Scientific
Research
Publishing

An Effective Prediction Method for Supporting Decision Making in Real Estate Area Selection

Haoying Jin, Song Yang, Mingzhi Zhao

School of Telecommunications Engineering, Xidian University, Xi'an, China
Email: 23012100036@stu.xidian.edu.cn

Abstract

Real estate has been a dominant industry in many countries. One problem for real estate companies is determining the most valuable area before starting a new project. Previous studies on this issue mainly focused on market needs and economic prospects, ignoring the impact of natural disasters. We observe that natural disasters are important for real estate area selection because they will introduce considerable losses to real estate enterprises. Following this observation, we first develop a self-defined new indicator named *Average Loss Ratio* to predict the losses caused by natural disasters in an area. Then, we adopt the existing ARIMA model to predict the *Average Loss Ratio* of an area. After that, we propose to integrate the TOPSIS model and the Grey Prediction Model to rank the recommendation levels for candidate areas, thereby assisting real estate companies in their decision-making process. We conduct experiments on real datasets to validate our proposal, and the results suggest the effectiveness of the proposed method.

Keywords

Real Estate, Natural Disaster, Decision Making, Prediction Model

1. Introduction

With the rapid development of economics, investment and development in real estate have entered a new era of development [1] [2]. The area selection of real estate projects is the first step in real estate investment [3]. The success or failure of a real estate project development depends on the area of the project. How to effectively evaluate the development value of an area is an important and difficult part of scientific decision-making for real estate developers.

There are many factors that affect the area selection of real estate projects [4]-[8]. The area selection of a real estate project is a comprehensive weighing of various factors, so the area selection of a project often depends on the expe-

rience, cognition, and subjective thoughts of decision-makers. While previous studies on this issue mainly focused on market needs and economic prospects, ignoring the impact of natural disasters, we observed that natural disasters are important for real estate area selection because they will introduce considerable losses to real estate enterprises. The values of real estate are highly impacted by severe weather and natural disasters because they will affect the construction progress of houses and destroy existing buildings. Extreme weather events, exacerbated by climate change, are increasingly disrupting lives and threatening property security [9]. Property owners rely more on insurance for protection, yet insurers, facing claims in 2022 more than double the 30-year average, are hiking premiums and scaling back coverage. This has widened the global insurance protection gap to 57%, underscoring a growing crisis for both insurers and property owners [10]. Real estate developing companies are encouraged to pursue market expansion, diversifying their offerings across various areas while striving to minimize premium hikes. Nonetheless, these firms must be equipped with practical risk assessment tools to avoid incurring substantial losses, particularly in the face of natural disasters. There is an urgent need to develop a more sophisticated and rational decision-making model tailored to evaluating and managing the risks associated with natural catastrophes [9] [10].

In this paper, we study the approach for real estate developing companies to select the most valuable areas when they plan to start a new real estate development project. Overall, the main contributions of the paper are as follows:

- We propose a self-defined new indicator called *Average Loss Ratio* to measure the probability of natural disasters in an area. We experimentally demonstrate that the new indicator can provide a foundation for decision-making in real estate area selection.
- We present a decision model based on the ARIMA model to predict the *Average Loss Ratio* of an area. The evaluation results on real datasets, including EM-DAT, NAIC, and KPMG, show that the proposed *Average Loss Ratio* can predict the possible loss of an area effectively.
- We improve the TOPSIS model by integrating *Average Loss Ratio* into the model and use the enhanced TOPSIS model to solve the real estate area selection problem. The results on real datasets, including EM-DAT, BEA, and USA-GDP, show that our approach is effective in selecting real estate areas.

The remainder of the paper is structured as follows. Section 2 reviews related literature. Section 3 introduces assumptions and notations. Section 4 details our models and results. Finally, Section 5 concludes the whole paper and discusses future work.

2. Literature Review

Real estate area selection refers to the process of choosing the optimal location for a real estate project, such as residential housing, commercial buildings, or other property developments [3]. It involves evaluating various factors to determine the best area for the project's success, profitability, and marketability.

The primary objective is to identify a location that maximizes the project's potential for success. There are many factors that affect the area selection of real estate projects [4]-[8]. The area selection of a real estate project is a comprehensive weighing of various factors, such as market demand [4], geographic conditions [7], transportation accessibility [8], land prices [5], and other relevant considerations [6]. Therefore, the area selection of a project often depends on the experience, cognition, and subjective thoughts of decision-makers.

When conducting real estate area selection, developers or investors typically conduct extensive market research to understand the needs and preferences of potential buyers or tenants. They also consider the economic prospects of the area, population growth trends, and future infrastructure plans [11]-[13]. Other important considerations may include land costs, local government planning and regulations, the proximity and influence of existing competitors, availability of essential services such as healthcare, education, and shopping centers, as well as natural environmental factors like landscapes and conservation requirements.

Existing work on real estate area selection encompasses a range of research and practical approaches [3] [6]-[8]. For example, previous studies have considered location factors and examined the significance of these factors and their impact on area selection decision-making [3]. Risk evaluation is essential in area selection to mitigate potential challenges and uncertainties. Researchers have explored methods for assessing and managing risks associated with factors like environmental hazards, legal constraints, market fluctuations, and financial feasibility [13]. With increasing emphasis on sustainability, researchers have focused on integrating environmental considerations into area selection processes [14] [15]. This includes evaluating areas based on energy efficiency, green building practices, environmental impact assessments, and the promotion of sustainable communities. Advancements in technology, such as big data analytics, machine learning, and artificial intelligence, have facilitated data-driven area selection approaches [16] [17]. Researchers have explored the use of these technologies to analyze large datasets, predict market trends, optimize area selection, and automate decision-making processes.

Overall, research on real estate area selection encompasses a multidisciplinary approach, combining elements of economics, geography, urban planning, and decision sciences. The aim is to develop robust methodologies and tools that assist developers, investors, and policymakers in making informed area selection decisions that align with market demands, financial objectives, and sustainable development principles. However, few studies have focused on the impact of natural disasters on real estate area selection. To the best of our knowledge, this study is the first one that proposes a new indicator, average loss ratio, to study the impact of natural disaster on real estate area selection.

3. Assumptions and Notations

3.1. Assumptions

Before presenting the solution to the problem, we first make the following as-

sumptions.

1) We assume that the natural disaster damage data obtained are authentic and credible, with no invalid values.

Since the losses caused by natural disasters are generally tallied and reported by national agencies, we consider such data to have a high level of authority and reliability. Additionally, natural disaster losses are highly volatile, and hastily removing outliers could potentially lead to the loss of critical features, affecting the prediction precision. Therefore, we assume that all acquired data are authentic and credible, and we do not discard any data.

2) We assume that the disaster conditions, population count, and population growth rate are independent variables that do not influence each other.

Currently, there is no clear evidence to suggest a significant correlation between the aforementioned three variables. Therefore, for decision analysis, we can assume that these three criteria are mutually independent, and a change in one criterion will not affect the utility values of the others.

3) We assume that there are no other policies, economic factors, or such influences affecting real estate developers in their development activities.

This study focuses solely on the impact of natural disasters and population demand. We regard all other factors related to housing development as irrelevant. These factors do not influence real estate developers' decisions. By doing this, we simplify the model and keep it targeted to our main objectives.

3.2. Notations and Datasets

The main symbols we use in this paper and the explanations of them are put in Table 1. The symbols which are not frequently used will be introduced once we use them.

Table 1. Main symbols used in this study.

Symbol	Description
Pft	Predicted annual profits based on natural conditions.
P	Predicted annual profits based on market conditions.
$Prem$	Annual premium of insurance covering natural disasters.
$Clms$	Annual claim of insurance covering natural disasters.
$Loss$	Annual disaster loss amount.
LR	Loss Ratio.
$\overline{LR}$	Average Loss Ratio.
PV_t	The total asset value of a year.
GDP	Gross Domestic Product.
PIS	Positive Ideal Solution.
NIS	Negative Ideal Solution.
CSI	Composite Score Index.

The datasets used in this study are summarized in Table 2. Overall, we use six datasets, but each task only uses one or more datasets. All datasets are public on the Web.

Table 2. Datasets used in this study.

Dataset	Description	Source
EM-DAT	Public-EMDAT	https://public.emdat.be
NAIC	National Insurance	https://content.naic.org
CEIC	CEIC DATA	https://www.ceicdata.com
KPMG	KPMG Australia	https://kpmg.com/au/en/home
BEA	Bureau of Economic Analysis	https://www.bea.gov
USA-POP	U.S. Census Bureau	https://www.census.gov

4. Models and Verification

In this section, we detail the models and verification for the problem of real estate area selection. We first describe the model and then present the model's verification results.

4.1. Average Loss Ratio

In this paper, we define a new indicator named *Average Loss Ratio* to reflect the impact of natural disasters on real estate area selection. Such an indicator is used to predict the possible losses of an area according to historical data.

First, in order to get the loss information about a specific area, we refer to the historical insurance data that are associated with particular insurance covering natural disasters. Insurance companies usually release two main types of information: the annual premium and the annual claim. Thus, we can establish an equation that maps the annual claim caused by natural disasters to the disaster loss amount, yielding Equation (1), where *Loss* represents the annual disaster loss amount in the area.

$$Clms = Loss \tag{1}$$

However, predicting the exact value of *Loss* is highly challenging because the total property value, as well as the scale and frequency of disasters within an area, varies from year to year. As a result, there will be wide fluctuations in the value of *Loss*, complicating the task of making reliable predictions. To verify this analysis, we refer to the EM-DAT database (see Table 2) to experimentally compare the annual disaster loss amount caused by extreme weather, geological, hydrological, and storm disasters in the state of Texas, USA, from 2016 to 2023. The results are shown in Figure 1. We can see that the annual disaster loss amount fluctuates significantly, making it difficult to fit a trend. This reflects the extreme difficulty in directly predicting the disaster loss amount.
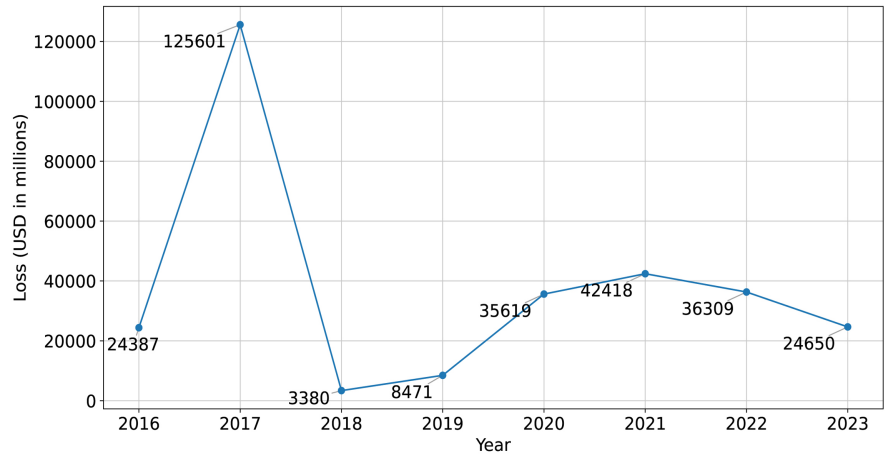
Figure 1. Annual disaster loss in Texas.

To eliminate the interference of total property value on the prediction, we introduce a new parameter, the loss ratio. The loss ratio can be defined by Equation (2).

$$LR = \frac{Loss}{PV_t} \tag{2}$$

Here, *Loss* refers to the annual disaster loss amount, and PV_t represents the total asset value for the year. *LR* is defined as the Loss Ratio. By using this ratio, we eliminate the interference of the total property value.

The intensity and frequency of natural disasters in an area are closely related to its geographical location and climatic conditions. For instance, areas located in tropical monsoon areas receive substantial and concentrated rainfall almost every year, leading to floods, while inland areas situated in the central parts of the continents are almost free from such risks. Although the global climate is changing, the climatic conditions of a place are unlikely to undergo significant alterations over shorter periods (within 10 years). Taking into account the factors above, we believe that *LR* (Loss Ratio) conforms to statistical characteristics, meaning that *LR* for a given area should have a constant theoretical value.

Based on the data from the Public EM-DAT database, we take Texas as an example and calculate the *Loss Ratio* (***LR***) from 2016 to 2023, and the results are shown in **Figure 2**. We can see that the data volatility has been significantly reduced, with most data points concentrated within a very small range. Accordingly, we use the *Average Loss Ratio* (denoted as $\overline{LR}$) to assess the theoretical disaster severity of the area. The average loss ratio represents the likelihood and extent of disaster losses in an area due to its geographical and climatic conditions. The average loss ratio can be calculated using Equation (3). Here, $\overline{LR}$ represents the average loss ratio, where *LR* is the Loss Ratio for each year, and *n* is the total number of years.

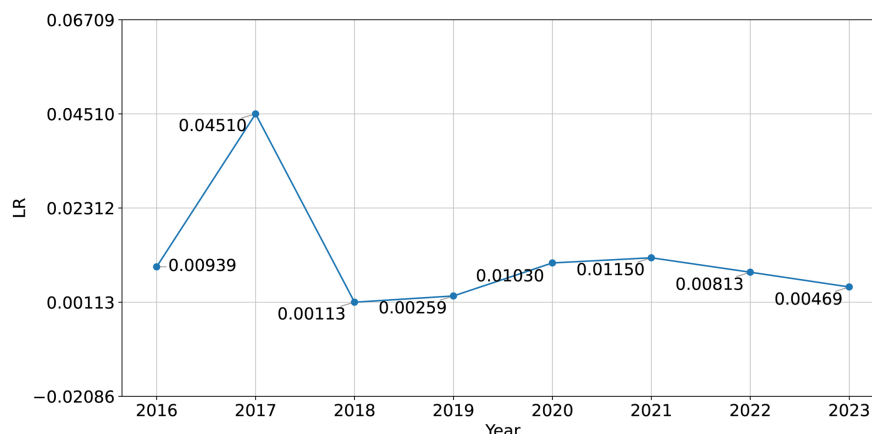$$\overline{LR} = \frac{1}{n} \sum_{i=1}^{n} LR \tag{3}$$

Figure 2. The Loss ratio (LR) of Texas.

Having obtained $\overline{LR}$, we can then calculate the expected loss amount for a given year using PV_t for that year, which in turn yields the payout for that year. The calculation method is demonstrated in Equation (4).

$$Clms = Loss = \overline{LR} * PV_t \qquad (4)$$

Subsequently, we obtain the annual *Prem*, PV_t, and *P* for a certain area from 2016 to 2023 and predict their future values using the ARIMA model [18] [19]. The ARIMA model, short for AutoRegressive Integrated Moving Average, is a popular statistical method for time-series prediction. The ARIMA model is particularly suitable for short to medium-term prediction when the data exhibits signs of non-stationarity, as it can capture the dynamics of past values and the randomness in the data, making it quite fitting for the prediction of this Task. The ARIMA model has been widely used in economics for forecasting future sales, stock market trends, industrial production, and macroeconomic indicators. Its adaptability to different types of input data and forecasting requirements makes it a versatile tool in time series analysis. In this study, we use the IBM SPSS 26.0 software to apply the ARIMA model and predict *Prem*, PV_t, and *P* for 2024. Subsequently, we will predict the expected loss of an area.

We use the EM-DAT database (see **Table 2**) to verify the model. Particularly, we chose two areas to verify our model: Texas in the United States and Australia. They are located in North America and Oceania, respectively.

For Texas, we obtained relevant data from the EM-DAT database, compiling and calculating the annual *Loss* for Texas from 2016 to 2023, adjusted to the 2023 currency value. We also retrieved the corresponding annual PV_t from the Texas Department of Treasury website. Based on these two datasets, we calculated the annual *LR* and determined $\overline{LR}$. At the same time, through the NAIC, we acquired the property insurance industry's annual *Prem* and *P* for the state for those years. We conducted the ARIMA analysis on PV_t, *Prem*, and *P* in IBM SPSS 26.0. Due to space constraints, we only present the analysis report for PV_t and *Prem*; the analysis procedures and results for the other variables are similar.
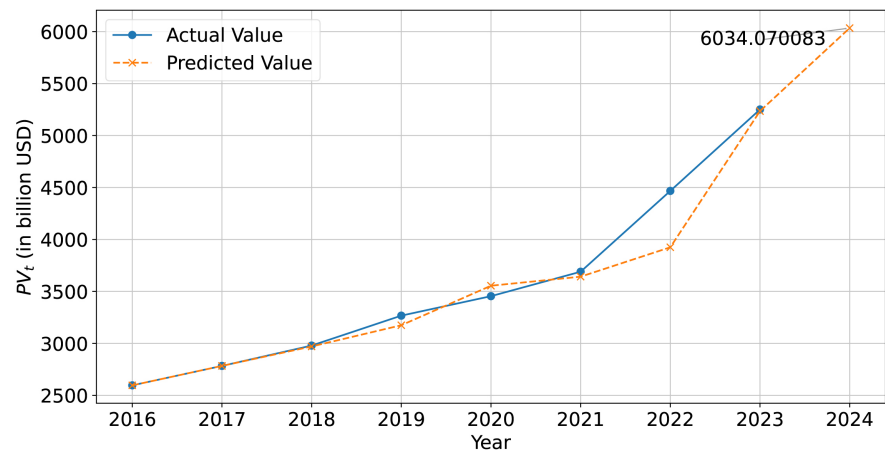
Figure 3. Predicted PV_t result for Texas.

Figure 3 shows the ARIMA analysis results for PV_t. According to the analytical report provided by IBM SPSS 26.0, the model has an R^2 of 0.944, indicating a good fit. Consequently, the predicted value of PV_t for the year 2024 is 6034.070083 billion USD.
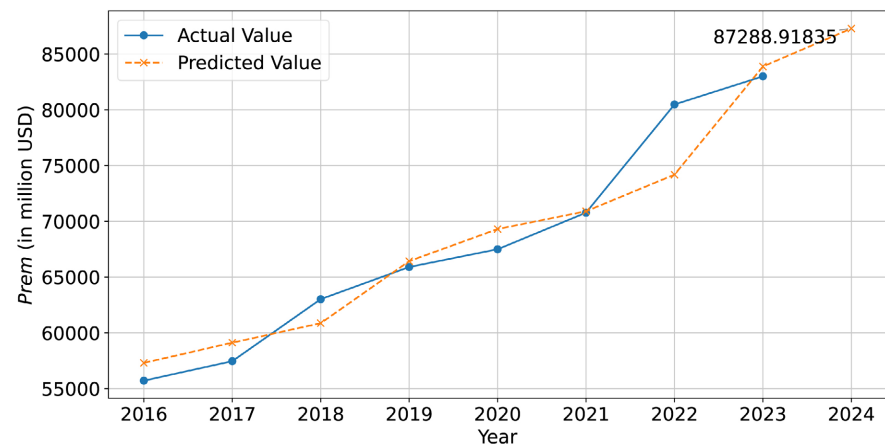

Figure 4. Predicted *Prem* result for Texas.

The *Prem* result of the ARIMA model for Texas is shown in **Figure 4**. The model has an R^2 of 0.917, indicating a good fit. From this, we can infer that the predicted value for *Prem* in the year 2024 is 87288.91835 million USD.

Continuing with the calculations for the remaining variables, we ultimately obtained the final results of the ARIMA model, as shown in **Table 3**.

For Australia, we obtained relevant data from the EM-DAT database, compiling and calculating the annual *Loss* for Australia from 2016 to 2023, adjusted to the 2023 currency value. We also retrieved the corresponding annual PV_t from the KPMG Database (see **Table 2**). Based on these two datasets, we calculated the annual *LR* and subsequently determined the $\overline{LR}$. At the same time, through the KPMG Database, we acquired the property insurance industry's annual *Prem* and *P* for the country for those years.

Table 3. The predicted results for Texas in 2024.

Variables	Value	Unit
PV_t	6034.070083	billion USD
$\overline{LR}$	0.011608	N/A
Loss	70043.48552	million USD
Clms	70043.48552	million USD
Prem	87288.91835	million USD
Pft	17245.43283	million USD
P	23131.56336	million USD

We conducted the ARIMA analysis on PV_t, *Prem*, and *P* using IBM SPSS 26.0. Due to the space limit, we present only the *Prem* result; the analysis procedures and results for the other variables are similar.
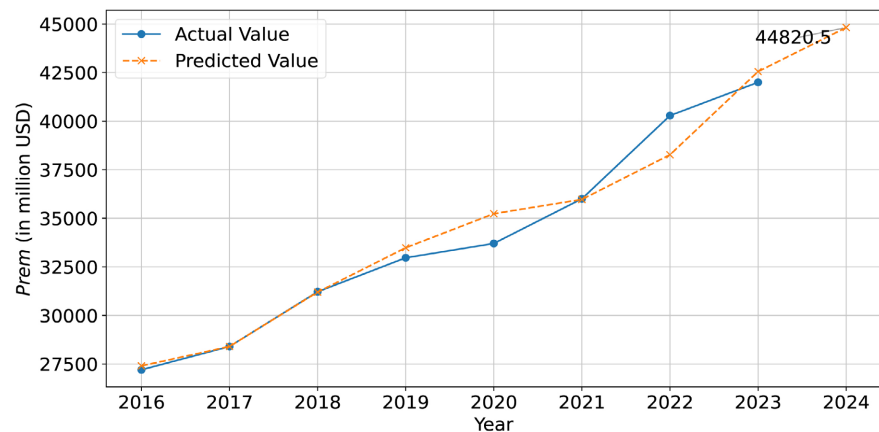

Figure 5. Predicted *Prem* result for Australia.

Figure 5 shows the *Prem* result of the ARIMA analysis. According to the analytical report provided by IBM SPSS 26.0, the model has an R^2 of 0.956, indicating a good fit. Consequently, the predicted value of *Prem* for the year 2024 is 44820.5 million USD.

Continuing with the calculations for the remaining variables, we ultimately obtained the final results of the model, as shown in **Table 4**.

Table 4. The predicted results for Australia in 2024.

Variables	Value	Unit
PV_t	5630	billion USD
$\overline{LR}$	0.001012	N/A
Loss	5697.56	million USD
Clms	5697.56	million USD
Prem	44821	million USD
Pft	39123.44	million USD
P	18600.712	million USD

4.2. Real Estate Area Selection

In this subsection, we present the model design and verification to offer decision support for real estate developing companies to select appropriate areas. The new contribution of this part is that we propose an enhanced TOPSIS model integrating the newly proposed indicator, *Average Loss Ratio*.

4.2.1. Enhancing the TOPSIS Model for Real Estate Area Selection

We need to establish a model to assist real estate companies in assessing which area is most worthwhile for development. According to the previous analysis, we need to consider disaster factors and the demand of the regional population. Therefore, we will take into account four factors: $\overline{LR}$ (Average Loss Ratio), *population*, *population growth rate*, and *GDP*.

Further, we propose to use the TOPSIS model to support decisions for real estate area selection. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) [20] [21] is a widely used MCDM (Multi-Criteria Decision-Making) tool suitable for the multi-criteria decision scenario presented in this question. TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the *Positive Ideal Solution* (PIS) and the longest geometric distance from the *Negative Ideal Solution* (NIS). TOPSIS is straightforward to implement and easy to understand, which helps in explaining the decision-making process to managers.

The novelty of our model is that we introduce the newly proposed indicator, $\overline{LR}$ (*Average Loss Ratio*), into the original TOPSIS model to improve the effectiveness of the model.

We will use the states of Alabama, California, Florida, Georgia, and Washington as examples for TOPSIS analysis and provide recommendations. Before conducting the analysis, we first need to obtain data on the population count, population growth rate, GDP, and $\overline{LR}$ for these areas in the year 2024.

After obtaining the data, we apply the Grey Prediction Model [22] [23] to predict each set of data. The Grey Prediction Model is a forecasting technique that falls under the category of Grey System Theory. The Grey Prediction Model is particularly valuable in scenarios where traditional modelling techniques struggle due to a lack of data or high levels of uncertainty. It offers a unique approach by leveraging the information available, no matter how incomplete, to generate forecasts that can guide decision-making in complex and uncertain environments. In addition, the Grey Prediction Model does not require a large volume of data and is particularly suitable for situations where the data fluctuates significantly. This model is appropriate for handling data with a degree of randomness, such as population growth rates and GDP, making it suitable for the scenario of this study.

Integrating the enhanced TOPSIS and the Grey Prediction Model, we will ultimately obtain a ranking of the recommendation levels for the above five states, assisting real estate companies in their decision-making process.

4.2.2. Model Verification

The datasets (see Table 2) used in this task include the EM-DAT database and two other datasets, including the USA-POP dataset and the BEA dataset. The USA-POP dataset consists of population-related data for each state in the USA from 2016 to 2023. The BEA dataset consists of the GDP data for each state in the USA.

First, we complete the prediction for the relevant data for the year 2024. After organizing the data, we apply the *Grey Prediction Model* in IBM SPSS 26.0 to derive the predicted values for 2024. With a variety of data types, the model results are similar. Due to space limitations, we will take the population growth rate of Georgia as an example to analyze the results of the Grey Prediction Model.
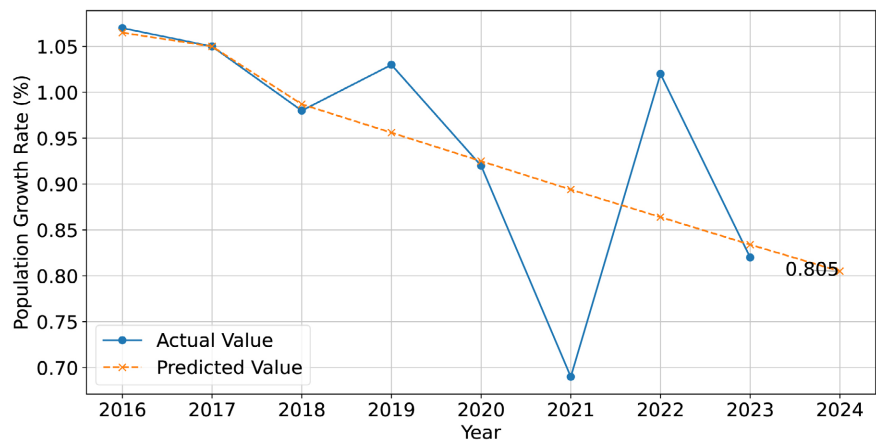

Figure 6. Predicted population growth rate.

We input the raw data into IBM SPSS 26.0, select Grey Prediction, and obtain results as shown in **Figure 6**. According to the analysis report from IBM SPSS 26.0, the model has an average relative error of 7.866%, indicating a good fit. From this, we obtain the predicted population growth rate for Georgia in 2024, which is 0.805%. The other predicted values for Task 2 can be obtained in the same manner.

For $\overline{LR}$, we use the same methods and data types as in Section 2 for calculation. In addition to the EM-DAT database, we also use the CEIC database (see **Table 2**) to calculate the *Average Loss Ratio* for other states.

After completing all calculations and predictions, we get **Table 5**. **Table 5** displays all the input data required for conducting the TOPSIS analysis.

Then, we proceed with the TOPSIS model processing flow. According to Equation (5), we complete the data normalization.

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}} \tag{5}$$

Here, x_{ij} is the original data in the decision matrix, and R_{ij} is the value after normalization. Subsequently, we utilize SPSS PRO to calculate the weights of

Table 5. TOPSIS input data for the year 2024.

Area	Population	GDP (Trillions $)	$\overline{LR}$	Growth Rate (%)
California	41,372,000	3.898	0.00058	3.757
Alabama	5,097,641	0.302	0.00559	0.748
Washington	7,951,150	0.808	0.00037	1.052
Florida	22,610,726	1.595	0.00386	1.833
Georgia	11,000,000	0.811	0.00066	0.805

each indicator using the *Entropy Weight Method* [24]. The calculation results are shown in Table 6.

Table 6. The calculated indicator weights.

Indicator	Information Entropy (*e*)	Information Utility (*d*)	Weight (%)
GDP	0.657	0.343	25.354
Population	0.644	0.356	26.293
Growth Rate	0.527	0.473	34.912
$\overline{LR}$	0.818	0.182	13.441

After obtaining the weights for each indicator, we use Equation (6) and Equation (7) to calculate the ideal and negative-ideal solution vectors, with the results shown in Table 7.

$$V_{ij} = w_j \times R_{ij} \tag{6}$$

$$\begin{cases} PIS = \left\{ \max\left(V_{ij}\right) \mid j \in J_{benefit} \quad \min\left(V_{ij}\right) \mid j \in J_{cost} \right\} \\ NIS = \left\{ \min\left(V_{ij}\right) \mid i \in J_{benefit} \quad \max\left(V_{ij}\right) \mid i \in J_{cost} \right\} \end{cases} \tag{7}$$

Table 7. Calculation of PIS and NIS values.

Indicator	Positive Ideal Solution	Negative Ideal Solution
GDP	0.99996451	0.00003549
Population	0.99996336	0.00003664
Growth Rate	0.99996253	0.00003747
$\overline{LR}$	0.99995927	0.00004073

Finally, we calculate the distance between each option and the *Positive Ideal Solution* (*PIS*) and the *Negative Ideal Solution* (*NIS*), and we compute the relative closeness. We use Equation (8) for these calculations.

$$\begin{cases} S_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - PIS\right)^2} \\ S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - NIS\right)^2} \end{cases} \tag{8}$$

Finally, we score each option based on S_i^+ and S_i^-, with the scoring method as shown in Equation (9). With this, we have completed the TOPSIS analysis, resulting in the table presented in Table 8.

$$CSI_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{9}$$

Table 8. The TOPSIS result for the year 2024.

Area	PIS Distance (S_i^+)	NIS Distance (S_i^-)	CSI	Rank
California	0.01423101	0.99479635	0.98589631	1
Alabama	0.99992562	0	0	5
Washington	0.83212112	0.38026516	0.31365017	3
Florida	0.61400106	0.39274119	0.39011096	2
Georgia	0.84112637	0.36339509	0.3016925	4

From Table 8, we can see that California has the highest *Composite Score Index* (*CSI*) and ranks first, while Alabama has the lowest Index and ranks last. Therefore, we recommend that real estate developers prioritize development in California. By meeting the local community and population needs while experiencing lower risks of natural disasters, they can achieve higher profits.

5. Conclusions and Future Work

In this paper, we presented an effective approach for predicting the most valuable area for real estate development. We proposed a sefl-defined new indicator called *Average Loss Ratio* to measure the probability of natural disasters in an area, based on which we presented a decision model based on ARIMA to predict the average loss ratio of an area. In addition, we proposed an enhanced TOPSIS model for real estate area selection. Combined with the Grey Prediction Model, we demonstrated that such a model can offer high effectiveness for real estate companies to select areas. We verified the effectiveness of the proposed models on various datasets, and the results suggested the effectiveness of our proposal.

Some limitations of this study are as follows. First, the current models in this study only consider a few existing models, such as ARIMA and TOPSIS. Many other models could also be used as the fundamental models. In the future, we will consider other models or hybrid models to improve the prediction performance. Second, the datasets used in this study only include the USA and Australia. Thus, the conclusions dropped could only be meaningful to these countries. In the future, we will try to obtain datasets from a wide range of countries, like Asian and European countries, enhancing the scalability and adaptivity of the proposed approach. Third, the proposed approaches in this study were evaluated on a static dataset. When a dataset is frequently updated in some scenarios, it is necessary to refine the models to make them adaptable to dynamic da-

tasets.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Mauri, M., Rancati, G., Riva, G. and Gaggioli, A. (2024) Comparing the Effects of Immersive and Non-Immersive Real Estate Experience on Behavioral Intentions. *Computers in Human Behavior*, **150**, Article ID: 107996.
https://doi.org/10.1016/j.chb.2023.107996

[2] Baur, K., Rosenfelder, M. and Lutz, B. (2023) Automated Real Estate Valuation with Machine Learning Models Using Property Descriptions. *Expert Systems with Applications*, **213**, Article ID: 119147. https://doi.org/10.1016/j.eswa.2022.119147

[3] Sandeep Kumar, E., Talasila, V. and Pasumarthy, R. (2021) A Novel Architecture to Identify Locations for Real Estate Investment. *International Journal of Information Management*, **56**, Article ID: 102012.
https://doi.org/10.1016/j.ijinfomgt.2019.09.008

[4] Xiong, X., Guo, H. and Hu, X. (2020) The Housing Demand Analysis and Prediction of the Real Estate Based on the AWGM (1, *n*) Model. *Grey Systems: Theory and Application*, **11**, 222-240. https://doi.org/10.1108/gs-09-2019-0035

[5] Jie, Z. and Qi, C.H. (2023) An Equilibrium Analysis of the Impact of Real Estate Price Volatility on Macroeconomics Based on Ant Colony Algorithm. *Journal of Combinatorial Optimization*, **45**, Article No. 70.
https://doi.org/10.1007/s10878-023-00995-x

[6] Lewis, E.J. (2022) A Literature Review on the Marketing Partnership Challenge. *International Journal of Smart Education and Urban Society*, **13**, 1-47.
https://doi.org/10.4018/ijseus.299045

[7] Di Pinto, V. and Rinaldi, A.M. (2018) A Configurational Approach Based on Geographic Information Systems to Support Decision-Making Process in Real Estate Domain. *Soft Computing*, **23**, 2853-2862.
https://doi.org/10.1007/s00500-018-3142-9

[8] Efthymiou, D. and Antoniou, C. (2015) Measuring the Effects of Transportation Infrastructure Location on Real Estate Prices and Rents: Investigating the Current Impact of a Planned Metro Line. *EURO Journal on Transportation and Logistics*, **3**, 179-204. https://doi.org/10.1007/s13676-013-0030-4

[9] Boston Consulting Group (2023) An Insurance Risk Framework for Climate Adaptation.

[10] Munich, R.E. (2022) Hurricanes, Cold Waves, Tornadoes: Weather Disasters in USA Dominate Natural Disaster Losses in 2021.
https://www.munichre.com/en/company/media-relations/media-information-and-corporate-news/media-information/2022/natural-disaster-losses-2021.html

[11] Yuan, J. (2022) Real Estate Risk Based on Combination of Factor Analysis and Spatial Statistics. *Journal of Computational Methods in Sciences and Engineering*, **22**, 2007-2021. https://doi.org/10.3233/jcm-226379

[12] Rabiei-Dastjerdi, H., McArdle, G., Matthews, S.A. and Keenan, P. (2020) Gap Analysis in Decision Support Systems for Real-Estate in the Era of the Digital Earth. *International Journal of Digital Earth*, **14**, 121-138.

https://doi.org/10.1080/17538947.2020.1808719

[13] Zhang, X., Ma, Y. and Wang, M. (2023) An Attention-Based Logistic-CNN-Bilstm Hybrid Neural Network for Credit Risk Prediction of Listed Real Estate Enterprises. *Expert Systems*, **41**, e13299. https://doi.org/10.1111/exsy.13299

[14] He, W., Zhang, Y., Kong, D., Li, S., Wu, Z., Zhang, L., *et al.* (2024) Promoting Green-Building Development in Sustainable Development Strategy: A Multi-Player Quantum Game Approach. *Expert Systems with Applications*, **240**, Article ID: 122218. https://doi.org/10.1016/j.eswa.2023.122218

[15] Wu, S. (2023) Green Building Development for a Sustainable Environment with Artificial Intelligence Technology. *International Journal of Computer Applications in Technology*, **73**, 203-216. https://doi.org/10.1504/ijcat.2023.135590

[16] Munawar, H.S., Qayyum, S., Ullah, F. and Sepasgozar, S. (2020) Big Data and Its Applications in Smart Real Estate and the Disaster Management Life Cycle: A Systematic Analysis. *Big Data and Cognitive Computing*, **4**, Article 4. https://doi.org/10.3390/bdcc4020004

[17] Battisti, E., Shams, S.M.R., Sakka, G. and Miglietta, N. (2019) Big Data and Risk Management in Business Processes: Implications for Corporate Real Estate. *Business Process Management Journal*, **26**, 1141-1155. https://doi.org/10.1108/bpmj-03-2019-0125

[18] Hamilton, J. (1994) Time Series Analysis. Princeton University Press.

[19] Guerra, R.R., Vizziello, A., Savazzi, P., Goldoni, E. and Gamba, P. (2024) Forecasting Lorawan RSSI Using Weather Parameters: A Comparative Study of ARIMA, Artificial Intelligence and Hybrid Approaches. *Computer Networks*, **243**, Article ID: 110258. https://doi.org/10.1016/j.comnet.2024.110258

[20] Yoon, K. and Hwang, C.L. (1981) Multiple Attribute Decision Making: Methods and Applications. Springer-Verlag.

[21] Pandey, V., Komal and Dincer, H. (2023) A Review on TOPSIS Method and Its Extensions for Different Applications with Recent Development. *Soft Computing*, **27**, 18011-18039. https://doi.org/10.1007/s00500-023-09011-0

[22] Liu, G. and Yu, J. (2007) Gray Correlation Analysis and Prediction Models of Living Refuse Generation in Shanghai City. *Waste Management*, **27**, 345-351. https://doi.org/10.1016/j.wasman.2006.03.010

[23] Cai, K. and Wu, L. (2024) Grey Prediction of Carbon Emission and Carbon Peak in Several Developing Countries. *Engineering Applications of Artificial Intelligence*, **133**, Article ID: 108210. https://doi.org/10.1016/j.engappai.2024.108210

[24] Zhai, S., Li, G., Wu, G., Hou, M. and Jia, Q. (2023) Cooperative Task Allocation for Multi Heterogeneous Aerial Vehicles Using Particle Swarm Optimization Algorithm and Entropy Weight Method. *Applied Soft Computing*, **148**, Article ID: 110918. https://doi.org/10.1016/j.asoc.2023.110918