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FFA Working Paper 2/2026

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Bibliographic information:

Folprecht M. (2026). Measuring Flood Risk in Czechia with Stress Testing and a Gumbel copula based VaR. FFA Working Paper 2/2026, FFA, Prague University of Economics and Business, Prague.

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Abstract

Prices of houses in flood risk zones are subject to a price discount reflecting the risk of losses caused by floods. First, the article establishes a framework for pricing flood risk using the expected discounted loss approach, based on the capital asset pricing model and the Gumbel mixture model of estimated likelihood and impacts of flood risk events. The measure of flood risk advantage is dimensionality reduction and interpretability. Second, the resulting measure of is tested to assess whether it can explain differences in house prices using a large data sample from the Czech Republic in 2024. I show that the flood risk measure, expected discounted loss, can be a significant predictor of house prices, but its explanatory power depends critically on the data source used for determining flood risk zones. The results indicate that the market does price flood risk but tends to underestimate its magnitude. Moreover, it does not adjust the weight assigned to flood risk even after severe flood events. Lastly, I discuss the potential use of the obtained flood risk loss distributions for the calculation of Value at Risk and other risk measures of portfolios, including direct real estate or real estate used as collateral.

AMS/JEL classification: R31, Q53, G32

Keywords: Expected discounted loss, Flood risk, House prices, Hedonic pricing model, Czech Republic

Acknowledgement

The author gratefully acknowledges Seznam.cz and its real estate portal Sreality.cz for providing the extensive house prices dataset used in this study.

Funding

The study was supported by the Czech Grant Agency (24-10008S) and Vysoká Škola Ekonomická v Praze (IGS F1/27/2025).

I. Introduction

Flood risk is becoming an increasingly important factor in real estate valuation in the context of ongoing climate change with the growing evidence of extreme weather events. One in 6 English properties are projected to be exposed to medium or high flood risk in 2050 (Lux and Andrew, 2023). Inundation event is reported to be the most economically damaging type of natural disaster in the United States (Shu et al., 2022) and the most frequent natural disaster in the world (CRED, 2020). However, traditional property valuation methods employed by appraisers and financial institutions likely ignore or undervalue the valuation discount associated with houses situated in flood zones (Harrison et al., 2001). Such ignorance might lead to negative consequences. First, banks ignoring negative flood valuation effect end up giving loans that would otherwise violate risk thresholds of LTV (loan to value). Moreover, credit risk of such loans would be underestimated as borrowers might default during the inundation event so that the bank ends up receiving depreciated house (LGD underestimation).

In some countries such as the USA or UK, property tax is based on its assessed value (ER, 2025). Purchasers of houses there may face disproportionately higher tax burden. Finally, ignorance of flood risk by investors may decrease returns for the ignorant investor when floods realize. Besides ignorance in the valuation methods, imperfections in flood map modelling or completely missing flood maps for certain regions lead to overvalued property markets (Shu et al., 2022).

The purpose of this article is to develop a theoretically well-grounded method of pricing houses in flood zones using the EDL (expected discounted loss) framework and suggest a practical percentage price discount table for Czech houses based on an empirical analysis which could be applied by house pricing experts. The advantages of EDL method are interpretability, a simple, linear relationship to the house price and accounting for continuous nature of flood risk, meaning the varying severity of flood risk (e.g., precise water depth calibrated to a flood hazard map) rather than relying on discrete, categorical indicators. While the EDL method is not completely new, expected losses were so far calculated using insurance premiums (Harrison et al., 2001) as a proxy rather than based on raw risk hazard maps. Secondly, the discount rate applied in previous research was rather often an arbitrary constant (Harrison et al., 2001) while this paper uses the more robust CAPM model, adapted for real estate by (Damodaran, 2012). Each house is geolocated with high precision, allowing for an accurate assessment of flood risk. This contrasts with previous studies (Lux and Andrew, 2023) which rely on simplifications such as postcode-level flood zone matching. As far as I know, this study is one of the first large-scale empirical studies linking flood risk to house prices in Central Europe, a region that remains underrepresented in literature. Most existing research focuses either on major economies like the US and UK, or on flood-vulnerable cities in developing countries. The Czech context therefore provides a valuable case study for understanding how flood risk is priced in a mid-sized, developed economy with a history of severe flood events. The first hypothesis to be tested is:

- **H1:** *Market house prices are significantly influenced by flood risk.*

A secondary research goal is to test whether market house prices are influenced by official administrative flood zones, in Czechia governed by Water Act (Czechia, 2001) provided by VUV (T. G. Masaryk Water Research Institute, 2025) or rather by more granular hazard datasets, such as the JRC river flood hazard maps (European Commission, JRC, 2025), which provide high-resolution water depth information across a significantly broader range of return periods. Current research suggests that administrative classification rather than objective flood risk is perceived by the market as changes in map classification have an impact on property prices as well as media attention to that topic (Shu et al., 2022). If markets had their own view of flood risk, reclassification of administrative flood zones would not affect house prices. The next hypothesis to be tested is:

- **H2:** *Market house prices are more significantly influenced by official administrative flood maps (VUV) than by more granular hazard datasets (JRC).*

A third research goal is to test whether market participants reflect flood risk in house prices. Current research (Harrison et al., 2001) suggests that market prices reflect flood risk only partially as sellers prefer to transact with buyers whose subjective expectation of flood related losses are relatively low. The assumption is that market participants do not have homogeneous assumptions regarding flood risk. This information asymmetry leads to the market that absorbs information about flood risk only partially, to the extent that the most optimistic buyers see it. The hypothesis is tested using a hedonic price regression model (Harrison and Rubinfeld, 1978). The house price against EDL regression introduces an endogeneity problem as EDL is itself calculated from the dependent variable, price. The solution is presented in chapter III. The hypothesis being tested is:

- **H3:** *Market participants systematically underestimate flood risk due to the selection bias of optimistic buyers, as proposed by Harrison et al. (2001).*

The fourth hypothesis is related to the time dimension of flood risk. Markets are known to by cyclical, for example by switching from fear phases to greed phases (or equivalently risk-on and risk-off phases). Since there has been a big flood event in 9/2024, the house prices in the fourth quarter might suffer from risk-on effect (market pricing higher part of the flood risk compared to calm periods).

- **H4:** *Sensitivity of house prices to flood risk is higher in Q4 2024 than in previous periods*

II. Literature review

Various studies have registered that houses located in flood zones are inclined to sell at a discount compared to equivalent houses outside of these zones (Harrison et al., 2001); (Lux and Andrew, 2023); (Shu et al., 2022); (Bosker et al., 2014). Not only actual flood risk but also the quality of data matters. Changes in map classification might have an impact on property prices as well as media attention to that topic (Shu et al., 2022). Other studies find that severe flood event has an effect on the house prices in the area (Bui et al., 2024).

A common empirical approach is to distribute properties to discrete flood zone categories and estimate their impact on prices using a hedonic price model (Lux and Andrew, 2023); (Shu et al., 2022). However, this approach has several limitations. Mainly, the use of discrete flood zone indicators fails to capture the continuous nature of flood risk and its financial impact. Alternative approach is to use insurance premiums and estimate the impact of its present value on prices. It might be tempting to assume that the reduction in flood risk zone house value should be equal to the present value cost of all future flood insurance premiums. However, (Harrison et al., 2001) shows that the cost of flood insurance serves only as a limit for the negative valuation effect because house sellers prefer to transact with buyers which are not willing to pay the insurance (personal expectation of present value of flood losses is less than the insurance premium) which drives the house prices above the level predicted by this valuation method. In fact, only less than half of the structures in the FEMA flood zones are insured. Moreover, the authors note that not all structures within flood zones are insurable. Next, insurance has limited availability in certain regions, for example (Phung et al., 2017) report underdeveloped flood insurance market in Vietnam due to effects such as loss aversion or wishful thinking (the belief that flooding will not happen again). Finally, insurance premiums may be distorted by factors such as insurer margins and regulatory pricing rather than reflecting the expected present value of losses.

This paper bridges this gap by developing a theoretically grounded method for pricing flood risk using the expected discounted loss (EDL) framework, consistent with the capital asset pricing model proposed by (Damodaran, 2012). By calibrating the likelihood and severity of flood events through a Gumbel (or other) distribution to fit flood hazard maps, the EDL approach allows for a quantification of flood risk at each individual property. This enables us to find a linear relationship between flood risk and property prices, overcoming the limitations of categorical flood zone indicators. While conceptually resembles approaches based on the flood insurance premiums as a proxy for flood risk valuation, the method developed in this paper differs in several key aspects. First, it is based on raw flood hazard data, the estimated likelihood and severity of flood events, rather than on insurance premiums, which may be distorted by factors discussed above. Moreover, the framework can be extended beyond expected value calculations to assess tail risks, making it suitable not only for pricing but also for risk management applications such as Value at Risk and stress testing (Folprecht, 2026).

Next contribution of this study is the use of an extensive dataset covering house advertisement details across the whole Czech Republic in 2024. Each house is geolocated with high precision, allowing for an accurate assessment of flood risk. This contrasts with previous studies (Lux and Andrew, 2023) which rely on simplifications such as postcode-level flood zone matching. As far as I know, this study is one of the first large-scale empirical studies linking flood risk to house prices in Central Europe, a region that remains underrepresented in literature. Most existing research focuses either on major economies like the US and UK, or on flood-vulnerable cities in developing countries. The Czech context therefore provides a valuable case study for understanding how flood risk is priced in a mid-sized, developed economy with a history of severe flood events.

The rest of the paper is organized as follows. First, the EDL research method is presented in Section III. Next, calibration of the model to available data is discussed, followed by a section on how to integrate EDL into the hedonic pricing framework. Next, data description and variables are discussed in Section IV and empirical results of the house price model are presented in Section V. Advantages of the method and its limitations are discussed in Section VI.

III. Research Method

The research methodology adjusts the established framework of expected discounted (Harrison et al., 2001) by calculating flood losses based on raw data, specifically flood hazard maps combined with depth-damage functions adopted from (Huizinga et al., 2016). Secondly, it uses the CAPM method of (Damodaran, 2012) for discounting these losses.

The modelled expected discounted loss is then used as a predictor in a regression model to get the market sensitivity parameter for the calculated EDL. The sensitivity parameter is used to test hypotheses H1–H4 and, by multiplying EDL with market sensitivity, a flood discount table, which could be practically used by appraisers, is calculated.

Valuation Model: Integrating Flood Risk via Expected Discounted Loss

The starting point of the analysis is a simple theoretical relationship between flood risk and house prices in flood zones. In the absence of flood risk, the value of a property reflects the market value of a counterfactual (the house with same parameters but not located in a flood zone), denoted as V_0. The presence of flood risk shifts this value by the present value of expected financial losses associated with potential flooding (*EDL*):

$$V = V_0 - EDL \tag{1}$$

The V_0 itself is a present value of expected yields related to owning the house. In case of holding the house for investment, it is the present value of future expected rental yields. In case of holding the house for living, (in the absence of tax effects) it is also the rental yield because by living in the house, the owner sacrifices the rental income (it is the opportunity cost). This concept is referred to as imputed rent.

The value V_0 therefore can be expressed as the sum of discounted expected yearly rental income $E[R_t]$ over time t going over the years *t=1, 2…T*, where *T* is the lifespan of the house and r is the required rate of return. In this study, 100 years is used as a lifespan as a proxy (in reality, it depends on the building type). Rental income can be estimated using its current market value and projection of its future growth.

$$V_0 = \sum_{\mathrm{t=1}}^{\mathrm{T}} \frac{E[R_t]}{(1+r)^t} \tag{2}$$

By analogy, as losses are conceptually nothing else but negative returns, expected discounted loss *EDL* can be expressed as the sum of discounted expected yearly losses $E[L_t]$ over time *t* going over the years *t=1, 2…T*:

$$EDL = \sum_{t=1}^{T} \frac{E[L_t]}{(1+r)^t} \tag{3}$$

A key question arises – how to calculate the required rate of return? Earlier study by (Harrison et al., 2001) used a fixed rate of 8 percent. Although the chosen value is inside the range of a typical yield of house investment, it is rather arbitrary. In this study, the CAPM approach of (Damodaran, 2012) is adopted.

The proposition of (Damodaran, 2012) is that valuation models developed for financial assets are applicable for real assets as well. The CAPM model (Sharpe, 1964) claims that risk premium (excess expected return of the asset over the risk-free rate) of an asset is fully determined by β, measuring the part of asset´s return variance that cannot be diversified away:

$$E[R_i] = r_f + \beta\big(E[R_m] - r_f\big) \tag{4}$$

Where $E[R_i]$ is the expected return of an asset, r_f is the risk-free rate, and $E[R_m]$ is the expected return of the market portfolio (optimal portfolio in mean-variance portfolio construction sense).

Even though the original CAPM has been most widely used for valuation of stocks, it can be extended to also include real assets like houses. The CAPM equation remains the same while $E[R_i]$ can be expected return of financial asset (like a stock) as well as real asset (like a house). The market portfolio then consists of a combination of stocks and real estate investments.

While theoretically straightforward, extension of CAPM to real estate investments has some limitations related to the size of an investment and relative illiquidity of the real estate market (Damodaran, 2012).

The first counterargument, size of the investment, states that the proposition of CAPM that the investor is well diversified does not hold because real estate investment requires large capital. The argument can be refuted first by the fact that many investors are institutional and have huge capital to diversify and second that even large real estate investments can be broken into smaller pieces or indirect real estate investments can be used (like buying funds tracking the performance of real estate investments).

The second counterargument, relative illiquidity, makes calculation of the variables – periodic returns of real estate investment and market portfolio problematic. A single piece of property is not sold on a continuous basis so that we cannot obtain a monthly return series. Fortunately, return series are available for classes of assets (like a house in Prague) as well as for investment in the general real estate market (real estate investment funds performance). Returns of asset classes may be obtained from price indices and serve as a proxy for the price of individual house. However, it is only a proxy so that one must keep in mind that it is already aggregated and it may undervalue the actual volatility of individual assets. Return of market portfolio can be constructed as a combination of return in stock index and a return in general real estate investment (like a real estate investment fund) where weights of each can be determined by mean-variance optimization. Finally, the original CAPM does not include a liquidity risk premium. Real estate investments may therefore have higher weight in the market portfolio first because of the aggregation effect of individual house prices in a class underestimates return volatility and second as the risk-adjusted return is not reduced by accounting for illiquidity premium. As both effects are difficult to estimate and required yield is not a central focus in the study, CAPM is used without additional adjustments. Although higher weight of real estate investment may be found, it may be argued that the ability of an investor to diversify a real estate investment is limited and higher weight is therefore, at least partially, justified.

Estimating Flood Risk: Calibration of Loss Distributions

Hundred-year flood (100-year flow) is the water flow (in m^3/s) that has a 1% probability of occurring in any given year at a specific location (U.S. Geological Survey 2018; (Chow et al., 1988). Return period (N years) generalizes this idea: an N-year flow has an annual probability of 1/N of occurring. Alternatively, return period may be defined as the average recurrence interval between events equalling or exceeding specified flow magnitude (Chow et al., 1988). Assume that we are given a water depth flood map for different return periods (such as 1-in-20 or 1-in-100 years). These are essentially functions that for each place (or region) on the map return the water depth conditional on the floods realizing. By combining the house dataset, which includes the geographic coordinates of each property, water depth is assigned to each house conditional on floods of different return periods occurring.

These flood maps are not independent. If a house is flooded in a lower return period (e.g., 1-in-20), it is automatically flooded in higher return periods (e.g., 1-in-100) and the severity, measured by water depth, is higher in that higher return period flood. An illustrative example of flood zones is captured in Figure 1. The first aspect of flood risk is frequency. The house H_01 is clearly riskier than house H_02 as it is damaged by flooding on average every 20 years. The house H_02 is less risky as it is damaged on average only every 100 years. The other aspect of flood risk is flood severity. The house H_01 is damaged every 20 years only slightly. But when the 1-in-100 year floods happen, it is damaged much more. There must be more water so that it already hits the H_02 house. To conclude, flood risk has a ring-shaped nature. Both flood frequency and flood severity are negatively related to the distance from the river.

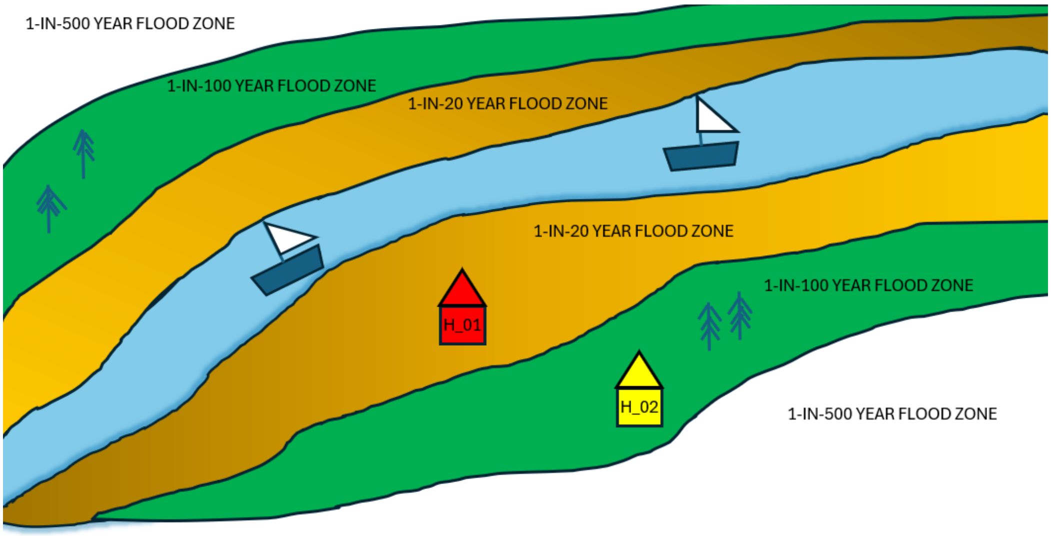

Figure 1 Illustrative example of flood zones

So far, we have a list of water depths for each house in the dataset. It may look as follows:

House id	1-in-20 Year Flood Depth (m)	1-in-100 Year Flood Depth (m)	1-in-500 Year Flood Depth (m)
H_01	0.3	0.8	1.3
H_02	0.0	0.4	0.9

Table 1 Example of extracted flood depth data from flood maps

Flood zone is the lowest return period for which a house is impacted by flood risk (water depth is positive)[1]. In the example above, house H_01 is in the 1-in-20 years flood zone and house H_02 is in the 1-in-100 years flood zone.

Note that we are only given quantiles of flood depth distribution for a set of discrete probability values. The 1-in-20 year flood depth corresponds to the 95th percentile of the water depth distribution, while the 1-in-100-year flood depth corresponds to the 99th percentile. Now the task is to fit a continuous model which can closely reproduce these quantiles. This is solved by fitting a Gumbel mixture distribution to the flood depth data.

The term mixture represents the fact that the flood depth distribution is divided into 2 subcases. First, there is a high probability, p_0, of flood depth being zero (no floods happening). Second, there is a probability of $1 - p_0$ of flood depth being positive. So, with a probability of p_0, the first mixture component is realized. This is essentially a degenerate random variable with Dirac delta function probability density function. In other words, the flood depth is equal to zero with 100% probability if this mixture component is realized. Second, with a

[1] Note: In this study, Return Period (RP) refers to the frequency of a flood event (the 'how often'), whereas Flood Zone (FZ) represents the spatial classification of a property based on the threshold RP at which it first experiences positive water depth.

probability of $1 - p_0$, the second mixture component is realized. Then, a flood depth based on a draw from the Gumbel distribution is applied.

In this study, to ensure more robustness against outliers and incomplete location information, flood depth quantiles are aggregated for each flood zone by applying the average. In other words, instead of fitting a loss distribution for each house separately, the loss distribution is fitted for an average house representant within a flood zone. First, for each location within a flood zone, flood scenarios associated with different return periods are identified from flood hazard maps. These maps provide water depth conditional on the occurrence of floods of different return periods.

Second, for each return period, water depth quantiles are averaged across all locations within the flood zone to obtain a representative flood-depth profile for a typical house in that zone. This representative depth profile is then used to fit the corresponding loss distribution. Quantile calculation was done for each flood zone in two ways: first, across all points on the flood map (excluding water courses), and second, at the actual locations of houses. Since both approaches yielded similar results, the former was adopted, as it is not limited to house locations. The resulting aggregation in Table 2 displays an example of the average quantiles of water depth on flood zone level instead of individual house level as it is the case in Table 1.

Flood zone	1-in-20 Year Flood Depth (m)	1-in-100 Year Flood Depth (m)	1-in-500 Year Flood Depth (m)
1-in-20	0.2	0.7	1.3
1-in-100	0.0	0.5	0.9

Table 2 Example of aggregated flood depth data from flood maps

Water depth for a specific return period (1-in-20 Year, 1-in-100 Year…) corresponds to a particular quantile of the water depth distribution, specifically:

- The water depth for a 20-year flood corresponds to the 95th percentile
- The water depth for a 100-year flood corresponds to the 99th percentile

The quantile represents the water depth at the flood annual probability (p=1-1/return period).

Subsequently, for each flood zone (*FZ*), the water depth $X \geq 0$ is modeled using a Gumbel mixture distribution:

$$F_{mix}(X \mid FZ) = p_0(FZ) + \left(1 - p_0(FZ)\right) \cdot F_{Gumbel}(X, loc(FZ), scale(FZ)) \tag{5}$$

Where: F_{Gumbel} represents the CDF of Gumbel distribution, $p_0(FZ)$ gives the probability of no floods, $loc(FZ)$ and $scale(FZ)$ denotes the location and scale of Gumbel distribution. Parameters are separately fitted for each flood zone (*FZ*).

To calibrate the mixture parameters (p_0, loc, and scale), a non-linear curve-fitting procedure was used. The method finds parameters that minimize the squared vertical distance between the observed discrete CDF points from flood maps (where each flood hazard map provides one data point corresponding to its return period) and the corresponding theoretical quantiles of the Gumbel mixture distribution. The resulting calibrated model provides a continuous water depth distribution for each flood zone

The Gumbel distribution is a limiting distribution of block maxima of random variables and is widely used in hydrology and finance to model extreme values. The Gumbel distribution was chosen first because it is right tailed and therefore captures the fact that flood losses can be severe with low probability and second because it fitted the observed data points of CDF well. In Table 3, there is a comparison between three different choices for the second mixture component. First, the in-sample R^2 is calculated and is near 1 for all three models. Second, the LOO (leave one out) R^2 and MAE is computed using predicted residuals obtained from successively omitting each observation from the estimation sample. Fréchet and Gumbel mixture have a high predictive performance with LOO R^2 around 90% while lognormal mixture has a medium predictive performance of 69%. Gumbel mixture has the lowest MAE while Fréchet mixture has the highest. Overall, Gumbel mixture was chosen as it has the best MAE and second best R^2 out of sample performance.

	Gumbel mixture	Fréchet mixture	Lognormal mixture (loc=0)
Global in-sample R^2	99.89%	**99.98%**	99.71%
Global LOO R^2	87.44%	**95.22%**	68.55%
Global in-sample MAE	**0.000492**	0.001271	0.000824
Global LOO MAE	**0.002585**	0.004453	0.003137

Table 3 Fit of different models to observed average water depth quantiles

How does the CDF differ for different flood zones? It is expected that the p_0 parameter is negatively related to flood zone frequency. The probability of no floods in the lower frequency (e.g., 1-in-100) flood zone is higher than the corresponding probability in the higher frequency (e.g. 1-in-20) flood zone, where floods are more likely. At the same time, the severity of floods, represented by the *loc* parameter of the distribution, is expected to be positively related to flood zone frequency (e.g., 1-in-100-year floods cause more damage in the 1-in-20 year flood zone than in the 1-in-100-year flood zone as houses in 1-in-20 year flood zone are already damaged by 1-in-20 year floods and so 1-in-100-year floods cause even more damage there).

Once the model is calibrated, it enables us to generate Monte Carlo scenarios of yearly future water depths for every house in the dataset. Last step in calculating losses is to transform the simulated water depth into monetary value. This can be done by applying flood depth-damage functions. These are mappings between the flood depth and a percentage reduction in the house price and are based on empirical statistics. Functions for Residential buildings in Europe from (Huizinga et al., 2016) below are used in this study:

Flood depth, [m]	0	0.5	1	1.5	2	3	4	5	6
Damage	0.00	0.25	0.40	0.50	0.60	0.75	0.85	0.95	1.00

Table 4 Flood depth-damage function

Note that using numerical method such as Monte Carlo is necessary to value the flood losses in this setup because even though we know the analytical formulas to calculate the expected value of flood water depths given by the Gumbel mixture distribution, by applying nonlinear transformation using flood depth-damage function, we can no longer analytically track what is the resulting expected value after that transformation (due to Jensen´s inequality).

Finally, the EDL calculation process under the Monte Carlo simulation is summarized as follows:

1. Simulate house price at a every future time t=1, 2, …T (using current house price and expected future growth rates). In this study, a two-stage dividend discount model (Damodaran, n.d.) is used. First, a non-constant growth of house prices is assumed for a finite period (Stage 1), reflecting current market trends followed by a constant, conservative rate indefinitely (Stage 2), reflective of long run average growth of house prices.
2. Simulate percentage loss (flood depth-damage function applied to simulated sample from Gumbel mixture distribution). First, a random realization from the standard uniform distribution is taken. Say it is equal to 0.9. This result represents a 1-in-10 year flood event. By drawing a horizontal line at the 0.9 probability level across the calibrated Gumbel mixture CDFs, we can determine the projected water depth for houses in each flood zone (see Figure 2Figure 1. In other words, we take the Gumbel mixture quantile given the uniformly

sampled probability. Second, by applying water depth to damage function (see Table 4), we obtain percentage loss. The percentage loss is applied to the simulated house price from step 1:

$$\mathrm{L_t} = \mathrm{perc\_loss_t P_t}$$

3. To get expected discounted loss (EDL), average sum of discounted expected losses (assuming n_scen number of Monte Carlo paths and T years of house existence):

$$EDL = \frac{1}{\mathrm{n\_scen}} \sum_{\mathrm{i}=1}^{\mathrm{n\_scen}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \frac{\mathrm{L_t}}{(1+\mathrm{r})^{\mathrm{t}}} \tag{6}$$

Financial loss model calibration results

We observe only discrete points of CDF for each house, saying the water depth at each return period corresponds to one empirical quantile. Each house is assigned to a flood zone. Empirical quantiles are averaged for all houses within a flood zone. The average quantiles are displayed as points in Figure 2, together with fitted Gumbel mixture CDF. Parameters of the fitted distribution are listed in Table 5.

To interpret the results, let´s simulate a flood event by taking a random draw from continuous standard uniform distribution. Let´s say it is equal to 0.9. The result represents a 1-in-10 year flood event. Now draw a horizontal line at 0.9. The line crosses flood zone FZ 10. In other words, houses in the 10-year flood zone are flooded on average at about 1.8 meters of water. The line also touches the 20-year flood zone at water depth of zero. It means that houses in 20-year flood zone are not flooded yet. Let´s simulate a more extreme flood by drawing 0.96. The horizontal line touches houses in the 10-, 20- and 30-year flood zones. Houses in the 10-year flood zone are hit the most while houses in the 30-year flood zone are hit only slightly. The model behaves as expected, the riskiest areas are hit the most and less risky areas are protected until a more extreme event happens. As the FZ 10 function is an outlier and may distort the results of the analysis, houses located in the zone are removed when the JRC flood map is used. Furthermore, it is a question whether such houses really exist, e.g. who would like to live in a house that is flooded every 10 years on average? Many of those data points are considered data errors and special cases like houseboats (designed to live on the water). If still these data points would need to be used in any future application or research, suggested approach is to use less outlier estimate of RP 10 using maps from (World Resources Institute, 2020) in Appendix C.

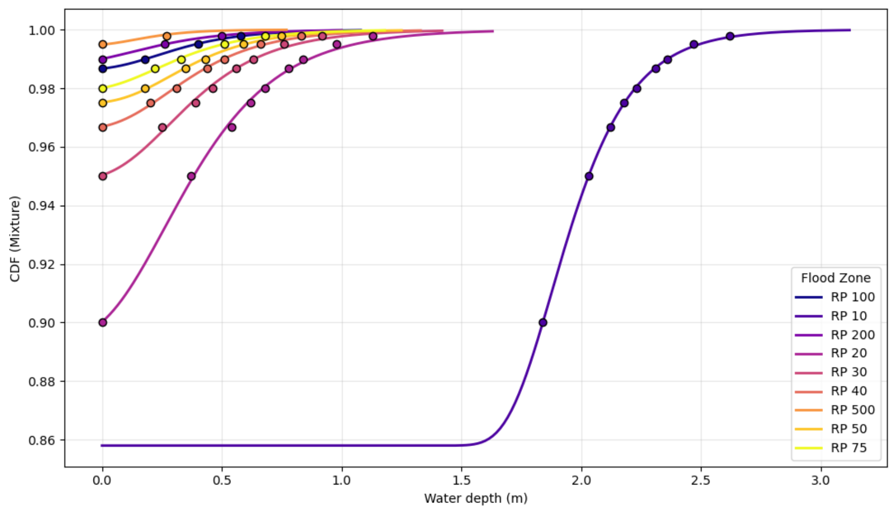

Figure 2 Calibrated Gumbel mixture CDF

Flood zone	p0	loc	scale
1-in-10	0.857956	1.876300	0.185048
1-in-20	0.893333	0.263168	0.260081
1-in-30	0.948369	0.277348	0.232692
1-in-40	0.965765	0.273125	0.220430
1-in-50	0.974638	0.281502	0.206623
1-in-75	0.978882	0.226617	0.212262
1-in-100	0.986140	0.231646	0.197719
1-in-200	0.987953	0.124831	0.218769
1-in-500	0.994535	0.135007	0.135002

Table 5 Calibrated Gumbel mixture model parameters

Integration of EDL into hedonic price model

A hedonic price model is used to determine the value of a house by breaking it down into its constituent characteristics. The hedonic function translates a linear combination of housing attributes into a price (Inoue, Ryo and Komori, Daisuke, 2017):

$$\mathrm{P_i} = \beta_0 + \beta_1 \mathrm{x}_{1\mathrm{i}} + \beta_1 \mathrm{x}_{2\mathrm{i}} + \ldots + \beta_\mathrm{k} \mathrm{x}_{\mathrm{ki}} + \varepsilon_\mathrm{i} \tag{7}$$

Where β_j is the weight of attribute j and ε_i is a disturbance term.

Hedonic function assumes that all consumers are accurately informed about the attributes and market is in a short-run equilibrium (Harrison and Rubinfeld, 1978). House prices reflect evaluations by market participants and reflect property attributes, such as size, building condition and proximity to infrastructure. Flood risk is an attribute that could affect house prices if market participants include it in their evaluations.

It is useful now to reformulate the model by grouping attributes into 2 parts. The second part in the following equation is the EDL attribute while the first part are all other control variables (size, building condition etc.)

$$P_i = controls + \beta_{EDL} EDL_i + \varepsilon_i \tag{8}$$

According to the valuation model developed earlier, controls represent the value of a counterfactual (house outside flood zones), V_0 while β_{EDL} = -1. Value of β_{EDL} > -1 indicate that market participants underestimate flood risk and vice versa, value of β_{EDL} < -1 indicates that market participants overestimate flood risk impacts.

The hedonic pricing equation can be estimated by regression techniques. However, introducing *EDL* as an independent variable creates an issue. Since it is calculated based on the current price (it is a basis for future price evolution), its correlation with the error term is likely non-zero and the resulting estimate of β_{ED} is likely biased. To illustrate the EDL dependence on the current house price P_i, the EDL equation (6) is used where the future price P_t which determines loss L_t is further decomposed into the current price P_i and it´s future yearly growth rates:

$$EDL = \frac{1}{n\_scen} \sum_{\mathrm{i}=1}^{\mathrm{n\_scen}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \frac{perc\_loss_t \cdot P_t}{(1+r)^t} \tag{9}$$

Where the house price grows each year at a growth rate g_k:

$$P_t = P_i \cdot \prod_{k=1}^{t} (1 + g_k)^k \tag{10}$$

One solution is to express *EDL* in relative terms by dividing it by the current house price. The relative EDL does not depend on the current price P_i anymore as this term cancels out:

$$EDL_{rel} = \frac{\frac{1}{n\_scen}\sum_{\mathrm{i=1}}^{\mathrm{n\_scen}}\sum_{\mathrm{t=1}}^{\mathrm{T}}\frac{P_i \cdot \prod_{k=1}^{t}(1+g_k)^k}{(1+r)^t}}{P_i} \tag{11}$$

Introduction of EDL in relative terms solved the potential problem of endogeneity, i.e. having an independent variable which is influenced by the same error term as the dependent variable. However, by introducing *EDL* in relative terms the interpretation of beta would change and would not fit the proportional logic of the pricing problem. In other words, the proportionality requirement breaks down as the original parameter β_{EDL} cannot be estimated from the regression specification having absolute price as dependent variable and relative EDL as independent variable. The original pricing problem becomes:

$$P_i = controls + \beta_{EDL} \cdot P_i \cdot EDL_{rel} + \varepsilon_i \tag{12}$$

In this specification, estimating an interpretable sensitivity parameter of the price with respect to EDL is problematic.

The solution is to express the dependent variable price in natural logarithms:

$$ln(P_i) = controls^* + \gamma_{EDL} EDL_{rel} + \varepsilon_i \tag{13}$$

The γ_{EDL} in the model measures semi-elasticity. In this model, we can again assume proportionality ($\gamma_{EDL} = -1$), as it was in the original model (8). Say *EDL* is 10% of the price, the model would predict approximately 10% discount in price due to the flood risk. For example, if the price of a counterfactual (house outside flood zone) is 1 000 000 CZK and EDL is 100 000 CZK, price of the house (assuming $\beta_{EDL} = -1$) is 900 000 CZK. The log model (assuming $\gamma_{EDL} = -1$) says that EDL_rel is 10% and the log price equals ln(1 000 000) - 10% so that the price equals exp(ln(1 000 000) - 10%) = 904 837.4 CZK. The following text formally shows the sensitivity parameters relation.

The log model specified using the original EDL variable:

$$ln(P_i) = controls^* + \gamma_{EDL}\frac{1}{P_i}EDL + \varepsilon_i \tag{14}$$

The original sensitivity parameter in the absolute price model, β_{EDL}:

$$\beta_{EDL} = \frac{\partial P_i}{\partial EDL} \tag{15}$$

The new sensitivity parameter in the log price model, γ_{EDL}:

$$\gamma_{EDL}\frac{1}{P_i} = \frac{\partial ln(P_i)}{\partial EDL} \tag{16}$$

Using $\partial ln(P_i) = \frac{\partial P_i}{P_i}$, (which holds only approximately for finite ΔP) we can rewrite as:

$$\gamma_{EDL} \frac{1}{P_i} = \frac{\frac{\partial P_i}{P_i}}{\partial EDL} \tag{17}$$

The P_i term cancels out and finally:

$$\gamma_{EDL} = \frac{\partial P_i}{\partial EDL} \tag{18}$$

So that:

$$\gamma_{EDL} \sim \beta_{EDL} \tag{19}$$

The log transformation preserved the logic of proportional discounting while the relative EDL eliminated the problem of EDL endogeneity. Moreover, the log price model is a very common choice for modeling house prices (Harrison and Rubinfeld, 1978); (Bui et al., 2024) as it can help reduce the negative effect of outliers and heteroskedasticity common in the house market (prices of more expensive houses tend to be more volatile or explained by other factors).

IV. Data and Variable Measurement

Data

All the data regarding house attributes has been given to me by real estate portal *Sreality.cz* for the purpose of this article. *Sreality.cz* is one of the largest and most influential reality portals in the Czech Republic. The data cover 40 different parameters of 236 226 house advertisements over the period 12/2023 – 12/2024, including the bid price of the house, house qualitative parameters (condition, estate and usable area, building type, room count, garage and cellar indicator) and location information (district, geographic coordinates, address).

The data required a high degree of data cleaning as it is data entered by customers on the website, subject to error or manipulation. First, houses located outside the Czech borders or located inside rivers from a waterways map (Humanitarian OpenStreetMap Team, 2025) were removed. Next, houses with suspiciously extreme prices (under 300 000 CZK and over 300 000 000 CZK) were removed. Next, estate and usable areas are considered data error and swapped if estate < usable area. Houses with extreme usable area were removed (under 20 m^2 or above 1 000 m^2). Houses with extreme estate area (above 100 000 m^2) were removed. Houses with insufficient address information were removed (minimum requirement is street name and for towns with less than 1 000 inhabitants, the minimum is municipality name and house number). Inhabitants were downloaded from (Czech Statistical Office, 2025a). Finally, only last advertisement for each house was kept as there were many repeated advertisements for the same house (on average 4). This operation reduced the complexity of the regression analysis as otherwise data would be in an unbalanced panel format with many near duplicate entries.

Apart from house information, regional information was added. First, the town population and average age of population from (Czech Statistical Office, 2024), both scaled to the interval (0,1) using the min-max method. Next, the life quality index from (Obce v datech, 2024), also scaled to (0,1) interval. As an additional variable, the distance to the region center was calculated, since proximity to big cities is a key determinant of price. It was calculated based on the region center geographic coordinates extracted using (Google, 2025) and the house geographic coordinates using the Haversine formula. The exception was the Central Bohemian region, which is centered around the capital, so Prague was chosen as the center.

Regarding the valuation model, regional house price indices were extracted from (Czech Statistical Office, 2025b). The risk free rate used is the yield of 10-year Czech government bond from (FRED, 2025). The market portfolio was constructed using total return of PX index from (Prague Stock Exchange, 2025) for stock market returns and a combination of aggregate index of real estate prices from (Czech National Bank, 2025) to represent the real estate price return and (UniCredit Bank, 2022); (UniCredit Bank, 2025) to represent net rental yield. The net rental yield was observed only for a subset of historical periods. However, it is stable and fluctuates around 2% so it was extrapolated for unknown periods using the nearest known value.

Regarding the flood maps, two sources were used, plus one extra source for alternative model calibration. First, the JRC (European Commission, JRC, 2025) river flood hazard dataset and second the VUV (T. G. Masaryk Water Research Institute, 2025) flood zone map. While the former source has more details – it maps every point in the country directly to water depth at given return period and covers a broader range of return periods (10, 20, 30, 40, 50, 75, 100, 200 and 500), the latter is an official, local source whose responsibilities are governed by law (Czechia, 2001) and may therefore be more accepted by the market participants. However, it only maps every point in the country to a flood zone and is available only for the 20, 100 and 500 return frequency. As a data error was encountered in the 500 years map, only 20 and 100 maps were used in this study. The study makes use of both sources. The JRC map is used to calibrate the Gumbel mixture model. As an alternative source, (World Resources Institute, 2020) baseline maps are used to challenge the obtained model. Then, the calibrated model is used separately for JRC flood zones and the local flood zones to produce alternative measures of EDL. The VUV flood map for Prague houses in May 2024 is captured in Figure 3. Comparison of flood maps is done using the confusion matrix in Figure 4 where in each cell, the number of advertisements is displayed. In 461 cases, both maps agree that a house is in a flood zone. However, there are 706 + 1070 cases when only one of the sources assigns the house to a flood zone.

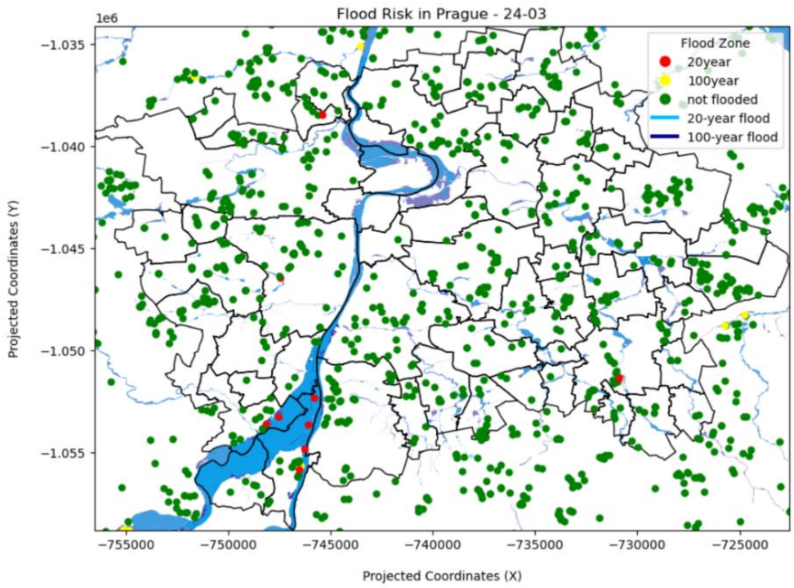

Figure 3 houses over VUV flood map

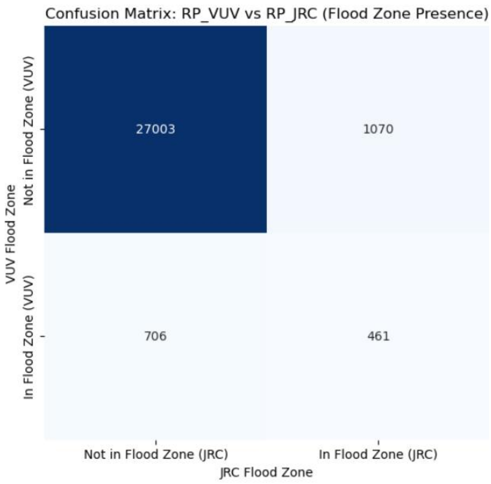

Figure 4 Flood map comparison

Software

Data preprocessing, including the spatial join operations between house coordinates and flood hazard maps, was performed using the geopandas library in Python. All subsequent Monte Carlo simulations, Gumbel mixture calibrations, and hedonic regressions were conducted utilizing the scipy.stats and statsmodels packages.

Model calibration results

We observe only discrete points of CDF for each house, saying the water depth at each return period corresponds to one empirical quantile. Each house is assigned to a flood zone. Empirical quantiles of flood depth, capped at 6 m (the maximum damage is at 6m), are averaged for all houses within a flood zone. The average quantiles are displayed as points in Figure 2, together with fitted Gumbel mixture CDF. Parameters of the fitted distribution are listed in Table 5.

To interpret the results, let´s simulate a flood event by taking a random draw from continuous standard uniform distribution. Let´s say it is equal to 0.9. The result represents a 1-in-10 year flood event. Now draw a horizontal line at 0.9. The line crosses flood zone FZ 10. In other words, houses in the 10-year flood zone are flooded on average at about 1.8 meters of water. The line also touches the 20-year flood zone at water depth of zero. It means that houses in 20-year flood zone are not flooded yet. Let´s simulate a more extreme flood by drawing 0.96. The horizontal line touches houses in the 10-, 20- and 30-year flood zones. Houses in the 10-year flood zone are hit the most while houses in the 30-year flood zone are hit only slightly. The model behaves as expected, the riskiest areas are hit the most and less risky areas are protected until a more extreme event happens. As the FZ 10 function is an outlier and may distort the results of the analysis, houses located in the zone are removed if JRC maps are used. Furthermore, it is a question whether such houses really exist, e.g. who would like to live in a house that is flooded every 10 years on average? Many of those data points are considered data errors and special cases like houseboats (designed to live on the water). If still these data points would need to be used in any future application or research, suggested approach is to use less outlier estimate of RP 10 using maps from (World Resources Institute, 2020) in Appendix C.

An alternative estimate of the model is done using the baseline maps from (World Resources Institute, 2020) in Appendix C. Although the return periods differ, the general magnitude of the water depth levels for different return periods (except RP 10) is similar.

A second ingredient of the valuation model is the CAPM. First, the quarterly total PX stock index returns (price and dividend yield), together with real estate (price and net rent) returns are calculated on quarterly basis and annualized descriptive statistics are calculated in Table 6, together with the optimal weights of each based on maximization of Sharpe ratio. Real estate returns exhibit lower volatility and low correlation with the stock market. This is consistent with earlier studies (Linneman, 2004). The optimal portfolio, based on Sharpe ratio maximization, includes approximately 90% real estate and 10% stocks.

Next, the CAPM equation is estimated by regressing regional house price indices plus net rental return on the market portfolio (90 percent real estate and 10 percent stocks) return. Individual beta parameters obtained are in Table 7. The parameter values are reasonable in the sense that the capital, Prague, is the least risky to invest while more remote regions are more risky investments. This is also reflected in the resulting average required yield in Table 7 (required yield oscillates every month due to changes in risk-free return so average was chosen to simplify the table).

Expected return of stocks (annualized)	11.45%
Expected return real estate (annualized)	8.05%
Volatility of stocks (annualized)	18.31%
Volatility of real estate (annualized)	4.26%
Return correlation	-7.83%
Optimal weight stocks	9.66%
Optimal real estate	90.34%

Table 6 Determining market portfolio weights (Sharpe ratio max)

District name	CAPM Beta	Required yield (year average)
Czech Republic	0.66	7.91%
Czech Republic without Prague	0.73	8.36%
Prague	0.10	4.59%
Central Bohemian Region	0.74	8.34%
South Bohemian Region	0.39	6.34%
Pilsen Region	0.70	8.15%
Carlsbad Region	0.22	5.27%
Ústí nad Labem Region	0.82	8.90%
Liberec Region	0.88	9.25%
Hradec Králové Region	0.53	7.14%
Pardubice Region	0.85	9.04%
Vysočina Region	0.99	9.92%
South Moravian Region	0.89	9.29%
Olomouc Region	0.59	7.48%
Zlín Region	0.44	6.62%
Moravian-Silesian Region	0.74	8.42%

Table 7 Regional house CAPM model results

For the projection of house prices, a two-step dividend growth model is used, see Table 8. The first period price growth is estimated based on average of more recent regional price growth (staring from 2015). From the 6th year and on, the long run mean g_inf is applied. It is the annualized geometric average return of real estate return index over 2009-2024, excluding the outlier period 2020-2022. The prices are expected to revert to this conservative long-term mean of 4% in the 6th year of the forecast.

District name	g1	g2	g3	g4	g5	g_inf
Czech Republic	7.32%	6.65%	5.97%	5.29%	4.61%	3.93%
Czech Republic without Prague	7.34%	6.66%	5.98%	5.30%	4.62%	3.93%
Prague	7.32%	6.64%	5.97%	5.29%	4.61%	3.93%
Central Bohemian Region	8.40%	7.51%	6.61%	5.72%	4.83%	3.93%
South Bohemian Region	6.25%	5.79%	5.32%	4.86%	4.40%	3.93%
Pilsen Region	8.95%	7.95%	6.94%	5.94%	4.94%	3.93%
Carlsbad Region	6.61%	6.08%	5.54%	5.01%	4.47%	3.93%
Ústí nad Labem Region	4.86%	4.67%	4.49%	4.30%	4.12%	3.93%
Liberec Region	7.90%	7.11%	6.31%	5.52%	4.73%	3.93%
Hradec Králové Region	6.90%	6.31%	5.71%	5.12%	4.53%	3.93%
Pardubice Region	6.14%	5.70%	5.26%	4.82%	4.38%	3.93%
Vysočina Region	5.40%	5.11%	4.81%	4.52%	4.23%	3.93%
South Moravian Region	7.88%	7.09%	6.30%	5.51%	4.72%	3.93%
Olomouc Region	6.52%	6.00%	5.48%	4.97%	4.45%	3.93%
Zlín Region	6.84%	6.26%	5.68%	5.10%	4.52%	3.93%
Moravian-Silesian Region	5.76%	5.40%	5.03%	4.67%	4.30%	3.93%

Table 8 Two stage dividend discount model growth parameters

After having all the ingredients, EDL is calculated for each house separately using the local VUV flood maps and JRC flood maps. Histogram of obtained EDL as a percentage of the offered house price is in Figure 5 and Figure 6. Results are grouped using the flood zone. While houses were assigned to multiple flood zones using JRC maps, all houses using the local flood maps were categorized into the 1-in-20 or 1-in-100 years flood zone. As expected, EDL is usually much lower than the house price. Most frequent EDL values are under 10 percent but there are even EDL values of 30 percent or more.

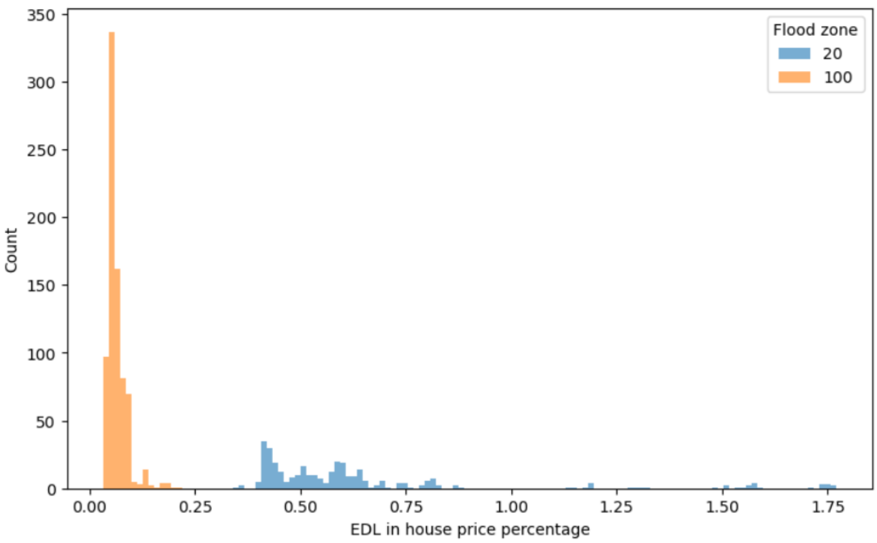

Figure 5 EDL histogram based on the local VUV flood maps

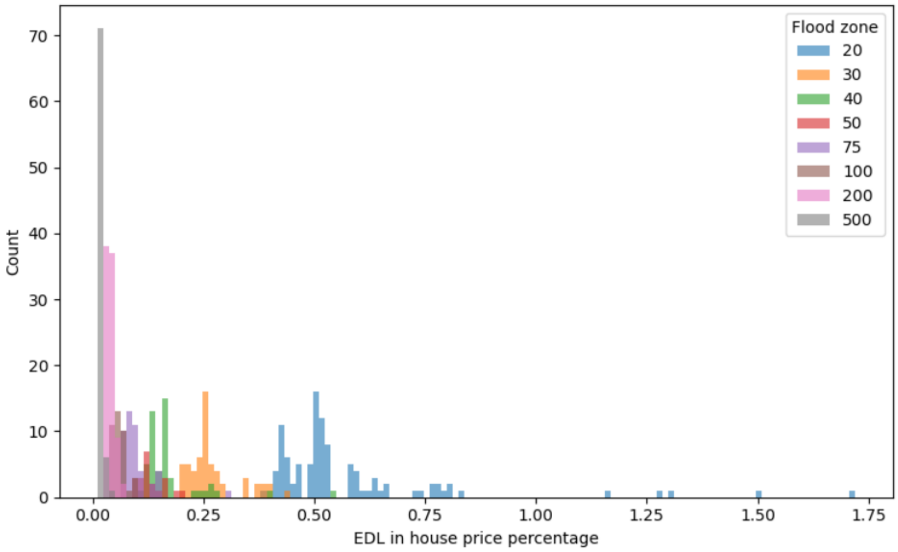

Figure 6 EDL histogram based on the JRC flood maps

Finally, the EDL model is integrated into a hedonic price model. The purpose is to test if market accommodates flood risk into house price. The hedonic price model is estimated on the data separately using the VUV and JRC flood maps. The results of OLS regression with heteroscedasticity robust standard error are displayed in Appendix A. and B. , respectively. Also, other methods were tested (robust regression, bootstrap standard errors) with very similar results.

V. Empirical Results

Overall, the explanatory variables exlain about 72% of the variability of the dependent variable, log house price. The out of samle (LOO) R-suared is 71.2 percent. Some variables are region- or time-dependent. Region dependence is necessary to capture the space dependent price of different house components. The time dimension is necessary to capture inflation. Time is measured in quarters. All the variables in the input fil from Seznam.cz were used, plus additional region-dependent parameters from public data sources (distance to the region center, life quality index).

The most important result is the effect of the variable of interest, EDL expressed as a percentage of house price, across different quarters of the year. The effect on the dependent variable, log price, of the variable of interest (EDL) is captured in Table 9, using the VUV flood maps.

Since a typical issue in house price data is heteroskedasticity & non-normality, two estimation methods were applied. First, OLS with heteroskedasticity-robust standard errors (HC3) was used. Second, a robust regression with a Huber loss function was estimated. The results are consistent across methods and the estimated parameters are of similar magnitude. The full OLS regression results are reported in Appendix A. using the VUV flood maps and in Appendix B. using the JRC flood maps. The heteroskedasticity was confirmed by Breusch-Pagan test on OLS residuals with p-value of 0.00% and the Jarque-Bera test (Appendix A.) also strongly rejected normality with p-value of 0.00%.

While the effect of flood risk is negative when using the VUV maps (Table 9 and Appendix A.), the effect is statistically insignificant when using the JRC maps (Appendix B.). Moreover, the estimated effect is relatively stable over time, with no sharp change in sensitivity to flood risk following the severe floods in Q4 2024 (Czech Hydrometeorological Institute, 2025). The floods in September 2024 were especially intensive, as 55 measuring stations recorded 1-in-100-year flood events.

In conclusion, the explanatory power of the flood variable depends critically on the data source used to determine flood risk zones. The market appears to rely primarily on the local official flood maps provided by

VUV. The results indicate that the market does price flood risk but tends to underestimate its magnitude, as the absolute value of market sensitivity to EDL is less than one, the constant EDL parameter is estimated around 10 percent and is statistically significant . The time-varying parameters are estimated from -21 to 1.4 percent in Table 9.

Model	OLS		Robust regression (Huber loss)	
	Market sensitivity Coefficient	Heteroskedasticity robust st. error (HC3), p-value in paranthesis	Market sensitivity Coefficient	Bootstrap standard error (200 replications)
Time varying EDL model parameters (see Appendix A. for full regression results)				
EDL_VUV_perc:C(time)[Q1_24]	-21.0%	8.3% (1.2%)	-21.4%	8.3%
EDL_VUV_perc:C(time)[Q2_24]	1.4%	6.3% (82.8%)	5.9%	5.9%
EDL_VUV_perc:C(time)[Q3_24]	-15.0%	7.6% (5.0%)	-14.4%	7.9%
EDL_VUV_perc:C(time)[Q4_24]	-6.7%	4.7% (15.5%)	-5.6%	4.0%
Constant EDL model parameter				
	-9.6%	3.2% (3.2%)	-8.6%	3.0%

Table 9 Flood risk discount estimates

Regarding the control variables (see Appendix A. and Appendix B.), first, there is the region dependent intercept. Next, there is a time trend, prices in the later part of the 2024 year are higher compared to the reference category, first quarter, followed by building condition – the better the condition, the higher the price. Next is the usable and estate area, both having positive relationships to the price, followed by different categories of building condition. Generally, the better the condition, the higher the price. Similarly different object types and different subtypes of houses affect the price. Next is energy efficiency. The more energy efficient house, the higher the price. After that, there are the garage and parking lot indicator variables, contributing to higher house prices. Similarly, there is an indicator of cellar, surprisingly having a negative relationship to the price in several regions. The negative parameter could be explained by possible omitted variable bias as in the Czech Republic, older houses tend to have cellar and a lower price at the same time. The effect of missing variable "age" could be absorbed by the cellar variable. The last control variable is the inverse of the distance from the house to the region center. The closer the house is, the higher price it is expected to have.

The model uses relatively high number observation as well as a high number of explanatory variables, therefore it is a question whether multicollinearity is an issue. The condition number of 899 in Appendix A. is under the threshold of high multicollinearity of 1000 (Chen, n.d.). The Table 10 reports the maximum variance inflation factor (VIF) by groups of explanatory variables. VIF measures the increase in the squared standard error relative to a hypothetical case in which explanatory variables are uncorrelated. High VIF values (above 10) indicate substantial multicollinearity, i.e. a situation in which regressors can be largely explained by a linear combination of other regressors. For example, land area and usable area are typically highly correlated, leading to high VIF values. However, both variables are important for housing valuation, and the analysis does not focus on formal hypothesis testing regarding these controls individually; therefore, they are retained in the model despite elevated VIF values. Importantly, the key variable of interest, EDL × Time, has a VIF close to one, indicating no problematic collinearity. To conclude, the model exhibits medium to high levels of multicollinearity but mostly affects the coefficient uncertainty of control variables and not the variables of interest.

Variable group	highest VIF variable name	VIF
Flood risk	EDL_VUV_perc:C(time)[Q4_24]	1.02
Size effects, region-specific	l_usable_area:C(region)[Hlavní město Praha]	164.81
Land size effects	l_estate_area:C(region)[Hlavní město Praha]	141.04
Town-level characteristics	population_town	35.30
Energy efficiency	C(energy_efficiency_rating_name)[T.G_mimoradne_nehospodarna]	15.59
House amenities & location	inv_distance:C(region)[Hlavní město Praha]	5.09
Building characteristics	C(building_condition_name)[T.novostavba]	2.02

Table 10 VIF multicollinearity analysis

Since houses are categorized into regions while each region shares the same expected house price growth rate and discount rate the model output can be summarized using Flood risk discount (Table 11).

In Table 11, the two columns on the right report model-implied expected discounted losses (with standard deviation in parenthesis), expressed as a percentage of the house price outside any flood zone. In some cases, the expected loss exceeds 100% of the house value. This outcome reflects the model assumption of recurrent flood events affecting the same property over time, with the house being repaired after each event rather than permanently destroyed. Consistent with the model assumptions that housing markets capitalize only 0–20% of flood risk, the two columns on the left present suggested price discounts after applying a 10% market sensitivity adjustment.

For example, if the expected discounted loss for a house located in Prague within the 1-in-100-year flood zone is 18.45%, the corresponding market-implied price discount equals 1.85%. Under a more conservative valuation assumption—where the market capitalizes 20% of flood risk—the implied discount would increase to 3.7%.

Table 11 can serve as a practical input for residential property valuation, allowing practitioners to apply flood-related price discounts without the need to explicitly model flood risk. In practice, an appraiser would first estimate the house price as if flood risk were absent and subsequently apply the appropriate flood percentage discount based on flood zone classification.

For greater robustness, future work could replicate the analysis under alternative assumptions or provide officially published discount tables by public authorities, thereby facilitating more consistent flood risk pricing in residential real estate markets.

Flood risk discount				
Region	EDL after market sensitivity adjustment (10%)		EDL before market sensitivity adjustment	
	VUV Flood zone			
	1-in-20 year	1-in-100 year	1-in-20 year	1-in-100 year
Capital City of Prague	16.34 %	1.85 %	163.43 % (10.21 %)	18.45 % (1.17 %)
Central Bohemian Region	5.16 %	0.59 %	51.58 % (1.57 %)	5.87 % (0.33 %)
Hradec Králové Region	6.63 %	0.76 %	66.31 % (2.69 %)	7.57 % (0.42 %)
Karlovy Vary Region	12.2 %	1.34 %	121.95 % (6.96 %)	13.38 % (0.82 %)
Liberec Region	4.31 %	0.48 %	43.11 % (1.58 %)	4.84 % (0.3 %)
Moravian-Silesian Region	4.77 %	0.54 %	47.68 % (1.32 %)	5.41 % (0.33 %)
Olomouc Region	6.01 %	0.69 %	60.11 % (2.1 %)	6.92 % (0.37 %)
Pardubice Region	4.25 %	0.49 %	42.53 % (1.25 %)	4.87 % (0.3 %)
Pilsen Region	5.57 %	0.62 %	55.71 % (1.77 %)	6.21 % (0.31 %)
South Bohemian Region	8.18 %	0.94 %	81.82 % (2.94 %)	9.39 % (0.48 %)
South Moravian Region	4.4 %	0.48 %	43.98 % (0.93 %)	4.84 % (0.26 %)
Vysočina Region	3.6 %	0.39 %	35.99 % (0.92 %)	3.94 % (0.27 %)
Zlín Region	7.7 %	0.87 %	76.98 % (3.63 %)	8.74 % (0.52 %)
Ústí nad Labem Region	4.24 %	0.48 %	42.41 % (1.45 %)	4.82 % (0.28 %)

Table 11 Flood risk discount estimates

The following text summarizes key findings of the study:

- **H1 & H2:**

  "*Market house prices are significantly influenced by flood risk.",*

  „Market house prices are more significantly influenced by official administrative flood maps (VUV) than by more granular hazard datasets (JRC)."

  The H1 hypothesis was confirmed. According to the model, house prices reflect flood risk discount. The effect is related to the flood maps of official authority and is not statistically significant for the JRC flood hazard maps.

- **H3:**

  "Market participants systematically underestimate flood risk due to the selection bias of optimistic buyers, as proposed by Harrison et al. (2001)."

  The hypothesis was confirmed. Markets absorb approximately only 0-30% of the estimated flood risk using the EDL method.

- **H4:** "*Sensitivity of house prices to flood risk is higher in Q4 2024 than in previous periods"*

The hypothesis was not confirmed. Market sensitivity in Q4 was not significantly higher than in previous periods.

VI. Discussion

The proposed EDL method is a natural way to integrate flood zone variables into a single monetary measure with a linear impact on price. The effectiveness of the method grows with more granular data on different flood return periods as well as simulated water depths inside flood zones. Some sources provide very detailed information (JRC); other sources are more limited (VUV). In this study, two data sources were combined. The results were significant when a simplification was used. The local VUV flood zones were combined with flood depth model fitted on JRC data to compensate for the missing information about the exposure at each place inside the local flood zone. In this way, the local awareness and authority of VUV maps could be equipped with flood zone loss distribution. Another limiting factor is that last bid house prices of an advertisement were used (and not actual transaction data). Bid prices tend to be higher than actual prices.

VII. Further research

The flood risk valuation model used could be extended to not only giving price of the flood risk but also as a tool to generate flood scenarios for calculating portfolio risk in climate stress testing or VaR models from the perspective of institutional real estate portfolio or collateral holders. These applications will be explored in a follow-up paper, preliminary research can be found in (Folprecht, 2026)

VIII. Conclusion

The study established a theoretical framework for pricing the impact of flood risk on house prices using the expected discounted loss (EDL) approach. The advantage of the proposed measure is the dimensionality reduction and interpretability it offers; it is a single measure with linear effect on house prices. The proposed EDL measure was empirically tested and found to be a significant determinant of house price discounts observed in flood zone locations. However, its explanatory power depends critically on the data source used for determining flood risk zones. The results indicate that the market does price flood risk but tends to underestimate its magnitude. Moreover, it does not adjust the weight assigned to flood risk even after severe flood events. The flood risk underestimation is consistent with earlier study by (Harrison et al., 2001) who conclude that flood zone properties appear to be overassessed.

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Appendix

A. OLS Regression Results, VUV source of flood map

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Dep. Variable:	l_price_summary	R-squared:	0.720
Model:	OLS	Adj. R-squared:	0.718
Method:	Least Squares	F-statistic:	606.1
Date:	Fri, 07 Nov 2025	Prob (F-statistic):	0.00
Time:	19:23:29	Log-Likelihood:	-14212.
No. Observations:	29240	AIC:	2.869e+04
Df Residuals:	29107	BIC:	2.979e+04
Df Model:	132		
Covariance Type:	HC3		

==

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
Intercept	10.1309	0.1575	64.3073	0.0000	9.8221	10.4397
C(region)[T.South Moravian Region]	3.0022	0.1818	16.5172	0.0000	2.6459	3.3584
C(region)[T.South Bohemian Region]	3.1010	0.1969	15.7494	0.0000	2.7151	3.4870
C(region)[T.Karlovy Vary Region]	2.6341	0.2372	11.1049	0.0000	2.1692	3.0991
C(region)[T.Vysočina Region]	2.8686	0.2088	13.7379	0.0000	2.4593	3.2778
C(region)[T.Hradec Králové Region]	2.9863	0.1994	14.9733	0.0000	2.5954	3.3772
C(region)[T.Liberec Region]	3.0532	0.2206	13.8382	0.0000	2.6208	3.4857
C(region)[T.Moravian-Silesian Region]	2.8100	0.2072	13.5628	0.0000	2.4039	3.2160
C(region)[T.Olomouc Region]	2.8985	0.2038	14.2229	0.0000	2.4991	3.2980
C(region)[T.Pardubice Region]	2.8672	0.2329	12.3106	0.0000	2.4107	3.3236
C(region)[T.Pilsen Region]	3.4843	0.2023	17.2203	0.0000	3.0877	3.8808
C(region)[T.Central Bohemian Region]	2.6752	0.1647	16.2390	0.0000	2.3523	2.9981

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
C(region)[T.Zlín Region]	2.9372	0.2348	12.5102	0.0000	2.4770	3.3974
C(region)[T.Ústí nad Labem Region]	3.3716	0.1816	18.5704	0.0000	3.0158	3.7275
C(time)[T.Q2_24]	0.0324	0.0079	4.1111	0.0000	0.0170	0.0478
C(time)[T.Q3_24]	0.0529	0.0079	6.7054	0.0000	0.0375	0.0684
C(time)[T.Q4_24]	0.1224	0.0066	18.6463	0.0000	0.1095	0.1352
C(building_condition_name)[T.new]	0.4111	0.0100	40.9591	0.0000	0.3915	0.4308
C(building_condition_name)[T.after_reconstruction]	0.3094	0.0094	33.0348	0.0000	0.2910	0.3277
C(building_condition_name)[T.before_reconstruction]	-0.3141	0.0080	-39.1039	0.0000	-0.3298	-0.2983
C(building_condition_name)[T.project]	0.2785	0.0408	6.8228	0.0000	0.1985	0.3584
C(building_condition_name)[T.bad]	-0.5416	0.0306	-17.6925	0.0000	-0.6016	-0.4816
C(building_condition_name)[T.in_reconstruction]	-0.1805	0.0225	-8.0049	0.0000	-0.2247	-0.1363
C(building_condition_name)[T.under_construction]	0.1556	0.0211	7.3668	0.0000	0.1142	0.1970
C(building_condition_name)[T.very_good]	0.3039	0.0061	49.7059	0.0000	0.2920	0.3159
C(building_type_name)[T.wooden]	-0.0047	0.0144	-0.3256	0.7447	-0.0330	0.0236
C(building_type_name)[T.stone]	-0.1885	0.0283	-6.6546	0.0000	-0.2440	-0.1330
C(building_type_name)[T.modular]	-0.1168	0.2665	-0.4383	0.6612	-0.6392	0.4056
C(building_type_name)[T.prefabricated]	-0.0768	0.0342	-2.2456	0.0247	-0.1439	-0.0098
C(building_type_name)[T.panel]	0.0296	0.0371	0.7971	0.4254	-0.0432	0.1023
C(building_type_name)[T.skeleton]	0.0848	0.0302	2.8053	0.0050	0.0255	0.1440
C(building_type_name)[T.mixed]	-0.1119	0.0060	-18.7040	0.0000	-0.1236	-0.1002
C(object_type_name)[T.ground_floor]	-0.1197	0.0060	-19.8957	0.0000	-0.1314	-0.1079
C(category_sub_name)[T.multigenerational]	0.1041	0.0144	7.2544	0.0000	0.0760	0.1323
C(category_sub_name)[T.villa]	0.3057	0.0172	17.7406	0.0000	0.2719	0.3395
C(energy_efficiency_rating_name)[T.B_very_efficient]	-0.0736	0.0142	-5.1902	0.0000	-0.1014	-0.0458
C(energy_efficiency_rating_name)[T.C_efficient]	-0.1241	0.0154	-8.0619	0.0000	-0.1543	-0.0939
C(energy_efficiency_rating_name)[T.D_less_efficient]	-0.2045	0.0170	-12.0169	0.0000	-0.2378	-0.1711
C(energy_efficiency_rating_name)[T.E_nehospodarna]	-0.2495	0.0209	-11.9143	0.0000	-0.2905	-0.2085
C(energy_efficiency_rating_name)[T.F_very_inefficient]	-0.2732	0.0251	-10.8889	0.0000	-0.3224	-0.2240
C(energy_efficiency_rating_name)[T.G_exceptionally_inefficient]	-0.3244	0.0151	-21.5172	0.0000	-0.3539	-0.2948
C(energy_efficiency_rating_name)[T.missing]	-0.3050	0.0157	-19.4724	0.0000	-0.3357	-0.2743
l_usable_area:C(region)[Capital City of Prague]	0.3405	0.0256	13.2871	0.0000	0.2903	0.3907
l_usable_area:C(region)[South Moravian Region]	0.3701	0.0209	17.6828	0.0000	0.3291	0.4112
l_usable_area:C(region)[South Bohemian Region]	0.3223	0.0231	13.9324	0.0000	0.2770	0.3677
l_usable_area:C(region)[Karlovy Vary Region]	0.3913	0.0329	11.9084	0.0000	0.3269	0.4557
l_usable_area:C(region)[Vysočina Region]	0.3216	0.0282	11.3858	0.0000	0.2662	0.3769
l_usable_area:C(region)[Hradec Králové Region]	0.3716	0.0262	14.1845	0.0000	0.3203	0.4230
l_usable_area:C(region)[Liberec Region]	0.3354	0.0281	11.9331	0.0000	0.2803	0.3905
l_usable_area:C(region)[Moravian-Silesian Region]	0.3456	0.0247	13.9786	0.0000	0.2971	0.3940
l_usable_area:C(region)[Olomouc Region]	0.4296	0.0297	14.4514	0.0000	0.3714	0.4879

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
l_usable_area:C(region)[Pardubice Region]	0.4235	0.0314	13.4887	0.0000	0.3619	0.4850
l_usable_area:C(region)[Pilsen Region]	0.3169	0.0238	13.3010	0.0000	0.2702	0.3636
l_usable_area:C(region)[Central Bohemian Region]	0.3574	0.0108	33.1949	0.0000	0.3363	0.3785
l_usable_area:C(region)[Zlín Region]	0.3398	0.0281	12.0879	0.0000	0.2847	0.3949
l_usable_area:C(region)[Ústí nad Labem Region]	0.2364	0.0184	12.8754	0.0000	0.2004	0.2724
l_estate_area:C(region)[Capital City of Prague]	0.2748	0.0197	13.9713	0.0000	0.2363	0.3134
l_estate_area:C(region)[South Moravian Region]	0.1266	0.0127	9.9996	0.0000	0.1018	0.1514
l_estate_area:C(region)[South Bohemian Region]	0.1403	0.0137	10.2596	0.0000	0.1135	0.1671
l_estate_area:C(region)[Karlovy Vary Region]	0.1274	0.0194	6.5837	0.0000	0.0895	0.1653
l_estate_area:C(region)[Vysočina Region]	0.1478	0.0168	8.7734	0.0000	0.1148	0.1808
l_estate_area:C(region)[Hradec Králové Region]	0.1056	0.0142	7.4561	0.0000	0.0778	0.1333
l_estate_area:C(region)[Liberec Region]	0.1352	0.0162	8.3218	0.0000	0.1033	0.1670
l_estate_area:C(region)[Moravian-Silesian Region]	0.1219	0.0137	8.9081	0.0000	0.0951	0.1487
l_estate_area:C(region)[Olomouc Region]	0.0564	0.0190	2.9701	0.0030	0.0192	0.0937
l_estate_area:C(region)[Pardubice Region]	0.0808	0.0169	4.7823	0.0000	0.0477	0.1140
l_estate_area:C(region)[Pilsen Region]	0.0774	0.0159	4.8737	0.0000	0.0463	0.1085
l_estate_area:C(region)[Central Bohemian Region]	0.1806	0.0066	27.3938	0.0000	0.1677	0.1935
l_estate_area:C(region)[Zlín Region]	0.1248	0.0236	5.2922	0.0000	0.0786	0.1710
l_estate_area:C(region)[Ústí nad Labem Region]	0.1419	0.0107	13.2718	0.0000	0.1209	0.1628
age_average_town	-0.3157	0.0301	-10.4719	0.0000	-0.3748	-0.2566
population_town	2.9220	0.0584	50.0605	0.0000	2.8076	3.0364
life_quality_index	0.0375	0.0172	2.1836	0.0290	0.0038	0.0712
garage:C(region)[Capital City of Prague]	0.0152	0.0167	0.9120	0.3618	-0.0175	0.0479
garage:C(region)[South Moravian Region]	0.0620	0.0165	3.7702	0.0002	0.0298	0.0943
garage:C(region)[South Bohemian Region]	0.0517	0.0207	2.5005	0.0124	0.0112	0.0923
garage:C(region)[Karlovy Vary Region]	0.0455	0.0303	1.5038	0.1326	-0.0138	0.1048
garage:C(region)[Vysočina Region]	0.0740	0.0261	2.8357	0.0046	0.0229	0.1252
garage:C(region)[Hradec Králové Region]	0.0461	0.0237	1.9492	0.0513	-0.0003	0.0925
garage:C(region)[Liberec Region]	0.0774	0.0244	3.1699	0.0015	0.0296	0.1253
garage:C(region)[Moravian-Silesian Region]	0.0630	0.0201	3.1392	0.0017	0.0237	0.1024
garage:C(region)[Olomouc Region]	0.1283	0.0258	4.9655	0.0000	0.0777	0.1789
garage:C(region)[Pardubice Region]	0.0355	0.0256	1.3849	0.1661	-0.0147	0.0856
garage:C(region)[Pilsen Region]	0.0468	0.0200	2.3429	0.0191	0.0076	0.0859
garage:C(region)[Central Bohemian Region]	0.0602	0.0086	6.9898	0.0000	0.0434	0.0771
garage:C(region)[Zlín Region]	0.0470	0.0260	1.8117	0.0700	-0.0038	0.0979
garage:C(region)[Ústí nad Labem Region]	0.0942	0.0170	5.5402	0.0000	0.0608	0.1275
cellar:C(region)[Capital City of Prague]	0.0399	0.0165	2.4236	0.0154	0.0076	0.0722
cellar:C(region)[South Moravian Region]	-0.0025	0.0155	-0.1610	0.8721	-0.0329	0.0279
cellar:C(region)[South Bohemian Region]	-0.0179	0.0208	-0.8634	0.3879	-0.0587	0.0228

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
cellar:C(region)[Karlovy Vary Region]	-0.1289	0.0297	-4.3398	0.0000	-0.1871	-0.0707
cellar:C(region)[Vysočina Region]	-0.0173	0.0244	-0.7082	0.4788	-0.0652	0.0306
cellar:C(region)[Hradec Králové Region]	-0.0219	0.0234	-0.9378	0.3483	-0.0678	0.0239
cellar:C(region)[Liberec Region]	-0.0046	0.0244	-0.1895	0.8497	-0.0524	0.0432
cellar:C(region)[Moravian-Silesian Region]	-0.1066	0.0201	-5.2951	0.0000	-0.1460	-0.0671
cellar:C(region)[Olomouc Region]	-0.0159	0.0254	-0.6257	0.5315	-0.0656	0.0338
cellar:C(region)[Pardubice Region]	-0.0363	0.0250	-1.4530	0.1462	-0.0852	0.0127
cellar:C(region)[Pilsen Region]	-0.0220	0.0201	-1.0944	0.2738	-0.0614	0.0174
cellar:C(region)[Central Bohemian Region]	-0.0035	0.0090	-0.3929	0.6944	-0.0211	0.0141
cellar:C(region)[Zlín Region]	0.0464	0.0272	1.7034	0.0885	-0.0070	0.0998
cellar:C(region)[Ústí nad Labem Region]	-0.0384	0.0168	-2.2842	0.0224	-0.0713	-0.0054
parking_lots:C(region)[Capital City of Prague]	-0.0423	0.0168	-2.5201	0.0117	-0.0751	-0.0094
parking_lots:C(region)[South Moravian Region]	0.0819	0.0155	5.2875	0.0000	0.0515	0.1123
parking_lots:C(region)[South Bohemian Region]	0.0789	0.0208	3.7931	0.0001	0.0381	0.1197
parking_lots:C(region)[Karlovy Vary Region]	0.1056	0.0306	3.4475	0.0006	0.0456	0.1657
parking_lots:C(region)[Vysočina Region]	0.0807	0.0250	3.2217	0.0013	0.0316	0.1298
parking_lots:C(region)[Hradec Králové Region]	0.0923	0.0228	4.0466	0.0001	0.0476	0.1369
parking_lots:C(region)[Liberec Region]	0.0669	0.0251	2.6620	0.0078	0.0176	0.1161
parking_lots:C(region)[Moravian-Silesian Region]	0.0827	0.0191	4.3410	0.0000	0.0454	0.1201
parking_lots:C(region)[Olomouc Region]	0.0445	0.0249	1.7887	0.0737	-0.0043	0.0932
parking_lots:C(region)[Pardubice Region]	0.0985	0.0246	3.9996	0.0001	0.0502	0.1467
parking_lots:C(region)[Pilsen Region]	0.0397	0.0213	1.8676	0.0618	-0.0020	0.0814
parking_lots:C(region)[Central Bohemian Region]	0.0277	0.0083	3.3441	0.0008	0.0115	0.0440
parking_lots:C(region)[Zlín Region]	0.1052	0.0251	4.1892	0.0000	0.0560	0.1544
parking_lots:C(region)[Ústí nad Labem Region]	0.0518	0.0164	3.1646	0.0016	0.0197	0.0838
inv_distance:C(region)[Capital City of Prague]	2.7254	0.1765	15.4425	0.0000	2.3795	3.0713
inv_distance:C(region)[South Moravian Region]	0.0404	0.0324	1.2462	0.2127	-0.0231	0.1040
inv_distance:C(region)[South Bohemian Region]	0.0870	0.0225	3.8675	0.0001	0.0429	0.1310
inv_distance:C(region)[Karlovy Vary Region]	0.1516	0.0645	2.3485	0.0189	0.0251	0.2781
inv_distance:C(region)[Vysočina Region]	0.1068	0.0353	3.0206	0.0025	0.0375	0.1760
inv_distance:C(region)[Hradec Králové Region]	0.1740	0.0379	4.5952	0.0000	0.0998	0.2482
inv_distance:C(region)[Liberec Region]	0.0158	0.0151	1.0464	0.2954	-0.0138	0.0453
inv_distance:C(region)[Moravian-Silesian Region]	0.0947	0.0403	2.3519	0.0187	0.0158	0.1737
inv_distance:C(region)[Olomouc Region]	0.0367	0.0566	0.6492	0.5162	-0.0742	0.1476
inv_distance:C(region)[Pardubice Region]	0.0521	0.0185	2.8222	0.0048	0.0159	0.0883
inv_distance:C(region)[Pilsen Region]	0.0611	0.0762	0.8014	0.4229	-0.0883	0.2104
inv_distance:C(region)[Central Bohemian Region]	8.4332	0.2341	36.0165	0.0000	7.9743	8.8922
inv_distance:C(region)[Zlín Region]	0.1030	0.1212	0.8501	0.3953	-0.1345	0.3406
inv_distance:C(region)[Ústí nad Labem Region]	0.1577	0.0239	6.6060	0.0000	0.1109	0.2044

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
EDL_VUV_perc:C(time)[Q1_24]	-0.2100	0.0833	-2.5203	0.0117	-0.3732	-0.0467
EDL_VUV_perc:C(time)[Q2_24]	0.0137	0.0633	0.2170	0.8282	-0.1104	0.1379
EDL_VUV_perc:C(time)[Q3_24]	-0.1501	0.0765	-1.9634	0.0496	-0.3000	-0.0003
EDL_VUV_perc:C(time)[Q4_24]	-0.0668	0.0469	-1.4229	0.1548	-0.1587	0.0252

==

Omnibus: 1669.812 Durbin-Watson: 1.819

Prob(Omnibus): 0.000 Jarque-Bera (JB): 3985.672

Skew: -0.354 Prob(JB): 0.00

Kurtosis: 4.665 Cond. No. 899.

B. OLS Regression Results, JRC source of flood map

Note: Reduced sample compared to A. (Houses in 1-in-10 year flood zone excluded as outliers)

==

Dep. Variable:	l_price_summary	R-squared:	0.723
Model:	OLS	Adj. R-squared:	0.722
Method:	Least Squares	F-statistic:	593.1
Date:	Fri, 07 Nov 2025	Prob (F-statistic):	0.00
Time:	19:21:07	Log-Likelihood:	-13637.
No. Observations:	28209	AIC:	2.754e+04
Df Residuals:	28076	BIC:	2.864e+04
Df Model:	132		
Covariance Type:	HC3		

==

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
Intercept	10.0979	0.1600	63.1195	0.0000	9.7843	10.4114
C(region)[T.South Moravian Region]	3.0610	0.1853	16.5179	0.0000	2.6978	3.4242
C(region)[T.South Bohemian Region]	3.2095	0.1950	16.4624	0.0000	2.8274	3.5916
C(region)[T.Karlovy Vary Region]	2.6302	0.2424	10.8490	0.0000	2.1551	3.1054
C(region)[T.Vysočina Region]	2.8999	0.2120	13.6783	0.0000	2.4844	3.3154
C(region)[T.Hradec Králové Region]	3.0006	0.2034	14.7509	0.0000	2.6019	3.3993
C(region)[T.Liberec Region]	3.0967	0.2221	13.9439	0.0000	2.6614	3.5320
C(region)[T.Moravian-Silesian Region]	2.8218	0.2104	13.4125	0.0000	2.4095	3.2342
C(region)[T.Olomouc Region]	2.8681	0.2070	13.8532	0.0000	2.4624	3.2739
C(region)[T.Pardubice Region]	2.8809	0.2411	11.9512	0.0000	2.4085	3.3534
C(region)[T.Pilsen Region]	3.5408	0.2044	17.3264	0.0000	3.1402	3.9413
C(region)[T.Central Bohemian Region]	2.7088	0.1672	16.2049	0.0000	2.3812	3.0364
C(region)[T.Zlín Region]	2.9317	0.2430	12.0629	0.0000	2.4554	3.4081

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
C(region)[T.Ústí nad Labem Region]	3.4317	0.1841	18.6421	0.0000	3.0709	3.7925
C(time)[T.Q2_24]	0.0316	0.0080	3.9580	0.0001	0.0160	0.0473
C(time)[T.Q3_24]	0.0536	0.0080	6.6886	0.0000	0.0379	0.0693
C(time)[T.Q4_24]	0.1208	0.0067	18.0949	0.0000	0.1077	0.1338
C(building_condition_name)[T.new]	0.4126	0.0102	40.3916	0.0000	0.3926	0.4326
C(building_condition_name)[T.po_rekonstrukci]	0.3084	0.0095	32.3913	0.0000	0.2897	0.3270
C(building_condition_name)[T.before_reconstruction]	-0.3134	0.0082	-38.4334	0.0000	-0.3294	-0.2974
C(building_condition_name)[T.project]	0.2846	0.0416	6.8486	0.0000	0.2031	0.3660
C(building_condition_name)[T.bad]	-0.5399	0.0307	-17.5931	0.0000	-0.6001	-0.4798
C(building_condition_name)[T.in_reconstruction]	-0.1782	0.0227	-7.8530	0.0000	-0.2227	-0.1338
C(building_condition_name)[T.under_construction]	0.1615	0.0214	7.5387	0.0000	0.1195	0.2035
C(building_condition_name)[T.very_good]	0.3039	0.0062	48.8022	0.0000	0.2917	0.3161
C(building_type_name)[T.wooden]	-0.0021	0.0147	-0.1435	0.8859	-0.0309	0.0267
C(building_type_name)[T.stone]	-0.1934	0.0286	-6.7556	0.0000	-0.2495	-0.1373
C(building_type_name)[T.modular]	-0.1104	0.2688	-0.4106	0.6814	-0.6372	0.4165
C(building_type_name)[T.prefabricated]	-0.0658	0.0333	-1.9753	0.0482	-0.1311	-0.0005
C(building_type_name)[T.panel]	0.0317	0.0378	0.8396	0.4011	-0.0423	0.1057
C(building_type_name)[T.skeleton]	0.0877	0.0311	2.8180	0.0048	0.0267	0.1487
C(building_type_name)[T.mixed]	-0.1100	0.0061	-18.1294	0.0000	-0.1219	-0.0981
C(object_type_name)[T.ground_floor]	-0.1203	0.0061	-19.6943	0.0000	-0.1322	-0.1083
C(category_sub_name)[T.multigenerational]	0.1051	0.0145	7.2696	0.0000	0.0768	0.1335
C(category_sub_name)[T.villa]	0.3055	0.0175	17.4352	0.0000	0.2711	0.3398
C(energy_efficiency_rating_name)[T.B_very_efficient]	-0.0759	0.0146	-5.2036	0.0000	-0.1045	-0.0473
C(energy_efficiency_rating_name)[T.C_efficient]	-0.1237	0.0158	-7.8180	0.0000	-0.1547	-0.0927
C(energy_efficiency_rating_name)[T.D_less_efficient]	-0.2084	0.0175	-11.9388	0.0000	-0.2427	-0.1742
C(energy_efficiency_rating_name)[T.E_nehospodarna]	-0.2505	0.0216	-11.5777	0.0000	-0.2929	-0.2081
C(energy_efficiency_rating_name)[T.F_very_inefficient]	-0.2808	0.0255	-11.0140	0.0000	-0.3308	-0.2308
C(energy_efficiency_rating_name)[T.G_exceptionally_inefficient]	-0.3279	0.0155	-21.0922	0.0000	-0.3583	-0.2974
C(energy_efficiency_rating_name)[T.missing]	-0.3066	0.0161	-19.0051	0.0000	-0.3382	-0.2749
l_usable_area:C(region)[Capital City of Prague]	0.3391	0.0260	13.0276	0.0000	0.2881	0.3901
l_usable_area:C(region)[South Moravian Region]	0.3662	0.0212	17.2692	0.0000	0.3246	0.4077
l_usable_area:C(region)[South Bohemian Region]	0.3026	0.0229	13.1885	0.0000	0.2576	0.3476
l_usable_area:C(region)[Karlovy Vary Region]	0.4051	0.0334	12.1142	0.0000	0.3395	0.4706
l_usable_area:C(region)[Vysočina Region]	0.3230	0.0285	11.3417	0.0000	0.2672	0.3788
l_usable_area:C(region)[Hradec Králové Region]	0.3732	0.0270	13.8373	0.0000	0.3203	0.4260
l_usable_area:C(region)[Liberec Region]	0.3307	0.0280	11.8137	0.0000	0.2759	0.3856
l_usable_area:C(region)[Moravian-Silesian Region]	0.3513	0.0250	14.0697	0.0000	0.3023	0.4002
l_usable_area:C(region)[Olomouc Region]	0.4416	0.0302	14.6093	0.0000	0.3824	0.5009

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
l_usable_area:C(region)[Pardubice Region]	0.4264	0.0325	13.1114	0.0000	0.3626	0.4901
l_usable_area:C(region)[Pilsen Region]	0.3111	0.0238	13.0492	0.0000	0.2644	0.3578
l_usable_area:C(region)[Central Bohemian Region]	0.3618	0.0110	32.8310	0.0000	0.3402	0.3834
l_usable_area:C(region)[Zlín Region]	0.3412	0.0289	11.7942	0.0000	0.2845	0.3979
l_usable_area:C(region)[Ústí nad Labem Region]	0.2349	0.0185	12.6632	0.0000	0.1985	0.2713
l_estate_area:C(region)[Capital City of Prague]	0.2797	0.0199	14.0488	0.0000	0.2407	0.3187
l_estate_area:C(region)[South Moravian Region]	0.1262	0.0128	9.8844	0.0000	0.1012	0.1513
l_estate_area:C(region)[South Bohemian Region]	0.1440	0.0137	10.5467	0.0000	0.1173	0.1708
l_estate_area:C(region)[Karlovy Vary Region]	0.1245	0.0194	6.4207	0.0000	0.0865	0.1625
l_estate_area:C(region)[Vysočina Region]	0.1481	0.0169	8.7599	0.0000	0.1150	0.1813
l_estate_area:C(region)[Hradec Králové Region]	0.1062	0.0146	7.2840	0.0000	0.0776	0.1348
l_estate_area:C(region)[Liberec Region]	0.1375	0.0163	8.4395	0.0000	0.1056	0.1695
l_estate_area:C(region)[Moravian-Silesian Region]	0.1226	0.0139	8.8467	0.0000	0.0955	0.1498
l_estate_area:C(region)[Olomouc Region]	0.0556	0.0192	2.8993	0.0037	0.0180	0.0932
l_estate_area:C(region)[Pardubice Region]	0.0808	0.0176	4.6033	0.0000	0.0464	0.1153
l_estate_area:C(region)[Pilsen Region]	0.0782	0.0157	4.9857	0.0000	0.0474	0.1089
l_estate_area:C(region)[Central Bohemian Region]	0.1776	0.0067	26.4667	0.0000	0.1644	0.1907
l_estate_area:C(region)[Zlín Region]	0.1288	0.0240	5.3640	0.0000	0.0817	0.1758
l_estate_area:C(region)[Ústí nad Labem Region]	0.1399	0.0108	12.9633	0.0000	0.1187	0.1610
age_average_town	-0.3146	0.0305	-10.3236	0.0000	-0.3743	-0.2549
population_town	2.9368	0.0592	49.6174	0.0000	2.8208	3.0528
Life_Quality_index	0.0313	0.0175	1.7867	0.0740	-0.0030	0.0656
garage:C(region)[Capital City of Prague]	0.0112	0.0168	0.6656	0.5057	-0.0218	0.0441
garage:C(region)[South Moravian Region]	0.0705	0.0169	4.1723	0.0000	0.0374	0.1036
garage:C(region)[South Bohemian Region]	0.0550	0.0208	2.6491	0.0081	0.0143	0.0957
garage:C(region)[Karlovy Vary Region]	0.0472	0.0310	1.5234	0.1277	-0.0135	0.1079
garage:C(region)[Vysočina Region]	0.0715	0.0265	2.6963	0.0070	0.0195	0.1235
garage:C(region)[Hradec Králové Region]	0.0471	0.0243	1.9375	0.0527	-0.0005	0.0948
garage:C(region)[Liberec Region]	0.0785	0.0245	3.2021	0.0014	0.0305	0.1266
garage:C(region)[Moravian-Silesian Region]	0.0603	0.0204	2.9544	0.0031	0.0203	0.1003
garage:C(region)[Olomouc Region]	0.1224	0.0265	4.6122	0.0000	0.0704	0.1745
garage:C(region)[Pardubice Region]	0.0414	0.0266	1.5561	0.1197	-0.0107	0.0936
garage:C(region)[Pilsen Region]	0.0538	0.0204	2.6344	0.0084	0.0138	0.0939
garage:C(region)[Central Bohemian Region]	0.0645	0.0087	7.3918	0.0000	0.0474	0.0816
garage:C(region)[Zlín Region]	0.0471	0.0272	1.7301	0.0836	-0.0062	0.1004
garage:C(region)[Ústí nad Labem Region]	0.0967	0.0171	5.6485	0.0000	0.0631	0.1302
cellar:C(region)[Capital City of Prague]	0.0373	0.0166	2.2489	0.0245	0.0048	0.0698
cellar:C(region)[South Moravian Region]	-0.0008	0.0158	-0.0476	0.9620	-0.0318	0.0303

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
cellar:C(region)[South Bohemian Region]	-0.0210	0.0209	-1.0028	0.3159	-0.0619	0.0200
cellar:C(region)[Karlovy Vary Region]	-0.1363	0.0304	-4.4845	0.0000	-0.1958	-0.0767
cellar:C(region)[Vysočina Region]	-0.0193	0.0249	-0.7754	0.4381	-0.0681	0.0295
cellar:C(region)[Hradec Králové Region]	-0.0166	0.0241	-0.6869	0.4921	-0.0639	0.0307
cellar:C(region)[Liberec Region]	-0.0085	0.0246	-0.3471	0.7285	-0.0567	0.0397
cellar:C(region)[Moravian-Silesian Region]	-0.1054	0.0204	-5.1739	0.0000	-0.1453	-0.0655
cellar:C(region)[Olomouc Region]	-0.0146	0.0260	-0.5622	0.5740	-0.0657	0.0364
cellar:C(region)[Pardubice Region]	-0.0288	0.0259	-1.1121	0.2661	-0.0796	0.0220
cellar:C(region)[Pilsen Region]	-0.0181	0.0203	-0.8917	0.3726	-0.0580	0.0217
cellar:C(region)[Central Bohemian Region]	-0.0034	0.0092	-0.3730	0.7092	-0.0213	0.0145
cellar:C(region)[Zlín Region]	0.0520	0.0283	1.8361	0.0663	-0.0035	0.1076
cellar:C(region)[Ústí nad Labem Region]	-0.0427	0.0170	-2.5129	0.0120	-0.0760	-0.0094
parking_lots:C(region)[Capital City of Prague]	-0.0405	0.0169	-2.3953	0.0166	-0.0736	-0.0074
parking_lots:C(region)[South Moravian Region]	0.0755	0.0159	4.7529	0.0000	0.0443	0.1066
parking_lots:C(region)[South Bohemian Region]	0.0827	0.0208	3.9704	0.0001	0.0419	0.1235
parking_lots:C(region)[Karlovy Vary Region]	0.0932	0.0312	2.9838	0.0028	0.0320	0.1544
parking_lots:C(region)[Vysočina Region]	0.0776	0.0254	3.0578	0.0022	0.0278	0.1273
parking_lots:C(region)[Hradec Králové Region]	0.0973	0.0234	4.1507	0.0000	0.0514	0.1433
parking_lots:C(region)[Liberec Region]	0.0726	0.0252	2.8846	0.0039	0.0233	0.1219
parking_lots:C(region)[Moravian-Silesian Region]	0.0747	0.0194	3.8536	0.0001	0.0367	0.1126
parking_lots:C(region)[Olomouc Region]	0.0561	0.0255	2.1955	0.0281	0.0060	0.1061
parking_lots:C(region)[Pardubice Region]	0.0873	0.0256	3.4113	0.0006	0.0372	0.1375
parking_lots:C(region)[Pilsen Region]	0.0371	0.0215	1.7235	0.0848	-0.0051	0.0793
parking_lots:C(region)[Central Bohemian Region]	0.0275	0.0084	3.2761	0.0011	0.0110	0.0440
parking_lots:C(region)[Zlín Region]	0.1049	0.0262	4.0021	0.0001	0.0535	0.1563
parking_lots:C(region)[Ústí nad Labem Region]	0.0509	0.0165	3.0859	0.0020	0.0186	0.0833
inv_distance:C(region)[Capital City of Prague]	2.7670	0.1810	15.2873	0.0000	2.4123	3.1218
inv_distance:C(region)[South Moravian Region]	0.0396	0.0318	1.2456	0.2129	-0.0227	0.1019
inv_distance:C(region)[South Bohemian Region]	0.0772	0.0221	3.4943	0.0005	0.0339	0.1204
inv_distance:C(region)[Karlovy Vary Region]	0.1454	0.0668	2.1769	0.0295	0.0145	0.2764
inv_distance:C(region)[Vysočina Region]	0.1035	0.0350	2.9575	0.0031	0.0349	0.1721
inv_distance:C(region)[Hradec Králové Region]	0.1608	0.0347	4.6316	0.0000	0.0927	0.2288
inv_distance:C(region)[Liberec Region]	0.0301	0.0120	2.5126	0.0120	0.0066	0.0536
inv_distance:C(region)[Moravian-Silesian Region]	0.0912	0.0418	2.1824	0.0291	0.0093	0.1731
inv_distance:C(region)[Olomouc Region]	0.0366	0.0561	0.6538	0.5133	-0.0732	0.1465
inv_distance:C(region)[Pardubice Region]	0.0467	0.0188	2.4763	0.0133	0.0097	0.0836
inv_distance:C(region)[Pilsen Region]	0.0562	0.0764	0.7351	0.4623	-0.0936	0.2060
inv_distance:C(region)[Central Bohemian Region]	8.4157	0.2368	35.5376	0.0000	7.9516	8.8799

Term	Coef	Std Err	t/z	P>|t|/P>|z|	[0.025	0.975]
inv_distance:C(region)[Zlín Region]	0.1024	0.1221	0.8385	0.4018	-0.1370	0.3418
inv_distance:C(region)[Ústí nad Labem Region]	0.1580	0.0241	6.5697	0.0000	0.1109	0.2052
EDL_JRC_perc:C(time)[Q1_24]	0.1403	0.1014	1.3830	0.1667	-0.0585	0.3391
EDL_JRC_perc:C(time)[Q2_24]	0.0309	0.1019	0.3028	0.7621	-0.1690	0.2307
EDL_JRC_perc:C(time)[Q3_24]	0.4075	0.2897	1.4068	0.1595	-0.1602	0.9752
EDL_JRC_perc:C(time)[Q4_24]	0.1819	0.1040	1.7497	0.0802	-0.0219	0.3857

==

Omnibus: 1577.526 Durbin-Watson: 1.817

Prob(Omnibus): 0.000 Jarque-Bera (JB): 3785.287

Skew: -0.344 Prob(JB): 0.00

Kurtosis: 4.657 Cond. No. 894.

==

Notes:

[1] Standard Errors are heteroscedasticity robust (HC3)

C. Alternative Gumbel mixture CDF estimate using (World Resources Institute, 2020)

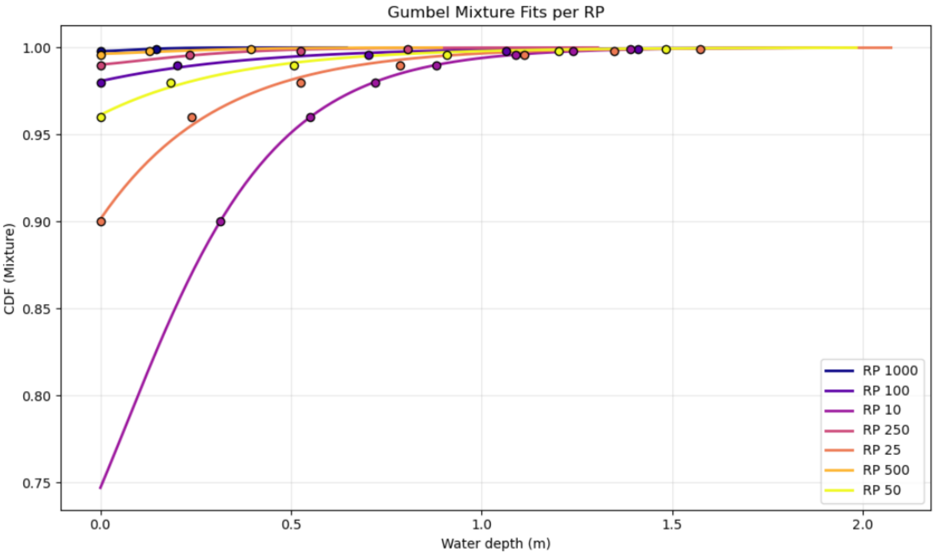

Figure 7

Flood zone	p0	loc	scale
1-in-10	0.746389	0.067191	0.23098
1-in-25	0.902053	0	0.231718
1-in-50	0.961724	0	0.260666
1-in-100	0.980993	0	0.297793
1-in-250	0.990001	0.010418	0.232661
1-in-500	0.996335	0.125065	0.15959
1-in-1000	0.997886	0.068664	0.066043

Table 12 Note: loc param was restricted on non-negativity

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