SCIREA Journal of Environment
ISSN: 2995-6919
http://www.scirea.org/journal/Environmental
July 23, 2024
Volume 8, Issue 2, April 2024
https://doi.org/10.54647/environmental610401

Did the Temperatures Change in Kurume Region over Recent Years?

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Abstract

This paper investigates climate change, with a specific focus on temperature variations in Kurume, Fukuoka, Japan.

The summer temperatures in the Kurume region have shown a significant increase, progressively warming in recent years. To substantiate this observation, we conducted numerical analyses using climate data sourced from the Japan Meteorological Agency website.

Firstly, we provide a brief overview of the geographical characteristics of the Kurume region and outline our analytical methods. Secondly, we apply our proposed statistical analysis to the relevant temperature datasets. Lastly, we present our findings and provide concluding remarks on the observed trends.

1. Introduction

Kurume region is situated in the southern part of Fukuoka Prefecture, within the Chikugo Plain, traversed by the Chikugo River flowing from the northeast to the southwest, which largely defines its boundaries.

The region encompasses Kurume city and its surrounding areas. The main area of Kurume city extends from downtown and Nishitetsu Kurume Station to JR Kurume Station, located approximately 40 km from Fukuoka City. Following the incorporation of surrounding municipalities in 2005, the city expanded to approximately 32 km east to west and 16 km north to south, resulting in an elongated shape.

The city’s population is about 400,000 and hosts key industries such as tyre manufacturing plants, establishing it as the largest city in southern Fukuoka Prefecture.

To the south and southeast of the city lies a mountainous area known as Minourenzan, featuring interconnected mountains including Takatori-yama, Hasshin-yama, and Minou-yama. While winter brings occasional snowfall, summer is characterized by high humidity and temperatures. Figure 1 shows the 3D photo of Kurume Region(from Google Earth, June, 2024)[1].

Figure 1: 3D Photo of Kurume Region

In recent years, there has been a notable increase in maximum temperatures. According to statistics from the Japan Meteorological Agency, the frequency of days with maximum temperatures reaching 35 degrees Celsius or higher has risen since 1994. Between 1910 and 1939, the annual average of such days was 0.8. However, in the last 30-year period from 1990 to 2019, this average increased to about 2.3 days, nearly tripling to approximately 2.9 times [2].

Figure 2 illustrates the evolution of yearly maximum and minimum temperatures from 1978 to 2022. As observed, there appears to be a rising trend in temperatures over the past 20 years. These data will be utilised in the analyses presented below.

The data used in this study were sourced from the Website of Japan Meteorological Agency[3]. And the descriptive statistics for maximum and minimum temperatures are presented in Table 1.

Table 1: Descriptive statistics

n=45	mean	sd	median	skew	kurtosis	min	max
$temp_{max}$	36.40	1.40	36.2	-0.28	-0.02	32.6	39.5
$temp_{min}$	-3.63	1.15	-3.8	5.4	-0.30	-6.5	-1.1

Hereafter, we conduct analyses using the aforementioned temperature dataset.

Firstly, we apply change point detection to identify any shifts in the temperature series. A change point signifies a turning point in temperature trends and helps pinpoint when climate shifts occur.

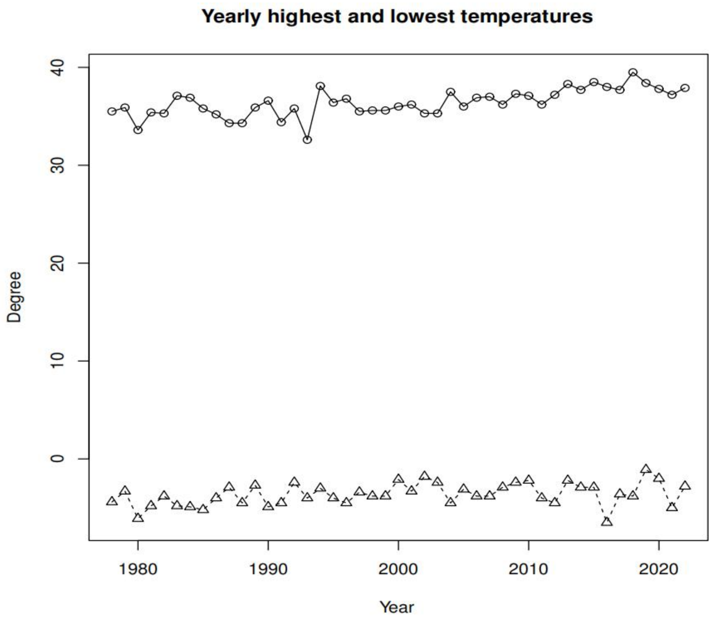


Figure 2: Yearly Max Temperature from 1978 to 2022

Secondly, we analyse extreme temperature values to explore the statistical properties of maximum and minimum temperatures and determine their return levels.

The remainder of this paper is structured as follows: Section 2 provides an overview of change point identification and extreme value analysis. Section 3 presents the results of our empirical research. Finally, Section 4 summarises our concluding remarks.

2. Methodologies

In this section we simply review the methodologies we apply to the data, namely, detection of a change point(CP) and Generalised Extreme Value(GEV) theory.

2.1 Detecting a Change Point

We carry out a change point detection in our numerical research. It can help us to find out the change point of the temperature series.

Several methodologies of change point detection can be utilised.

1) Non-parametric method: Pettitt's test

Pettitt's test for single change-point detection has been carried out[4].

Pettitt's test is a rank-based nonparametric statistical test applied to detecting change point in time series.

Assuming we have a time series $X_1, X_2, ..., X_T$ with change point at time τ , namely, before and after τ , there exists two different distributions, $x_t \sim F_1(x_t)$, where $t = 1, 2, ..., \tau$, and $x_t \sim F_2(x_t)$, where $t = \tau + 1, ..., T$.

So that, the hypothese $H0$ of having no change point is to be $F_1(X) = F_2(X)$ and the counterpart $H1$ of having change point becomes $F_1(X) \neq F_2(X)$.

In order to identify a change point, the statistic $U_{t,T}$ is utilised as follows.

$$U_{t,T} = \sum_{i=1}^{t} \sum_{j=t+1}^{T} sgn(x_i - x_j), 1 \leq t < T \tag{1}$$

where $sgn(x)$ is a signal function.

A change point candidate τ should be satisfied

$$K_\tau = U_{\tau,T} = max[U_{t,T}|, 1 \le t < T] \quad (2)$$

Simultaneously, the corresponding *p* value is defined as follows based upon the asymptotic property. *H*0 would be rejected where *p*<*α* for a given significance level *α*.

$$p \approx 2exp\{\frac{-6K_\tau^2}{T^2 + T^3}\} \quad (3)$$

2) Mean or variance shift method

One can determine if there exists a mean or variance shift in the time series between different segments. In both scenarios, a normal distribution with the same variance or mean is assumed, with a change point dividing the entire time interval into two subintervals with different mean or variance[5].

3) Bayesian Inference

MCMC Bayesian inference is also employed to estimate the change point, assuming prior distributions for certain parameters. Usually, a Gibbs sampler or Metropolis-Hastings (MH) sampler is implemented to obtain the posterior distribution[6][7][8][9][10].

2.2 The Generalised Extreme Value Distribution

Generally speaking, a Generalised extreme value distribution can be summarised as follows.

$$G(z) = exp\{-[1 + \xi(\frac{z-\mu}{\sigma}]^{-\frac{1}{\xi}}\} \quad (4)$$

On the other hand, it can be represented by three different distribution families: Gumbel, Fr´echet, and Weibull.

The estimated return level can be shown as follows.

$$z_t = \begin{cases} \mu - \frac{\sigma}{\xi}[1 - (-log(1-p))^{-\xi} & \xi \neq 0 \\ \mu - \sigma log(-log(1-p)) & \xi = 0 \end{cases} \quad (5)$$

where $G(z_p) = 1 - p.$ Thus, the return period is corresponding to $\frac{1}{p}$, it means that the event occurs on average once every $\frac{1}{p}$ years.

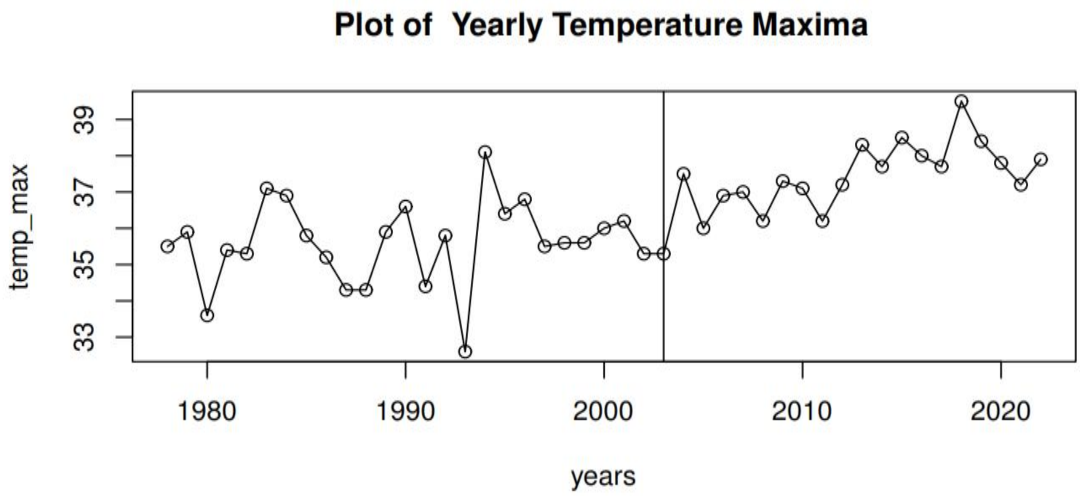
3. Numerical Analysis

3.1 Change Point Detection

As mentioned above, we firstly apply Pettitt's test to detecting change point. The numerical results are summarised as follows.

U^*=423, p-value=1.976e-05; alternative hypothesis: two.sided; sample estimates: probable change point at time K 26(Year 2003).

Namely, the change point for yearly temperature maxima is at the position No.26. This indicates that the year 2003 is the detected change point. The results of Pettitt's test are shown in Figure 3.



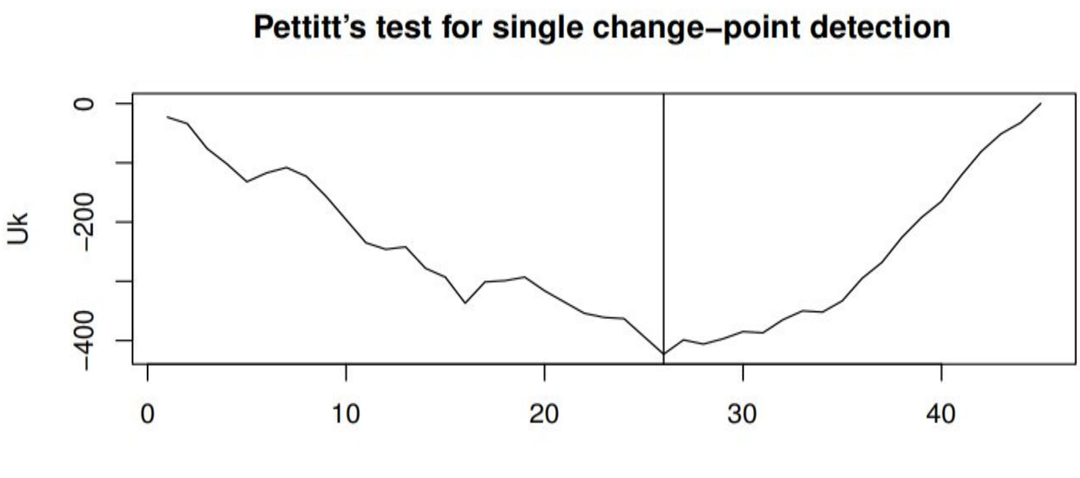


Figure 3: Change Point detected in Year 2003

Change point detection in mean or variance is also carried out. Consequently, two change points have been identified as shown in Figure 4. The positions of two change points are displayed by vertical lines.

It shows that the year 2003 is also the change point in mean shift (MBIC value: 11.41999), which is in accord with the result of Pettitt's test. Besides, the year 2012 is identified as the change point in variance (MBIC value: 15.22665).

Furthermore, MCMC Bayesian inference is immplemented and the results are displayed in Figure 5.

The estimated change points are at positions No.16 (1993), No.26 (2003), and No.35 (2012), with corresponding probabilities of a change in mean estimated at 0.686, 0.204, and 0.302, respectively.

Thus, the non parametric test, mean or variance shift method, and Bayesian inference all yield similar results, indicating that 2003 is the change point. Additionally, 2012 is identified as a change point by two methods. Moreover, the Bayesian inference identifies 1993 as a change point, which aligns with JMA's data indicating that temperatures began to rise significantly since 1994. The change point in variance in 2012 indicates, that temperatures before 2012 had a larger variance of 1.3446, whereas after 2012, the variance decreased to 0.9592, showing the maximum temperatures have remained somewhat stable at high levels.

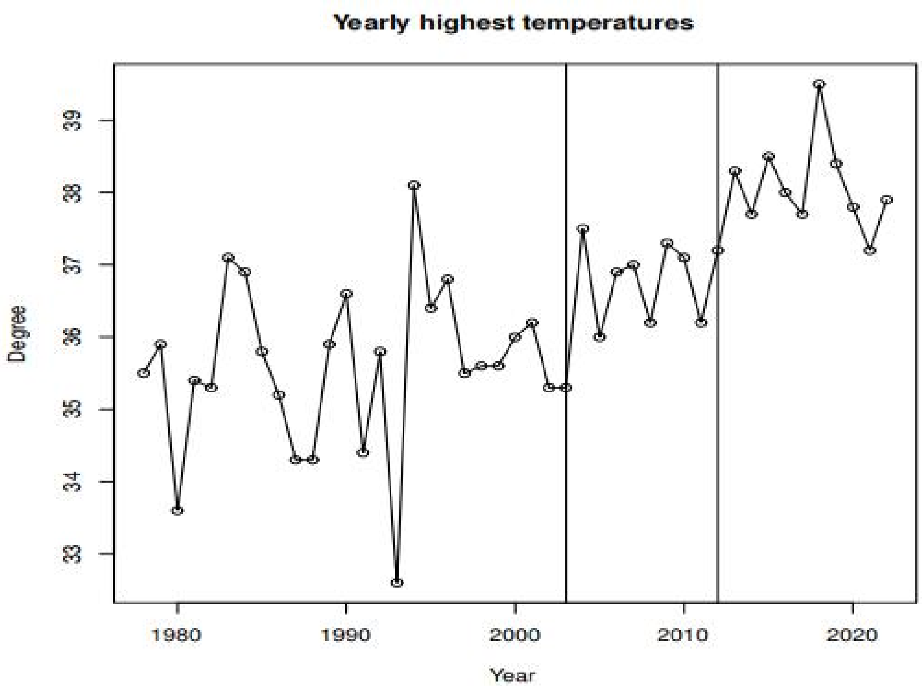


Figure 4: Yearly Max Temperature

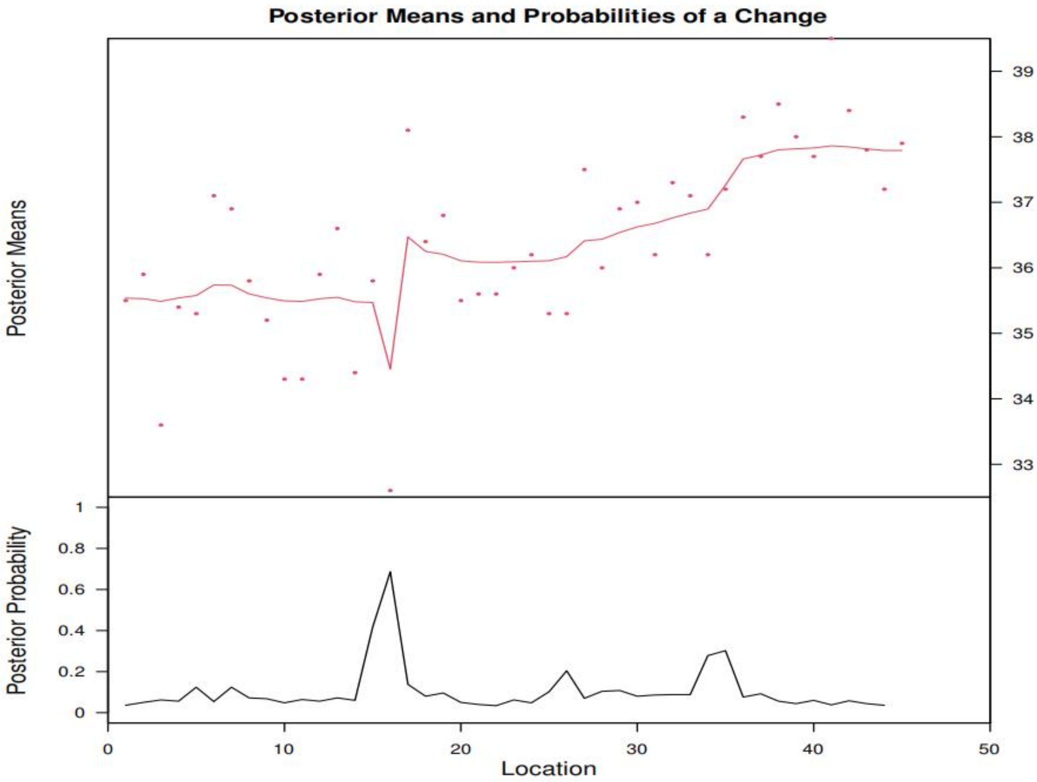


Figure 5: Yearly Max Temperature

Actually, the mean of the annual maximum temperatures before the change point 2003 is 35.604 degrees, and after 2003 it becomes 37.385 degrees. It is clear that the mean maximum temperature before 2003 is lower than after 2003.

On the other hand, the mean minimum temperatures before 2003 is -3.876 degrees, and it becomes -3.32 degrees after 2003. The variances before and after 2003 are 1.0686 and 1.5091, respectively. Sightly higher mean minimum temperatures and larger variance after 2003 indicate an increase in variability.

Based upon the results of our change point detections, we conclude that temperatures after 2003 have a rising trend.

3.2 Fitting GEVT model

In this section, as to find out the evidence of climate change in Kurume region, we fit the GEVT model by using the same temperature series gathered from the Website of Japan Meteorological Agency[3].

Case A presents the results of our study on the maximum temperatures, so does the minimum temperatures in Case B.

{**Case A**}The annual maximum temperatures from 1978 to 2022, in the above-mentioned data records.

We apply the block-maxima approach of the EVT(Extreme Value Theory) to the data and obtained the fitted GEV distribution. The results are summarised below.

Maximum Likelihood Estimation(MLE)(Negative Log-Likelihood Value) is 78.14073. Meanwhile, AIC and BIC are 162.2815 and 167.7014, respectively. And the corresponding distributional parameters(location, scale and shape) are shown in Table 2.

Table 2: Estimated parameters

location	scale	shape
35.9478225	1.4376303	-0.3446851

And the standard errors(SE) of location, scale and shape are given in Table 3.

Table 3: Standard error estimates

SE(location)	SE(scale)	SE(shape)
0.23192715	0.16142260	0.07711532

The estimated parameter covariance matrix is displayed in Table 4.

The fitted GEV distribution is shown in Figure 6. Seen from the figure, the estimated distribution matches the data well. In the context of the GEV

Table 4: Estimated parameter covariance matrix

	location	scale	shape
location	0.053790205	-0.004270681	-0.006329867
scale	-0.004270681	0.026057257	-0.007557518
shape	-0.006329867	-0.007557518	0.005946773

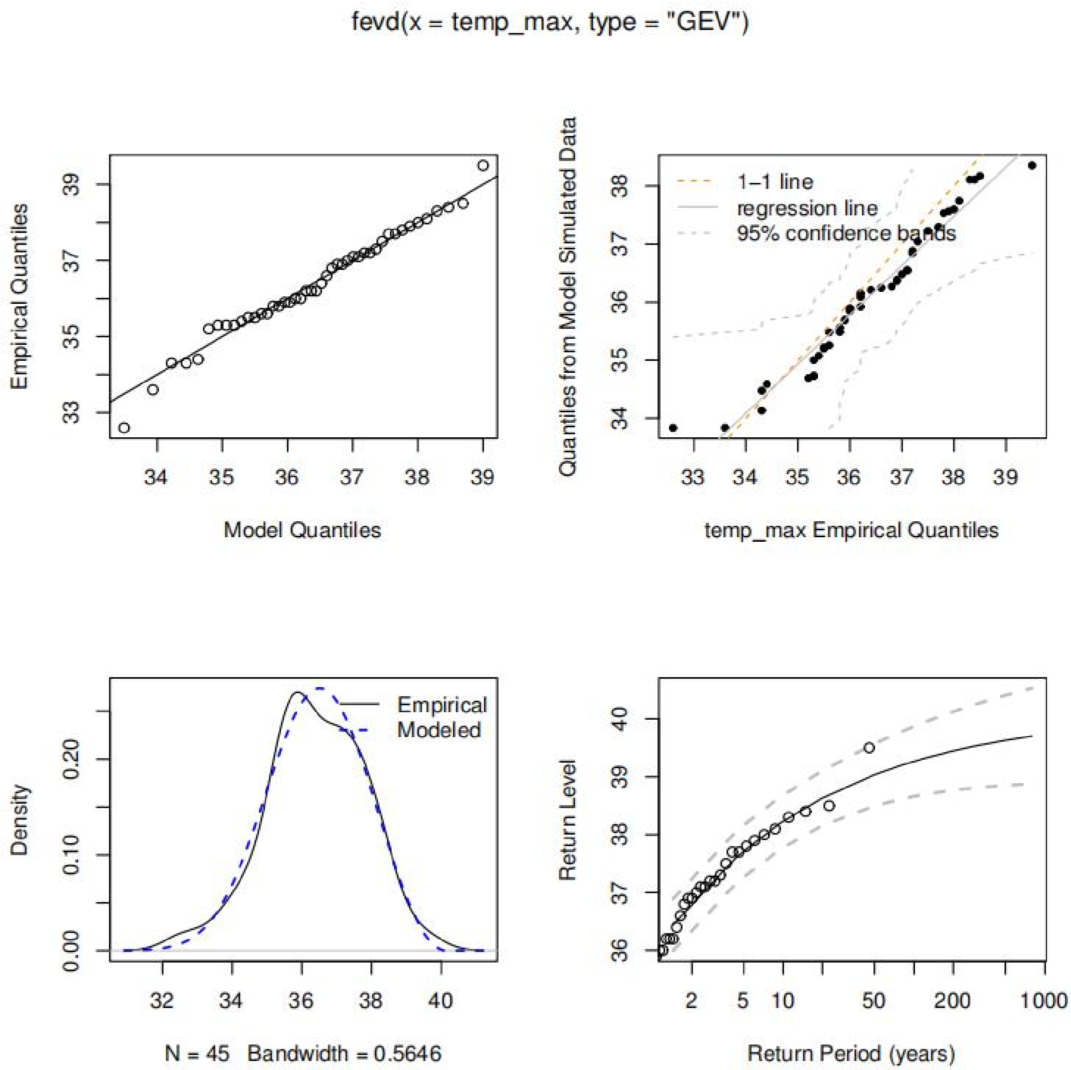


Figure 6: Fitted GEV distribution for temperature maxima

distribution, the return level and return period are important for predicting an extreme event for the future.

1)Return level

The return level is a statistical measure that represents the expected value of an extreme event exceeded once in a specified period of time.

2)Return period

The return period is the average time between occurrences of an event of a given magnitude(or greater).

Therefore, based upon the above-fitted GEV distribution, for return levels for 37.63 degrees, 38.2 degrees, 38.62 degrees, and 39.03 degrees correspond to return periods of 5, 10, 20 and 50 years, respectively. The confidence intervals(CI) are summarised in Table 5.

Table 5: Confidence Intervals for Return Periods

Return period	95% lower CI	Estimate	95% upper CI
5-year	37.18291	37.63158	38.08026
10-year	37.74692	38.19843	38.64994
20-year	38.14747	38.62036	39.09326
50-year	38.49544	39.03194	39.56844

Local people and governments might consider these return levels when planning to build special facilities, such as shelters for people during extremely hot weather, or monitoring dam water levels during heatwaves, to protect people, animals and agriculture.

*{***Case B***}*The annual lowest temperatures from 1978 to 2022.

Similarly, we get the fitted GEV distribution for the lowest temperatures from 1978 to 2022.

Negative Log-Likelihood Value of MLE is 69.27044. Meanwhile AIC and BIC are 144.5409 and 149.9609 respectively. And the distributional parame ters(location, scale and shape) are shown in Table 6.

Table 6: Estimated parameters

location	scale	shape
3.1987778	1.0947314	-0.2229843

And the standard errors(SE) of location, scale and shape are given in Table 7.

Table 7: Standard errors

SE(location)	SE(scale)	SE(shape)
0.1800263	0.1257378	0.0922704

The corresponding parameter covariance matrix is displayed in Table 8.

Table 8: Estimated parameter covariance matrix

	location	scale	shape
location	0.032409468	0.002097815	-0.006148066
scale	0.002097815	0.015809992	-0.005998112
shape	-0.006148066	-0.005998112	0.008513826

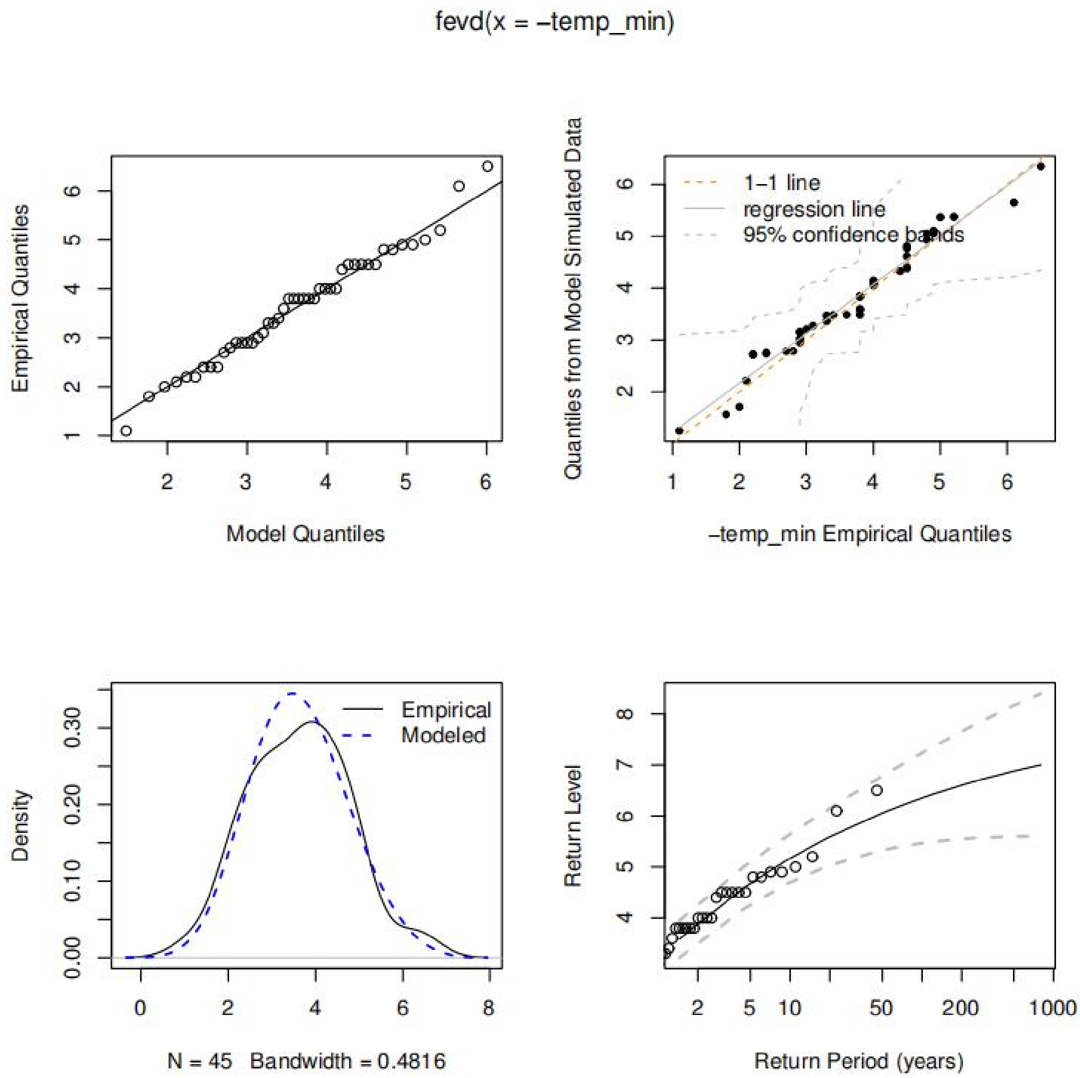


Figure 7: Fitted GEV distribution for temperature minima

The fitted GEV distribution is shown in Figure 7. Seen from the figure, the estimated distribution matches the data well.

Thus, based upon the above-fitted GEV distribution, for return periods and the Confidence Intervals(CI) are summarised in Table 9.

The impact of minimum temperature, such as, frozen roads, crop damage might also be considered.

According to the fitted GEV results for the maximum temperatures, 37.18 degrees would occur every five years, which is higher than the mean maximum temperatures before 2003. This indicates that the local climate is experiencing a rising trend as well.

Table 9: Confidence Intervals for Return Periods

Return period	95% lower CI	Estimate	95% upper CI
5-year return level	4.180964	4.594426	5.007889
10-year return level	4.670616	5.135843	5.601069
20-year return level	5.023321	5.576621	6.129921
50-year return level	5.327167	6.051555	6.775942

4. Concluding Remarks

This study primarily investigates temperature changes in the Kurume region, utilising data records that provide crucial evidence of local climate change. Numerical analyses of change point detections and extreme value approaches have shown and supported a rising trend in maximum temperatures.

Furthermore, the analysis of extreme values indicates an increased frequency of extreme weather events, such as heatwaves, occurring more frequently than before 2003. The return levels suggest a potential recurrence of these hazardous events, posing risks of disasters.

In recent years, the Kurume region has also experienced more frequent floods and extreme precipitation events compared to previous periods. These issues will be the focus of our future research efforts.

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