Journal in Urban and Regional Planning

UP School of Urban and Regional Planning
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How Flood Risk, Accessibility, and Zonal Household Income Affect Residential Property Rental Prices: Evidence from Metro Manila

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Abstract

This study estimated the relationship between rental prices of residential properties and flood risk, accessibility, and income level for local areas in Metro Manila, Philippines, using a spatial hedonic price approach. The residential property data were collected from an online Metro Manila real-estate marketplace in October 2020 using a web scraping technique, whereas the flood risk, accessibility, and neighborhood data were compiled using a geographic information system from available data sources, including flood hazard maps. Ordinary least squares models and spatial error models were estimated using a dataset containing 17,494 residential properties. The results showed that rental prices of residential properties in flood-prone zones are 4.0 to 4.6% lower than those outside such zones. In addition, the analysis revealed that the reduction in rental prices in flood-prone zones was lower for properties with better accessibility and in zones with high average household income. The results suggest that the effect of flood risk on rental prices can be reduced by better accessibility.

Keywords: flood risk; spatial hedonic model; accessibility; rental prices of residential property; developing city

1. Introduction

Flood risk has recently increased in many parts of the world, particularly in developing countries, where it is expected to increase due to the rapid growth in population and economic activity (Visser, Petersen, & Ligtvoet, 2014), whereas the frequency of floods has increased due to climate change (Hirabayashi, Mahendran, Koirala, Konoshima, Yamazaki, Watanabe, & Kanae, 2013). This is also the case in Metro Manila, Philippines. In 2009, Typhoon “Ketsana” struck Metro Manila, causing a flood disaster, which resulted in 241 deaths, 394 injuries, and damage to 65,521 buildings (Sato & Nakasu, 2011). In addition, flash floods negatively affect social activities. These include the collapse of urban activities due to severe traffic jams caused by road blockages from floodwater (Lagmay, Mendoza, Cipriano, Delmendo, Lacsamana, Moises, & Tingin, 2017). Factors contributing to higher flood risk in Metro Manila were poor infrastructure and substandard residential environments. For instance, many pumping stations in Metro Manila are old—built in the 1970s—meaning the quality of urban drainage in Metro Manila has worsened (World Bank Group, 2021). The Asian Development Bank (ADB) (2017) stated that considerable investment in flood control is needed to handle the effects of climate change. In 2017, the Government of the Philippines, the World Bank, and the Asian Infrastructure Investment Bank (AIIB) approved the Metro Manila Flood Management Project, which aimed to improve flood management in Metro Manila (World Bank Group, 2021).

In addition to the efforts made by the public sector, individuals are expected to take action against flooding. This may include the voluntary relocation of local inhabitants from flood-prone areas to other places with lower flood risk to avoid flood damage.

However, local inhabitants in flood-prone areas may be unwilling to migrate, likely because they believe the benefits of staying outweigh the risk of flooding (Kates, 1962; Fordham, 1992; Chan, 1995).

This suggests that accessibility may be critical for residential location choice, even when the vulnerability of the place is considered. For instance, in a Sri Lankan case study, Askman, Nilsson, and Becker (2018) found that approximately 40% of residents in flood-prone areas considered easy access to public services a benefit of living there. Another study (World Bank Group, 2018) found that cheap residential property prices attract them to flood-prone areas. Although a balanced strategy incorporating flood risk evaluation and accessibility is required to realize sustainable development in vulnerable cities, little evidence exists to show the trade-off between accessibility and flood risk in the context of developing urban areas. That is, how do local populations evaluate the balance between flood risk and the benefits of living in developing cities?

This study aims to empirically estimate the relationship between the rental prices of residential properties and flood risk and accessibility in Metro Manila to delve into the trade-off between these factors made by residents. Hedonic price models (HPMs) incorporating spatial autocorrelation are employed to analyze rental prices of residential properties, alongside socioeconomic factors other than flood risk and accessibility. To the best of the researchers' knowledge, no study has analyzed the relationship between flood risk, accessibility, and regional income level using HPMs in the Philippines. Thus, the study contributes to the literature on the analysis of residential property value, as indicated by rental prices, in the Philippines and identifies and discusses possible implications of disaster risk management policy. It considers the interaction between flood risk and the benefits of locating in parts of cities in developing countries.

The remainder of this paper is organized as follows: The next section reviews the literature on the relationship between flood risk and residential property value. Subsequently, the study area and data are presented, followed by model formulation. Empirical results are shown with discussion of findings, and finally, the conclusions are presented.

2. Literature Review and Conceptual Framework

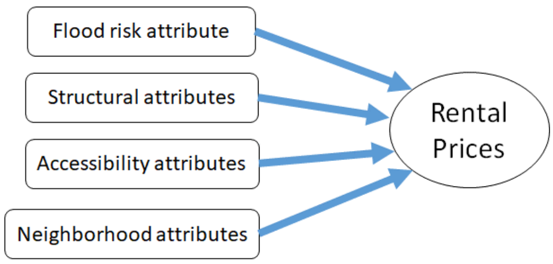
In developed countries, numerous studies have investigated the effects of flood risk or actual flood events on residential property values. Notably, the US introduced the National Flood Insurance Program, which is the mandated insurance program for higher flood risk zones. Many studies in the US compared the reduction of residential property value with capitalized flood insurance premiums. It was found that people tend to underestimate the flood risk. This is seen in the reduction in property prices in floodplains after the occurrence of a major hurricane (Bin & Polasky, 2004), which implies that a recent event is needed to raise awareness of flood risk. Conversely, when residents are fully aware of the flood risk and are well insured, the reduction in residential property prices in the floodplain is equal to or greater than the capitalized flood insurance for a high-value house due to non-monetary damage from flooding and the disutility of being displaced (Bin & Polasky, 2004; Bin, Kruse, & Landry, 2008). Daniel, Florax, & Rietveld (2009) conducted a meta-analysis of 19 studies in the US and found that property prices decrease by 0.6% as the probability of flood risk increases by 1%. Because price reduction depends on people's perception of the probability of flooding, various factors affecting it have been investigated using HPM. Price reduction after flood events is often analyzed, as people may better recognize flood risk after such events. For instance, Bin and Polasky (2004) analyzed property price reductions in a floodplain in Pitt County, North Carolina, before and after Hurricane Floyd, and concluded that the post-Floyd discount was twice the pre-Floyd discount. Atreya, Ferreira, & Kriesel (2013) investigated the effect of the major 1994 flood on price differentials of residential property in Dougherty County, Georgia, which decreased over time. Zhang (2016) also analyzed the "forgetting" effect after the flood events in the Fargo–Moorhead metropolitan area, US, and found that the price discount of properties in a floodplain increased the most about a year after the major 2009 flood; however, this effect decreased after 2011. Samarasinghe and Sharp (2010) investigated the association between information disclosure about flood risk and people's perceptions of flooding, showing that property price reductions within a floodplain decreased after floodplain maps became available in a case study in North Shore City, New Zealand. Rajapaksa, Wilson, Managi, Hoang, & Lee (2016) compared the impact of the flood map with the actual flood incidence and found that the reduction in property prices from the flood map was 14- 18% lower than that caused by the actual flood event.

People's perceptions of flooding are also related to the distance to the floodplain. Zhang and Leonard (2019) focused on properties proximate to a 100-year floodplain. They suggested that the price discount of properties within the 100-year floodplain after the flood event, when the control group was 1000–1500 ft from the floodplain, was 8.6% higher than when the control group was just outside the floodplain. Atreya and Czajkowski (2019) analyzed waterfront property prices in Galveston County, Texas, and found that prices were 146% higher in areas near the coastline, despite the area being at high flood risk.

Meanwhile, in developing countries, a few studies have investigated the association between flood risk and property value using HPM. Cobián Álvarez and Resosudarmo (2019) investigated the impact of the 2007 floods in Jakarta, Indonesia, on residential property value using spatial HPM. The results revealed a significant negative effect of flood depth on property prices, with residential property values in flooded areas lower than in unflooded areas. Ismail, Karim, & Hasam (2019) analyzed the impact of flood depth on land property value in Peninsular Malaysia, revealing the significant negative effects of flood depth and proximity to a river. Mahaprashasta, Mukhopadhyay, & Pattanayak (2021) investigated flood risk and residential property values in Cuttack, India, and showed that an average flood would reduce rent by approximately 4.4% compared with areas without flood risk. Rabassa and Zoloa (2016) also performed a case study in La Plata, Argentina, concluding that the residential property value decreases by 3.5% for properties in the floodplain; the discount is doubled for properties in higher-risk zones, and the value of undeveloped parcels of land is more sensitive to flooding, which is worth 10.3% less than those in lower-risk areas.

In the Philippines, to the best of the researchers' knowledge, no studies have investigated the trade-off relationship between flood risk and accessibility using HPM, although some studies have applied HPM to estimate property values. For instance, Dann, Grohmann, Ho, Khoo, Kim, and Lal (2020) analyzed the housing market of Metro Manila and surrounding cities using spatial HPM and concluded that fuel for lighting, toilet facilities, and population density are significant determinants of property value. Rivera and Tiglao (2006) also used HPM to examine the effect of accessibility on land prices. North and Griffin (1993) investigated the association between water sources and monthly house rents in the Bicol region using HPM. Jimenez (1984) also used random sample data from a survey conducted by the Davao Action Information Center. A limitation of the HPM approach in developing countries is the poor availability of data on property values. Many empirical studies in the Philippines have also suffered from potentially biased results owing to their narrow scope of property data. Abad, Fillone, Banister, Hickman, & Biona (2016) investigated the relationship between property values and accessibility to CBDs and flood risk by overlaying maps; however, they did not control for other variables.

In summary, because only a few studies have used HPM in developing countries to evaluate the relationship between flood risk and residential property value, and because these studies did not simultaneously control for other variables such as neighborhood attributes, this study elucidates this relationship using firsthand evidence from the Philippines. Figure 1 shows the conceptual framework relating the identified property attributes that may affect rental prices. The details on each attribute are further discussed in the next section.



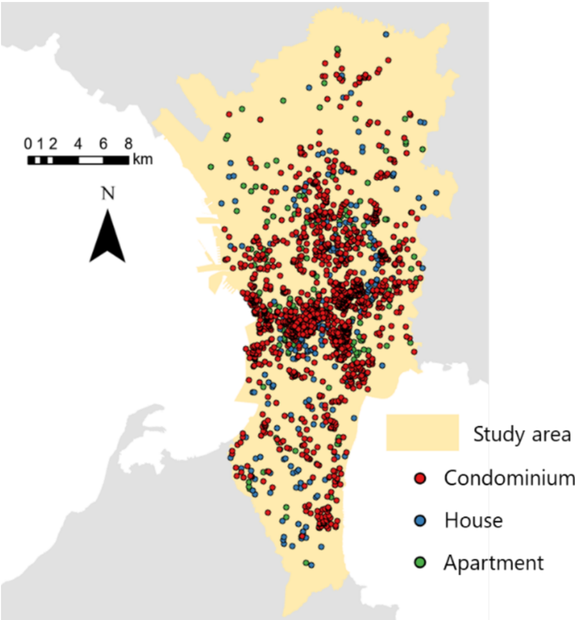
Source: Author's Construct

Figure 1. Conceptual Framework

A unique contribution of this paper is the proposed novel approach to data collection using web scraping, which has not been used in previous studies in the Philippines. This approach enables the analysis of property values using a large-scale dataset in a developing country.

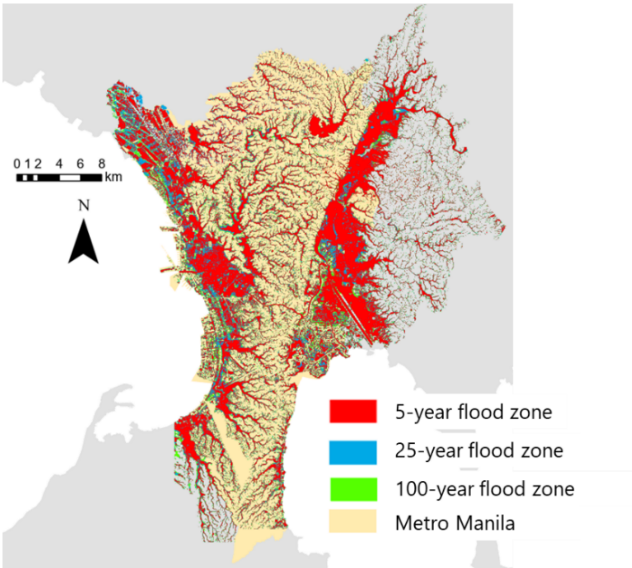
3. Data Collection and Processing

The study covers Metro Manila, located in the southwestern part of Luzon, Philippines. Metro Manila has a population of 12,877,253 as of 2015 [30], which is approximately one-eighth of the country's population. Metro Manila comprises 16 cities and 1 municipality. This region lies along the flat alluvial lands extending from Manila Bay in the west to the Marikina Valley in the east. Metro Manila is largely covered by the Pasig-Marikina-Laguna de Bay Complex, with a catchment area of 4678 km2 (Sato & Nakasu, 2011). The Pasig-Marikina-Laguna de Bay Complex comprises the Pasig River, Marikina River, and Laguna de Bay. The 5-year flood zone covers substantial areas of Metro Manila. Typhoon "Ketsana" hit Metro Manila in 2009 and caused devastating flood damage.



Source: Author's Construct

Figure 2. Location of the observed properties in the datase



Source: Author's Construct

Figure 3. Flood map of Metro Manila

In this study, the researchers developed a residential property dataset covering the entire Metro Manila for an empirical study. The property data were collected using a web scraping technique, an automated process that uses software to extract data from websites. This automation enabled the collection of large-scale data from Lamudi, an online real estate marketplace operated by Lamudi Philippines Inc. The data covers properties listed from October 9 to 10, 2020, which the researchers screened using four criteria. First, 409 properties whose coordinates were located outside the study area were excluded from this study. Second, properties whose rent, living area, and number of bedrooms were not disclosed on the website were classified as having missing values and thus excluded. Third, properties with outliers in their attributes, detected using the Smirnov–Grubbs test (5% significance level) for each property type (apartment, detached house, or condominium), were treated using two methods. When it was determined that the reviewed property information from other data sources differed from the data collected from Lamudi's website or if the re-review of the Lamudi website found that information had been updated after the first search, the researchers replaced the outliers with the most recent data to improve the robustness of the data set. However, if the reasons for the outliers could not be identified, they were excluded from the dataset because these were strongly suspected to contain some errors. Fourth, properties outside the scope of the study, such as shared rooms/apartment/, condominium buildings, and properties for sale, were excluded from the dataset. The above screening process reduced the dataset from 19,365 to 17,494 residential properties. This study covers rental properties only because they are traded more frequently than owned properties and thus are more likely to reflect current market prices.

Furthermore, the researchers estimated coordinates from the sample data to identify property locations rather than simply using the addresses reported on the websites. This was done because we found many instances of inaccurate information on the addresses compiled in the original data. Figure 2 illustrates the spatial distribution of the properties in the dataset. All data points are found within the boundaries as follows:

- Minimum latitude : 14°22'21" N
- Maximum latitude : 14°45'00" N
- Minimum longitude : 120°56'30"E
- Maximum longitude : 121° 5' 43" E

The derived dataset comprises structural, neighborhood, flood, and accessibility attributes. First, the structural attributes represent the basic structure of the property. They include the type of property, living area, number of bedrooms, number of bathrooms, availability of car spaces, Wi-Fi, air conditioners, balconies, and gyms, all of which were extracted from the website.

Second, the neighborhood attributes include population density, average zonal household income, and proximity to rivers, all of which are defined for the area within a 1-km buffer around the property. These were computed from geographic information system (GIS) data using ArcGIS Pro 2.5.1. Population density was estimated using the barangay-based data in 2015 by the Philippine Statistics Authority. A barangay is the smallest administrative division in the Philippines, which is smaller than a city or municipality. The average zonal household income was estimated from the household interview survey under the MMUTIS Update and Enhancement Project by the Japan International Cooperation Agency in 2012. River locations in and around Metro Manila were collected from OpenStreetMap. Note that a river is defined as a "linear flow of larger natural waterways" in OpenStreetMap.

Third, the flood attribute represents the flood risk of a property, defined as a 0/1 dummy variable indicating whether it lies within a 100-year floodplain. This indicates whether the property is located in the zone of a 1%–100% annual chance of flooding with a depth of 0.1 m or greater. This was also computed using GIS with a flood map and location maps of the observed properties. The flood map of Metro Manila, shown in Figure 3, was developed by the DOST-UP DREAM and Phil-LiDAR Program.

Fourth, accessibility attributes comprise distance to central business districts (CBDs), road density, number of universities, number of shopping malls, and number of stations within a 1 km buffer zone around the property. The distance to the CBD is defined as the straight-line distance from the property to the nearest CBD. CBDs are defined as areas where nighttime light intensity is significantly higher than in other places, using Visible Infrared Imaging Radiometer Suite nighttime light data from NASA/NOAA. The nighttime lights data observed from January 1 to December 31, 2019, were used to compute the average radiance per barangay on Google Earth Engine, and barangays with average radiance above $\mu+2\sigma$ (μ: average, σ: standard deviation) were assumed to be a part of the CBDs. The road density is defined as the total length of the roads within a 1 km buffer zone around the property, computed using road data in Metro Manila retrieved from OpenStreetMap. The data on universities were retrieved from the list of universities in Metro Manila by the Commission on Higher Education. Regarding data on shopping malls, the study team collected information from Wikipedia because Metro Manila does not have an official database on shopping malls. In total, 228 shopping malls and 280 universities were included in the database. The data on railway stations in Metro Manila include 77 stations from the Philippine National Railway, LRT-1, LRT-2, and MRT-3.

Table 1 presents the descriptive statistics of the dataset. The average and median monthly rents per square meter were 840.08 and 843.75 PHP/m2, respectively. They suggested a symmetric distribution of monthly unit rents. Meanwhile, the average and median monthly rents are PHP 85,658.57 and PHP 45,000, respectively. Note: S.D. represents the standard deviation.

This implied that extraordinarily high-grade (expensive) housing units skewed the distribution toward higher prices. Similarly, the living area has a much higher average (137.78 m^2) than the median (57 m^2). This is probably because of the biased distribution of property types: apartments (3%), houses (14%), and condominiums (83%). The average distance to CBDs is 3.15 km, indicating the observed properties are mostly located near CBDs. The table also shows that the average and median of the number of stations are 0.75 and 0, respectively. This implies that over half of the observed properties have poor accessibility to railway services. The average and median zonal average household incomes are 34,226.82 and 20,395.67, respectively. This suggests significant income inequality across localities in Metro Manila. In summary, the dataset mostly contains properties for middle- to high-income earners rather than low-income earners. This is mainly because the property data were collected from the formal database of a major real estate company, which does not cover informal settlements or properties.

Table 1 Descriptive statistics of residential property dataset in Metro Manila (N = 17,494)

Variables	Mean	S.D.	Median	Minimum	Maximum
Structural attributes					
Monthly rent per square meter (PHP/m^2)	840.08	335.94	843.75	50.00	3750.00
Monthly rent (PHP)	85658.57	95995.57	45000	2000	1000000
Living area (m^2)	137.78	238.01	57	4	3400
Number of bedrooms	1.89	1.21	1	1	15
Number of bathrooms	1.75	1.30	1	0	26.00
Car spaces (0/1)	0.26	0.44	0	0	1
Wi-fi (0/1)	0.17	0.38	0	0	1
Air conditioner (0/1)	0.45	0.50	0	0	1
Balcony (0/1)	0.26	0.44	0	0	1
Gym (0/1)	0.36	0.48	0	0	1
Apartment (0/1)	0.03	0.16	0	0	1
Detached house (0/1)	0.14	0.35	0	0	1
Flood attributes					
Flood zone (0/1)	0.31	0.46	0	0	1
Accessibility attributes					
Distance to the nearest CBDs (km)	3.15	2.77	2	0	21
Road density (/km)	25.91	5.88	26.46	9.45	44.23
Number of train stations	0.75	0.99	0	0	6
Number of shopping malls	4.75	3.76	4	0	16
Number of universities	3.45	3.28	3	0	22
Neighborhood attributes (within buffer zone)					
Zonal average household income (PHP)	34226.82	28271.72	20395.67	2117.96	126858.48
Zonal population density (/km^2)	21545.58	11077.64	20235.91	1245.51	84578.83
River (0/1)	0.65	0.48	1	0	1

4. Method of Analysis

This study employs HPM (Rosen, 1974), which has been widely used to estimate environmental values where no market price exists. Two types of models are formulated: ordinary least squares (OLS) regression models for Models 1-1 to 1-5 and spatial econometric models for Models 2-1 to 2-5. First, Model 1-1 is the basic model with a linear structure, which is expressed as

[Model 1-1]

$$lnP_n = \beta + \sum_j \sigma_j S_{nj} + \zeta F_n + \sum_k \alpha_k A_{nk} + \sum_l \nu_l N_{nl} + \sum_m \tau_m T_{nm} + \varepsilon_n \quad (1)$$

where lnP_n is the natural logarithm of the rent per square meter of the property n; S_{nj} is the structural attribute; F_n is the flood attribute; A_{nk} is the accessibility attribute; N_{nl} is the neighborhood attribute; T_{nm} is the type of property; β, σ_j, ζ, α_k, ν_l, and τ_m are coefficients; and ε_n is an error component. Models 1-2 to 1-4 introduce an interaction term between the flood attribute and accessibility attributes, whereas Model 1-5 introduces the interaction term between the flood attribute and neighborhood attributes, which are formulated as follows:

[Model 1-2, 1-3, and 1-4]

$$lnP_n = \beta + \sum_j \sigma_j S_{nj} + \zeta F_n + \sum_k \alpha_k A_{nk} + \sum_l \nu_l N_{nl} + \sum_m \tau \quad (2)$$

[Model 1-5]

$$lnP_n = \beta + \sum_j \sigma_j S_{nj} + \zeta F_n + \sum_k \alpha_k A_{nk} + \sum_l \nu_l N_{nl} + \sum_m \tau \quad (3)$$

Recent HPM studies have often incorporated spatial autocorrelation because the real estate market is expected to have spatial interactions, and the results of OLS estimation may be insufficient if a spatial relationship exists (Rabassa & Zoloa, 2016). This study employs a spatial error model to capture spatial interdependencies (Anselin, 1988). Although other models, such as the spatial lag model (Anselin, 1988), could also be used, the Lagrange multiplier and likelihood ratio tests in an empirical analysis indicated that the spatial error model is more appropriate than the spatial lag model. Model 2-1 is a basic spatial error model, expressed as

[Model 2-1]

$$lnP_n = \beta + \sum_j \sigma_j S_{nj} + \zeta F_n + \sum_k \alpha_k A_{nk} + \sum_l \nu_l N_{nl} + \sum_m \tau \quad (4a)$$

$$\varepsilon_n = \lambda W_n \varepsilon_n + u_n \quad (4b)$$

where λ is the spatial autoregressive parameter, W_n is the nth row of the spatial weight matrix, is the vector of error terms, and u_n is an error term that is assumed to be independent and identically distributed. The spatial weight matrix shows whether any pair of properties are neighbors.

This study assumes a neighborhood threshold of 0.4 km from the properties, based on multiple trials with various definitions of neighbors. The spatial weight matrix is standardized, meaning the sum of each row is 1. Similar to Model 1, the spatial error models with interaction terms are also formulated as

[Models 2-2, 2-3, and 2-4]

$$lnP_n = \beta + \sum_j \sigma_j S_{nj} + \zeta F_n + \sum_k \alpha_k A_{nk} + \sum_l \nu_l N_{nl} + \sum_m \tau_m T_{nm} + \omega_X F_n A_{nX} + \varepsilon_n \quad (5a)$$

$$\varepsilon_n = \lambda W_n \varepsilon_n + u_n \quad (5b)$$

[Model 2-5]

$$lnP_n = \beta + \sum_j \sigma_j S_{nj} + \zeta F_n + \sum_k \alpha_k A_{nk} + \sum_l \nu_l N_{nl} + \sum_m \tau_m T_{nm} + \omega_Y F_n N_{nY} + \varepsilon_n \quad (6a)$$

$$\varepsilon_n = \lambda W_n \varepsilon_n + u_n \quad (6b).$$

5. Results

Table 2 presents the estimation results of the OLS regression. The results of Model 1-1 reveal that the flood zone has a significant negative effect on residential property rental prices, suggesting that rental prices in flood zones are estimated to be 4.0% lower than those outside them. The distance to the nearest CBD has a statistically significant negative effect on property rental prices, likely because better access to CBDs is highly valued. Meanwhile, road density was estimated to have a significantly positive effect. The number of stations has a significantly negative effect on property rental prices. This might be attributed to the noise created by having many stations near a residential unit. The estimated coefficient of an average zonal household income is significantly positive. This might be because a higher average zonal household income may correspond to a better built environment with superior amenities and/or better public safety with a lower crime rate in the area. Table 2 also shows the estimation results for Models 1-2 to 1-5, where the interaction terms between the flood zone and distance to the nearest CBDs, the number of stations, and average zonal household income are statistically significant. This means the effects of these variables within the flood zones differed significantly from those outside them. Meanwhile, the interaction term between the flood zone and road density was estimated to be insignificant. This may imply that road density does not compensate for flood risk.

Table 3 presents the estimation results of the spatial error models. The results show that the spatial autoregressive parameters were estimated to be significant in all models. They suggest that the spatial autocorrelation of error components should be considered when estimating the rental property values. The AICs (Akaike Information Criterion) of Models 2-1 to 2-5 are also significantly improved over Models 1-1 to 1-5, respectively, implying that incorporating spatial autocorrelation improves model performance. The estimated coefficients in Models 2-1 to 2-5 are nearly identical to those in Models 1-1 to 1-5, implying that the results are robust. The results of Model 2-1 indicate the rental prices of residential properties in the flood zone are 4.6% lower than those outside the flood zone.

Table 4 summarizes comparisons of the marginal effects with respect to distance to the nearest CBDs, the number of stations, and average zonal household income on rental property prices between the inside and outside of the flood zones. The coefficients for the flood zone and its interaction terms with distance to the nearest CBDs, number of stations, and average zonal household income were estimated. This indicates that the marginal effect of the distance to the nearest CBD inside the flood zones is strongly negative, whereas that outside the flood zones is almost zero. The marginal effect of the number of stations inside the flood zones is positive; however, that outside the flood zones is almost zero. Note that the single term of the distance to the nearest CBDs is not statistically significant, as shown in Model 2-2. The significant negative effect of distance to the nearest CBDs on property rental prices only within flood zones may suggest that local people consider the effect of accessibility to CBDs more significant than the negative effect when the property has a higher flood risk. The positive effect of accessibility could be canceled out by the negative effect if the property is safer against flooding. This may indicate that those who choose flood-prone properties tend to commute to nearby CBDs more frequently or are possibly less concerned with the quality of the built environment and/or safety from floods than others are. Meanwhile, Models 2-4 show a statistically significant negative effect of the number of stations on property rental prices, even when a property is outside the flood zone. As mentioned earlier, this may suggest that local people generally consider proximity to a station to have negative impacts, such as poor urban environmental conditions. However, the negative effect might be offset for locations prone to flooding. This might be because existing rail services are generally elevated, as with LRT-1, LRT-2, and MRT-3, and these lines can continue operating even during flood events. Table 4 also reveals that the marginal effect of average zonal household income within the flood zones was higher than that outside them.

Table 2. Estimation results of OLS-based hedonic price models on residential property in Metro Manila

	Model 1-1		Model 1-2		Model 1-3		Model 1-4		Model 1-5	
Variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
(Intercept)	6.963***	0.086	6.948***	0.088	6.964***	0.086	6.968***	0.086	6.96***	0.086
ln(Living area)	-0.183***	0.008	-0.183***	0.008	-0.183***	0.008	-0.184***	0.008	-0.183***	0.008
ln(Number of bedrooms)	0.057***	0.011	0.058***	0.011	0.057***	0.011	0.057***	0.011	0.057***	0.011
Number of bathrooms	0.031***	0.004	0.031***	0.004	0.031***	0.004	0.031***	0.004	0.031***	0.004
Car spaces (0/1)	0.067***	0.007	0.068***	0.007	0.067***	0.007	0.068***	0.007	0.068***	0.007
Wi-fi (0/1)	0.074***	0.007	0.074***	0.007	0.074***	0.007	0.073***	0.007	0.074***	0.007
Air conditioner (0/1)	0.046***	0.006	0.045***	0.006	0.046***	0.006	0.046***	0.006	0.045***	0.006
Balcony (0/1)	-0.024***	0.006	-0.024***	0.006	-0.024***	0.006	-0.024***	0.006	-0.024***	0.006
Gym (0/1)	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Apartment (0/1)	-0.549***	0.026	-0.548***	0.026	-0.549***	0.026	-0.55***	0.026	-0.549***	0.026
Detached house (0/1)	-0.527***	0.014	-0.529***	0.014	-0.527***	0.014	-0.527***	0.014	-0.527***	0.014
Flood zone (0/1)	-0.040***	0.006	-0.016*	0.009	-0.040***	0.006	-0.056***	0.007	-0.041***	0.006
Distance to the nearest CBD	-0.011***	0.002	-0.009***	0.002	-0.011***	0.002	-0.011***	0.002	-0.011***	0.002
ln(Road density)	0.284***	0.021	0.279***	0.021	0.286***	0.023	0.275***	0.021	0.274***	0.022
Number of stations	-0.011***	0.003	-0.012***	0.003	-0.011***	0.003	-0.020***	0.004	-0.011***	0.003
Number of shopping malls	0.003***	0.001	0.003***	0.001	0.003***	0.001	0.004***	0.001	0.004***	0.001
Number of universities	0.001	0.001	0.001	0.001	0.001	0.001	0.0003	0.001	0.001	0.001
ln(Average household income)	0.074***	0.007	0.073***	0.007	0.074***	0.007	0.071***	0.007	0.069***	0.008
ln(Population density)	-0.054***	0.006	-0.053***	0.006	-0.055***	0.006	-0.054***	0.006	-0.053***	0.006
River (0/1)	-0.080***	0.008	-0.081***	0.008	-0.081***	0.008	-0.074***	0.008	-0.080***	0.008
Distance to the nearest CBDs×Flood zone			-0.008***	0.002						
ln(Road density)×Flood					-0.006	0.026				
Number of stations×Flood							0.020***	0.006		
ln(Average household income)×Flood									0.016*	0.008
Observations	17494		17494		17494		17494		17494	
R-squared	0.574		0.574		0.574		0.574		0.574	
AIC	8250.5		8238.2		8252.5		8239.3		8248.7	
LM err	1496.8***		1565.8***		1493.7***		1473.3***		1518.7***	
LM lag	0.05		0.16		0.05		0.12		0.01	
Robust LM err	1504.9***		1573.2***		1501.7***		1480.4***		1527.7***	
Robust LM lag	8.1***		7.5***		8.1***		7.3***		9.0***	
LR err	504.8***		543.8***		506.7***		498.4***		517.4***	
LR lag	0.05		0.16		0.05		0.12		0.01	
Moran's I statistics	39.5***		40.5***		39.6***		39.3***		39.9***	
Fixed city effects	Yes		Yes		Yes		Yes		Yes	

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.; a robust standard error is used.

Table 3. Estimation results of spatial error models on residential property in Metro Manila

	Model 2-1		Model 2-2		Model 2-3		Model 2-4		Model 2-5	
Variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
(Intercept)	6.945***	0.084	6.915***	0.085	6.941***	0.084	6.947***	0.084	6.937***	0.084
ln(Living area)	–0.202***	0.006	–0.202***	0.006	–0.202***	0.006	–0.202***	0.006	–0.201***	0.006
ln(Number of bedrooms)	0.085***	0.010	0.087***	0.010	0.085***	0.010	0.085***	0.010	0.086***	0.010
Number of bathrooms	0.026***	0.003	0.026***	0.003	0.026***	0.003	0.026***	0.003	0.026***	0.003
Car spaces (0/1)	0.060***	0.006	0.060***	0.006	0.060***	0.006	0.060***	0.006	0.061***	0.006
Wi–fi (0/1)	0.066***	0.007	0.067***	0.007	0.066***	0.007	0.066***	0.007	0.066***	0.007
Air conditioner (0/1)	0.042***	0.006	0.042***	0.006	0.042***	0.006	0.042***	0.006	0.042***	0.006
Balcony (0/1)	–0.021***	0.006	–0.021***	0.006	–0.021***	0.006	–0.021***	0.006	–0.021***	0.006
Gym (0/1)	0.012**	0.006	0.012**	0.006	0.012**	0.006	0.012**	0.006	0.012**	0.006
Apartment (0/1)	–0.550***	0.015	–0.545***	0.015	–0.550***	0.015	–0.550***	0.015	–0.550***	0.015
Detached house (0/1)	–0.507***	0.012	–0.507***	0.012	–0.507***	0.012	–0.507***	0.012	–0.506***	0.012
Flood zone (0/1)	–0.046***	0.006	0.001***	0.009	–0.047***	0.006	–0.058***	0.007	–0.047***	0.006
Distance to the nearest CBD	–0.003	0.002	0.001	0.002	–0.003	0.002	–0.003	0.002	–0.003	0.002
ln(Road density)	0.298***	0.022	0.29***	0.022	0.287***	0.023	0.294***	0.022	0.277***	0.023
Number of stations	–0.007*	0.004	–0.009**	0.004	–0.008**	0.004	–0.014***	0.005	–0.008**	0.004
Number of shopping malls	0.006***	0.001	0.006***	0.001	0.006***	0.001	0.006***	0.001	0.007***	0.001
Number of universities	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
ln(Average household income)	0.112***	0.008	0.113***	0.008	0.111***	0.008	0.109***	0.008	0.103***	0.008
ln(Population density)	–0.023***	0.006	–0.017***	0.006	–0.021***	0.006	–0.023***	0.006	–0.019***	0.006
River (0/1)	–0.069***	0.008	–0.070***	0.008	–0.067***	0.008	–0.063***	0.008	–0.066***	0.008
Distance to the nearest CBDs × Flood zone			–0.015***	0.002						
ln(Road density) × Flood					0.036	0.025				
Number of stations × Flood							0.014***	0.006		
ln(Average household income) × Flood									0.034***	0.008
Lambda	0.268***	0.009	0.282***	0.012	0.269***	0.008	0.267***	0.008	0.273***	0.008
Observations	17494		17494		17494		17494		17494	
R-squared	0.587		0.588		0.587		0.587		0.587	
AIC	7747.8		7696.5		7747.8		7742.9		7733.3	
Fixed city effects	Yes		Yes		Yes		Yes		Yes	

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

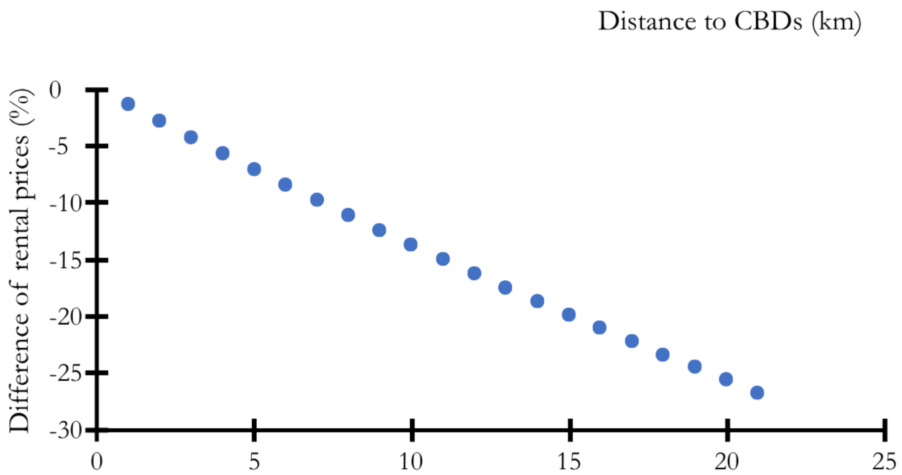
Table 4. Estimated marginal effects inside and outside the flood zone

Variables	Inside	Outside	Interaction term	Single term	Model
Distance to the nearest CBDs	–0.014	0.001	–0.015***	0.001	2-2
Number of stations	0.001	–0.014	0.014***	–0.014***	2-4
Average zonal household income	0.136	0.103	0.034***	0.103***	2-5

Note: *** p < 0.01; ** p < 0.05; * p < 0.1.

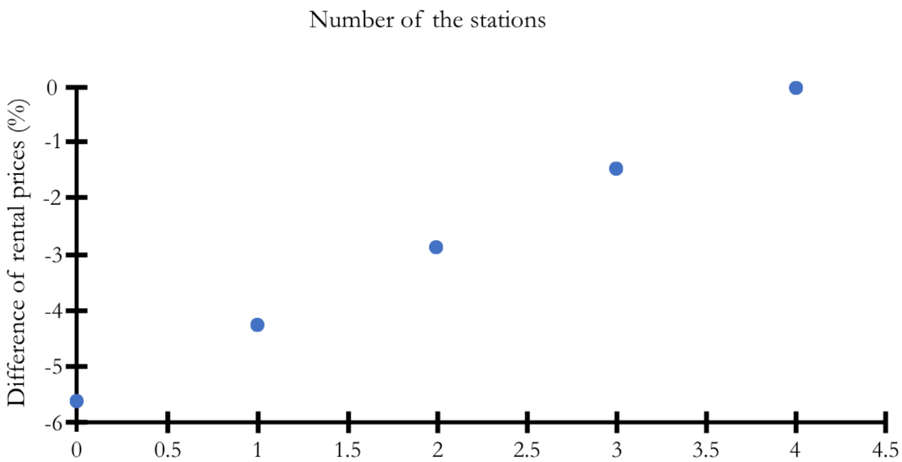
Figures 4, 5, and 6 illustrate the results of simple simulations by showing the computed percentage differences between rental prices of residential properties inside and outside the flood zones as distance to the nearest CBD increases, the number of stations increases, and the average zonal household income increases, respectively. Figure 4 shows smaller reductions in rental prices caused by flood zones at properties nearer to CBDs, whereas Figure 5 shows a smaller reduction in rental prices for properties with more nearby stations.

The reduction effect being smaller in areas with better accessibility may suggest that the flood risk is offset in areas with better accessibility. Figure 6 indicates a greater reduction in the properties in areas with higher average zonal household income. This may imply that flood risk is more sensitively evaluated in relatively lower-income areas. This may be attributed to low-income people having a higher awareness of flood risk, as shown in an earlier study (Wang, Wang, Huang, Kang, & Han, 2018).



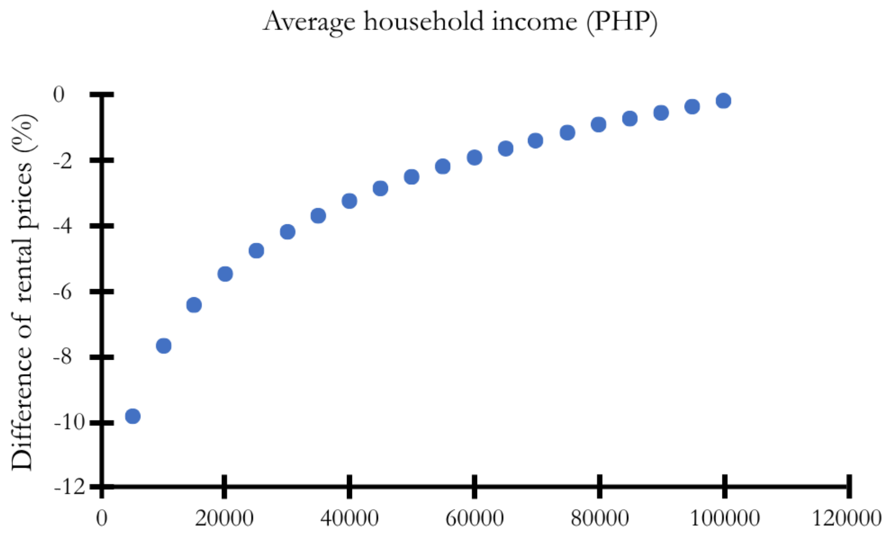
Source: Author's Construct

Figure 4. Differences in rental prices between the inside and outside of the flood zone versus distance to the nearest CBDs



Source: Author's Construct

Figure 5. Differences in rental prices between the inside and outside of the flood zone against the number of stations



Source: Author's Construct

Figure 6. Differences in rental prices between the inside and outside of the flood zone against average zonal household income

Although this study successfully estimated the rental prices under different conditions of residential properties with large-scale data in Metro Manila, the estimation results could be affected by some biases in the dataset. First, many properties in the dataset were condominiums. As flood risk perception may be related to building height, properties on higher floors in condominiums may be considered less susceptible to direct damage from flooding than detached houses on lower floors. This may have contributed to the possible relative underestimation of flood risk. Second, as shown earlier, the data may reflect the properties of middle- to high-income earners rather than those of low-income earners. If low-income earners are more sensitive to flooding, the estimation results would again underestimate the price reduction in flood zones. Third, property distribution may have biases that could also affect the interaction term of the flood zone and accessibility. For instance, low-income earners tend to choose areas with better accessibility but also higher flood risk owing to their financial constraints. In Metro Manila, over 104,000 informal settler households are estimated to reside in flood-prone areas exposed to recurrent flooding (World Bank Group, 2017). The dataset may not cover those who might choose these residential locations for accessibility at the expense of extremely high flood risk. Because the association of accessibility with reduced rental prices by flood zone may be significant for lower-income residents, the effects of interaction terms between flood zones and accessibility attributes may also have been underestimated in the models.

6. Conclusions

This study sought to estimate the extent to which residential property rental prices are related to flood risk, accessibility, and zonal household income in Metro Manila. Owing to the lack of official data on residential property transactions in Metro Manila, rental data were collected in October 2020 from an online real estate market via web scraping. Multiple GIS data sources, such as flood hazard maps and property locations, were also compiled, and accessibility and neighborhood attributes of the rental properties were calculated using GIS. The results of this study showed that the rental prices of residential properties located inside the flood zones with a 1% or greater annual chance of flooding with a depth of 0.1 m or greater are significantly lower, from a statistical viewpoint, than those of the properties outside the flood zones by 4.0 to 4.6%, a result similar to Mahaprashasta et al. (Mahaprashasta et al., 2021).

This study revealed that the negative effect of flood risk on rental prices is mitigated by better accessibility. In other words, rents in the flood zone were higher in areas with better accessibility. On the other hand, rents were lower in areas with lower average zonal household income. However, it is unclear whether rent levels "adjust" to residents' incomes, or whether lower-income residents choose places with lower rent. Overall, these observations demonstrate that this study's original contribution is the consideration of the combined effects of flood risk, accessibility, and household income on rental prices.

These findings also allow the researchers to emphasize the importance of flood risk awareness. If people cannot understand the risk appropriately, they might locate where they may experience more damage than expected, more than they can handle. Therefore, as part of preparing adequate flood control measures, promoting flood risk awareness is needed to protect people from flooding. In addition, the regulation of continued development in flood-prone areas may be necessary. For example, the mandatory disclosure of flood risk information as a part of the process of selling or renting out properties may improve the flood risk perception of buyers or renters. Furthermore, the public distribution of flood maps and web mapping services can further make this type of disclosure more effective. A previous study (Hagemeier-Klose & Wagner, 2009) showed that flood maps require a good balance between simplicity and complexity for flood risk communication. Although flood maps of Metro Manila are available online, there is room for improvement. In addition, areas with better accessibility could be highlighted or prioritized for the introduction of flood control and perception-promotion strategies, as these areas could serve as cores of the transportation network.

Future studies may also use models like these to simulate the effects of changes in accessibility and flood risk, possibly due to infrastructure improvements, and evaluate the impact on rental prices and overall housing costs.

7. Limitations of the Study

The present study has some limitations. First, this study defined flood zones as areas with an estimated probability of flooding, rather than relying on residents' past experiences of flooding. As residents' flood perceptions are highly related to experience, ideally historical data on local flooding should be used for property price estimation. However, this is a challenge because such data are not easily available in many developing cities, including Metro Manila. Second, the models in this study did not include information on newer or ongoing flood control measures, which may alter the potential risk of flooding. This again is a result of the poor availability of data on flood prevention. Third, the dataset covered only rental properties, and owned houses were not included. The flood risk management strategies of an individual may be different if they purchase the property instead of simply renting it. Fourth, some potential biases concerning the geographical distribution and risk perception of people may exist. Finally, as discussed earlier, the dataset may have some biases, although it was developed using an innovative data collection method and covered only properties that were unoccupied at the time. Additionally, the rental prices offered used in the analysis may differ from the actual, final transaction prices. Furthermore, the distribution of housing unit types in the data may not reflect the general distribution of housing types in Metro Manila. It may therefore have skewed the analysis in a different direction. To provide more reliable evidence, HPM estimation should be based on higher-quality empirical data to advance this type of study in developing cities.

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