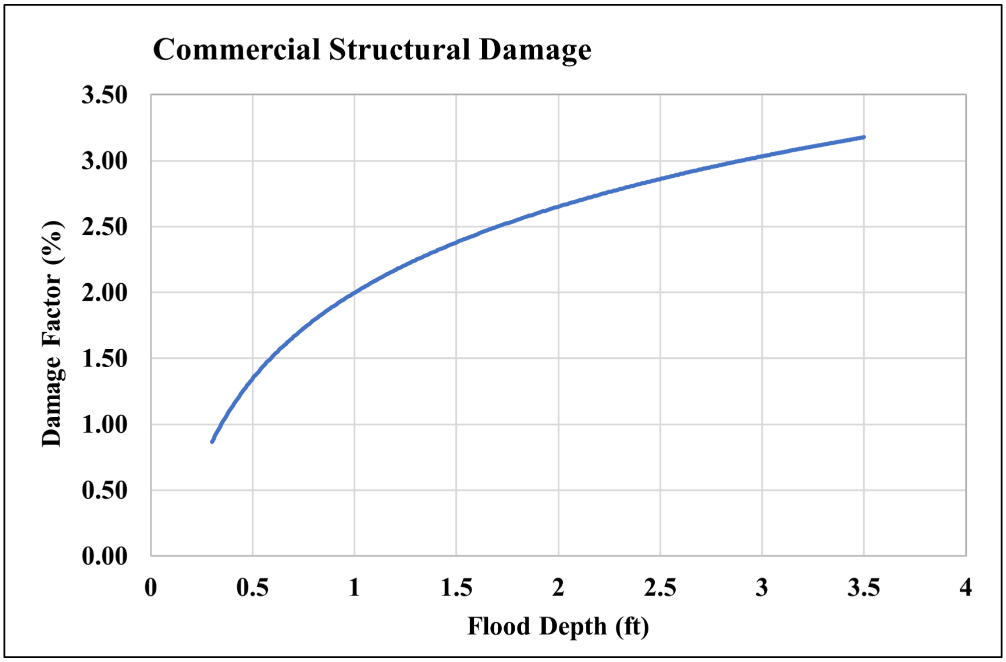
A comparative analysis assessed structural damage categories based on property prices. The results are graphically represented. It was found that the MPH category showed the highest residential content damage at a flood depth of 2.8 feet, reaching 58%. The HPH category displayed a damage rate of 57%, while the LPH curve showed the least content damage at 55%. Elevated damage percentages in HPH and MPH categories, compared to LPH, can be attributed to the heightened vulnerability of house contents like furniture and appliances to prolonged water exposure. The data signifies that content damage becomes notably evident from a flood depth of one foot for all house types, continuing until 2.5 feet, beyond which it stabilises due to the severity of the incurred damage. The more significant damage percentage of upscale houses is attributed to their potential use of more susceptible, expensive construction materials.

3.4.2 Commercial Category Depth-Damage Function Development

Table 5.Flood Depth-Damage Functions for the Commercial Sector

Category	**Depth-Damage Functions**	**R^2**
Commercial Structural Damage	$y = 0.9419\ln(x) + 1.9987$	0.85
Commercial Content Damage	$y = 16.933\ln(x) + 54.698$	0.86

Table 5 shows depth-damage functions tailored for the commercial sector, encompassing structural and content damages. The equation for commercial structural damage exhibits a substantial relationship with an R-squared value of 0.85, indicating its effectiveness in estimating damage based on varying flood depths. Similarly, the function for commercial content damage demonstrates a robust correlation with an R-squared value of 0.86. These functions are indispensable tools for businesses and stakeholders, facilitating accurate assessment and mitigation of flood-related damages in commercial properties.



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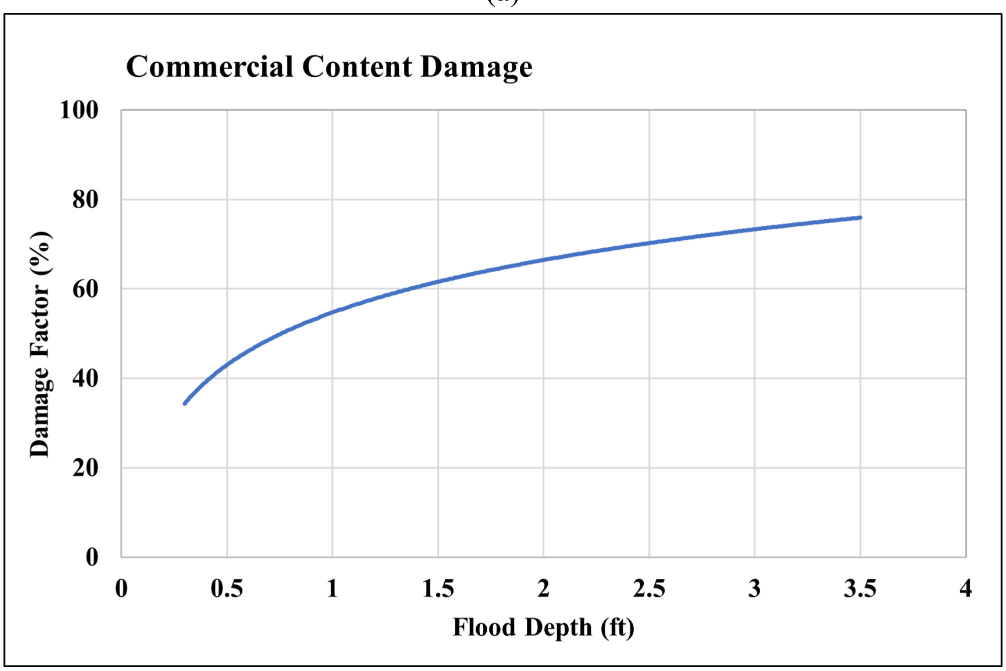

(b)

Figure 12. Flood depth-damage curve for the commercial sector (a) Commercial Structural Damage (b) Commercial Content Damage

The results indicate a potential surge in content damage to 77% at a flood depth of 3.5 feet, starkly contrasting the 3.2% for structural damage (Figure 12). This significant increase in content damage underscores the urgent need for effective mitigation strategies. This disparity can be attributed to the heightened vulnerability of delicate and valuable items within structures, even at moderate flood depths. This emphasises the critical need for special protection measures for these items. Additionally, the impact of floodwater on structural integrity may exert more pronounced effects at greater depths, explaining the comparatively lower proportion of structural damage.

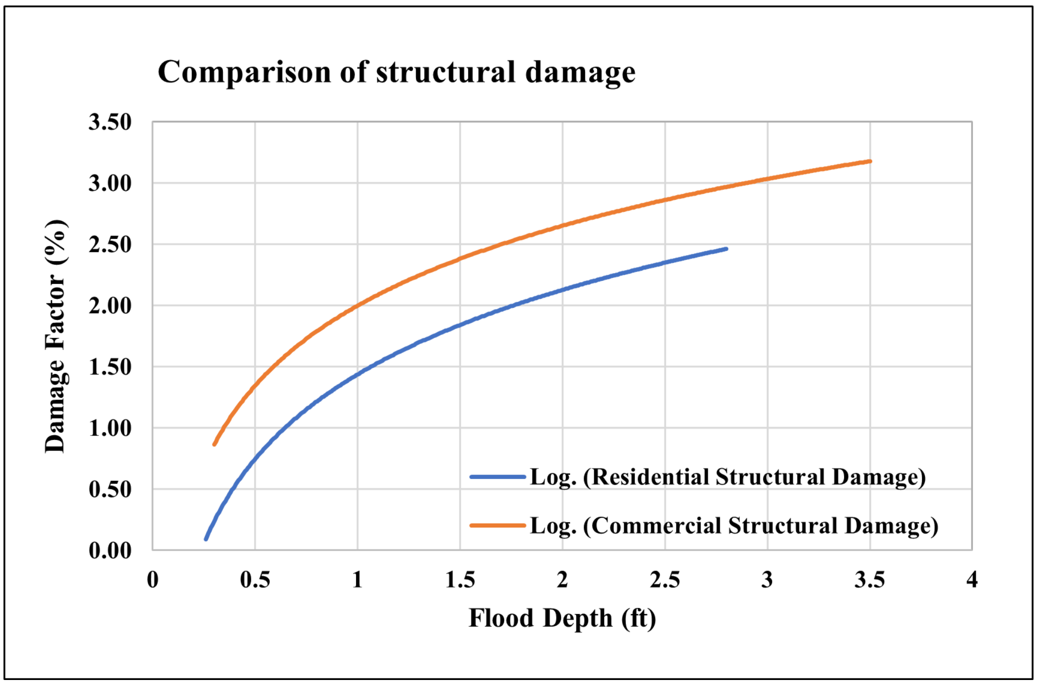

Figure 13. Comparison of the curve for residential and structural damage categories.

The evaluation highlights a significant contrast in structural damage between commercial structures and residential properties, as depicted in Figure 13. This discrepancy is notably evident in the average flood depths experienced; commercial buildings encounter an average depth of 1.47 feet, surpassing the comparatively lower 1.29 feet observed in residential areas. This discrepancy in flood depth exposure carries implications, with greater depths contributing to intensified structural deterioration. The urban location of commercial establishments adds a crucial dimension, exposing them to higher flood depths in town centres, thus amplifying damage. The graphical representation provides comprehensive comparative insights into structural damage across residential and commercial realms, revealing a noticeable divergence in flood depths and elevated damage percentages for commercial buildings. This can be attributed to using more vulnerable and costly materials like concrete and steel than the resilient wood and drywall common in residential constructions. However, acknowledging the multifaceted nature of this correlation, other variables, including building materials and construction quality, contribute to nuanced outcomes (Sulong and Romali 2022).

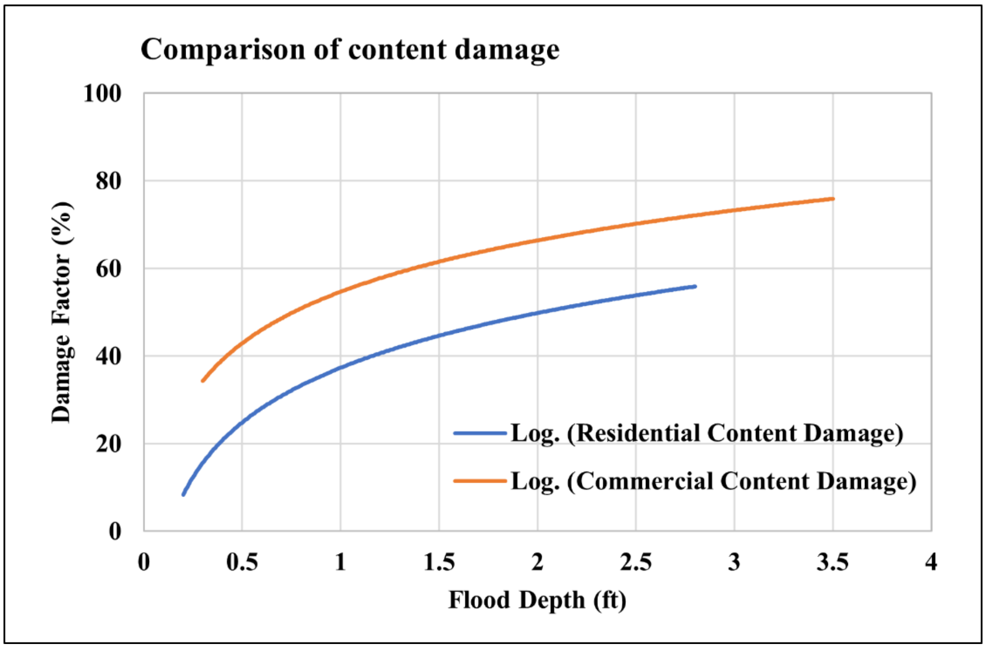

Figure 14. Comparison of the curve for residential and commercial content damage categories.

The comparison illustrated in Figure 14 highlights distinct asset damage trends between commercial structures and residential properties. Particularly at a flood depth of 2.5 feet, commercial damage peaks at 25%, surpassing the recorded 15% in residential areas. This contrast arises from differing material compositions; commercial buildings, often constructed with concrete and steel, are more vulnerable than primarily wood and drywall-based residential structures. While informing mitigation strategies and cost estimates, it's essential to note that the graph doesn't encompass all influencing factors. Despite relying on historical data, the graph offers valuable insights for understanding, although actual flood damage may vary due to contextual conditions.

4. Conclusions

The study used a thorough methodology to assess flood damage and created flood depth-damage curves tailored to residential and commercial sectors. The analysis looked at direct flood impacts, analysed data carefully, and used RF and various flood damage models with different regression techniques. These models generated curves demonstrating the relationship between flood depth and damage, providing a flexible approach that considers hydrological, socio-economic, and property factors specific to the area. This approach led to damage curves particular to the site, illustrating the complex link between flood characteristics and their impact on residential and commercial areas.

- The research highlights the importance of flood depth in causing damage to residential and commercial properties. RF analysis confirms that flood depth significantly affects structural and content-related impacts. It's worth noting that there is a positive correlation between flood depth and property price, indicating that valuable properties in flood-prone areas are likely to suffer more significant damage. Conversely, the negative correlation in the commercial sector suggests that higher property prices may be associated with better flood protection and reduced vulnerability. This emphasises the need for different mitigation strategies based on property values in residential and commercial settings. Besides flood depth, socio-economic and property characteristics significantly influence flood damage across residential and commercial sectors. Critical variables, including asset value and business and household income, were identified through the RF technique.
- Linear, logarithmic and polynomial models were explored to compare damage under various scenarios. The logarithmic model initially captured rapid changes and diminishing effects but was later found to be less effective across the entire data range. With its flexibility in handling complex, nonlinear relationships, the polynomial model provided a better overall fit, making it the preferred choice for developing flood damage curves. Thus, it was found that polynomial regression is a superior approach for forecasting flood-induced damages. Its precision and adaptability across diverse scenarios make it particularly effective for evaluating structural and content damages in residential and commercial settings.
- The developed flood damage curves illustrate diminishing damage with increasing flood depth. Regarding residential structural flood damage based on property price, the order is

Low Price House (LPH) > High Price House (HPH) > Medium Price House (MPH). However, for content damage, the sequence reverses: MPH > HPH > LPH. This implies medium and high-price houses experienced more content damage than low-price houses.

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Consent to Participate: Not Applicable

Consent to Publish: Not Applicable

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Competing Interests: The authors do not have competing interests that could have appeared to influence the work reported in this paper.

Availability of data and materials: The data are available from the corresponding author pending reasonable request.

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