

Research on Risk Management of Real Estate Development Projects Based on Comprehensive Evaluation Methods

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Abstract. In the context of escalating climate change and urbanization, this study explores the intricate relationship between risk, revenue, and real estate development in vulnerable regions. This research aims to construct a risk-revenue assessment model for real estate, focusing on the Composite Risk Index (CRI) to evaluate risk conditions in specific areas. To align the model closely with reality, this study employed a regional rasterization technique to differentiate among urban types. It also introduces a decision mechanism coefficient to balance risk and reward and employs the ARIMA algorithm for forecasting future risks. Additionally, the study incorporates Net Present Value (NPV) theory and a risk-adjusted discount rate to assess investment profitability. Social factors are considered through expert scoring to derive the Social Index (SI). The TOPSIS method is used to calculate housing protection status in Florida, with recommendations for focusing real estate development investments inland. Furthermore, a classification model using a Support Vector Machine (SVM) is developed to identify appropriate conservation measures for buildings based on various indicators.

Keywords: Urban rasterization, Net present value, Socio-economic factors, Risk revenue assessment.

1. Introduction

In today's rapidly globalizing and urbanizing world, real estate development faces both significant challenges and opportunities [1]. These projects are essential for urban growth and economic development, but they must navigate a complex landscape influenced by various factors [2]. Geographical specifics, like terrain and site, dictate construction scale and layout—rugged terrains limit large buildings while booming areas favor dense developments. Economic fluctuations affect costs, returns, sustainability, and competitiveness [3]. Moreover, societal aspects, such as infrastructure accessibility, cultural values, and public acceptance, are critical for success. Managing these diverse and evolving factors to mitigate risks and make informed decisions is a key challenge in real estate development [4].

This study refines the risk revenue assessment model to better suit the specific needs of real estate developers, through the introduction of a Decision Mechanism Coefficient. The methodology begins with the rasterization of urban layouts to classify cities into distinct zones—city center, urban, suburban, and rural fringe—based on geographical and economic parameters. This classification aids in determining the appropriate scale for building developments within these areas. Adjustments to the RR model include considerations for risk, revenue, and social factors, with statistical methods such as ARIMA being utilized for risk analysis and economic theories like Net Present Value (NPV) for financial viability assessment. Social indicators are also evaluated to gauge their impact on the profitability of real estate projects. By implementing these methodologies, the research provides a comprehensive tool for optimizing real estate development strategies within varied urban contexts, aiming to aid developers in making informed decisions regarding project scale and viability, while specifically focusing on the procedural aspects of the study rather than its outcomes.

2. Model overview and preparation

Specifically, the data for this study were sourced from the websites of international organizations or regional governments. In our exploration of exposure risk within real estate, we will first classify urban layouts and establish three key indicators to gauge the scale of buildings across different areas. The methodology and steps of our study are outlined in Figure 1, serving as the foundation for our investigation.

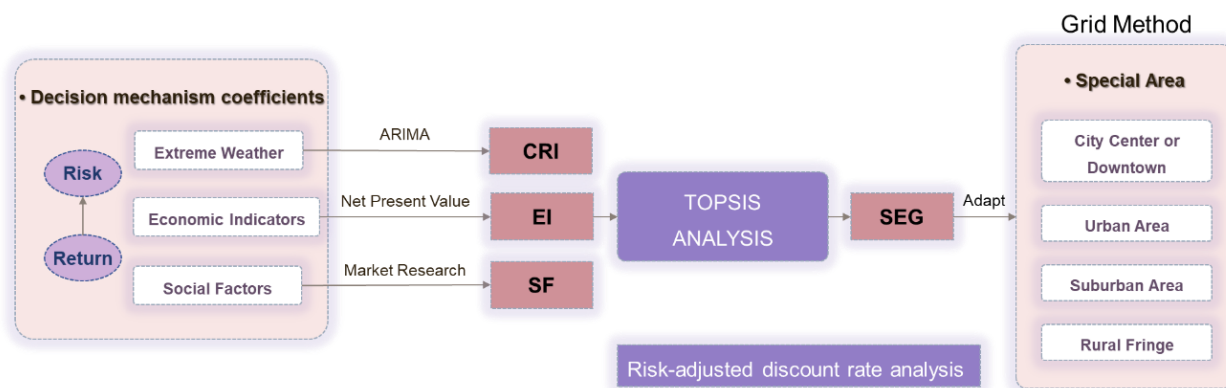


Figure 1. Real estate risk assessment workflow diagram

Before initiating this research, an attempt was made to construct the Risk-Revenue assessment model. In particular, this model assesses the risk conditions of a specific area by calculating its Composite Risk Index (CRI). The precise formula for the CRI calculation is presented as follows:

$$CRI = \sum_{i=1}^N RI_i \times \omega_i \quad (1)$$

In the formula, RI represents the risk level index for individual event nodes within the risk matrix constructed from risk severity and risk probability. Risk severity measures the intensity of extreme weather events, while risk probability denotes the likelihood of corresponding risk events occurring.

In practical analysis, it becomes clear that the geographical positioning and economic condition of a region profoundly affect the scale and layout of its buildings [5]. Mountainous terrains, for instance, often impede the construction of large structures, while regions of economic prosperity are inclined towards the development of high-density commercial and residential buildings. To enhance the examination of this dynamic, this study adopts a rasterization method to systematically classify cities into several distinct levels: city center, urban area, suburban area, and rural fringe. The definitions for each category are provided in Figure 2:

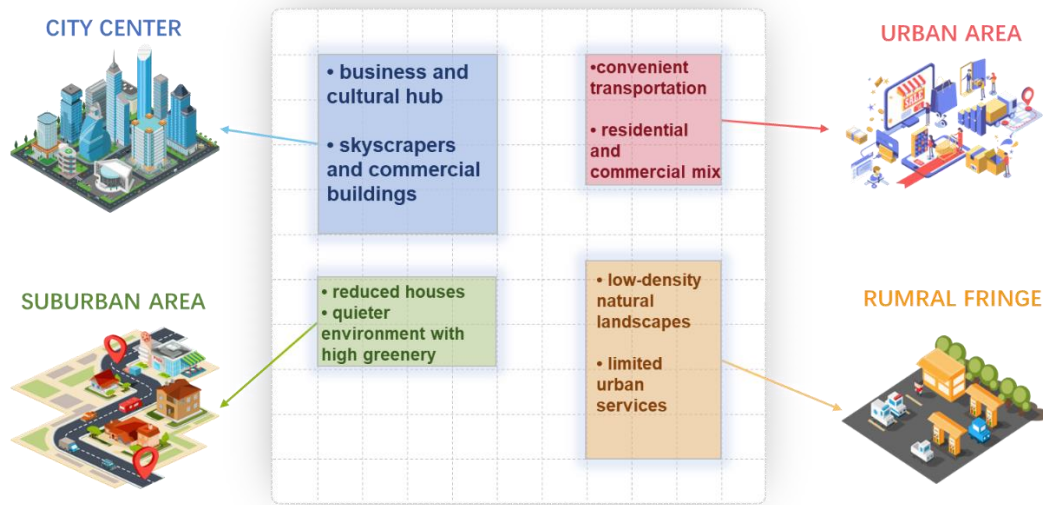


Figure 2. Diagram of region rasterization.

3. Balancing Risk and Reward in Real Estate

To better assess the revenue situation of real estate, we further adjust the calculation process of CRI by introducing the decision mechanism coefficient v . Specifically, the formula is as follows.

$$A = v \times CRI + (1 - v) \times CRVI \quad (2)$$

$$CRVI = DRI \left(\frac{a}{a + e^{-ks_i}} + b \right) \quad (3)$$

In the formula above, CRVI stands for Composite Revenue Index, which is used to express the potential revenue situation in the real estate industry. The variables a and b in the fraction are constants. The constant k is used to adjust sensitivity. If $v \geq 0.5$, decision-making prioritizes mechanisms that maximize collective benefits. Conversely, if $v \leq 0.5$, the direction of the decision-making mechanism is to minimize individual regret. When $v = 0.5$, it indicates a decision-making approach that equally values maximizing collective benefits and minimizing individual regret, representing a balance between the two.

Furthermore, to better assess the future risks of real estate development, it is essential to consider and predict the impact on development scope and initial investments, thereby maximizing the interests of real estate developers. To achieve accurate forecasting, this study introduces the Autoregressive Integrated Moving Average Model (ARIMA) algorithm [6]. This is a statistical model used for forecasting time series data, treating data sequences as approximations of random processes, and then predicting future values based on historical and current data. Specifically, the ARIMA model can be divided into the Autoregressive (AR) model and the Moving Average (MA) model. The AR model describes the relationship between current values and lagged values, utilizing historical data to predict future values. The MA model observes future residuals using a linear combination of past residual terms. The related formula is as follows:

Herein, this study forecasts the future CRI values for Florida, as depicted in Figure 3. The data reveal an annual fluctuating upward trend in the local CRI index.

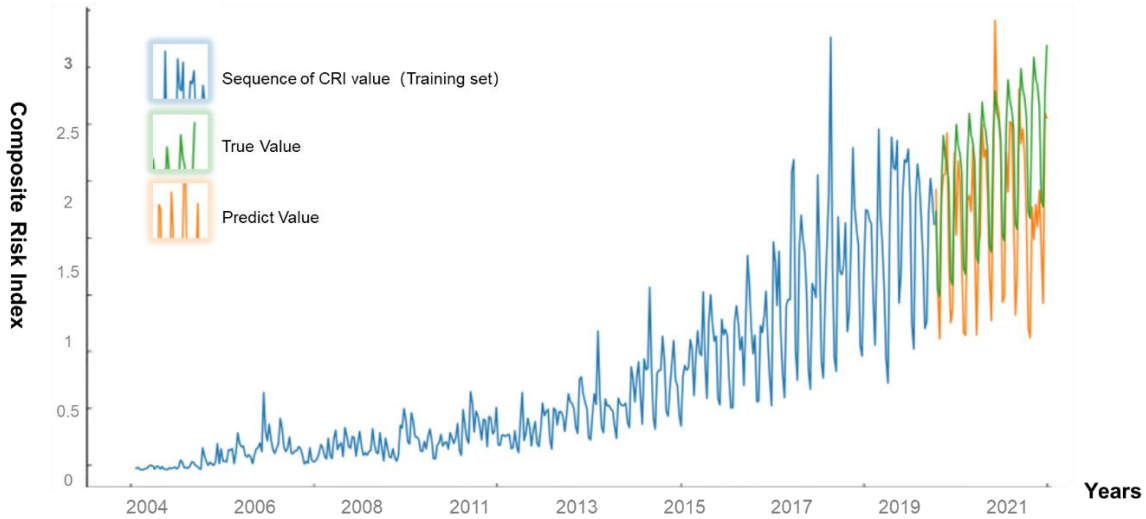


Figure 3. Forecasting the Florida CRI situation

Furthermore, the study takes into account that economic fluctuations can also impact the investment costs for real estate developers. For instance, extended project timelines and currency depreciation could harm profits. Therefore, in terms of economic indicators, this research incorporates Net Present Value (NPV) theory to calculate returns and introduces a risk-adjusted discount rate to account for risk, with the calculation formula presented as follows.

$$NPV = \sum_{t=0}^T \frac{R_t - C_t}{(1+i)^t} \quad (4)$$

In the formula, R_t and C_t represent the cash inflow and outflow, respectively, in year t , i is the discount rate, and T is the total duration of the project. NPV is an essential tool for assessing the profitability of project investments, taking into full account the cash inflows, outflows, and the discounting of future cash flows to their present value. Furthermore, when considering the risks associated with real estate investments, a risk-adjusted discount rate can be used to evaluate the project's NPV. This rate reflects the level of risk for the project. Higher-risk projects should employ a higher discount rate when calculating the net present value.

$$NPV' = \sum_{t=0}^T \frac{R_t - C_t}{(1+r)^t} \quad (5)$$

In the formula, r represents the risk-adjusted discount rate.

Additionally, social factors serve as a crucial reference indicator, such as the geographic location and the convenience level of surrounding infrastructure, which also affect the profitability of real estate. Here, we employ expert scoring to assess the impact of different indicators, thereby deriving the Social Index (SI) as shown in the following figure 4.

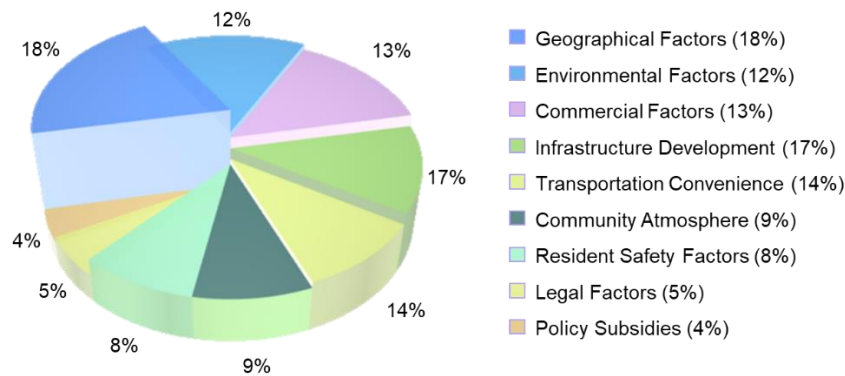


Figure 4. Social Indicators comprehensive score proportion chart

Considering all the factors mentioned above, this study opts to use the TOPSIS method to calculate the housing protection status in the Florida area. As illustrated in Figure 5, mild protection areas are predominantly located in the inland and northwestern regions of Florida. Most areas requiring intensive protection are concentrated along the coastline, which might be attributed to the ongoing global warming trend that continues unabated, posing a risk of rising sea levels. Therefore, it is recommended that real estate development investments focus more on the inland regions, which may yield more secure returns.

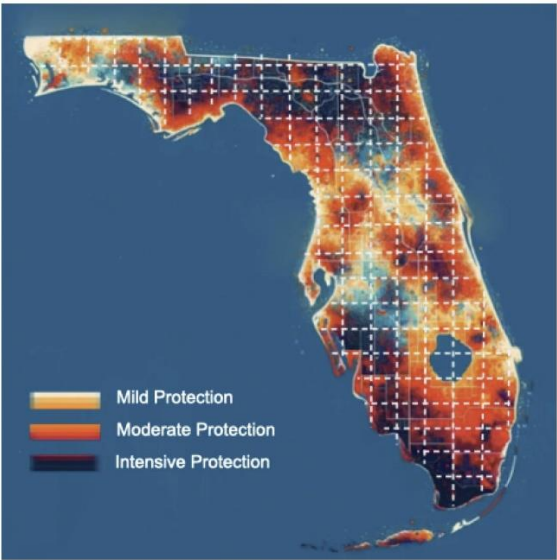


Figure 5. Heat map of Florida state grid division. The base map was sourced from <https://www.tianditu.gov.cn/>

4. Identification of Conservation Measures

To assist decision-makers in the area of building preservation, especially in unfamiliar regions, this research further develops a model to help identify appropriate conservation measures. A classification model is selected for this study. The study chooses the following variables as inputs based on the World Heritage Convention (WHC), the specific workflow is illustrated in Figure 6.

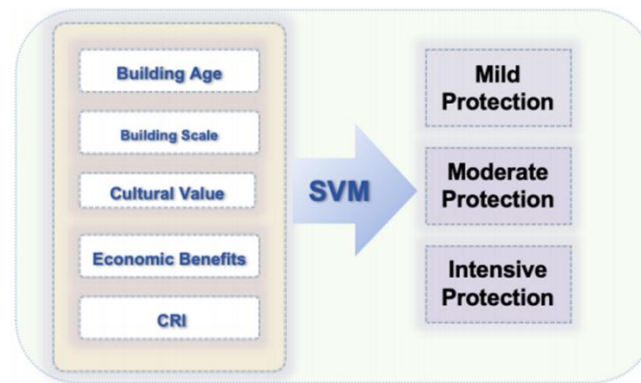


Figure 6. Real estate protection level classification workflow

Specifically, building Age (BA) is measured by the number of years since a building was constructed. Building Scale (BS) is defined by the total floor space of a building. Cultural Value (CV) and Economic Benefit (EB) are both assessed through expert scores, where CV evaluates the cultural significance of a building and EB measures its value as an engineering facility, tourist attraction, and other economic aspects. Lastly, the Composite Risk Index (CRI) represents the natural disaster risk associated with the building. In this study, real estate protection levels are categorized into three types: mild protection, moderate protection, and intensive protection. For each category, the study provides practical recommendations. For example, buildings under intensive protection should enhance their security measures and physical surveillance.

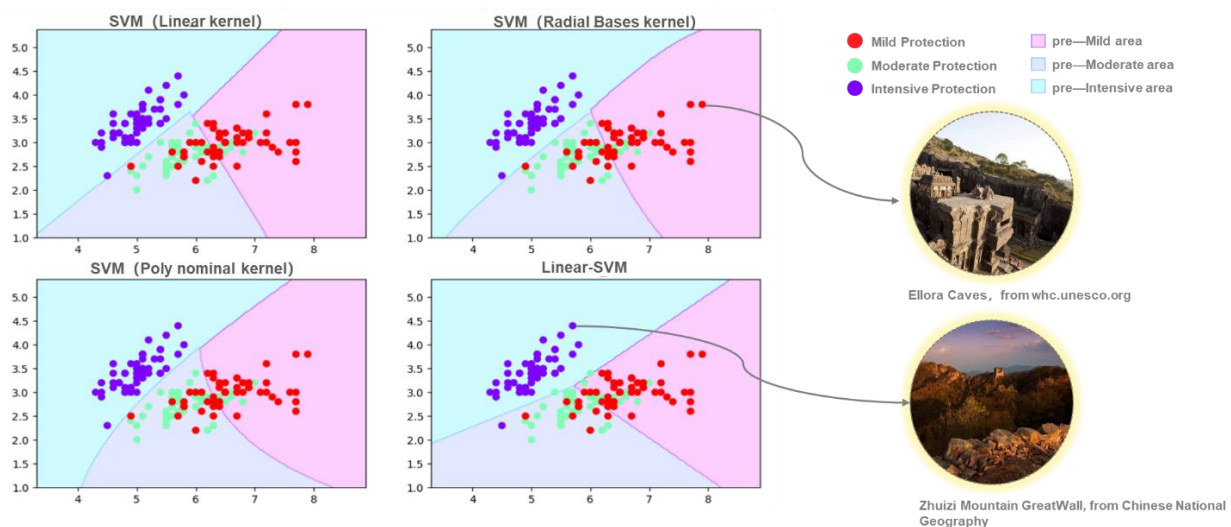


Figure 7. SVM training results

Regarding the specific modeling approach, this study opts for the Support Vector Machine (SVM) [7]. As a classification model extensively utilized in small sample learning, it has been applied across various related fields [8]. Within this system, the model employs Linear, Polynomial, and Radial Basis Function kernels and is constructed using the linear SVC algorithm within scikit-learn [9]. Both One-vs-One (for Binary Classification) and One-vs-All (for Logistic Regression) strategies are utilized to shape the model [10]. Following training, the model is capable of assigning a specific protection level to buildings based on four input indicators, thus enabling owners and leaders to devise tailored preservation strategies. These strategies are aligned with the determined protection level and the building's particular circumstances, with the training outcomes illustrated in Figure 7.

5. Conclusion

This study constructs a risk-revenue assessment model to evaluate the risk conditions of specific areas, introducing a method for calculating the composite risk index based on risk severity and

probability. By classifying urban layouts and setting three indicators to assess the scale of buildings in various areas, the study aims to evaluate the exposure risk in real estate. Additionally, the study adjusts the CRI calculation process by introducing the decision mechanism coefficient v to better assess the real estate revenue situation. It uses the ARIMA model to predict future risks of real estate development and applies NPV theory and a risk-adjusted discount rate to calculate investment returns. Social factors are also considered important reference indicators, assessed through expert scoring to derive the social index. Furthermore, the study employs the TOPSIS method to calculate the housing protection status in Florida, recommending real estate development investments in inland areas for safer returns. To assist decision-makers in identifying suitable building conservation measures, the study develops a classification model using building age, scale, cultural value, and economic benefit as input variables, with the SVM as the classification model.

This study aims to enhance real estate development risk management by integrating theoretical models with practical applications. By examining key factors and proposing an evaluation method, it offers a dynamic tool for informed decision-making in the face of uncertainties, benefiting developers, policymakers, and stakeholders.

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