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Cognitive limits of perceived flood risk on residential property values

Song Shi *, Mustapha Bangura, Sumita Ghosh

School of Built Environment, University of Technology Sydney, 15Broadway, Ultimo, NSW, 2007, Australia

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A B S T R A C T

Examining cognitive limits in flood risk perception for residential property values, we analyse the Richmond housing market in the state of New South Wales, Australia. Using micro-level home sales data, our study reveals that the market has integrated long-term flood risk into property values. A notable 10.8 % price discount is observed for properties within 1–100 Annual Exceedance Probability (AEP) flood zone, 4.4 % for those in an AEP 500 zone, with no discounts for AEP 1000 flood zone properties. Comparisons of 2019 and 2023 flood maps and property's Time-on-Market (TOM) affirm that people's cognitive limits constrain to the AEP 500 level.

1. Introduction

There is an escalating global trajectory of flood risk [1–3], with approximately 11.3 % of all built-up areas across the globe likely to face high or very high flood hazards that are characterised by an inundation depth of at least 50 cm during 1-in-100-year flood events [4]. This is raising significant concerns for the built environment. For instance, flooding, resulting from river overflow and intense rainfall in Australia is the most frequent and costliest natural disaster [5]. Startling statistics from the National Flood Information Database [NFID] indicate that 1.5 % of all Australian properties face a 1-in-20-year flood risk. These events are more perceptible due to advances in rainfall and river flood records, topographic surveys, and catchment characteristics.

This spate of flood occurrences has sparked a conversation around integrating modern flood risk assessments into climate change policies to aid homeowners in making informed housing choices. However, regarding individual decision-making, flood risk analysis remains a debated issue as consideration for environmental risks is still fraught with challenges. On the one hand, many believe that the market will naturally address this concern, assuming that homebuyers, recognising impending risks, will discount vulnerable properties, thereby diminishing their attractiveness and value. On the other hand, recent flood studies by Risa and Bolsen [6] and Gourevitch et al. [7] cast doubt on the assumption that the market will fully integrate long-term environmental risk, showing residential properties exposed to flood risk are overwhelmingly overvalued, especially in coastal areas. This shows actions are based on people's perceptions rather than objective risk, introducing cognitive biases. These mixed results show the cognitive limitation of homebuyers in flood risk analysis.

* Corresponding author.
E-mail addresses: song.shi@uts.edu.au (S. Shi), mustapha.bangura@uts.edu.au (M. Bangura), sumita.ghosh@uts.edu.au (S. Ghosh).

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To address this gap in the literature, using home sales data from the Richmond area in the state of New South Wales, Australia, along with the 2019 and 2023 flood maps for this region, we explore individual cognitive limits in perceiving flood risk and its impact on residential property values. This will shed light on the link between perceived risk and property values in flood-prone areas. We integrate location characteristics such as distance to the central business district (CBD), elevation, and proximity to the river, using four AEP flood measures as follows (i) high-risk for AEP $\leq$ 100, (ii) medium-risk for 100<AEP $\leq$ 500, (iii) low-risk for 500<AEP $\leq$ 1000, and (iv) extremely low or no risk for AEP>1000. On the back of this study design, we posit the hypothesis - the market will eventually devalue properties in flood-prone zones, while individuals may face cognitive limitations in navigating uncertainty – and document the following contributions to the literature.

The study is the first to use flood maps to evaluate the cognitive limits of households in flood risk analysis. Our comparisons between the 2019 and 2023 flood maps affirm cognitive limits at the AEP 500 level, with individuals struggling to differentiate perceived flood risk beyond this point. We find an average 10.8 % price discount for properties located in a 1-in-100 Annual Exceedance Probability (AEP) flood zone, 4.4 % in a 1-in-500 AEP zone, and no discount for properties in a 1-in-1000 AEP flood zone and beyond. Notably, properties within confirmed AEP flood zones by 2019 and 2023 flood maps generally exhibit higher price discounts than homes with unconfirmed AEP ratings. The findings remain robust across different flood maps, spatial regression analyses, and extended fixed-effect analyses accounting for omitted variables and submarket effects. With the ongoing expansion of urban areas leading to construction in riskier locations, including existing floodplains, a transparent and regularly updated flood risk rating system becomes paramount. Such a system plays a vital role in effectively communicating estimated future costs associated with flood risk to the public.

Secondly, existing flood studies have predominantly relied on factors such as distance from the flood zone and dwelling features to determine flood risk and estimate financial losses. While spatial analysis is critical in assessing housing value, especially during natural hazards, methods and data used in previous studies are somewhat limited in isolating location features, submarket influences, and temporal effects from perceived flood risk. We depart from existing flood studies by integrating location characteristics, checking for spatial correlations, and aligning digital flood data maps with the property transaction dataset using property (x, y) coordinates. This is the first comprehensive study that integrates housing features, distance to CBD, distance to the river and flood zones, and digital flood map analysis to examine the impact of flood risks on the value of residential properties. This analysis contributes to the aspect of behavioural economics such as bounded rationality [8–11] relating to environmental risk management in the housing market. The integration of localised factors in our methodological framework offers more reliable information that could be used in flood-risk management.

Finally, flood insurance can also be an effective tool in hazard reduction. Insurers have already lifted premiums for homes at risk, signalling the prospect of increased under-insuring in the future. For instance, a median house price at AUD 825,000 in Richmond in 2023 could see a calculated price discount of AUD 89,100 (approximate 10.8 % discount) for properties within a 1-in-100 AEP flood zone, translating to annualised flood insurance premiums of AUD 4606 over the next 70 years at a 5 % per annum interest rate. These results stress the financial cost of how critical land use regulations and building codes adapt to climate change. The results also illuminate the financial implications of flood risk mitigation strategies, including the introduction of flood levies, property buybacks, elevation of homes, or construction of levees in the highest-risk areas.

The paper proceeds as follows. Section 2 provides a brief background on the flood risk in the Hawkesbury-Nepean Region and literature on the flood risk studies. Section 3 presents the research design, Section 4 describes the data, and Section 5 discusses the empirical results. Section 6 concludes.

2. Background

2.1. Flood risk in the Hawkesbury-Nepean Region

Richmond, situated approximately 65 km north-west of Sydney, is a regional town nestled on the rich floodplains of the Hawkesbury-Nepean River. Comprising Richmond, Hobartville, and North Richmond, the total population for these suburbs stood at 14,500 during the 2021 census. The Hawkesbury River divides the area into two distinct zones, with North Richmond in the north and Richmond and Hobartville in the south.

At the state level, the Department of Planning and Environment, NSW Government's 'Flood Risk Management Manual' which includes the 'NSW Flood Prone Land Policy' and the 'Flood Risk Management Manual', aims to mitigate the impacts of flooding and flood liabilities on communities and individual landowners in flood-prone areas. It serves as a toolkit for councils, offering guidance for comprehending and managing risks [12]. In response to the recurring floods, the NSW Government introduced a specific "Resilient Valley, Resilient Communities – Hawkesbury-Nepean Valley Flood Risk Management Strategy" [13], a comprehensive strategy that outlines collaborative efforts between the government, local councils, businesses, and the community to mitigate flood risks in the Hawkesbury-Nepean Valley. In 2019, the NSW government conducted a new regional flood study for the Hawkesbury-Nepean, capitalising on advances in flood modelling and changes to the floodplain. The resulting digital flood map is used for public access and individual property flood risk assessments. The study was subsequently updated in 2023.

Hawkesbury-Nepean Valley has a long history of profound and perilous flooding that includes observations over 230 years [14]. The region has a history of over 130 'moderate' to 'major' floods, including 6 major and 21 other serious flood events since 1790 AD [15]. While floods are random, two types of cycles, drought-dominated and flood-dominated, occur here, which last for decades. The drought-dominated cycle lasted for twenty-eight years (1992–2020) without significant flooding. However, since February 2020, frequent flooding signals the commencement of a flood-dominated cycle in Hawkesbury-Nepean Valley [14]. Between 2020 and 2024, there were altogether five significant flood events. Two 'major' flood events happened in February 2020 and April 2022, where the water level reached more than 9 m above sea level, and 12 m above sea level is the threshold for a 'major' flood [16]. The other three flood events were in March 2021, July 2022, and March 2022, when the flood level was above 12 m, the 'major' flood level. In 2022 alone, three major flood events happened in this area, and two of them were above the major flood level of 12 m [16].

This evidence on frequent occurrences of flooding events, combined with the region's unique flood cycles, justifies the reasons for selecting the project area in Richmond, located in the Hawkesbury Nepean region, for this research. Richmond is also chosen for this flood research project due to its defined submarkets, consistent housing types, and a substantial number of properties located in flood-prone areas. Additionally, North Richmond serves as a control group, given its relative safety from floods and infrequent exposure to such events.

2.2. Literature review on flood risk studies

Floods, being the most frequent natural disasters, are experiencing an increasing impact globally [17]. The extent of this impact on properties is largely dependent on their location [18]. Numerous studies have delved into the relationship between flood risk and housing prices, utilising various methodologies and reporting diverse impacts across developed and developing nations.

The first strand of the literature examines the impact of flooding events on housing prices. Lamond et al. [19] use a repeat sales methodology to assess flood impact on residential properties in 13 UK locations and they find variability and transience in the impact with no effect of flood designation. In the United States, Daniel et al. (2009) employ a meta-analysis of 19 flood studies to evaluate the spatial incidence of risk and the implicit price of flood risk, reporting a 0.6 % drop in transaction prices for every 0.01 increase in the likelihood of flood risk. Mueller et al. [20] apply nonparametric matching techniques, revealing a 10 % decline in housing prices within 100m of a 5-year flood and 5 % within 2 km. Nguyen et al. [21], using a difference-in-difference analysis, report a 5 % discount for houses in minimum-floor level zones before flooding, with the discount tripling in flooded areas but vanishing within 15 months. Hennighausen and Suter [17] use a triple-difference hedonic framework, showing decreased prices for properties within flood-prone areas and relative increases outside the floodplain. Beltrán et al. [22], studying the price path of flooded properties in England from 1995 to 2014, report an average 24.9 % price reduction for flooded houses, which becomes statistically insignificant after 5 years. Belanger and Bourdeau-Brien [23] find a significant flood risk discount for waterfront properties, especially in the months after major flood events, but almost disappear in a hot market where homebuyers face fierce competition.

The second strand of the literature studies perceived risk using flood maps and other techniques. Bond and Dermisi [24] use Geographic Information Systems (GIS) hotspot analysis to identify spatial differentiations between pre-and-post-effects of natural disasters. They categorise their studied area into three Technical Categories (TC) to assess residents' perceptions of the risks. Mueller et al. [20] use distance to flood zones, while Wu et al. [25] incorporate riverbank landscaping to examine flood effects on housing prices. Rambaldi et al. [26] employ a hedonic model, incorporating the property's vertical distance to the flood level to study property prices in a flood-prone inner-city suburb of Brisbane, Australia. They find significant property price discounting of 5.5 % per meter below the defined once-every-100-years flood level. Tyndall [27] uses a repeat sales methodology along with the property's elevation to the sea level, showing that residential properties in Long Island, New York State, exposed to sea level rise appreciate approximately 1 % less annually than those not exposed. Tu et al. [28] use geographically weighted hedonic regression to estimate price attributes, finding price discounts for residential properties in high- and medium-risk flood zones compared to those outside the flood zone. Shi and Naylor [29] use post-quake insurance claims as a proxy for seismic risk in Christchurch, New Zealand, and find that residents underestimate the location seismic risk.

Other perspectives in the literature highlight strategies for flood risk reduction. Brandt et al. (2021) focus on the willingness of households to pay for flood insurance, revealing evidence that the National Flood Insurance Program (NFIP) in the United States is not fully utilising the information on how flood risk could lead to adverse selection as many flood-exposed households do not have coverage. Daniel et al. [30] find that household willingness to pay to avoid flood hazard ranges from −52 % to +58 % of the average property price associated with a risk exposure of 0.01 per year. In Australia, flooding accounted for over 54 % of insurance losses between 2018 and 2022 [31]. Other studies find that residents in flood-prone areas exhibit resilience, with property prices rebounding swiftly after major flood events [18,21–23,32]. Bakkensen and Ma [33] examine the role of race, ethnicity, and income in sorting out flood risk and they find that minority and low-income households are more likely to reside in high-risk flood areas. Due to rising flood risks, Vitale et al. [34] call for enhancing urban flood resilience, and Nordbeck et al. (2023) outline two hazard reduction strategies: flood defence mechanisms and load reduction to cap flood peaks using polders or controlled retention basins.

Overall, previous studies on floods have adopted several methodological approaches such as the hedonic pricing model, difference-in-difference framework, GIS, and other spatial analysis techniques including zonal delineations and property elevation from the sea level to gauge households' perception of flood risk and estimate the likely monetary effect of floods on housing prices (e.g., Ref. [35–37]; Shultz & Frigden, 2001; [27,38–40]). Their findings are somewhat limited due to the subjective nature of individual perceptions of flood risk, exclusion of location, and submarket features, highlighting cognitive limits in flood risk for residential property values. This cognitive limitation lends itself to further scrutiny that requires novel approaches to enhance the literature on flood. To fill this gap in the literature, we deploy a submarket methodological framework that is grounded on the use of flood maps to determine individual's perception of flood risk and the impact this may have on residential properties. We integrate location characteristics such as distance to the central business district (CBD), elevation, and proximity to the river, using four AEP flood measures to offer significant insights into the long-term integration of flood risk into property values.

3. Empirical estimation strategies

3.1. The models

An Ordinary Least Squares (OLS) fixed effect regression model is used to examine the financial impact of houses located in flood risk zones. The baseline OLS model is as follows:

$$\ln(P_{jst}) = \beta_0 + \beta_1 \textit{Flood Risk Zones}_{jt} + X_j + Y_j + L_s + m_t + \mu_{jt}. \tag{1}$$

where P_{jst} is the jth property's sales price in suburb s at time t. $\textit{Flood Risk Zones}_{jt}$ is a categorical variable indicating the jth property's flood risk at time t. Location flood risk is measured by AEP 100, 500, 1000, and no risk respectively. X_j is a set of time-invariant controls for covariates of property characteristics, including the number of bedrooms and bathrooms, car parks, and land area. Y_j is the property's location characteristics including the distance to the CBD, distance to the river, and elevation. L_s is the suburb fixed effect; m_t denotes the time (year and month) fixed effect; and μ_{jt} is the error term. Standard errors are clustered by AEP zones.[1]

The OLS fixed effect model is chosen for its effectiveness in disentangling causal effects, particularly in environmental and housing market analyses. It controls for time-invariant factors, such as unobserved locational amenities, that are roughly constant or slow to change. The year fixed effects account for other economic factors, such as inflation and flood events, while the month fixed effects address seasonal variations.[2] This approach helps to produce a consistent estimator by removing time-constant variables and effects. Compared to random effect models, the fixed effect model is preferred as unobserved effects are likely correlated with explanatory variables, such as locational amenities.

In the above Equation (1), AEP 100, 500, and 1000 are used as proxies for flood risk and the vector of coefficients β_1 captures the average price effect of properties located in a flood risk zone, controlling for property and location characteristics, and location and time fixed effects. To remove the effect of unobserved amenities, property characteristics are interacted with location to expand the granularity of the fixed effects. These comprehensive fixed effects capture the specific characteristics of each submarket and time period, helping to control for spatial, temporal, economic, and other factors, that may affect our results.

Spatial lag and error models are employed as robustness checks. These models are routine in environmental econometrics to account for potential location clustering and spatial spillovers, which are common in housing markets where house prices are influenced by nearby locations. Suppose that house prices are spatially correlated, Equation (1) is further extended by adding spatial lag or error, as follows:

$$\ln(P_{jst}) = \beta_0 + \beta_1 \textit{Flood Risk Zones}_{jt} + X_j + Y_j + L_s + m_t + \rho \mathrm{W} \ln(P_{jst}) + \varepsilon_{jt}. \tag{2}$$

$$\ln(P_{jst}) = \beta_0 + \beta_1 \textit{Flood Risk Zones}_{jt} + X_j + Y_j + L_s + m_t + \lambda \mathrm{W} \mu_{jt} + \varepsilon_{jt}. \tag{3}$$

In the above Equations (2) and (3), ρ is the spatial autoregressive parameter in the spatial lag model, λ is the spatial autoregressive parameter in the spatial error model, and W is the standardised spatial weights matrix. The standard Moran test is used to check for spatial correlations in the OLS residuals in Equation (1), and generalised spatial two-stage least squares are used for fitting the above spatial regressions. The Moran test checks if the OLS residuals are independent and identically distributed (i.i.d.) or if there is spatial correlation. While the two-stage least squares method is implemented to ensure consistent estimates in spatial regressions using Stata.

4. Data

4.1. House sales, sample period, property, and location characteristics

House sales data for the Richmond area, including Richmond, Hobartville, and North Richmond, are sourced from Pricefinder, a leading property intelligence platform fully owned by Domain Group and widely employed by real estate agents and property professionals across Australia. Given the challenge of infrequent transactions in high flood risk zones, we extend our data collection period from 1991 to 2023 to include the maximum number of property transactions. The potential limitations of the dataset include the lack of property condition records, and the availability of Time-on-Market (TOM) data only from 2006. While our comprehensive fixed effect models, in conjunction with spatial modelling, may help capture the specific characteristics of spatial, temporal, and economic factors, there might be still concerns of omitted variables bias that could affect our results (see Daniel et al. [30], for discussions). To minimise the influence of outliers, the sample is winsorised at 2.5 % in each tail.[3] The summary statistics for the sample data are

[1] Properties in flood-prone areas are more likely clustered according to their perceived flood risk as property transaction prices within the same flood zone are likely to be correlated. Therefore, we have clustered the standard errors at the AEP zone level.

[2] We thank the reviewer's suggestion and have re-estimated our models using real house prices, deflated by CPI. The results remain robust and are available upon request.

[3] Winsorisation is employed to mitigate the influence of outliers by replacing extreme values rather than removing them. The choice of 2.5 % is based on common practice, and while higher levels of winsorisation might distort the analysis, this level balances robustness and the potential impact of extreme values. We also verified our results without winsorisation, and our findings remained robust, though the coefficient for the high-risk zone slightly increased and its statistical significance decreased from 1 % to 5 %.

presented in Table 1.

In total, there are 6294 house sales during the sample period. The median house price stands at AUD 329,000, with a maximum of AUD 1,260,000 and a minimum of AUD 87,000. A typical house in this dataset features three bedrooms, one bathroom, and two carparks, situated on a 620 square meters land. In addition to these property characteristics, Table 1 also summarises property's location characteristics including distance to the CBD, distance to the river, and elevation. Fig. 1 displays the yearly median sale price and number of sales in the sample data since 1991, showing the price levels and transaction activities in the Richmond area over the studied period.

4.2. *Measures of location flood risk*

The location flood hazard rating relies on data from the 2019 Hawkesbury-Nepean Valley Regional Flood Study. The digital flood data map, sourced from the NSW Reconstruction Authority, is then aligned with the property transaction dataset using property (x, y) coordinates. In the 2019 Hawkesbury-Nepean flood study, flood risk is assessed through the Annual Exceedance Probability (AEP), such as AEP 5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000, to 9999, reflecting the likelihood of a flood occurrence in a given year. Since few properties fall under AEP 50, we group properties into broader classifications based on their flood risk level: (1) High risk for AEP $\leq$ 100, (2) Medium risk for 100$<$AEP $\leq$ 500, (3) Low risk for 500$<$AEP $\leq$ 1000, and (4) Extremely low or no risk for AEP$>$1000.

Fig. 2 shows property transactions and location flood risk over the study period. Graph (a) provides an overview of the entire Richmond area, Graph (b) delves into flood risk details for properties in Richmond and Hobartville, and Graph (c) focuses on flood hazard in North Richmond. It appears that the flood risk mainly pertains to the southern side of the Hawkesbury River, affecting properties on the fringe of the northern side of Richmond and the southern side of Hobartville. Notably, North Richmond experiences minimal flood impact, with high or medium flood risk is primarily confined to a few properties along the main road (Bells Line Road).

Fig. 3 depicts house price distributions and the number of sales by flood risk hazards. There are 37 house sales in the high risk zone, 943 in the medium risk zone, 853 in the low risk zone, and 4461 in the extremely low or no risk zone. The sale prices exhibit positive skewness, with prices in the medium risk zone lower than those in the low risk zone, and prices in the low risk zone lower than those in the extremely low or no risk zone. Notably, house prices in the high risk zone are higher than those in the extremely low or no risk zone. This highlights the importance of controlling for house characteristics, location, and other economic or time factors when analysing flood risk, as simple mean or median prices by flood risk zones can be misleading.

Another potential issue is that the sample distribution could distort the robustness of our results. For instance, if most property transactions occurred in a specific year, the results might be skewed, especially given the limited number of transactions in the high risk zone, where only 37 sales were recorded. To address this concern, we have included Table 1 in Appendix that displays the distribution of sales by year and flood risk zones. The table shows that the annual number of house sales is fairly distributed across the medium and low risk AEP zones. Although there are some years with zero transactions in the high risk zone, the annual number of sales is not overly concentrated in the high risk zone. Therefore, the impact of the small number of sales in the high risk zone is likely minimal.

5. Results

5.1. *Flood risk and sale price*

Table 2 presents the OLS estimation results of location flood risk on house sale prices, as outlined in Equation (1). Column (1) shows that the number of bedrooms, bathrooms, carparks, and land area are positively related to house sale prices. Meanwhile, the property's distance to the CBD negatively relates to house sale prices, indicating that all else being equal houses are generally less expensive when located farther from the town centre.

To account for potential flood risk, we further introduce two location variables in Column (2). One is the property's distance to the Hawkesbury River, and another is the property's elevation. Generally, properties located closer to rivers may be more susceptible to flooding, and higher elevation can reduce the risk of flooding. Results in Column (2) show that the distance to the river is statistically insignificant, whereas elevation is positive and weakly significant at the 10 % significance level in relation to house sale prices. These

Table 1
Summary statistics.

	House Sample (N = 6294)				
	Mean	Median	Maximum	Minimum	Std. Dev.
Sale Price (AUD)	402,717	329,000	1,260,000	87,000	282,655
Number of Bedrooms	3.35	3.00	5.00	2.00	0.71
Number of Bathrooms	1.45	1.00	3.00	1.00	0.61
Number of Carparks	1.78	2.00	4.00	1.00	0.87
Land Area (sqm)	1054	620	10,000	284	1665
Distance to CBD (m)	2131	1439	6996	50	1499
Distance to River (m)	2064	2248	3737	54	972
Elevation (m)	25.87	21.44	112.30	6.62	11.45

This table presents summary statistics of key variables for house sales in the Richmond area. The sample period is from January 1991 to October 2023.

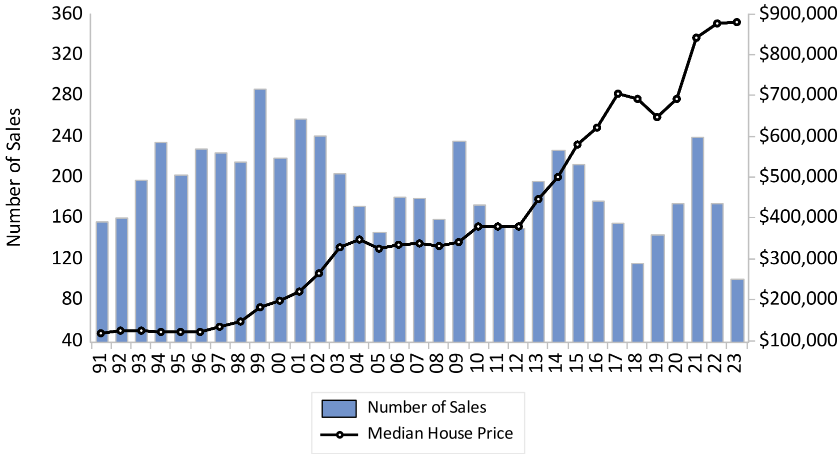

Fig. 1. Yearly median house sale prices and number of sales.
This figure displays the yearly median house sale prices and number of sales in the Richmond area during the sample period from January 1991 to October 2023.

findings suggest that, in the absence of a flood risk map, people rely on elevation rather than distance to the river to account for potential flood risk in the Hawkesbury-Nepean flood area.

Since distance to the river and elevation may also reflect other amenities such as water views, we replace them by using more accurate location AEP measures in Column (3). The location flood risk is categorised into four classes, with extremely low or no risk being the default class as discussed in Section 4.2. The results show that houses in the high risk zone (AEP $\leq$ 100) are sold at approximately 13.9 % lower on average and statistically significant at the 1 % level, compared to houses located in the extremely low or no risk zone. For houses in the medium risk zone (100<AEP $\leq$ 500), the price discounts are calculated at approximately 6.0 % and statistically significant at the 1 % level. Houses located in the low risk zone (500<AEP $\leq$ 1000) show no price discounts.

Column (4) presents the combined results from Columns (1) to (3), isolating location amenities from flood risk. It shows that elevation remains positive and statistically significant at the 5 % level to house prices in addition to AEP risk zones, which aligns with Daniel et al. [30] and Bin et al. [41] that it is important to disentangle the confounding positive and negative value exposure associated with water-related amenities. Overall, properties located in the high flood risk zone are on average sold at approximately 10.8 % lower compared to properties located in the extremely low or no risk zone. For houses located in the medium risk zone, they are sold at approximately 4.4 % lower compared to those in the extremely low or no risk zone. There are no price discounts for properties located in the low risk zone. All these results suggest that location flood risk has been capitalised into property transaction prices according to their AEP flood risk ratings but seems to be limited to the AEP 500 level. Any flood risk beyond AEP 500 tends to be ignored by the residents.

Our findings are comparable with those of Bin et al. [41]; [42], who examine hurricane-induced flood hazards in North Carolina. They find a 7.8–11 % price discount for properties within a 100-year floodplain and a 6.2 % discount for properties within a 500-year flood risk area. While our results are not directly comparable to those of Daniel et al. [30]—who report that a risk increase of 0.01 per year from the 100-year floodplain to the 50-year floodplain results in a 0.6 % drop in property value for similar houses—we observe a 10.8 % discount when moving from a no-risk zone to an AEP 100 zone and a 4.4 % discount when moving from a no-risk zone to an AEP 500 zone. However, we lack the data to analyse the price discount when risk increases from AEP 100 to AEP 50. It is worth noting that the price discount related to flood probability increases could be non-linear, especially when the risk increases from a very low-risk area to a high-risk area.

5.2. Spatial structure and omitted variables

Our baseline OLS regression results in Table 2 may be influenced by geographic relationships between sales. It is likely that house prices tend to exhibit location clustering and are subject to spatial spillovers. This is particularly apparent when house values are based on surrounding comparable properties. To address concerns that our OLS models might display some spatial clustering in the errors, we conduct additional spatial regression analysis for robustness checking. We first build a standardised spatial weights matrix based on the inverse great circle distances between sales, using property's (x, y) coordinates. The distance band is set within a 1 km circle from each sale.[4] The Moran test for spatial dependence among the OLS residuals from using the spatial weighting matrix obtained above, is moderately significant with a Chi-square value of 5.45 and a p-value of 0.0196. The modest Moran statistics align with expectations, as our baseline OLS models, bolstered by extensive fixed effects, perform well, as demonstrated in Table 2, with high R-squared values of

[4] We also conduct an analysis with a distance band of 0.5 km. The results are similar to the 1 km distance band and are available upon request from the authors.

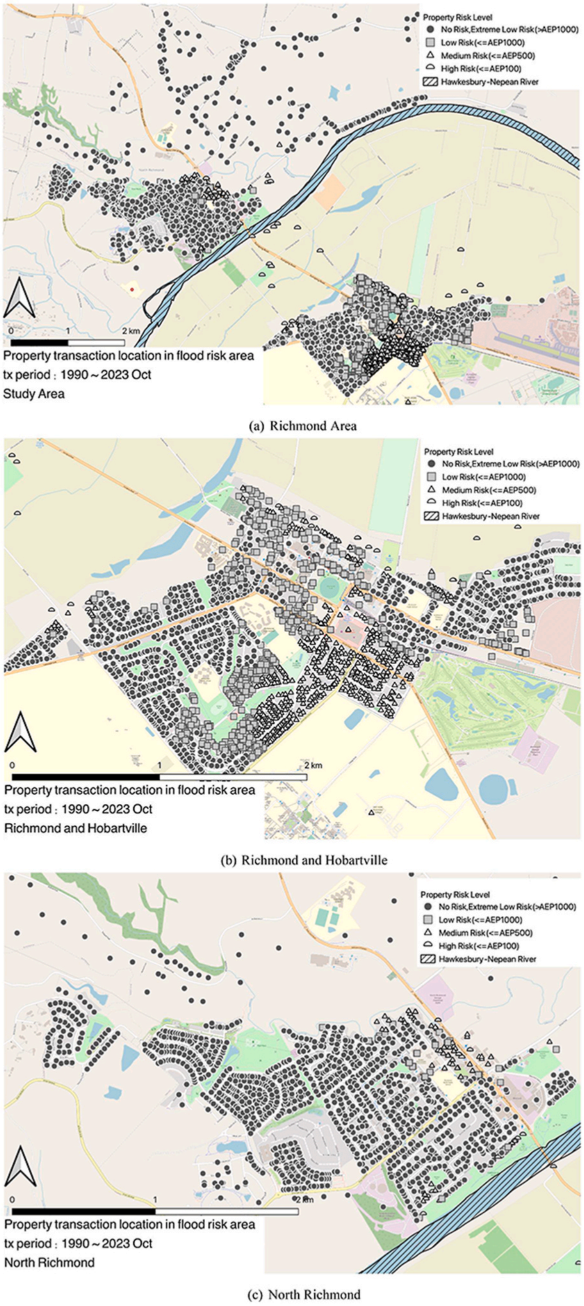

Fig. 2. Map of property transactions and location flood hazard.

around 0.879.

We then fit spatial lag and spatial error models to our sale data using generalised spatial two-stage least squares. The results, reported in Columns (1) and (2) of Table 3, indicate that the parameter of spatial lag in Column (1) is statistically insignificant, while the spatial error effect is statistically significant in Column (2). The results of these models indicated that spatial dependence is present in the error terms but not in house prices themselves, suggesting that while some omitted variables might influence house values, they are not causing spillover effects in the observed house prices (see Bin et al. [42], for spatial model discussions). Overall, the spatial regression results support our main findings that properties located in the high risk zone are sold at approximately 10.6 % price discounts, 4.4 % discounts for properties in the medium risk zone, and no price discounts for properties in the low risk zone.

To address concerns of omitted variables in our OLS models, we expand the granularity of the fixed effects as shown in Columns (3)–(4) to reduce the potential bias in our estimates. In addition to controlling for time effects, we apply additional locality (suburb), bedrooms, bathrooms, and car parks fixed effects in Column (3), and combined (locality x bedrooms x bathrooms x car parks) fixed

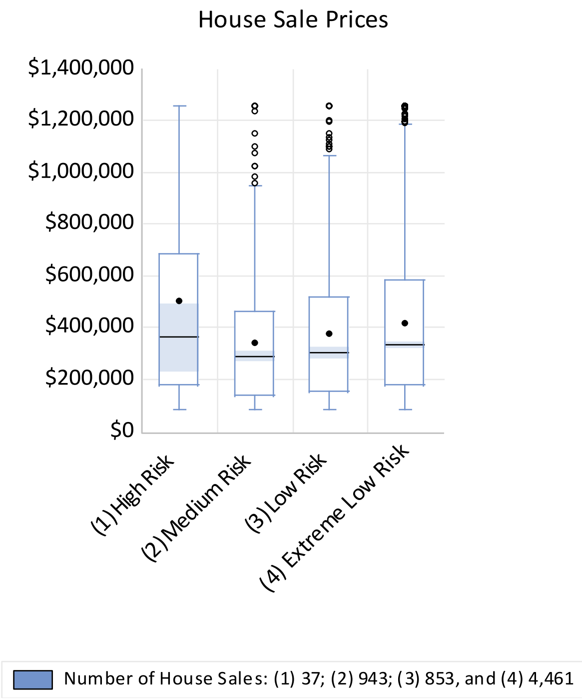

Fig. 3. Price distributions and number of sales by flood hazard.
This figure displays house price distributions and the number of sales by flood risk hazards during the sample period from January 1991 to October 2023. It underscores the importance of controlling for house characteristics, location, and other economic or temporal factors when analysing flood risk, as simple mean or median prices by flood risk zones can be misleading, particularly for properties in high-risk zones.

effects in Column (4). Although the impact of flood risk ratings on house prices appears slightly smaller in Column (4), the results are in line with our main findings.

5.3. Cognitive limits to the uncertainty of perceived flood risk

We have used the flood risk ratings from the 2019 Hawkesbury-Nepean Valley Regional Flood Study to assess the financial impacts of flood risk on house sale prices. It appears that flood risk has been capitalised into property transaction prices up to AEP 500. However, the accuracy of flood raises concerns, as assumptions with rainfall, topography, climate change and modelling techniques in these flood studies are subject to change, leading to uncertainty in flood risk ratings. In 2023, the NSW government conducted a review of flood study, providing updated flood risk maps for the Hawkesbury-Nepean Valley region. The new 2023 flood study provides a unique opportunity to explore people' cognitive limits in the face of the uncertainty associated with perceived flood risk.

Panel A of Table 4 describes the number of house sales based on the 2019 AEP ratings. Among the 6115 house sales, 4628 have confirmed AEP ratings, meaning both the 2019 and 2023 assessments assigned the same AEP ratings to these properties. Additionally, 1487 homes have upgraded AEP ratings from the 2023 flood map, signifying an increase in the level of flood risk. There are no observations with downgraded AEP ratings from the 2023 assessment. This absence suggests that the risk levels identified in the 2023 flood study are more severe than those in the 2019 flood study, reflecting worsening climate changes and their impact on regional flooding hazards.

Panel B of Table 4 presents the OLS regression results based on both the 2019 and 2023 AEP ratings, with the default flood risk level set as the confirmed extremely low or no risk class. For house sales with confirmed AEP ratings in the high or medium risk zones, their estimated price discounts are generally larger and statistically significant compared to their counterparts. For example, the average price discounts for properties in the high risk zone is 10.8 % according to the 2019 AEP rating, compared to 12.1 % for properties with confirmed 2023 AEP ratings in the high risk zone. Similar findings are also observed for properties in the medium risk zone, where a 4.4 % compared to 5.6 % price discount for confirmed AEP ratings. The results suggest that for properties located in confirmed high or medium AEP rating zone, the magnitude of price discount is generally reinforced. In addition, for properties in the extremely low or no risk zone, AEP confirmation has little impact on the property's sale price.

For houses with upgraded AEP ratings from AEP 1000 to AEP 500, their values decrease, with the magnitude being statistically significant. Since the upgrade or downgrade of AEP ratings most likely occurs for properties situated close to the associated AEP boundaries on either side, their perceived levels of flood risk may not be clearly identified in practice. The coefficient for an upgraded flood risk from AEP 500 to AEP 100 is −0.057, which is reasonable compared to −0.121 for confirmed AEP 100, given these houses are likely located close to the AEP 100 boundary on the AEP 500 side. However, the coefficient for an upgraded flood risk from AEP 1000

Table 2
Baseline OLS regression results.

	(1)		(2)		(3)		(4)	
	Dependent Variable: Ln(Sale Price)							
Ln(Number of Bedrooms)	0.133	b	0.131	b	0.133	b	0.131	b
	(0.034)		(0.036)		(0.035)		(0.036)	
Ln(Number of Bathrooms)	0.166	a	0.163	a	0.165	a	0.163	a
	(0.012)		(0.012)		(0.012)		(0.013)	
Ln(Number of Carparks)	0.077	a	0.076	a	0.075	a	0.075	a
	(0.010)		(0.010)		(0.010)		(0.010)	
Ln(Area)	0.179	a	0.169	a	0.183	a	0.176	a
	(0.009)		(0.009)		(0.006)		(0.005)	
Ln(Distance to CBD)	−0.052		−0.056	c	−0.066	b	−0.062	b
	(0.023)		(0.020)		(0.016)		(0.013)	
Ln(Distance to River)			−0.014				−0.013	
			(0.013)				(0.012)	
Ln(Elevation)			0.090	c			0.061	b
			(0.035)				(0.013)	
High Risk (AEP ≤ 100)					−0.139	a	−0.108	a
					(0.015)		(0.012)	
Medium Risk (100<AEP ≤ 500)					−0.060	a	−0.044	a
					(0.004)		(0.003)	
Low Risk (500<AEP ≤ 1000)					−0.006		0.003	
					(0.005)		(0.002)	
Adjusted R squared	0.877		0.877		0.877		0.879	
N	6294		6294		6294		6294	
Locality FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	

This table presents our baseline OLS regression results for assessing the impact of location flood risk on transaction prices. Column (1) is the basic OLS regression accounting for factors influencing house prices, while Columns (2)–(4) employ various flood risk specifications to explore the financial impact of flood risk on house prices. Flood risk is a categorical variable which is classified into high, medium, low, and extremely low or no risk, based on their associated AEP levels in the 2019 Hawkesbury-Nepean Valley Regional Flood Study. The default category is the extremely low or no risk class in Columns (3) and (4). The sample is based on house sales in the Richmond area, encompassing Richmond, Hobartville, and North Richmond in New South Wales, spanning from January 1991 to October 2023. The standard errors are shown in parentheses and are clustered by AEP levels. Significance levels:.

[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

to AEP 500 is −0.002 and statistically insignificant, compared to −0.056 for confirmed AEP 500, suggesting that people have limitations and barriers in perceiving flood risk beyond AEP 500. It appears that people's perceived flood risk is bounded by a threshold. When the event probability falls below a certain level, the risk is simply ignored, which aligns with the existing behavioural theory [8–11]. This finding is further supported when the risk level is upgraded from AEP>1000 to AEP 1000, where the coefficient is statistically insignificant. Our findings are consistent with those of Lamond et al. [19], who find no discernible difference between properties inside and outside the 1000-year floodplain, and with Daniel et al. [30], who highlight the challenges associated with subjective perceptions of very small risks. Overall, our results suggest that people can reasonably distinguish risk for high-frequency events, and their cognitive ability to assess flood risk is limited to the AEP 500 level.

5.4. Days to sell

Liquidity is a concern as it might take longer to sell if properties are in a rated flood zone. Literature shows that the property's time-on-market is influenced by factors such as the seller's motivation, specifically the list price, in addition to the property's physical characteristics and market conditions [43–45]. To assess the impact of flood ratings on a property's time-on-market (TOM), we conduct a two-stage least squares (2SLS) method to account for the potential endogeneity issue between the property's transaction price, list price, and its marketing time, similar to the estimation strategy employed by Yavas and Yang (1995), Knight [44], Zahirovic-Herbert et al [46]. To be specific, we have

$$\ln\left(Tom_{jst}\right) = \beta_0 + \beta_1 \textit{Flood Risk Zones}_{jt} + \beta_2 \ln\left(\widehat{P_{jst}}\right) + \beta_3 \ln\left(LP_{jst} / \widehat{P_{jst}}\right) + L_s + m_t + \varepsilon_{jt}. \tag{4}$$

Where LP_{jst} is the jth property's list price in suburb s, and $\widehat{P_{jst}}$ is the predicted jth property's sale price based on the hedonic regression:

$$\ln\left(P_{jst}\right) = C_0 + X_j + L_s + m_t + \varepsilon_{jt}. \tag{5}$$

Where P_{jst} is the jth property's sale price, C_0 is constant, X_j is a vector of property's characteristics including number of bedrooms,

Table 3
Spatial regressions and expanded fixed effects.

	(1)		(2)		(3)		(4)	
	Dependent Variable: Ln(Sale Price)							
Ln(Number of Bedrooms)	0.131	a	0.132	a				
	(0.019)		(0.019)					
Ln(Number of Bathrooms)	0.162	a	0.160	a				
	(0.011)		(0.011)					
Ln(Number of Carparks)	0.075	a	0.075	a				
	(0.008)		(0.008)					
Ln(Area)	0.175	a	0.176	a	0.174	a	0.166	a
	(0.006)		(0.006)		(0.011)		(0.011)	
Ln(Distance to CBD)	−0.062	a	−0.064	a	−0.062	b	−0.070	a
	(0.010)		(0.010)		(0.017)		(0.007)	
Ln(Distance to River)	−0.013	b	−0.012	c	−0.012		−0.010	
	(0.006)		(0.007)		(0.010)		(0.012)	
Ln(Elevation)	0.061	a	0.062	a	0.061	b	0.059	b
	(0.016)		(0.017)		(0.023)		(0.015)	
High Risk (AEP ≤ 100)	−0.108	b	−0.106	b	−0.110	a	−0.100	a
	(0.044)		(0.044)		(0.056)		(0.007)	
Medium Risk (100<AEP ≤ 500)	−0.044	a	−0.044	a	−0.044	a	−0.040	a
	(0.010)		(0.010)		(0.012)		(0.001)	
Low Risk (500<AEP ≤ 1000)	0.004		0.004		0.004		0.006	c
	(0.011)		(0.011)		(0.012)		(0.002)	
Spatial Lag Effects (ρ)	0.014							
	(0.009)							
Spatial Error Effects (λ)			1.930	a				
			(0.142)					
Pseduo or Adjusted R squared	0.879		0.879		0.878		0.882	
N	6294		6294		6294		6294	
Locality FE	Yes		Yes		No		No	
Locality, Bedrooms, Bathrooms, Car parks FE	No		No		Yes		No	
Locality x Bedrooms x Bathrooms x Car parks FE	No		No		No		Yes	
Year FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	

This table presents the results of spatial regressions and expanded fixed effects to account for potential spatial correlation between house sales and omitted variables in our OLS estimations, based on Equations (2) and (3). Column (1) is testing for the spatial lag model and Column (2) is testing for the spatial error model. The standardised spatial weights matrix is based on the inverse great circle distances between sales with a distance band of a 1 km circle from each sale. The spatial regressions are analysed using generalised spatial two-stage least squares. Columns (3)–(4) show various expanded fixed effects to account for omitted variable bias. The standard errors are shown in parentheses. For Columns (3)–(4) standard errors are clustered by AEP levels. Significance levels.

[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

bathrooms, carparks, and property types. L_s is location (suburb) fixed effects, and m_t is the year and month fixed effects, and ε_{jt} is the error term.

In the above regressions, $\ln\left(\widehat{P_{jst}}\right)$ controls for the impact of the property sale price on the property's TOM, and $\ln\left(LP_{jst}/\widehat{P_{jst}}\right)$ accounts for the extent of overpricing of the property's list price during the marketing period. Since the property's TOM and list price data are not available before 2007, and not every sale in the supplied dataset has a recorded TOM or list price, this results in 2283 sales for the TOM analysis and 1033 sales when accounting for list prices.

The TOM results are reported in Table 5. Column (1) is based on the OLS regression for comparison purposes, while Columns (2) and (3) are based on the 2SLS regressions. Column (1) shows that properties located in the high risk zone take 38 % longer to sell, while properties in the medium risk zone sell 13 % faster, and there is no difference for properties in the low risk zone, compared to properties in the extremely low or no risk zone. As we discussed above, there are potential endogeneity issues between a property's sale price, list price, and TOM, which means the estimated coefficients in the OLS regression in Column (1) may be biased. Therefore, we use the 2SLS method to quantify the impact of flood risk zones on a property's TOM, controlling for its list price and predicted sale price. Column (2) shows that after controlling for the property's predicted sale price, TOMs are about 52 % and 7 % longer (significance at the 5 % level) for properties located in the high risk and low risk zones, respectively. Meanwhile, TOMs for properties located in the medium risk zone are not significantly different from those in the extremely low or no risk zone in the 2SLS regressions. The results are generally supported by Column (3), which accounts for the extent of overpricing by the property's list price. In addition, it shows that overpricing significantly affects the property's TOM - a higher list price relative to its predicted sale price results in a longer TOM, which is consistent with real estate transactions,

The finding that properties in the high risk zone take significantly longer to sell is not surprising, as these areas face liquidity issues due to limited buyer interest. In theory, there should be no difference in TOM between properties across different risk zones if they are

Table 4
Cognitive limits to the uncertainty of flood risk ratings.

Panel A: The Number of Sales by the 2019 and 2023 Flood Risk Ratings						
	2019 AEP		Confirmed AEP		Upgraded AEP	
High Risk (AE 100)	36		36			
Medium Risk (AEP 500)	923		901		22	
Low Risk (AEP 1000)	832		364		468	
Extreme Low or No Risk (AEP>1000)	4324		3327		997	
Total	6115		4628		1487	
Panel B: Estimated Regression Coefficients						
	2019 AEP Dependent Variable: Ln(Sale Price)		Confirmed AEP		Upgraded AEP	
High Risk (AEP 100)	−0.108	a	−0.121	a		
	(0.012)		(0.015)			
Medium Risk (AEP 500)	−0.044	a	−0.056	a	−0.057	b
	(0.003)		(0.003)		(0.015)	
Low Risk (AEP 1000)	0.003		−0.003		−0.002	
	(0.002)		(0.003)		(0.003)	
Extreme Low or No Risk (AEP>1000)					−0.006	
					(0.004)	

Panel A describes the number of house sales categorised by the 2019 AEP ratings, distinguishing between those confirmed or unconfirmed by the 2023 AEP ratings. Confirmed AEP ratings indicate consistent flood risk levels between the 2019 and 2023 assessments. Upgraded AEP ratings signify an increase flood risk level in the 2023 assessment compared to the 2019 assessment. The dataset contains no downgraded AEP observations. Panel B presents the OLS regression results based on Equation (1). The 2019 AEP results are directly exacted from Column (4) of Table 2. Confirmed AEP and upgraded AEP are treated as categorical variables and merged into a single variable in the OLS regression of Equation (1). The default category is the confirmed AEP class with extremely low or no risk. The standard errors are shown in parentheses and are clustered by AEP levels. Significance levels.

[a] $p < 0.01$.

[b] $p < 0.05$.

Table 5
Days to sell.

	(1)		(2)		(3)	
	Dependent Variable: Ln(Days to Sell)					
High Risk (AEP ≤ 100)	0.381	b	0.516	b	0.561	c
	(0.117)		(0.107)		(0.185)	
Medium Risk (100<AEP ≤ 500)	−0.132	b	−0.023		−0.002	
	(0.025)		(0.011)		(0.018)	
Low Risk (500<AEP ≤ 1000)	0.006		0.066	b	0.057	b
	(0.032)		(0.016)		(0.017)	
Ln(Sale Price-hat)			0.984	a	0.772	a
			(0.054)		(0.085)	
Ln(List Price/Sale Price-hat)					0.387	b
					(0.097)	
Adjusted R squared	0.1082		0.1033		0.1049	
N	2283		2283		1033	
Property and location Characters	Yes		No		No	
Locality FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	

This table presents the results of flood risk ratings on a property's time-on-market (TOM). Columns (1) is the basic OLS regression, and Columns (2)–(3) are estimated using a Two-Stage Least Squares (2sls) regression. Since not every sale has recorded a TOM or list price, this results in only 2283 observations in Columns (1) and (2), and 1033 observations in Column (3). Sale Price-hat is the predicted property sale price based on the hedonic regression model using Equation (1), and List Price is the property's first list price on the market. The standard errors are shown in parentheses and are clustered by AEP levels. Significance levels.

[a] $p < 0.01$.

[b] $p < 0.05$.

[c] $p < 0.1$.

appropriately priced within a liquid market. However, the slower sale of properties in the low risk zone compared to those in the medium and no risk zones might suggest that residents in the low risk zone are optimistic about potential flood risk.[5] This is possible as people in the low risk zone may infrequently experience flood risk (between AEP 500 and AEP 1000), which might lead to an 'optimism

[5] The market liquidity is similar between the medium and low risk zones. See Fig. 3 for the sales sample size in the medium and low risk zones.

or threshold bias' that contributes to a gap between perceived and objective risk [17,47,48]. In a meta-analysis of 19 empirical flood studies in the US, Daniel et al. [30] clearly demonstrate the problems associated with subjective perceptions of generally very small risks. Similarly, Lamond et al. [19] find flood designations in low risk areas, particularly in the absence of flood events, are not well received. These cognitive limitations, including challenges in obtaining information on probability, may lead to disaster myopia [49–51], where homeowners in the low risk zone exhibit undue optimism about potential flood risks, resulting in slightly longer TOM for selling real estates. Overall, our findings on TOM support previous results on property prices, suggesting that cognitive limitations are particularly evident at the AEP 500 level.

6. Conclusion and policy implications

Floods are one of the most common and devastating natural disasters that affect millions of people across the globe each year. Flood episodes often impact property values and highlight the importance of households' perception of flood risk, which collectively feeds into climate change and sustainability discourse. As evident in contemporary literature, flood events are pervasive, further deepening the interest of academics, advocacy groups, and policymakers. The findings from previous studies are somewhat limited in scope as they tend to ignore local factors. They also reveal that flood decisions are based on individual perceptions rather than objective risk, generating cognitive biases. We fill this gap in the literature by investigating the impact of perceived flood risk on property values. We case-study the Richmond area of New South Wales in Australia and accentuate the role of flood maps in shaping an individual's risk perceptions in housing decisions. Our submarket methodological framework draws from the 2019 and 2023 flood maps and integrates location characteristics such as distance to the central business district (CBD), elevation, and proximity to the river, using four AEP flood measures.

Analysing home sales data in Richmond, the study reveals that residents have indeed integrated long-term flood risk into their decision-making processes. Properties within a 1-in-100 AEP flood zone, on average, sell at an 10.8 % discount, while house values experience a discount of approximately 4.4 % in a 1-in-500 AEP flood zone. No discounts are observed for properties within a 1-in-1000 AEP and beyond flood zones, in comparison to properties located in areas with extremely low or no flood risk. Further examination indicates that discounts are more significant and reinforced when the property's flood risk ratings are confirmed by both the 2019 and 2023 flood maps. Individual cognitive limits related to perceived flood risk appear to be constrained to the AEP 500 level, as an upgrade in risk from AEP 1000 to AEP 500 does not affect house values. Interestingly, properties in high flood-prone areas generally take longer to sell. The slower pace of sales for properties in the low risk zone (between AEP 500 and AEP 1000) compared to those in the medium risk zone (between AEP 100 and AEP 500) may indicate a threshold bias in perceived flood risk. Residents in the low risk zone may be overly optimistic about the likelihood of flood damage due to the infrequency of such events in these areas. Therefore, the results of our time-on-market analysis support our main findings in the price analysis that perceived flood risk is limited to the AEP 500 level.

The implications of these findings extend to flood risk management, highlighting the substantial influence of flood maps on individuals' risk perceptions. Consequently, a modern, accurate, and regularly updated flood risk rating system emerges as crucial for effectively communicating potential flood risk awareness and future financial costs to the public. Throughout this process, a well-maintained flood rating system, coupled with risk-adjusted flood insurance premiums, can send a clear signal of flood risk to market participants and stakeholders, contributing to the mitigation of future flood risk.

For future research, it would be valuable to explore the cognitive limits of perceived risks associated with other types of environmental hazards, such as coastal inundation, bushfires, and earthquakes, particularly when probability factors are involved in assessing potential damages. Our empirical findings suggest that risk perception is limited to the AEP 500 level, but this threshold may vary depending on the type of risk and across different geographic regions. Investigating these variations could reveal whether the results are consistent in other contexts and provide insights into more effective risk communication strategies. Additionally, employing innovative methodologies in risk assessment, such as advanced data analytics, machine learning, or behavioural economics, could offer a deeper understanding of how risk perception influences property values, aiding in the development of policies that better integrate environmental risk forecasts into urban planning and property markets.

CRediT authorship contribution statement

Song Shi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mustapha Bangura:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization. **Sumita Ghosh:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

None. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table 1
Property transactions by year and AEP levels

	High Risk	Medium Risk	Low Risk	Extreme Low Risk	Total
Year	AEP 100	AEP 500	AEP 1000	AEP >1000	
1991	1	18	13	125	157
1992	0	25	22	113	160
1993	3	34	24	137	198
1994	1	33	31	170	235
1995	2	32	36	132	202
1996	0	62	41	125	228
1997	0	32	43	149	224
1998	2	29	30	154	215
1999	2	40	35	210	287
2000	1	40	24	154	219
2001	1	39	41	177	258
2002	3	37	35	166	241
2003	0	30	30	144	204
2004	1	28	17	126	172
2005	3	23	25	96	147
2006	0	22	24	135	181
2007	2	20	28	129	179
2008	0	31	22	106	159
2009	0	42	31	163	236
2010	0	25	30	118	173
2011	1	22	20	108	151
2012	4	26	16	104	150
2013	0	26	22	148	196
2014	1	28	21	177	227
2015	0	30	25	158	213
2016	1	30	27	119	177
2017	0	17	31	108	156
2018	1	23	12	80	116
2019	1	14	19	110	144
2020	1	20	22	131	174
2021	4	38	20	177	239
2022	1	19	26	129	175
2023	0	8	10	83	101
Total	37	943	853	4461	6294

This table presents the house sales by year and AEP zones in the studied area between January 1991 to October 2023.

Data availability

The authors do not have permission to share data.

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