# BIAS CORRECTION METHOD WITH SKEWED DISTRIBUTION FOR PROJECTION OF CARDIOVASCULAR DISEASES MORTALITY RATE BASED ON EXTREME TEMPERATURE

By

AINA IZZATI BINTI MOHD ESA

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Master of Science

May 2022

FS 2022 54

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Master of Science

**BIAS CORRECTION METHOD WITH SKEWED DISTRIBUTION FOR PROJECTION OF CARDIOVASCULAR DISEASES MORTALITY RATE BASED ON EXTREME TEMPERATURE**

By

**AINA IZZATI BINTI MOHD ESA**

**May 2022**

**Chairman : Syafrina Abdul Halim, PhD**
**Faculty : Science**

Bias correction method is useful in reducing the statistically downscaled biases of global climate models' outputs and preserving statistical moments of the hydrological series. However, bias correction method is less efficient under changed future conditions due to the stationary assumption and perform poorly for removing bias at extremes thereby causing unreliable bias-corrected data. Thus, the existing bias correction method with normal distribution needs to be improved by incorporating skewed distributions into the model with linear covariate to account for non-stationarity. This study develops bias correction method with skewed distribution using quantile mapping technique to reduce biases in the extreme temperatures data of peninsular Malaysia. The network input is the MIROC5 model output gridded data for the period 1976-2005, and the model target used for bias correcting the input data is the observed extreme temperatures sourced by the Malaysian Department of Irrigation and Drainage for the same period. Results indicate that the proposed model obtains more accurate estimates of future mortality rates based on model diagnostics and precision analysis. Bias correction method with skewed distribution is used for bias correction of MIROC5 modeled projected extreme temperatures for 2006-2100 corresponding to the representative concentration pathways emission scenarios and it can correct the biases of future data, assuming skewed distribution of future extreme temperatures data for emission scenarios. Lognormal and Gumbel with linear covariate are the most appropriate distributions to model the annual extreme temperatures. Simulation study was conducted to validate the results. It was found that Gumbel with covariate is the best fitted distribution for extreme temperature series than other distributions. Higher projection of extreme temperatures is more pronounced under RCP8.5 with precise estimates ranging between 33-42°C compared with that under RCP4.5 with precise estimates ranging 30-32°C. Finally, the projection of extreme temperatures is used to calculate the mortality rate of cardiovascular diseases across all regions in peninsular Malaysia which coincide with high extreme temperatures ranging between 0.002 to 0.014.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

**KAEDAH PEMETAAN KUANTIL PEMBETULAN PINCANG DENGAN TABURAN CONDONG UNTUK UNJURAN KADAR KEMATIAN PENYAKIT KARDIOVASKULAR BERDASARKAN UNJURAN SUHU MELAMPAU**

Oleh

**AINA IZZATI BINTI MOHD ESA**

**Mei 2022**

**Pengerusi : Syafrina Abdul Halim, PhD**
**Fakulti : Sains**

Kaedah pembetulan pincang berguna dalam mengurangkan kecenderungan menurun secara statistik output model iklim global dan memelihara momen statistik siri hidrologi. Walaubagaimanapun, kaedah pembetulan pincang kurang cekap di bawah keadaan masa depan yang berubah-ubah kerana andaian pegun dan menunjukkan prestasi yang tidak memuaskan untuk menghilangkan pincang pada suhu lampau sehingga menyebabkan data pincang yang diperbetulkan tidak boleh dipercayai. Oleh itu, kaedah pembetulan pincang sedia ada dengan taburan normal perlu diperbaiki dengan memasukkan taburan condong ke dalam model dengan kovariat selanjar untuk mengambil kira andaian tidak pegun. Kajian ini membangunkan kaedah pembetulan pincang dengan taburan condong menggunakan teknik pemetaan kuantil untuk mengurangkan pincang dalam data suhu lampau semenanjung Malaysia. Input rangkaian adalah output model MIROC5 data grid untuk tempoh 1976-2005, dan sasaran model yang digunakan untuk membetulkan pincang data input adalah suhu lampau yang diperhatikan yang diperoleh oleh Jabatan Pengairan dan Saliran Malaysia untuk tempoh yang sama. Keputusan menunjukkan bahawa model yang dicadangkan memperoleh anggaran yang lebih tepat mengenai kadar kematian masa depan berdasarkan diagnostik model dan analisis ketepatan. Kaedah pembetulan pincang dengan taburan condong digunakan untuk membetulkan pincang suhu lampau model MIROC5 untuk 2006-2100 sepadan dengan laluan wakil penumpuan senario lepasan dan ia boleh membetulkan data pincang masa depan, dengan mengandaikan taburan condong data suhu lampau masa depan untuk senario lepasan. Lognormal dan Gumbel dengan kovariat selanjar adalah taburan yang paling sesuai untuk memodelkan suhu lampau tahunan. Kajian simulasi telah dijalankan bagi mengesahkan keputusan tersebut. Didapati bahawa Gumbel dengan kovariat adalah taburan yang paling sesuai untuk siri suhu lampau daripada taburan lain. Unjuran suhu lampau yang lebih tinggi lebih ketara di bawah RCP8.5 dengan anggaran tepat antara 33-42°C berbanding dengan yang di bawah RCP4.5 dengan anggaran tepat an-

tara 30-32°C. Akhir sekali, unjuran suhu lampau digunakan untuk menganggar kadar kematian CVD di semua daerah di semenanjung Malaysia yang bertepatan dengan suhu ekstrem yang tinggi antara 0.002 hingga 0.014.

## ACKNOWLEDGEMENTS

Alhamdulillah, first of all I would like to thank, Allah S.W.T for granting me with His blessing as finally I was able to complete my Master's studies.

It is my pleasure to express my deep sense of respects and gratitude to my beloved supervisor, Dr. Syafrina Abdul Halim and co-supervisor, Dr. Norhaslinda Ali for their guidance, advices, supervision and helps from the beginning till I have completed this research timely. During these two years, I have learned a lot from this research with many experiences and challenges. Thanks to my beloved supervisor and co-supervisor who gave an opportunity for me to explore and learn as well as giving me positive comments, ideas and suggestions in order to improve this research.

I would like to express my sincere appreciation to the lecturers and staffs of department of Mathematics and Statistics who always assisted me during my difficult time. Next, these acknowledgments would not be completed without mentioning my main financial support during my studies, School of Graduate Studies, Universiti Putra Malaysia for choosing me to be one of the grantees of the Special Graduate Research Assistant (SGRA) under Fundamental Research Grant Scheme (FRGS) from Ministry of Education, Malaysia.

I am extremely grateful to my parents and my family who always been there for me when I had problems. Their support always gave me strength and motivation to complete this research. Thank you so much for being so supportive and understanding. Besides, an immeasurable gratitude goes to my dear friends and colleagues, especially friends who are under the same supervision of mine for sharing valuable knowledge and always give support to me. Thank you.

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

**Syafrina Abdul Halim, PhD**
Senior Lecturer
Faculty of Science
Universiti Putra Malaysia
(Chairperson)

**Norhaslinda Ali, PhD**
Senior Lecturer
Faculty of Science
Universiti Putra Malaysia
(Member)

______________________________

**ZALILAH MOHD SHARIFF, PhD**
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 12 January 2023

**Declaration by graduate student**

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scho- larly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature:________________________ Date:________________________

Name and Matric No: Aina Izzati binti Mohd Esa

## TABLE OF CONTENTS

## LIST OF TABLES

## LIST OF FIGURES

## LIST OF ABBREVIATIONS

| | |
|---|---|
| AIC | Akaike information criterion |
| AAD | Attributable annual deaths |
| ADF | Augmented Dickey-Fuller test |
| BIC | Bayesian information criterion |
| BCM | Bias correction method |
| CVD | Cardiovascular disease |
| CI | Confidence interval |
| CDF | Cumulative density function |
| ENSO | El-Niño Southern/Oscillation |
| FRE | Frèchet distribution |
| GAM | Gamma distribution |
| GEV | Generalized extreme value distribution |
| GCM | Global climate model |
| GUM | Gumbel distribution |
| KPSS | Kwiatkowski–Phillips–Schmidt–Shin test |
| LRT | Likelihood ratio test |
| LGNORM | Lognormal distribution |
| MLE | Maximum likelihood estimation |
| MAE | Mean absolute error |
| M1 | Model 1 |
| M2 | Model 2 |
| M3 | Model 3 |
| M4 | Model 4 |

| | |
|---|---|
| P3 | Pearson type 3 distribution |
| PBIAS | Percent bias |
| PP | Predictive precision |
| PDF | Probability density function |
| QM | Quantile mapping |
| RCP | Representative concentration pathways |
| RMSE | Root mean square error |
| SE | Standard error |
| WEI | Weibull distribution |

**Symbols**

| | |
|---|---|
| $x$ | Annual extreme temperature |
| $\mu$ | Location parameter |
| $\rho$ | Real number |
| $n$ | Sample size |
| $\sigma$ | Scale parameter |
| $\alpha$ | Shape parameter |

**Subscripts**

| | |
|---|---|
| $x_o$ | Annual extreme temperature of observation |
| $x_m$ | Annual extreme temperature of historical GCM |
| $y_o$ | Baseline mortality |
| $x_{corr}$ | Corrected extreme temperature between observation and historical GCM |
| $x_{RCP4.5(corr)}$ | Projection of future annual extreme temperature under RCP4.5 |
| $x_{RCP8.5(corr)}$ | Projection of future annual extreme temperature under RCP8.5 |

# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

Bias correction method (BCM) is a well-known method in statistical downscaling as they can reduce biases between global climate model (GCM) outputs and observations and are skillful to reduce the coarse resolution of GCMs outputs into finer resolution of observation scale (Cannon et al., 2015; Ngai et al., 2022; Hong et al., 2022). BCM was successful in reproducing the main features of the observed hydrometeorology from the retrospective climate simulation, when applied to statistically downscaled of GCM outputs, as well as competent to preserve the statistical moments of the hydrological series (Sennikovs and Bethers, 2009). BCM is one of the downscaling methods where the procedure employs transfer function to correct the biases in the GCM outputs relative to observations. The underlying idea is the identification of possible biases between observed and historical GCM outputs. BCM is widely used in various applications such as hydrological and meteorological applications due to the advantages of BCM that can capture the biases of GCM outputs. However, the BCM's algorithm is assumed to be stationary and valid for future conditions (Teutschbein and Seibert, 2012). Several BCMs have been developed to downscale the meteorological variables such as temperature from the GCM outputs, ranging from the simple or linear method to sophisticated or nonlinear method (Jakob Themeßl et al., 2011; Teutschbein and Seibert, 2012; Fang et al., 2015). The statistical transformation involving transforming the distribution functions of the modeled variables into the observed ones using a mathematical function, which can be mathematically expressed as $x_o = f(x_m)$ where, $x_o$ is observed variable, $x_m$ is modeled variable, and $f(x_m)$ is transformation function (Piani et al., 2010; Enayati et al., 2021). Given that the quantile mapping (QM) technique use the quantile-quantile relation to converge the simulated variables' distribution function to the observed one, with the cumulative distribution function (CDFs) of both observed and simulated variables' time series, their quantile relation can also be determined, as $x_o = F_o^{-1}[F_m(x_m)]$ (Ringard et al., 2017), where, $F_m(x_m)$ is the CDF of $x_m$ and $F_o^{-1}$ is the inverse form of the CDF of $x_o$, which technically referred to as the quantile function.

## 1.2 Study Background

Cardiovascular diseases (CVDs) have been recognized as the leading cause of death throughout the world. CVDs, also known as circulatory diseases, are categorized as heart and blood vessel disorders (Patel et al., 2022). According to the Department of Statistics Malaysia (DOSM), coronary heart disease (CHD), one of the CVDs, was the principal causes of death in Malaysia showing an increasing trend between 2016 and 2019 (DOSM, 2017, 2018, 2019, 2020). CVD is sensitive to climate conditions;

hence, temperature-related CVDs have become a growing public health concern. The influence of extreme heat events on human health are significant and diverse (Balbus et al., 2016). The health sector has been identified as the most vulnerable to extreme heat events (Patel et al., 2022). According to Center for Disease Control and Prevention of United States, extreme heat events caused by high temperature are the most influential cause of heat-related human mortality responsible for more deaths per year than hurricanes, fires, tornadoes, floods, and earthquakes (Vaidyanathan et al., 2020). Such events are expected to occur more often and predicted to last longer due to global climate change. Extreme heat events caused more than 150,000 deaths globally from 1990 to 2018 with 2018 recorded as the warmest especially between June and July where extreme heat events swept through Asia, Europe, and North America, hospitalizing thousands of people with heat-related illness and recorded more than 700 deaths in the immediate after-math (WHO, 2014). The World Health Organization (WHO) predicted that there will be almost 92,000 deaths per year from heatwave by 2030 with sub-Saharan Africa, Latin America, and Southeast Asia bearing the largest burdens (WHO, 2014). The Intergovernmental Panel on Climate Change (IPCC) stated that Southeast Asian countries, developing countries such as Malaysia, will be at the greatest risk of the emergence of extreme heat events (Stocker, 2014). To assess climate change on local scales, an approach known as downscaling is used to bridge the gap between the resolution of GCM outputs and the local climatic process (Noor et al., 2018). BCM as one of downscaling methods is widely used in reducing the biases between observed and historical GCM outputs to achieve an understanding of the current pattern of seasonal variations assists in estimating the impact of future climate change.

## 1.3 Problem Statement

Future climate change exposures are typically derived using simulations from computationally expensive climate models. Even though these models reflect state-of-the-art knowledge on the climate system, their outputs are known to exhibit complex spatial–temporal biases when compared to observations. Factors contributing to this bias include errors in parameters describing physical and chemical processes, incorrect representation of the underlying processes with mathematical equations, and discretization of meteorological fields in space and in time. Hence, climate-model simulations for the projection period need to be bias-corrected prior to estimating future health impacts (Holthuijzen et al., 2021). BCM is renowned in statistical downscaling because it can reduce biases between GCM outputs and observations, and it skillfully reduces the coarse resolution of GCMs outputs into finer resolution of observation scale (Teutschbein and Seibert, 2012; Cannon et al., 2015; Fang et al., 2015; Ringard et al., 2017; Hong et al., 2022; Ngai et al., 2022). Wood et al. (2004) employed BCM to reduce the statistically downscaled biases of GCM outputs. BCM was successful in reproducing the main features of the observed hydrometeorology from the retrospective climate simulation, when applied to statistically downscaled GCM outputs, and competent to preserve the statistical moments of the hydrological series (Sennikovs and Bethers, 2009). Generally, BCM for future simulation is accomplished in two steps. First, the bias between observations and simulations during the historical period is assessed. Then a correction algorithm is applied to future simulations by assuming the bias can be extrapolated to future periods. Olsson et al. (2015) had stated that QM technique was able to provide temperature data that were sufficiently close to observed discharges in the control period and produced more realistic projections for mean annual and seasonal changes compared to the uncorrected GCM data. Putra et al. (2020) has found that BCM could reduce biases in the GCM outputs relative to observations with coefficient of determination of 0.81 for spatial distribution. Tadese et al. (2020) also showed that BCM and variance scaling performed well in correcting the biases GCM outputs despite the corrected maximum and minimum temperature being slightly overestimated for the mean and standard deviation. Despite the fact that BCM has shown considerable skill in reducing the biases, there are few limitations that need to be addressed. Firstly, the remaining uncertainty regarding how well a calibrated BCM performs for conditions different from those used for calibration. Although a good performance of BCM during the calibration period has been shown, that does not guarantee a good performance under changed future conditions due to the stationary assumption of BCM. Secondly, BCM is less efficient in downscaling both high and low temperature extremes (Maurer and Hidalgo, 2008; Abatzoglou and Brown, 2012). The most commonly used BCMs were based on shifting or scaling climate model simulations that have been shown to perform poorly for removing bias at extremes (Räisänen and Räty, 2013). Thus, BCM has a tendency to overfit on calibration data, especially at extremes where data is scarce and highly variable (Piani et al., 2010; Lafon et al., 2013; Grillakis et al., 2013; Mamalakis et al., 2017; Holthuijzen et al., 2021). The limitation of BCM is mainly because it assumes that the temperature follows the normal distribution (Hempel et al., 2013; Gaitán et al., 2019; Lange, 2019). Pastén-Zapata et al. (2020) tested BCM in simulating the temperature and observed that the existing BCM with normal distribution did not improve the representation of daily temporal variability especially the extremes. These findings are significant for tackling the main part of the statistical modeling process which is the selection of appropriate distribution for the BCM that could be overlooked in the past research. Various studies were conducted to fit a suitable statistical distribution on extreme temperatures and different conclusions were drawn depending on factors such as the area and duration of study. Particularly, the right distribution may enhance the BCM's performance in simulating the extremes. In summary, no single distribution can be concluded to perform the best. Therefore, it is crucial to thoroughly analyze various aspects while selecting the most appropriate distribution for the extreme temperatures to achieve an accurate projection of the CVD mortality rate to avoid misleading results.

## 1.4 Objectives

The aim of this study is to improvise the existing BCM technique associated with normal distribution by fitting the skewed statistical distribution on annual extreme temperatures into the model which then be used to project the CVD mortality rate based on extreme temperatures projection in peninsular Malaysia.

Hence, the main objectives of this study are

1.4.1 to capture the non-stationary and extreme values in the annual extreme temperature data by incorporating the linear covariate and skewed distributions (i.e., lognormal (LGNORM), gamma (GAM), Pearson type 3 (P3), generalized extreme value (GEV), Gumbel (GUM), Weibull (WEI), and Frèchet (FRE)) in the QM-BCM,

1.4.2 to conduct the simulation study of QM-BCM with best skewed distributions and linear covariate, and

1.4.3 to estimate the future CVD mortality rate based on future annual extreme temperatures projected by the QM-BCM using the attributable annual death (AAD) equation.

## 1.5 Significance of Study

The growing number of CVD mortality corresponding to the global warming is becoming a major concern nowadays. Future information on the CVD mortality rate is believed to provide valuable inputs to the stakeholders for taking precautions and preventive measures to flatten the curve trend. The significance of this study rests on the fact that the health sector in Malaysia heavily depends on climatic conditions. Thus, studying future scenarios may provide important information to researchers and local governments, to propose appropriate adaptation measures and increase resilience. Furthermore, appropriate policies and plans can be sanctioned to prepare the public for changes because of extreme temperatures particularly; on CVD mortality. Using the accurate predictions of future mortality rates of CVD, the government can play a crucial role by enacting policies that encourage the provision of preventive healthcare services and promotion of a healthy lifestyle.

## 1.6 Scope and Limitations Study

In this study, there are several limitations need to be addressed. This study is bounded to constant value of population that assume the population for future period remains the same as in present period (i.e. does not change). The projection is also based on only one GCM output using the secondary data of CVD mortality which were sourced from Global Burden of Disease Collaborative Network based on age-standardized (rate) per 100,000 individuals for both genders. Furthermore, biases that are considered in this study is within the GCM output thereby the biases from other sources such as diversity of model projections, number of projections, multiple BCMs, and model quality are not considered. Finally, the meteorological stations are limited to 58 stations across peninsular Malaysia due to availability of temperature data.

## 1.7 Outline of Thesis

The thesis comprises of 7 chapters. Chapter 1 consists of introduction, research background, problem statements, objectives, significance of study, scope and limitations, as well as an outline of the thesis. A literature review of previous studies on downscaling and statistical distribution of temperature series is presented in Chapter 2. Chapter 3 describes the meteorological data and present the descriptive statistics of observed annual extreme temperature in peninsular Malaysia. Chapter 4 describes the process of selecting the suitable skewed statistical distribution. To determine the trend in data, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Augmented Dickey Fuller (ADF) tests are used. The Akaike information criterion (AIC), Bayesian information criterion (BIC), and likelihood ratio test (LRT) are used to select the most appropriate distribution to fit peninsular Malaysia's extreme temperatures. An evaluation of the performance of developed model is conducted by using simulation studies and the mathematical formulations of corrected extreme temperatures, as well as the projection of future extreme temperatures under RCP4.5 and RCP8.5 are presented in Chapter 5. A precision analysis of corrected extreme temperatures is analyzed using the mean absolute error (MAE), root mean square error (RMSE), percent bias (PBIAS), and predictive precision (PP). The projection of future CVD mortality rates is presented in the following Chapter 6. The correlation coefficient is calculated to determine the magnitude of the relationship of future extreme temperatures with CVD mortality rate. Lastly, Chapter 7 presents the conclusions from this study and some recommendations for future research has been discussed in this chapter.

## REFERENCES


Abatzoglou, J. T. and Brown, T. J. (2012). A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*, 32(5):772–780.

Adeyeri, O., Laux, P., Lawin, A., and Oyekan, K. (2020). Multiple bias-correction of dynamically downscaled cmip5 climate models temperature projection: a case study of the transboundary komadugu-yobe river basin, lake chad region, west africa. *SN Applied Sciences*, 2(7):1–18.

Amin, N. A. M., Ismail, M. S., and Hamid, H. A. (2018). Modelling extreme temperature in perlis using block maxima method. In *AIP Conference Proceedings*, volume 2013, page 020010. AIP Publishing LLC.

An, D., Du, Y., Berndtsson, R., Niu, Z., Zhang, L., and Yuan, F. (2020). Evidence of climate shift for temperature and precipitation extremes across gansu province in china. *Theoretical and Applied Climatology*, 139(3):1137–1149.

Anderson, T. W. (2011). *The statistical analysis of time series*. John Wiley & Sons.

Arias, P., Bellouin, N., Coppola, E., Jones, R., Krinner, G., Marotzke, J., Naik, V., Palmer, M., Plattner, G.-K., Rogelj, J., et al. (2021). Climate change 2021: The physical science basis. contribution of working group14 i to the sixth assessment report of the intergovernmental panel on climate change; technical summary.

Baaghideh, M. and Mayvaneh, F. (2017). Climate change and simulation of cardiovascular disease mortality: A case study of mashhad, iran. *Iranian Journal of Public Health*, 46(3):396.

Balbus, J., Crimmins, A., Gamble, J., Easterling, D., Kunkel, K., Saha, S., and Sarofim, M. (2016). Climate change and human health. *The impacts of climate change on human health in the United States: A scientific assessment*, pages 25–42.

Barrow, E. and Hulme, M. (1996). Changing probabilities of daily temperature extremes in the uk related to future global warming and changes in climate variability. *Climate Research*, 6(1):21–31.

Berger, Y. G. (2004). Variance estimation for measures of change in probability sampling. *Canadian Journal of Statistics*, 32(4):451–467.

Bettolli, M. L., Solman, S. A., Da Rocha, R., Llopart, M., Gutierrez, J. M., Fernández, J., Olmo, M. E., Lavin-Gullon, A., Chou, S., Rodrigues, D. C., et al. (2021). The cordex flagship pilot study in southeastern south america: a comparative study of statistical and dynamical downscaling models in simulating daily extreme precipitation events. *Climate Dynamics*, 56(5):1589–1608.

Cannon, A. J., Sobie, S. R., and Murdock, T. Q. (2015). Bias correction of gcm precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, 28(17):6938–6959.

Chu, Y.-K. and Ke, J.-C. (2012). Computation approaches for parameter estimation of weibull distribution. *Mathematical and computational applications*, 17(1):39–47.

Clatworthy, J., Buick, D., Hankins, M., Weinman, J., and Horne, R. (2005). The use and reporting of cluster analysis in health psychology: A review. *British journal of health psychology*, 10(3):329–358.

Cohen, A. C. and Whitten, B. J. (1981). Estimation of lognormal distributions. *American Journal of Mathematical and Management Sciences*, 1(2):139–153.

Coles, S., Bawa, J., Trenner, L., and Dorazio, P. (2001). *An introduction to statistical modeling of extreme values*, volume 208. Springer.

Conlon, K. C., Kintziger, K. W., Jagger, M., Stefanova, L., Uejio, C. K., and Konrad, C. (2016). Working with climate projections to estimate disease burden: perspectives from public health. *International Journal of Environmental Research and Public Health*, 13(8):804.

Croux, C. and Dehon, C. (2010). Influence functions of the spearman and kendall correlation measures. *Statistical methods & applications*, 19(4):497–515.

De'Donato, F. K., Leone, M., Scortichini, M., De Sario, M., Katsouyanni, K., et al. (2015). Changes in the effect of heat on mortality in the last 20 years in nine european cities. results from the phase project. *International journal of environmental research and public health*, 12(12):15567–15583.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a):427–431.

DOSM (2017). Statistics and causes of death in malaysia.

DOSM (2018). Statistics and causes of death in malaysia.

DOSM (2019). Statistics and causes of death in malaysia.

DOSM (2020). Statistics and causes of death in malaysia.

Enayati, M., Bozorg-Haddad, O., Bazrafshan, J., Hejabi, S., and Chu, X. (2021). Bias correction capabilities of quantile mapping methods for rainfall and temperature variables. *Journal of Water and Climate Change*, 12(2):401–419.

Esa, A. I. M., Halim, S. A., Ali, N., Chung, J. X., and Mohd, M. S. F. (2022). Optimizing future mortality rate prediction of extreme temperature-related cardiovascular disease based on skewed distribution in peninsular malaysia. *Journal of Water and Climate Change*.

Etemadi, H., Samadi, S., and Sharifikia, M. (2014). Uncertainty analysis of statistical downscaling models using general circulation model over an international wetland. *Climate dynamics*, 42(11-12):2899–2920.

Fang, G., Yang, J., Chen, Y., and Zammit, C. (2015). Comparing bias correction methods in downscaling meteorological variables for a hydrologic impact study in an arid area in china. *Hydrology and Earth System Sciences*, 19(6):2547–2559.

Folland, C., Miller, C., Bader, D., Crowe, M., Jones, P., Plummer, N., Richman, M., Parker, D., Rogers, J., and Scholefield, P. (1999). Workshop on indices and indicators for climate extremes, asheville, nc, usa, 3–6 june 1997 breakout group c: temperature indices for climate extremes. *Climatic Change*, 42(1):31–43.

Fougères, A.-L., Nolan, J. P., and Rootzén, H. (2009). Models for dependent extremes using stable mixtures. *Scandinavian Journal of Statistics*, 36(1):42–59.

Gaitán, E., Monjo, R., Pórtoles, J., and Pino-Otín, M. R. (2019). Projection of temperatures and heat and cold waves for aragón (spain) using a two-step statistical downscaling of cmip5 model outputs. *Science of the Total Environment*, 650:2778–2795.

Ganguli, P. and Coulibaly, P. (2017). Does nonstationarity in rainfall require nonstationary intensity–duration–frequency curves? *Hydrology and Earth System Sciences*, 21(12):6461–6483.

Gasparrini, A. (2013). Distributed lag linear and non-linear models for time series data. *Document Is Available at R Project*.

Gilliland, D. and Melfi, V. (2010). A note on confidence interval estimation and margin of error. *Journal of Statistics Education*, 18(1).

Grillakis, M. G., Koutroulis, A. G., and Tsanis, I. K. (2013). Multisegment statistical bias correction of daily gcm precipitation output. *Journal of Geophysical Research: Atmospheres*, 118(8):3150–3162.

Groeneveld, R. A. and Meeden, G. (1984). Measuring skewness and kurtosis. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 33(4):391–399.

Gu, S., Zhang, L., Sun, S., Wang, X., Lu, B., Han, H., Yang, J., and Wang, A. (2020). Projections of temperature-related cause-specific mortality under climate change scenarios in a coastal city of china. *Environment International*, 143:105889.

Hajat, S., Kovats, R. S., Atkinson, R. W., and Haines, A. (2002). Impact of hot temperatures on death in london: a time series approach. *Journal of Epidemiology and Community Health*, 56(5):367–372.

Hajat, S., Vardoulakis, S., Heaviside, C., and Eggen, B. (2014). Climate change effects on human health: projections of temperature-related mortality for the uk during the 2020s, 2050s and 2080s. *J Epidemiol Community Health*, 68(7):641–648.

Hasan, H., Salam, N., and Kassim, S. (2013). Modeling annual extreme temperature using generalized extreme value distribution: A case study in malaysia. In *AIP Conference Proceedings*, volume 1522, pages 1195–1203. American Institute of Physics.

Hasan, H., Salleh, N. H. M., and Kassim, S. (2014). Stationary and non-stationary extreme value modeling of extreme temperature in malaysia. In *AIP Conference Proceedings*, volume 1613, pages 355–367. American Institute of Physics.

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., and Piontek, F. (2013). A trend-preserving bias correction–the isi-mip approach. *Earth System Dynamics*, 4(2):219–236.

Higgins, J. P., Thomas, J., Chandler, J., Cumpston, M., Li, T., Page, M. J., and Welch, V. A. (2019). *Cochrane handbook for systematic reviews of interventions*. John Wiley & Sons.

Holthuijzen, M. F., Beckage, B., Clemins, P. J., Higdon, D., and Winter, J. M. (2021). Constructing high-resolution, bias-corrected climate products: a comparison of methods. *Journal of Applied Meteorology and Climatology*, 60(4):455–475.

Hong, J., Agustin, W., Yoon, S., and Park, J.-S. (2022). Changes of extreme precipitation in the philippines, projected from the cmip6 multi-model ensemble. *Weather and Climate Extremes*, 37:100480.

Horton, E., Folland, C., and Parker, D. (2001). The changing incidence of extremes in worldwide and central england temperatures to the end of the twentieth century. *Climatic change*, 50(3):267–295.

Huang, C., Barnett, A. G., Wang, X., and Tong, S. (2012). Effects of extreme temperatures on years of life lost for cardiovascular deaths: a time series study in brisbane, australia. *Circulation: Cardiovascular Quality and Outcomes*, 5(5):609–614.

Huang, J., Zeng, Q., Pan, X., Guo, X., and Li, G. (2019). Projections of the effects of global warming on the disease burden of ischemic heart disease in the elderly in tianjin, china. *BMC Public Health*, 19(1):1–9.

Huynen, M.-M., Martens, P., Schram, D., Weijenberg, M. P., and Kunst, A. E. (2001). The impact of heat waves and cold spells on mortality rates in the dutch population. *Environmental Health Perspectives*, 109(5):463–470.

Huynh, V.-N. (2013). *Uncertainty analysis in econometrics with applications*. Springer.

Imam, A., Habiba, D., and Atanda, B. T. (2016). On consistency of tests for stationarity in autoregressive and moving average models of different orders. *American Journal of Theoretical and Applied Statistics*, 5(3):146–153.

Isa, N. S., Akhir, M. F., Kok, P. H., Daud, N. R., Khalil, I., and Roseli, N. H. (2020). Spatial and temporal variability of sea surface temperature during el-niño southern oscillation and indian ocean dipole in the strait of malacca and andaman sea. *Regional Studies in Marine Science*, 39:101402.

Jackson, J. E., Yost, M. G., Karr, C., Fitzpatrick, C., Lamb, B. K., Chung, S. H., Chen, J., Avise, J., Rosenblatt, R. A., and Fenske, R. A. (2010). Public health impacts of climate change in washington state: projected mortality risks due to heat events and air pollution. *Climatic change*, 102(1):159–186.

Jakob Themeßl, M., Gobiet, A., and Leuprecht, A. (2011). Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. *International Journal of Climatology*, 31(10):1530–1544.

Jolliffe, I. T. and Philipp, A. (2010). Some recent developments in cluster analysis. *Physics and Chemistry of the Earth, Parts A/B/C*, 35(9-12):309–315.

Jones, P., Horton, E., Folland, C., Hulme, M., Parker, D., and Basnett, T. (1999). The use of indices to identify changes in climatic extremes. *Climatic Change*, 42(1):131–149.

Jose, D. M., Vincent, A. M., and Dwarakish, G. S. (2022). Improving multiple model ensemble predictions of daily precipitation and temperature through machine learning techniques. *Scientific Reports*, 12(1):1–25.

Kallner, A. (2017). *Laboratory statistics: methods in chemistry and health sciences*. Elsevier.

Kappenman, R. F. (1985). Estimation for the three-parameter weibull, lognormal, and gamma distributions. *Computational Statistics & Data Analysis*, 3:11–23.

Kharin, V. V. and Zwiers, F. W. (2005). Estimating extremes in transient climate change simulations. *Journal of Climate*, 18(8):1156–1173.

Kouis, P., Kakkoura, M., Ziogas, K., Paschalidou, A. K., and Papatheodorou, S. I. (2019). The effect of ambient air temperature on cardiovascular and respiratory mortality in thessaloniki, greece. *Science of The Total Environment*, 647:1351–1358.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics*, 54(1-3):159–178.

Kynast-Wolf, G., Preuß, M., Sié, A., Kouyaté, B., and Becher, H. (2010). Seasonal patterns of cardiovascular disease mortality of adults in burkina faso, west africa. *Tropical Medicine and International Health*, 15(9):1082–1089.

Lafon, T., Dadson, S., Buys, G., and Prudhomme, C. (2013). Bias correction of daily precipitation simulated by a regional climate model: a comparison of methods. *International journal of climatology*, 33(6):1367–1381.

Lange, S. (2019). Trend-preserving bias adjustment and statistical downscaling with isimip3basd (v1. 0). *Geoscientific Model Development*, 12(7):3055–3070.

Lee, H. and Ghosh, S. K. (2009). Performance of information criteria for spatial models. *Journal of statistical computation and simulation*, 79(1):93–106.

Li, G., Guo, Q., Liu, Y., Li, Y., and Pan, X. (2018). Projected temperature-related years of life lost from stroke due to global warming in a temperate climate city, asia: disease burden caused by future climate change. *Stroke*, 49(4):828–834.

Li, T., Horton, R. M., and Kinney, P. (2013). Future projections of seasonal patterns in temperature-related deaths for manhattan. *Nature climate change*, 3:717.

Lima, L. R. and Neri, B. (2013). A test for strict stationarity. In *Uncertainty Analysis in Econometrics with Applications*, pages 17–30. Springer.

Liu, T., Ren, Z., Zhang, Y., Feng, B., Lin, H., Xiao, J., Zeng, W., Li, X., Li, Z., Rutherford, S., et al. (2019). Modification effects of population expansion, ageing, and adaptation on heat-related mortality risks under different climate change scenarios in guangzhou, china. *International Journal of Environmental Research and Public Health*, 16(3):376.

Mahdi, A., Abdul, H. G., Yuk, F. H., and Aimrun, W. (2016). Downscaling daily precipitation and temperatures over the langat river basin in malaysia: a comparison of two statistical downscaling approaches. *International Journal of Water Resources and Environmental Engineering*, 8(10):120–136.

Mahdi, S. and Cenac, M. (2005). Estimating parameters of gumbel distribution using the methods of moments, probability weighted moments and maximum likelihood. *Revista de Matemática: Teoría y Aplicaciones*, 12(1-2):151–156.

Mamalakis, A., Langousis, A., Deidda, R., and Marrocu, M. (2017). A parametric approach for simultaneous bias correction and high-resolution downscaling of climate model rainfall. *Water Resources Research*, 53(3):2149–2170.

Martins, E. S. and Stedinger, J. R. (2000). Generalized maximum-likelihood generalized extreme-value quantile estimators for hydrologic data. *Water Resources Research*, 36(3):737–744.

Maurer, E. P. and Hidalgo, H. G. (2008). Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods. *Hydrology and Earth System Sciences*, 12(2):551–563.

McGeehin, M. A. and Mirabelli, M. (2001). The potential impacts of climate variability and change on temperature-related morbidity and mortality in the united states. *Environmental Health Perspectives*, 109(suppl 2):185–189.

Milly, P. C., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., Stouffer, R. J., Dettinger, M. D., and Krysanova, V. (2015). On critiques of “stationarity is dead: Whither water management?”. *Water Resources Research*, 51(9):7785–7789.

Moghadamnia, M. T., Ardalan, A., Mesdaghinia, A., Keshtkar, A., Naddafi, K., and Yekaninejad, M. S. (2017). Ambient temperature and cardiovascular mortality: a systematic review and meta-analysis. *PeerJ*, 5:e3574.

Morris, T. P., White, I. R., and Crowther, M. J. (2019). Using simulation studies to evaluate statistical methods. *Statistics in medicine*, 38(11):2074–2102.

Murphy, J. (1999). An evaluation of statistical and dynamical techniques for downscaling local climate. *Journal of Climate*, 12(8):2256–2284.

Mushtaq, R. (2011). Augmented dickey fuller test.

Ng, J., Chan, K., Noh, N. M., Razman, R., Surol, S., Lee, J., and Al-Mansob, R. (2022). Statistical modelling of extreme temperature in peninsular malaysia. In *IOP Conference Series: Earth and Environmental Science*, volume 1022, page 012072. IOP Publishing.

Ngai, S. T., Juneng, L., Tangang, F., Chung, J. X., Supari, S., Salimun, E., Cruz, F., Ngo-Duc, T., Phan-Van, T., Santisirisomboon, J., et al. (2022). Projected mean and extreme precipitation based on bias-corrected simulation outputs of cordex southeast asia. *Weather and Climate Extremes*, 37:100484.

Ni, Y. (2005). Modeling insurance claim sizes using the mixture of gamma & reciprocal gamma distributions.

Noor, M., Ismail, T., Chung, E.-S., Shahid, S., and Sung, J. H. (2018). Uncertainty in rainfall intensity duration frequency curves of peninsular malaysia under changing climate scenarios. *Water*, 10(12):1750.

Olsson, T., Jakkila, J., Veijalainen, N., Backman, L., Kaurola, J., and Vehviläinen, B. (2015). Impacts of climate change on temperature, precipitation and hydrology in finland–studies using bias corrected regional climate model data. *Hydrology and Earth System Sciences*, 19(7).

Paravantis, J., Santamouris, M., Cartalis, C., Efthymiou, C., and Kontoulis, N. (2017). Mortality associated with high ambient temperatures, heatwaves, and the urban heat island in athens, greece. *Sustainability*, 9(4):606.

Pastén-Zapata, E., Jones, J. M., Moggridge, H., and Widmann, M. (2020). Evaluation of the performance of euro-cordex regional climate models for assessing hydrological climate change impacts in great britain: A comparison of different spatial resolutions and quantile mapping bias correction methods. *Journal of Hydrology*, 584:124653.

Patel, L., Conlon, K. C., Sorensen, C., McEachin, S., Nadeau, K., Kakkad, K., and Kizer, K. W. (2022). Climate change and extreme heat events: how health systems should prepare. *NEJM Catalyst Innovations in Care Delivery*, 3(7):CAT–21.

Piani, C., Weedon, G., Best, M., Gomes, S., Viterbo, P., Hagemann, S., and Haerter, J. (2010). Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. *Journal of Hydrology*, 395(3-4):199–215.

Putra, I. D. G. A., Rosid, M. S., Sopaheluwakan, A., and Sianturi, Y. C. U. (2020). The cmip5 projection of extreme climate indices in indonesia using simple quantile mapping method. In *AIP Conference Proceedings*, volume 2223, page 050008. AIP Publishing LLC.

Radinović, D. and Ćurić, M. (2014). Measuring scales for daily temperature extremes, precipitation and wind velocity. *Meteorological Applications*, 21(3):461–465.

Raggad, B. (2018). Stationary and non-stationary extreme value approaches for modelling extreme temperature: the case of riyadh city, saudi arabia. *Environmental Modeling & Assessment*, 23(1):99–116.

Räisänen, J. and Räty, O. (2013). Projections of daily mean temperature variability in the future: cross-validation tests with ensembles regional climate simulations. *Climate dynamics*, 41(5):1553–1568.

Ramos, P. L., Louzada, F., Ramos, E., and Dey, S. (2020). The fréchet distribution: Estimation and application-an overview. *Journal of Statistics and Management Systems*, 23(3):549–578.

Raychaudhuri, S. (2008). Introduction to monte carlo simulation. In *2008 Winter simulation conference*, pages 91–100. IEEE.

Ringard, J., Seyler, F., and Linguet, L. (2017). A quantile mapping bias correction method based on hydroclimatic classification of the guiana shield. *Sensors*, 17(6):1413.

Roth, G. A., Abate, D., Abate, K. H., Abay, S. M., Abbafati, C., Abbasi, N., Abbastabar, H., Abd-Allah, F., Abdela, J., Abdelalim, A., et al. (2018). Global, regional, and national age-sex-specific mortality for 282 causes of death in 195 countries and territories, 1980–2017: a systematic analysis for the global burden of disease study 2017. *The Lancet*, 392(10159):1736–1788.

Salas, J. D. and Obeysekera, J. (2014). Revisiting the concepts of return period and risk for nonstationary hydrologic extreme events. *Journal of Hydrologic Engineering*, 19(3):554–568.

Salleh, N. H. M. and Hasan, H. (2018). Generalized pareto distribution for extreme temperatures in peninsular malaysia. *Sci Int (Lahore)*, 30:63–67.

Seimela, A. M. (2021). *Modelling temperature extremes in the Limpopo Province of South Africa using extreme value theory*. PhD thesis.

Semenov, M. A. (2008). Simulation of extreme weather events by a stochastic weather generator. *Climate Research*, 35(3):203–212.

Sennikovs, J. and Bethers, U. (2009). Statistical downscaling method of regional climate model results for hydrological modelling. In *Proceedings of the 18th World IMacS/MODSIM congress*, pages 3962–3968. Citeseer.

Shaaban, A. J., Amin, M., Chen, Z., and Ohara, N. (2011). Regional modeling of climate change impact on peninsular malaysia water resources. *Journal of Hydrologic Engineering*, 16(12):1040–1049.

Shreffler, J. and Huecker, M. R. (2022). Exploratory data analysis: Frequencies, descriptive statistics, histograms, and boxplots. In *StatPearls [Internet]*. StatPearls Publishing.

Shrestha, R. R., Schnorbus, M. A., Werner, A. T., and Zwiers, F. W. (2014). Evaluating hydroclimatic change signals from statistically and dynamically downscaled gcms and hydrologic models. *Journal of Hydrometeorology*, 15(2):844–860.

Smid, M. and Costa, A. C. (2018). Climate projections and downscaling techniques: a discussion for impact studies in urban systems. *International Journal of Urban Sciences*, 22(3):277–307.

Sridhar, S., Fazelpour, M., Gill, A. S., and Summers, J. D. (2016). Accuracy and precision analysis of the graph complexity connectivity method. *Procedia CIRP*, 44:163–168.

Stephanou, M. and Varughese, M. (2021). Sequential estimation of spearman rank correlation using hermite series estimators. *Journal of Multivariate Analysis*, 186:104783.

Stocker, T. (2014). *Climate change 2013: The physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Suhaila, J. and Yusop, Z. (2018). Trend analysis and change point detection of annual and seasonal temperature series in peninsular malaysia. *Meteorology and Atmospheric Physics*, 130(5):565–581.

Suparta, W. and Yatim, A. N. M. (2017). An analysis of heat wave trends using heat index in east malaysia. In *Journal of Physics: Conference Series*, volume 852, page 012005.

Suparta, W. and Yatim, A. N. M. (2019). Characterization of heat waves: A case study for peninsular malaysia. *Geographia Technica*, 14(1).

Supian, N. M. and Hasan, H. (2021). Selecting the probability distribution of annual maximum temperature in malaysia. In *ITM Web of Conferences*, volume 36. EDP Sciences.

Tadese, M. T., Kumar, L., and Koech, R. (2020). Climate change projections in the awash river basin of ethiopia using global and regional climate models. *International Journal of Climatology*, 40(8):3649–3666.

Tangang, F., Chung, J. X., Juneng, L., Salimun, E., Ngai, S. T., Jamaluddin, A. F., Mohd, M. S. F., Cruz, F., Narisma, G., Santisirisomboon, J., et al. (2020). Projected future changes in rainfall in southeast asia based on cordex–sea multi-model simulations. *Climate Dynamics*, 55:1247–1267.

Tangang, F., Juneng, L., and Ahmad, S. (2007). Trend and interannual variability of temperature in malaysia: 1961–2002. *Theoretical and Applied Climatology*, 89(3):127–141.

Teutschbein, C. and Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of Hydrology*, 456:12–29.

Underwood, F. (2013). Describing seasonal variability in the distribution of daily effective temperatures for 1985–2009 compared to 1904–1984 for de bilt, holland. *Meteorological Applications*, 20(4):394–404.

Vaidyanathan, A., Malilay, J., Schramm, P., and Saha, S. (2020). Heat-related deaths—united states, 2004–2018. *Morbidity and Mortality Weekly Report*, 69(24):729.

Vasiliades, L., Galiatsatou, P., and Loukas, A. (2015). Nonstationary frequency analysis of annual maximum rainfall using climate covariates. *Water Resources Management*, 29(2):339–358.

Vicedo-Cabrera, A. M., Sera, F., and Gasparrini, A. (2019). Hands-on tutorial on a modeling framework for projections of climate change impacts on health. *Epidemiology (Cambridge, Mass.)*, 30(3):321.

Villafuerte, M. Q. and Matsumoto, J. (2015). Significant influences of global mean temperature and enso on extreme rainfall in southeast asia. *Journal of Climate*, 28(5):1905–1919.

Villarini, G., Smith, J. A., and Napolitano, F. (2010). Nonstationary modeling of a long record of rainfall and temperature over rome. *Advances in Water Resources*, 33(10):1256–1267.

Wang, J., Moore, J. C., Zhao, L., Yue, C., and Di, Z. (2022). Regional dynamical and statistical downscaling temperature, humidity and windspeed for the beijing region under stratospheric aerosol injection geoengineering. *Earth System Dynamics Discussions*, pages 1–33.

Wayne, G. (2013). The beginner's guide to representative concentration pathways. *Skeptical Science*, 25.

West, E. N. and Kempthorne, O. (1972). A comparison of the chi2 and likelihood ratio tests for composite alternatives1. *Journal of Statistical Computation and Simulation*, 1(1):1–33.

Wetterdienst, D. (2018). Climate predictions and climate projections, how are statements about future climate made? `https://www.dwd.de/SharedDocs/broschueren/EN/climate/brochure_climateresearch.pdf?__blob=publicationFile&v=8`.

WHO (2014). *Quantitative risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s*. World Health Organization.

Wilby, R. L., Hay, L. E., Gutowski Jr, W. J., Arritt, R. W., Takle, E. S., Pan, Z., Leavesley, G. H., and Clark, M. P. (2000). Hydrological responses to dynamically and statistically downscaled climate model output. *Geophysical Research Letters*, 27(8):1199–1202.

Williams, C., Allan, R., and Kniveton, D. (2012). Diagnosing atmosphere–land feedbacks in cmip5 climate models. *Environmental Research Letters*, 7(4):044003.

Wilson, M. K. (2016). *Modelling Extreme Temperature Behaviour in Upper East Region, Ghana*. PhD thesis.

Wong, C., Venneker, R., Jamil, A., and Uhlenbrook, S. (2011). Development of a gridded daily hydrometeorological data set for peninsular malaysia. *Hydrological Processes*, 25(7):1009–1020.

Wood, A. W., Leung, L. R., Sridhar, V., and Lettenmaier, D. (2004). Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. *Climatic Change*, 62(1):189–216.

Yanagawa, T. and Tajiri, R. (2018). Usefulness of akaike information criterion for making decision in two-sample problems when sample sizes are too small. *Japanese Journal of Statistics and Data Science*, 1(2):333–346.

Yi, Y. and Wang, X. (2011). Comparison of wald, score, and likelihood ratio tests for response adaptive designs. *Journal of Statistical Theory and Applications*, 10(4):553–569.

Zhan, W., He, X., Sheffield, J., and Wood, E. F. (2020). Projected seasonal changes in large-scale global precipitation and temperature extremes based on the cmip5 ensemble. *Journal of Climate*, 33(13):5651–5671.

Zhang, Y., Li, R., and Tsai, C.-L. (2010). Regularization parameter selections via generalized information criterion. *Journal of the American Statistical Association*, 105(489):312–323.

## LIST OF PUBLICATIONS

**Journals:**

Aina Izzati Mohd Esa, Syafrina Abdul Halim, Norzaida Abas, Jing Xing Chung and Mohd Syazwan Faisal Mohd (2020). Projection of Temperature in Relation to Cardiovascular Disease using Bias Correction Method, In *Journal of Quality Measurement and Analysis*. 16(2):193-206.

M. E. Aina Izzati and A. H. Syafrina (2020). Quantile Mapping with Three Parameters of Projection of Cardiovascular Disease Mortality Rate, In *Advances in Mathematics: Scientific Journal*. 9(12):10903-10913.

Aina Izzati Mohd Esa, Syafrina Abdul Halim and Norhaslinda Ali (2021). Projections of Cardiovascular Disease Mortality in Peninsular Malaysia Using Statistical Downscaling Based on Cluster Approach, In *Environment and Ecology Research*. 9(3):119-133.

Esa, A. I. M., Halim, S. A., Ali, N., Chung, J. X., & Mohd, M. S. F. (2022). Optimizing future mortality rate prediction of extreme temperature-related cardiovascular disease based on skewed distribution in peninsular Malaysia, In *Journal of Water and Climate Change*. DOI: 10.2166/wcc.2022.215 (Waiting to be published in November issue of Journal of Water and Climate Change).