A Fitted Modeling Study of Past Weather Extremes in Canada

Danning Zhang *

College of Life Sciences, Sichuan University, Chengdu, China, 610065

* Corresponding Author Email: 2607374469@qq.com

Abstract. Extreme weather events have left deep imprints in the long history of humankind, and these imprints have formed historical landmarks of great value. These landmarks are not only records of natural phenomena, but also witnesses to the social, cultural and economic development of humankind. The study of these historical landmarks can provide a better understanding of the relationship between human beings and the natural environment, and provide a useful reference for future sustainable development. This paper analyzes and learns that these historical landmarks are records and warnings of natural disasters. Extreme weather events, such as floods, hurricanes, droughts and extreme heat, have wreaked havoc and impact on human societies. Therefore, this paper determines the past temperature trends by fitting past weather data, temperature data, and terrain data. The occurrence of these events reminds people of the power and unpredictability of natural forces. Through in-depth study of these historical landmarks, people can better understand the formation mechanism and scope of impact of natural disasters, so as to take effective preventive measures and reduce disaster losses.

Keywords: Extreme Weather Events, Landmarks, Unpredictability, A Fitted Modeling.

1. Introduction

As the effects of global climate change become more evident, the frequency and intensity of extreme weather events are increasing. Extreme weather events such as heavy rains, floods, hurricanes, droughts and scorching heat have caused tremendous losses and impacts on human society and economy. Property insurance, as one of the important means to cope with these risks, has also been severely challenged in the context of climate change [1-2].

The sustainable development of property insurance is not only related to the survival and development of the insurance industry, but also to the stability and sustainable development of society and economy. However, due to the unpredictability and complexity of extreme weather events, property insurance faces many difficulties and challenges in addressing these risks. For example, as a result of climate change, some traditional insurance products may no longer be able to cover some new risks, and existing insurance terms and policies face the need for continuous adjustment and improvement [3].

Therefore, the study of extreme weather and the sustainability of property insurance has important practical significance and theoretical value. Through the research on the occurrence pattern, influence degree and response strategy of extreme weather, we can gain a deeper understanding of the impact of climate change on property insurance, and then provide scientific basis and technical support for the insurance industry, promote the innovation and development of insurance products, and enhance the sustainability of property insurance [4].

At the same time, research on extreme weather and property insurance sustainability can also help promote cooperation and communication between the insurance industry and other related industries, and promote sustainable social and economic development. For example, insurance companies can cooperate with meteorology, environment, construction and other related fields to jointly study and respond to the risks posed by climate change and promote the formulation and implementation of relevant policies and standards.

2. The fundamental of cluster analysis

The normalized linear transformation method is used to standardize the row and column data and solve the problem of comparability between data indicators. After the raw data supplied by different impact factors are standardized, the indicators are in the same order of magnitude, which facilitates comprehensive comparison and evaluation. Therefore, the use of standardization can make them distributed between 1 and 100, and the total score of their evaluation can be obtained after weighted processing, so as to get their importance.

$$S = \frac{R_t - R_{\min}}{R_{\max} - R_{\min}} \times T \tag{1}$$

The problem studied in this paper requires temperature data for certain areas of Canada. In this paper, the Canadian province of British Columbia was chosen for the study because it is located in the southwestern part of Canada, bordering the Atlantic Ocean to the west, and most of the province is covered by forests, with the province roughly in the shape of a parallelogram [5-6]. Therefore, based on its geomorphology and latitude and longitude, weather station data from 13 locations were selected as the study data. These data were obtained from the Canadian website : http://climate.weather.gc.ca/historical_data/search_historic_data_e.html.

Preprocessing mainly includes removing unique attributes, dealing with missing values and outliers, feature coding and so on. The specific processing methods and steps are as follows:

(1) Remove unique attributes

The unique attributes are usually some id attributes, which cannot describe the distribution of the samples themselves, so we only need to remove these attributes. In addition to the temperature data needed for this question, there are a large number of other climate data (rainfall, snowfall, precipitation, etc.), so it is necessary to delete other useless data.

(2) Handling missing values and outliers

Missing data means that a part of the required data is missing from the dataset. Data anomalies are when the collected data deviates significantly from other data or defies common sense. In general, the data we collect often have missing values and outliers due to equipment failures, data logging errors, data loss, and other external factors.

This model uses the control variable method to control for a series of different dimensions (49°N, 52°N, 54°N, 56°N, 58°N) invariant and longitude changes, and a series of different longitudes (120°W, 123°W, 130°W) invariant and latitude changes. The model flow diagram is shown in Figure 4. Model flow diagram for the study of trends in historical temperature data for British Columbia, Canada.

The control variable method is used in the Monte Carlo method to reduce variancea technical approach. This method reduces the error in the estimation of unknown quantities by knowing the known quantities. In physics, for multi-factor (multi-variable) problems, the method of controlling factors (variables) is often adopted, turning multi-factor problems into multi-factor problems [7].

Linear fitting, also known as first-order fitting, is a form of curve fitting. Let sum x y be the observed quantities y, and is a function of : x, the curve fitting is through, and the observations of , to find the best $y = ax + b$ estimate of parameter b, and to find the best theoretical curve x y $y = ax + b$.

$$S(a,b) = \sum_{k=1}^{n} [(a + bx_k) - y_k]^2 \tag{2}$$

The geometric background of the problem is to find a straight line so that the sum of squares of the longitudinal distance between the line and the plane scatter determined by the data table is minimized [2], as shown in Figure 1 Scatterplot linear fit.

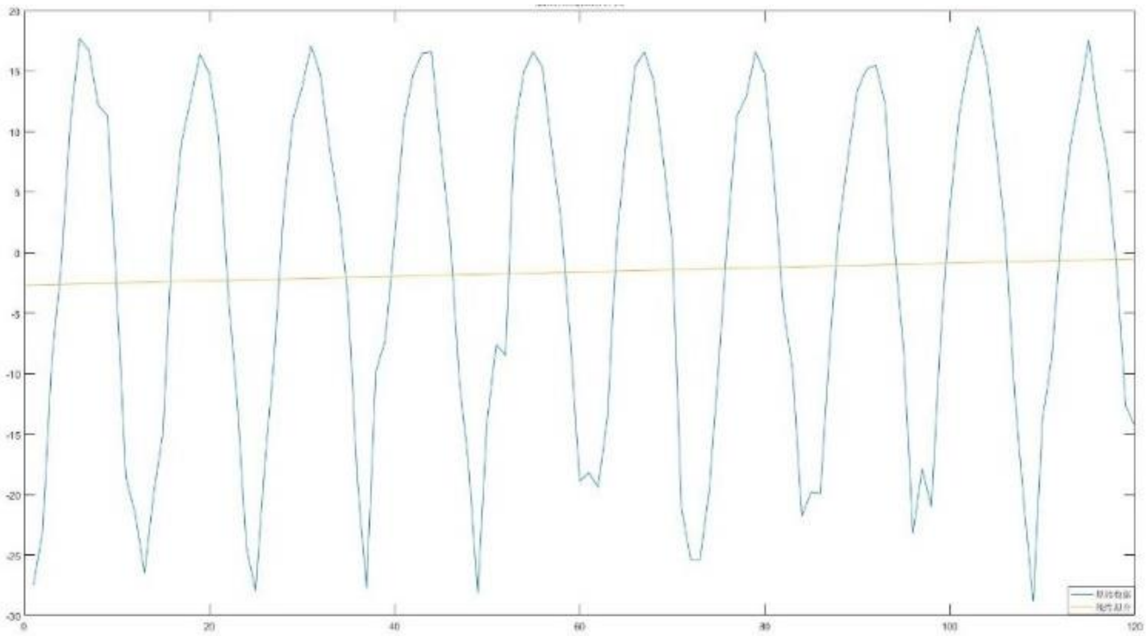


Figure 1: Scatter plot linear fit plot

The function derives the two variables:

$$\frac{\partial S}{\partial a} = 2\sum_{k=1}^{n}[(a + bx_k) - y_k] \tag{3}$$

$$\frac{\partial S}{\partial b} = 2\sum_{k=1}^{n}[(a + bx_k) - y_k]x_k \tag{4}$$

For equations (3) and (4), the simultaneous solution obtains:

$$\begin{cases} ma + \sum_{k=1}^{n} x_k b = \sum_{k=1}^{n} y_k \\ \sum_{k=1}^{n} x_k a + \sum_{k=1}^{n} x_k^2 b = \sum_{k=1}^{n} x_k y_k \end{cases} \tag{5}$$

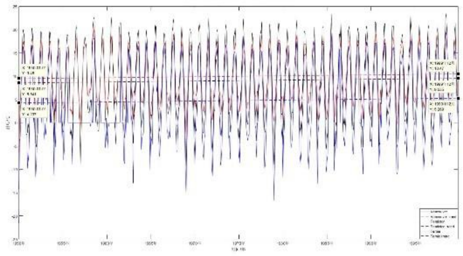
Solving the system of equations (5) gives the values of two constants a , b and thus gives the linear fitting function $y = ax + b$.

3. Results

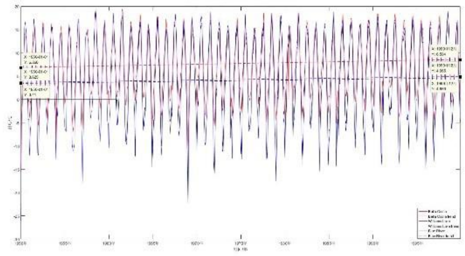
3.1. The establishment of simulation model

According to the needs of the topic, the model processes and analyzes the data from the time dimension and the spatial dimension respectively [8].

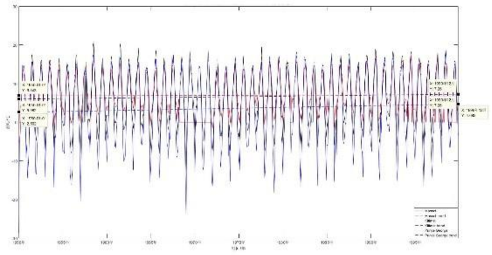
(1) Analysis of spatial dimension results



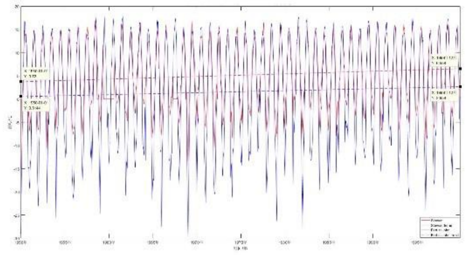
(a)



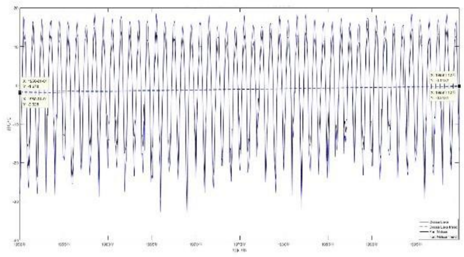
(b)



(c)



(d)



(e)

Figure 2: Historical average temperature for British Columbia, Canada as a function

(a) 49°N, (b) 52°N, (c) 54°N, (d) 56°N, (e) 58°N

The specific data changes are shown in Table 1. Table 1 Historical mean temperature changes with longitude in British Columbia, Canada [9].

From the average and median columns of Table 1 Historical mean temperature as a function of latitude in British Columbia, Canada, it can be analyzed that the temperature data shows a downward trend with the decrease of longitude (westward shift) when the latitude is unchanged, as shown in Figure 2.

The average and median of historical mean temperature as a function of longitude [10]. The standard deviation column shows an overall upward trend with decreasing longitude (westward shifting), as shown in Figure 6 Historical mean temperature standard deviation with longitude. The temperature rise fit from 1950 to 1999 was basically around 1.5°C.

Table 1: Historical mean temperature as a function of longitude in British Columbia, Canada

Latitude	Toponym	Longitude/°	Average	Median	Standard deviation	Heating fit/°C
49°N	Vancouver	-123.18	9.9743	9.6000	5.2751	0.99
	Penticton	-119.6	9.0380	8.7000	7.9504	0.994
	Fernie	-115.07	4.0732	2.4000	8.0212	1.032
52°N	Bella Coola	-126.69	7.7115	8.0000	6.6515	1.716
	Williams Lake	-122.05	4.1786	4.6500	8.7211	1.34
	Blue River	-119.28	4.2953	4.4000	9.0300	1.259
54°N	Masset	-132.3	6.9702	6.2000	5.0676	0.417
	Kitimat	-128.7	6.6393	6.5000	7.0086	1.278
	Prince George	-122.68	3.6228	4.9000	9.1948	2.121

In order to ensure that there is no change in latitude and longitude of the historical temperature data in British Columbia, a series of average temperature data with fixed latitude values (see Figure 3 for the spatial distribution of the data source distribution map) were taken to plot the results of temperature change with latitude, as shown in Figure 4 Trend of historical average temperature data with latitude in British Columbia, Canada.

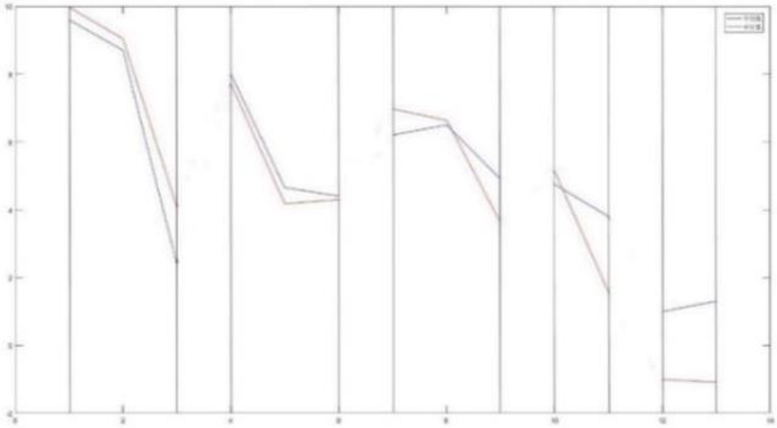


Figure 3: Historical mean and median temperatures as a function of longitude

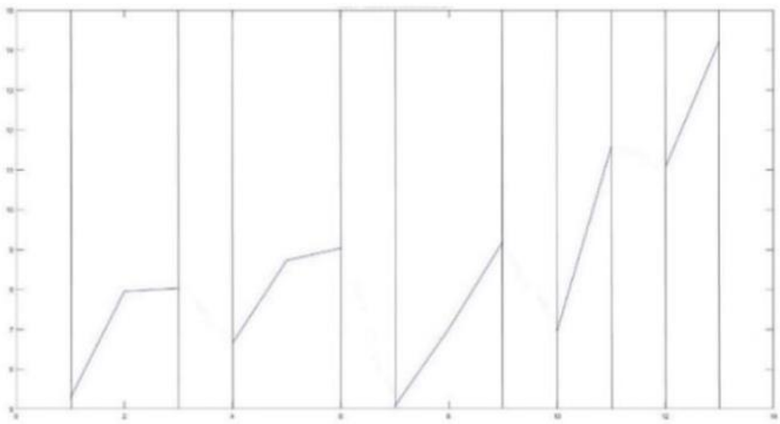


Figure 4: Historical mean temperature standard deviation as a function of longitude

The specific data changes are shown in Table 2 The change of historical mean temperature with latitude in British Columbia, Canada

Table 2: Historical mean temperature as a function of latitude in British Columbia, Canada

Longitude	Toponym	Latitude/°	Average	Median	Standard deviation	Heating fit/°C
120°W	Penticton	49.46	9.0380	8.7000	7.9504	0.994
	Blue River	52.15	4.2953	4.4000	9.0300	1.259
	Fort st John	56.24	1.5860	3.8000	11.5475	2.1436
123°W	Vancouver	49.2	9.9743	9.6000	5.2751	0.99
	Prince George	53.89	3.6228	4.9000	9.1948	2.121
	Fort Nelson	58.84	-1.0883	1.3000	14.2282	1.8798

From the mean and median columns of the historical mean temperature as a function of longitude in Tables 1 and 2, it can be analyzed that when the latitude is constant, the temperature data show a decreasing trend with the increase of longitude (shifting upward), while the column of the standard deviation shows an overall increasing trend with the increase of latitude (shifting westward) as shown in Fig. 5. The standard deviation of the historical mean temperature versus the latitude. The temperature increases from 1950 to 1999 is basically around 1.5°C. The standard deviation column shows a general increasing trend with increasing latitude (moving westward), as shown in Figure 5.

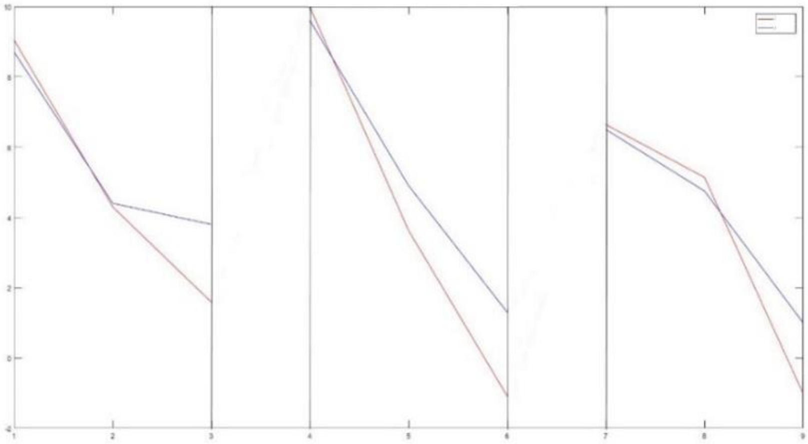


Figure 5: Historical mean and median temperatures as a function of latitude

The time dimension for British Columbia, Canada is analyzed below:

Historical mean temperatures have also been increasing over time, i.e., British Columbia, Canada has been warming between 1950 and 1999. Over the past 50 years, the average temperature in the region has increased by about 1.5 degrees Celsius. The study shows historical climate data for a more detailed study of four representative sites in the region. The trend of historical temperature data over time for British Columbia, Canada, shows an increase over time for all types of temperatures.

4. Conclusions

This paper describes the process of classifying ancient glassware with a degree of accuracy and ingenuity and can make scientifically sound decisions through a decision tree model. The random forest is extremely accurate, works effectively on large data sets, introduces randomness, and is not prone to overfitting [10]. Random forests are very resistant to noise but can overfit when the data is relatively noisy. Can handle very high dimensional data without dimensionality reduction. Can handle not only discrete data but also continuous data and does not require normalization of the data set. Decision trees are easy to understand and interpret and require less data for training than other machine learning models that typically require data normalization, such as constructing dummy variables and removing missing values. The number of data points used to train a decision tree result in an exponential distribution of the overhead of using decision trees (the time complexity of a training tree model is the logarithm of the number of data points participating in the training). Although the random forest algorithm is fast enough, when faced with many decision trees in a random forest, the space and time required for training can be significant, resulting in a slower model. Therefore, in practice, it is better to choose other algorithms if real-time requirements are very high. The decision tree model tends to produce an overly complex model, which has a poor generalization performance to the data. This is known as overfitting and some strategies like pruning, setting the minimum number of samples needed for a leaf node or setting the maximum depth of the number are the most effective ways to avoid this problem. The analysis of this problem can also be applied to the problem of siting and dispatching of other transport exchanges, e.g. e-bikes, where the parameters can be adjusted to solve the problem with reference to this model. In addition, the model is also useful for optimal path planning and selection.

References

[1] Guo Jia, Zhai Guofang, Ge Yifu. Construction and Empirical Study of the Comprehensive Resilience Index for Rural Human Settlements: A Case Study of Jiangsu Province [J]. Shanghai Urban Planning, 2023, (02): 15-22

[2] Zhao Yanxia, Chen Sining. Progress in Theory and Practice of Weather Risk Management [J]. Progress in Meteorological Science and Technology, 2023,13 (02): 26-37

[3] Wu Chao. Exploration and Innovation of China's Comprehensive Strengthening of Social Construction in the Decade of the New Era [J]. Contemporary Chinese History Research, 2023,30 (02): 9-26+156

[4] Zhang Haifeng, Kong Feng, Fang Jian. International comparative study on the response to extraordinary extreme rainstorm and flood disaster: taking the rainstorm and flood disaster in Germany and China in 2021 as an example [J]. Water Resources and Hydropower Technology (Chinese and English), 2023,54 (07): 1-13.

[5] Tan Qiuxia, Wu Zilin. Research on the Protection of the Rights and Interests of Delivery Riders from the Perspective of Interest Balance [J]. Journal of Fujian Jiangxia University, 2023,13 (01): 47-58

[6] Hou Xuhua, Tang Yuhui. Research on the Path to Achieve the "Dual Carbon" Goal with Forest Insurance: A Case Study of Hunan Province [J]. Hunan Social Sciences, 2022, (06): 64-74

[7] Zhang Qingjian. Research on the Marketing Strategy of Home Property Insurance through the Gas Channel of Shandong Zhonghua Property and Casualty Insurance [D]. Shandong University, 2022.

[8] Liu Zhongzheng. Risk Management for Business Development of China Tower Corporation's X Branch [D]. Nanjing University of Posts and Telecommunications, 2021.

[9] Zhang Xi. Research on Planning Elements of Climate Adaptable Cities [D]. Beijing Jianzhu University, 2020.

[10] Cai Haijie Translation report of "Smart Response to Climate Change - Communication, Coordination and Cooperation" (excerpt) [D]. South China Agricultural University, 2020.