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DETECTION OF POINTS OF CLIMATIC CHANGES, A BAYESIAN APPROACH IN CLIMATIC DATA OF THE CITY OF SÃO PAULO

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ARTICLE

Abstract

In this study, we introduce a statistical model applied to climate change data (annual mean temperature and annual mean rain precipitation for a long period) obtained from a climate station in São Paulo City Brazil. The assumed model used in the data analysis consists of an autoregressive times series (AR) model which represents a type of random process. A Bayesian approach using MCMC (Markov Chain Monte Carlo) methods is considered to get the inferences of interest. The main goal of the study is to have a fitted statistical model to get good predictions for annual mean temperature and annual mean rain precipitation and also to be used to identify the time of possible climate change-points.

Keywords: AR Models, Change-Points, Annual Mean Temperature, Annual Mean Rain Precipitation, Bayesian Approach.

Resumo / Resumen

DETECÇÃO DE PONTOS DE MUDANÇAS CLIMÁTICAS, UMA ABORDAGEM BAYESIANA EM DADOS CLIMÁTICOS DA CIDADE DE SÃO PAULO

Neste estudo, introduzimos um modelo estatístico aplicado a dados de mudanças climáticas (temperatura média anual e precipitação média anual de chuva por um longo período) obtidos de uma estação climática na cidade de São Paulo, Brasil. O modelo assumido usado na análise de dados consiste em um modelo de séries temporais (AR) autorregressivo que representa um tipo de processo aleatório. Uma abordagem bayesiana usando métodos MCMC (Markov Chain Monte Carlo) é considerada para obter as inferências de interesse. O principal objetivo do estudo é ter um modelo estatístico ajustado para obter boas previsões para a temperatura média anual e precipitação média anual de chuva e também para ser usado para identificar o tempo de possíveis pontos de mudança climática.

Palavras-chave: Modelos AR, Pontos de Mudança, Temperatura Média Anual, Precipitação Média Anual de Chuva, Abordagem Bayesiana.

DETECCIÓN DE PUNTOS CRÍTICOS DEL CAMBIO CLIMÁTICO: UN ENFOQUE BAYESIANO EN DATOS CLIMÁTICOS DE LA CIUDAD DE SÃO PAULO

En este estudio, presentamos un modelo estadístico aplicado a datos de cambio climático (temperatura media anual y precipitación media anual durante un largo período) obtenidos de una estación climática en la ciudad de São Paulo, Brasil. El modelo asumido en el análisis de datos consiste en un modelo autorregresivo de series de tiempo (AR) que representa un tipo de proceso aleatorio. Se considera un enfoque bayesiano utilizando métodos MCMC (Markov Chain Monte Carlo) para obtener las inferencias de interés. El objetivo principal del estudio es contar con un modelo estadístico ajustado para obtener buenas predicciones de la temperatura media anual y la precipitación media anual, así como para identificar la cronología de posibles puntos de cambio climático.

Palabras-clave: Modelos AR, Puntos de Cambio, Temperatura Media Anual, Precipitación Media Anual, Enfoque Bayesiano.

INTRODUCTION

Over the past several decades, substantial and well-documented changes in global temperature and precipitation patterns have been observed across multiple regions of the world (e.g., NRC, 2011; NOAA, 2021). These changes are not isolated phenomena but part of a broader pattern of climate variability and long-term warming that has raised significant scientific, political, and societal concern (see also https://www.un.org /en/sections/issues-depth/climate-change/ - accessed on 01 July 2021). International organizations such as the United Nations have repeatedly emphasized the urgency of understanding and mitigating climate change and its associated impacts.

Observed climate-related changes include widespread glacier retreat, reductions in snow cover, and earlier melting of ice in rivers and lakes. In addition, shifts in the geographic distribution of plant and animal species have been documented, as well as phenological changes such as earlier flowering of trees and altered growing seasons in many regions (IPCC, 2007, 2013). These environmental transformations reflect the sensitivity of natural systems to sustained increases in temperature and modifications in precipitation regimes. Regional projections further suggest heterogeneous effects: for example, winter and spring precipitation is expected to increase in the northern United States while decreasing in the Southwest. Moreover, climate models indicate that heat waves are likely to become more frequent and intense in many parts of the world, whereas cold waves are projected to decrease in intensity and frequency (https://www.ncdc.noaa.gov/monitoring-references/faq/indicators.php).

Long-term instrumental records provide quantitative evidence of global warming. Between 1920 and 1940, global mean temperature increased by approximately 0.1°C (0.18°F) per decade. More recent decades show an even more pronounced rise, with the annual mean global temperature during 2000–2009 about 0.61°C (1.1°F) higher than the 1950–1980 baseline. These sustained upward trends highlight the importance of rigorous statistical methodologies capable of capturing both gradual changes and abrupt structural shifts in climate time series.

The analysis of climate data poses several statistical challenges. Climate series often exhibit temporal dependence, seasonality, nonstationarity, and potential structural breaks. As a result, statistical modeling has become indispensable in climate research. In particular, autoregressive and other time series models provide flexible tools to describe persistence structures in temperature and precipitation data. Beyond forecasting, these models can also be employed to detect structural changes—commonly referred to as change-points—that may indicate shifts in the underlying climate regime. The development of robust statistical models for identifying such change-points is of considerable scientific interest, as it enables researchers to determine whether observed variations reflect natural variability or more persistent climate transitions.

In this way, the climate change literature spans a broad spectrum of thematic and methodological perspectives. For example, Arnell and Lloyd-Hughes (2014) investigate the impacts of climate change on water resources and flooding, while Costello et al. (2009) examine its implications for public health. Long-term global temperature trends since the pre-industrial era are analyzed by Hawkins et al. (2017), and the conceptual relationship between global warming and climate change is discussed by Lineman et al. (2015).

Regional and sector-specific impacts have also been widely explored. Kabir et al. (2016) assess climate change effects on coastal areas of Bangladesh, whereas Levermann et al. (2013) address sea-level changes associated with global warming. The links between climate change and migration are examined by Kaczan and Orgill-Meyer (2020), and evolving patterns in temperature and humidity are discussed by Matthews (2018). Impacts on marine ecosystems are analyzed by Poloczanska et al. (2013), while Serdeczny et al. (2016) focus on consequences for sub-Saharan Africa. The health implications of future food production under climate change scenarios are investigated by Springmann et al. (2016), and threats to ecosystems are discussed by Turner et al.

(2020). Agricultural impacts, particularly the relationship between temperature increases and crop production, are explored by Zhao et al. (2017).

From a statistical standpoint, Richards (1993) provides an early statistical analysis of global temperature change, and Alexander et al. (2006) examine changes in extreme temperature indices. A Bayesian framework for jointly assessing temperature and precipitation changes from multiple climate models is proposed by Tebaldi and Sansó (2009). Additional related contributions include Powell (2016), Diaz-Nieto and Wilby (2005), Ribes et al. (2017), and Vanem (2016).

Within this broad literature, the detection of change-points in climate time series has received particular attention. Identifying the timing of abrupt or gradual shifts in temperature and precipitation is crucial for understanding climate dynamics and improving predictive models.

The identification of structural breaks in climate time series has been extensively investigated in the statistical literature. Early contributions by Barry and Hartigan (1993) and Carlin et al. (1992) proposed Bayesian frameworks for modeling change-point problems in climate data. Building on this line of research, Robbins et al. (2016) considered autoregressive structures for detecting change-points in climate series, while Gallagher et al. (2012) applied change-point detection methods to temperature and precipitation records. In a different methodological direction, Li and Lund (2012) introduced a genetic algorithm approach for identifying structural breaks in climate data.

Given the presence of potential change-points, Bayesian inference has become a widely adopted framework, particularly due to its flexibility in modeling uncertainty about both the number and location of structural breaks. In this context, Markov Chain Monte Carlo (MCMC) methods (Gilks et al. 1995) are frequently employed to obtain posterior estimates of model parameters. Foundational contributions to Bayesian change-point modeling and MCMC-based inference include the works of Achcar and Bolfarine (1989), Bacon and Watts (1971), Ferreira (1975), Gelfand and Smith (1990), and Gelman et al. (1995), in addition to the earlier studies by Barry and Hartigan (1993) and Carlin et al. (1992). Collectively, these works provide the theoretical and computational foundations for modern Bayesian change-point analysis in climate time series.

In the present study, we focus on estimating the locations of possible change-points in annual mean temperature and annual mean precipitation recorded at a climate station in São Paulo city, Brazil. São Paulo city is one of the largest metropolitan areas in the Southern Hemisphere, with more than 12 million inhabitants, and is characterized by rapid urbanization and significant environmental pressures. Understanding long-term climate patterns in such an urban context is particularly relevant, as changes in temperature and precipitation can directly affect water availability, public health, infrastructure planning, and energy demand.

We adopt an autoregressive modeling framework within a Bayesian paradigm to analyze the annual series of temperature and precipitation. Inference is performed using MCMC methods, specifically through Gibbs sampling, to generate posterior samples of the parameters of interest. From these samples, we compute Monte Carlo estimates of contrasts between consecutive yearly means, allowing us to quantify interannual changes. Additionally, we construct cumulative sum (CUSUM) control charts based on these estimated contrasts to identify potential years in which significant structural shifts may have occurred. This combined approach enables both probabilistic inference and visual diagnostic assessment of change-points in the climate series.

METHODOLOGY

Different existing times series models could be fitted for the annual mean climate variables as MA (moving average) models or ARIMA (Autoregressive Integrated Moving Average) models (see for example, Bell, 1984; Box et al., 1994; Montgomery et al., 2008). In this work, we

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consider the use of a AR (autoregressive) model in the analysis of climate (temperature and rain precipitation) variables which gives a good fit for the data. From the fitted model, we explore the behavior of the climate times series for possible change-points. Assuming temporal climate data, as for example, monthly or annual temperature or rain precipitation means, denoted by a random variable Y which could be transformed (e.g., logarithm transformation), we consider a autoregressive model AR(J) of order J.

Assuming J =2, that is, a AR(2) model, the model is defined by,

$y_1 = \alpha_0 + \varepsilon_1$,

$y_2 = \alpha_1 y_1 + \varepsilon_2$ and

$y_i = \alpha_1 y_{i-1} + \alpha_2 y_{i-2} + \varepsilon_i$, for i = 3, 4,...,n (sample size). (1)

Assuming J=3, that is, a AR(3) model, the model is defined by,

$y_1 = \alpha_0 + \varepsilon_1$,

$y_2 = \alpha_1 y_1 + \varepsilon_2$,

$y_3 = \alpha_1 y_2 + \alpha_2 y_1 + \varepsilon_3$, and

$y_i = \alpha_1 y_{i-1} + \alpha_2 y_{i-2} + \alpha_3 y_{i-3} + \varepsilon_i$ for i = 4, 5, ..., n. (2)

In general, assuming a AR(J) model, we have,

$$y_i = \alpha_1 y_{i-1} + \alpha_2 y_{i-2} + \cdots + \alpha_{J-1} y_1 + \varepsilon_i, \quad (3)$$

for the i^{th} observation (n is the sample size) where ε_i is an error term (a non observed random variable) assumed to be independent, identically distributed with a normal distribution $N(0, \sigma^2)$.

We assume a Bayesian analysis for the data assuming the AR(J) model defined in (3). Combining the joint prior distribution for the parameters of the assumed model with the likelihood function given by,

$$L(\alpha_0, \alpha_1, ..., \alpha_{J-1}, \sigma^2) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\sigma^2}} exp\left\{\frac{\epsilon_i^2}{2\sigma^2}\right\} , \quad (4)$$

where $\varepsilon_i = y_i - (\alpha_1 y_{i-1} + \alpha_2 y_{i-2} + \cdots + \alpha_{J-1} y_1)$ is obtained from (3), the joint posterior distribution for the parameters of the model is obtained using the Bayes formula (Box & Tiao, 1973). The posterior summaries of interest are obtained using Markov Chain Monte Carlo (MCMC) simulation methods as the popular Gibbs sampling algorithm or the Metropolis-Hastings algorithm (Gelfand & Smith, 1990; Chib & Greenberg, 1995) using the free existing OpenBUGS software (Lunn et al., 2000). Since the OpenBUGS software only requires the likelihood function and the prior distributions for the parameters of the model, we do not present here the conditional posterior distributions $p(\theta_j/\boldsymbol{\theta}_{(j)}, \text{data})$, where $\boldsymbol{\theta}_{(j)}$ denotes the vector of all p parameters of the model except θ_j, j = 1, 2,...,p, needed for the Gibbs sampling or Metropolis-Hastings algorithms (see for example, Bernardo and Smith, 1994).

For a Bayesian analysis, we assume independent prior distributions given by, normal distributions $N(0, a^2)$ for the parameters $\alpha_0, \alpha_1, ..., \alpha_{J-1}$ and a uniform prior distribution U(0,b) for the parameter $\phi = 1/\sigma^2$. The hyperparameters a and b, are assumed known

MODEL DISCRIMINATION CRITERION - DEVIANCE INFORMATION CRITERION (DIC)

In the discrimination of the better model, we use the DIC criterion that is very popular to discriminate Bayesian models using MCMC methods. In our case we discriminate different versions of the proposed model (1) considering different choices of AR(J) structures.

The DIC criterion (Spiegelhalter et al., 2002) is based on the posterior mean of deviance. The deviance is defined by

$$D(\theta) = -2 \ln L(\theta) + C, \quad (5)$$

where θ is a vector of unknown model parameters; L(θ) is the likelihood and C is a constant (not always known) when comparing two models. The DIC criterion is then given by,

$$D(\theta) = D(\widehat{\boldsymbol{\theta}}) + 2pD \quad (6)$$

where $D(\widehat{\boldsymbol{\theta}})$ is the deviation calculated on the posterior mean $\widehat{\boldsymbol{\theta}} = E(\theta|y)$ and pD is the number of model parameters, given by $p_D = \bar{D} - D(\widehat{\boldsymbol{\theta}})$ where $\bar{D} = E[D(\boldsymbol{\theta}|y)]$ is the posterior mean of the deviation that measures the goodness of fit of the data for each model. For the conclusion, the lowest DIC values indicate the best models. DIC also could have negative values.

CHANGE-POINT DETECTION

To detect the climate change-points, we get from the generated Gibbs samples for the joint posterior distribution obtained assuming model (1), the Monte Carlo estimates for the contrasts $\theta_i = \mu_i - \mu_{i-1}$, where $\mu_i = \alpha_1 y_{i-1} + \alpha_2 y_{i-2} + \cdots + \alpha_{j-1} y_1$, assuming y_i = log (mean.temperaturei) or y_i = log(mean.precipitationi). In this way, we detect a significant mean change-point in a specified year, if a 95% credible interval for θi does not contain the zero value (climate mean in year i is statistically different of climate mean in year i-1).

In the detection of year periods where the climate variable start a new behavior (could be above or below a standard climate behavior in a specified period of time), we use standard CUSUM (cumulative sum control) charts usually used in statistical quality control, which is used for monitoring change detection (Grigg et al., 2003; Barnard, 1959). The CUSUM assumed in this work considers the cumulative sum up to time i from all annual mean climate diferences in the previous years. Observe that if the climate variable do not have changes in long periods of years, in general, although the great volatility of the annual mean climate variables, we should have CUSUM close to zero along all years. In general although the great volatility of the annual mean climate variables, we should have CUSUM close to zero along all years. The purpose of cumulative sum chart (CUSUM) is to monitor the small shift in the process mean of the samples collects at a time intervals. These measurements of samples at a given time interval represents the subgroups. Instead of calculating the subgroups mean independently, the CUSUM chart represents the information of current and previous samples

APPLICATIONS WITH THE CLIMATE TIMES SERIES OF SÃO PAULO CITY

The data sets considered in this study consist of the annual mean temperature and annual mean rain precipitation measures extracted from the Research Data Archive site managed by the Data Engineering Section of the Computational and Information Systems Laboratory at the National Center for Atmospheric Research, United States of America. This site contains a large and diverse collection of meteorological and oceanographic observations (https://rda.ucar.edu/index.html?hash=datauser&action=register and https://rda.ucar.edu/datasets/ds570.0/#!subset.html, both accessed on 01 July 2021). It contains data from more than 4700 different climate stations (2600 in more recent years) from all around the world. Different follow-up periods are given for the different climate stations, and collection of data for some of them goes as far back as the mid-1700s.

The primary data sets consist of monthly mean temperatures and monthly mean rain precipitations. Since the data sets have many missing observations (months with no information), these missing observations were replaced by the monthly averages of the available data for that month. For instance, if in a given year we have missing data for the month of January, we fill the hole in the data by assigning to that month the mean obtained using the values for the month January from all the years in which they are available. The data used in our calculations were the annual temperature means and annual rain precipitation means.

The climate station considered in this study is located in the central region of São Paulo city, Brazil where the temperature and rain precipitation measures were observed in a period of T = 133 years from 1887 to 2019. Figure 1 show the map of São Paulo city with temperature variations for a summer Sunny morning in the year of 2019.

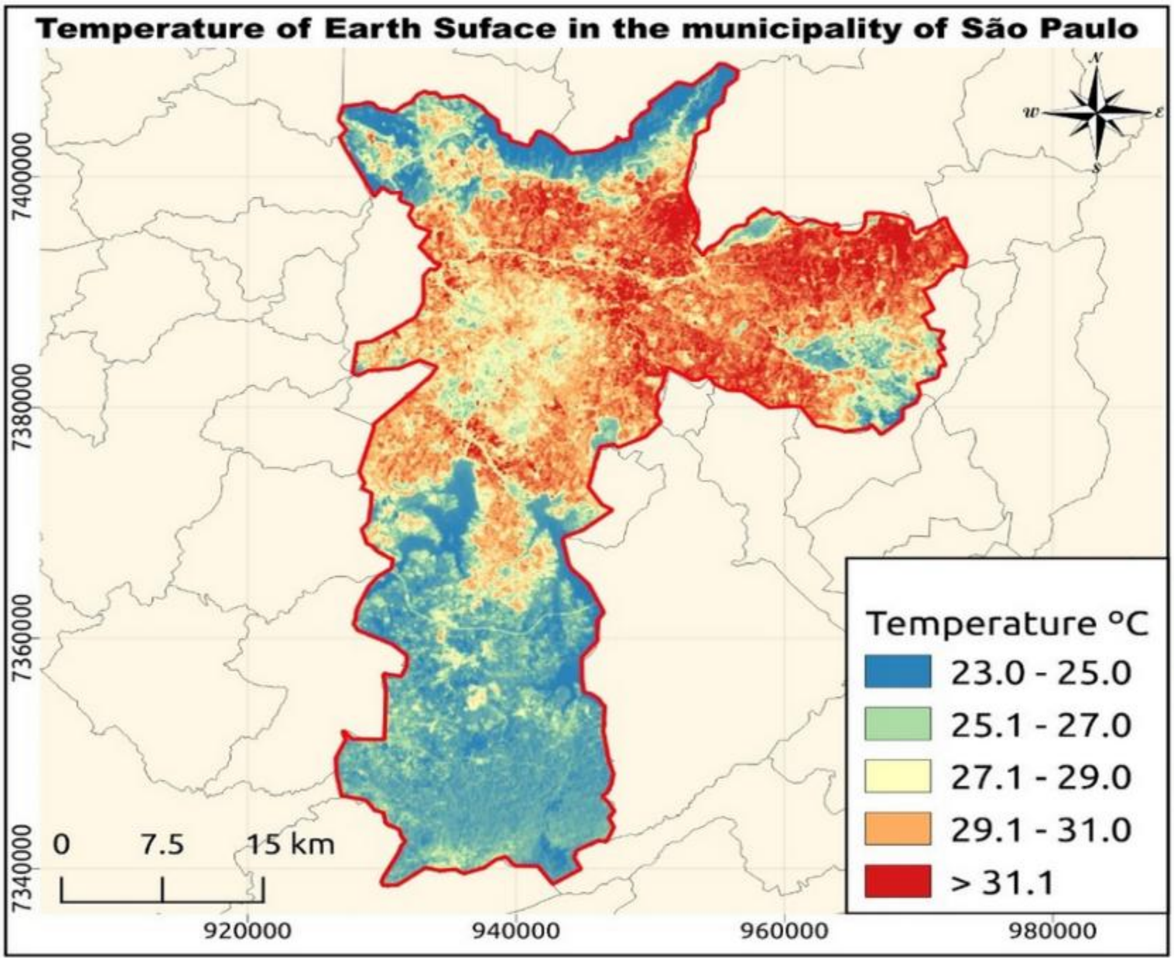

Figure 1- Temperature variations in São Paulo city for a summer sunny morning. Source: Authors form USGS (US Geological Survey) - São Paulo dates 21 st Jan 2019

Figure 2 shows the plots of the annual mean temperatures and annual rain precipitation given in logarithm scale (logarithm to the base 10) during their corresponding observational periods. From Figure 2, we see the possible presence of change points indicating changes from increasing/decreasing trends to decreasing/increasing where in the final years of the follow-up period, there is an indication of an increasing trend in the annual mean temperature. We also observe a decreasing/increasing behavior in the follow-up period for the annual mean rain precipitation with a stabilization of higher means of rain precipitation in the last years (an increasing behavior).

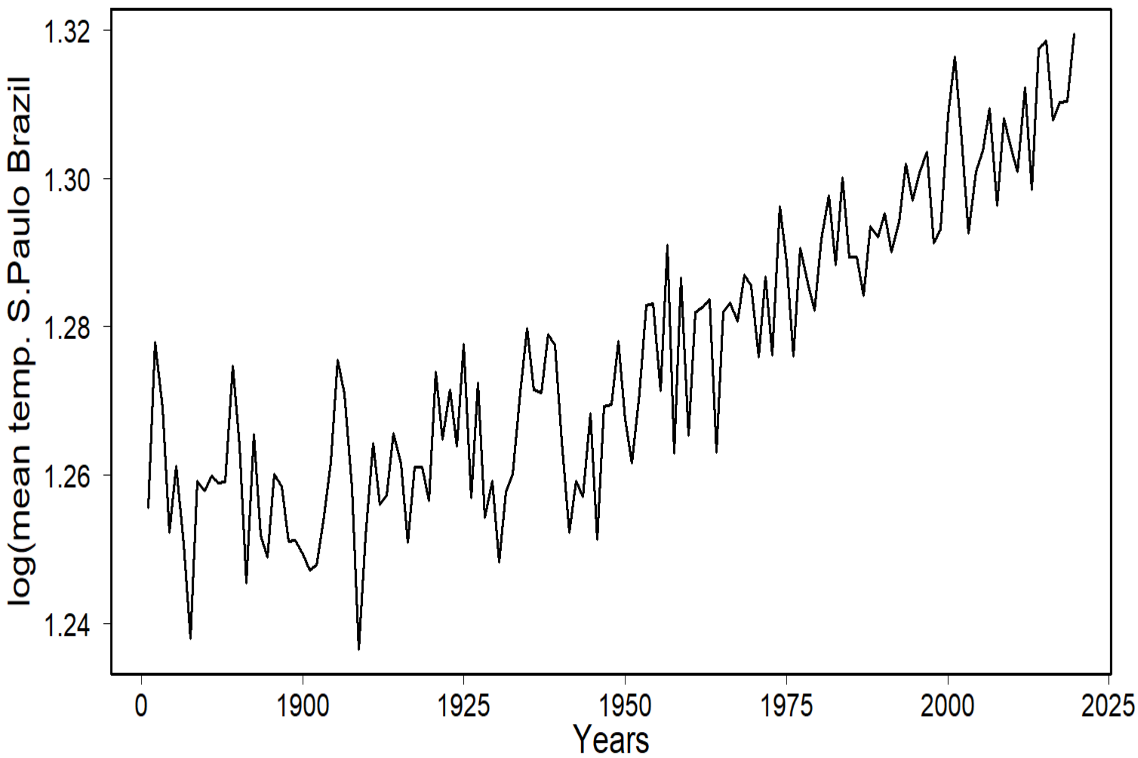

Figure 2 - Annual mean temperature and annual mean rain precipitation in the logarithmic scale (S. Paulo, Brazil).

For a Bayesian analysis of the AR(J) regression model (1), we assume independent prior distributions for the parameters α_0 , α_k , k =1,2,..,J, $\phi = 1/\sigma^2$ that is, $\alpha_0 \sim N(0,10)$, $\alpha_k \sim N(0,1)$, $\phi = 1/\sigma^2 \sim U(0,1000)$, considering the climate data of São Paulo city. Observe that we are assuming approximately non-informative priors for all parameters.

The posterior summaries of interest were obtained using the OpenBUGS software (Spiegelhalter et al. 2007). The convergence of the MCMC algorithm was monitored using the trace-plots of the generated Gibbs samples (Figure 3). In the simulation process to generate the samples of the joint posterior distribution of interest, we considered initially 200,000 Gibbs samples discarded to eliminate the effect of the initial values in the iterative process and taking a final sample of size 1,000 to get the Monte Carlo estimates for each parameter (taking every 100th sample of a total of 100,000 simulated samples).

From the DIC discrimination criterion, we observed that AR(2) model (1) gives better fit (parsimony) for the annual mean temperature and the annual mean rain precipitation (smaller Monte Carlo estimates for DIC in both cases). The DIC values were estimated by negative values. Table 1 shows the posterior summaries (posterior mean, posterior standard deviation and 95% credible intervals) for each parameter of the assumed model.

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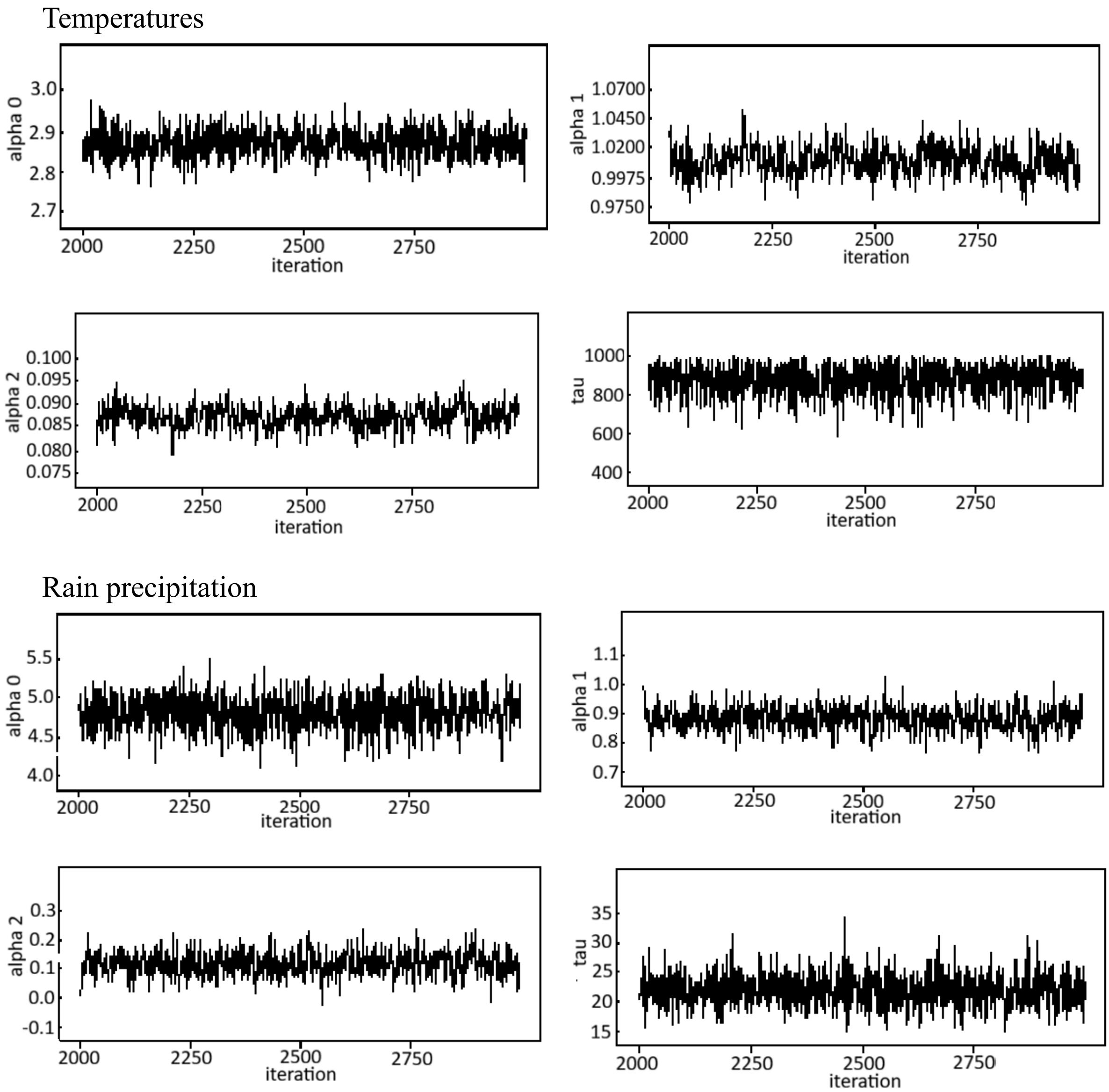

Figure 3 - Trace plots of the simulated Gibbs samples for the parameters of the model

Figure 4 shows the scatter plots of the estimated means obtained for each fitted model togetter with the observed annual mean temperatures and the annual mean rain precipitation, from where, we observe good fit of the proposed model for the two climate times series (see Appendix 2).

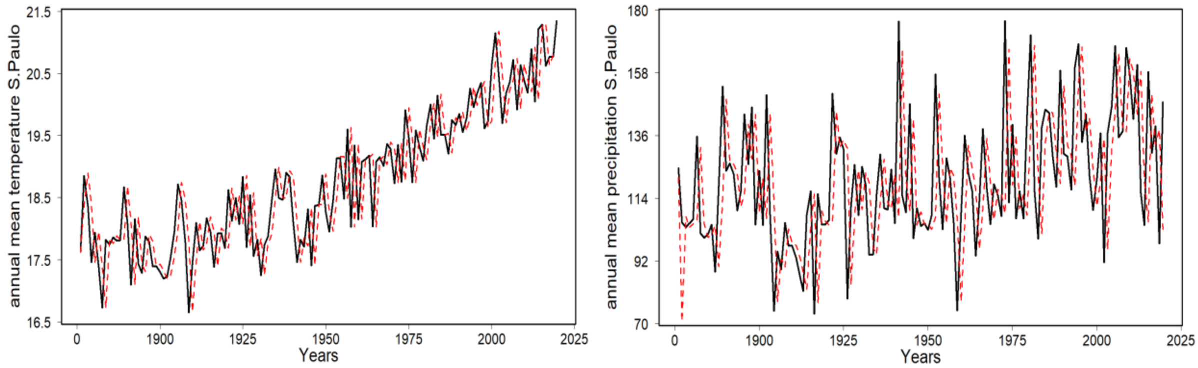

Figure 4 - Fitted and observed annual mean temperatures and annual mean rain precipitations for the data of the São Paulo climate station (period 1887-2019). Plots with dotted lines are associated to the fitted model

Figure 5 shows the normality plots of the residuals used to check if the assumption of normality of the errors is verified. In general we observe that the normality assumption for the residuals are well verified for both cases. Figure 6 shows the autocorrelation plots of the residuals, from where we observe non-correlated residuals. Thus the assumptions of the proposed model are satisfied in both cases.

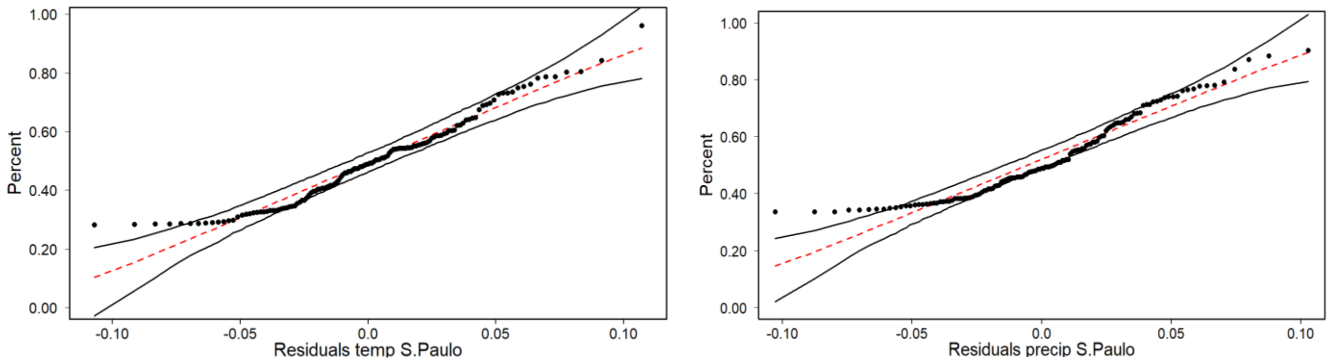

Figure 5 - Residual plots (São Paulo, Brazil).

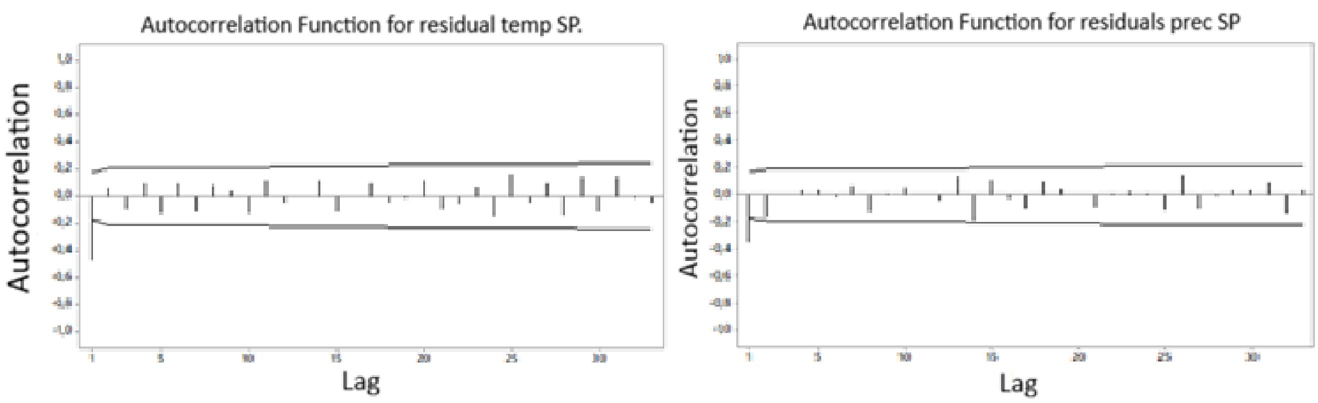

Figure 6 - Autocorrelation plots of the residuals

Annual mean temperature	mean	sd	Lower 95% c.i.	Upper 95% c.i
α_0	2.869	0.03312	2.807	2.939
α_1	1.014	0.01161	0.9924	1.038
α_2	- 0.014	0.01165	- 0.03708	0.009
$\phi = 1/\sigma^2$	875.900	78.770	709.700	991.800
Annual mean precipitation	mean	sd	Lower 95% c.i.	Upper 95% c.i.
α_0	4.798	0.219	4.343	5.195
α_1	0.883	0.040	0.806	0.962
α_2	0.117	0.040	0.041	0.195
$\phi = 1/\sigma^2$	21.890	2.696	17.020	27.360

Table 1 - Posterior summaries (temperature and precipitation - São Paulo, Brazil)

From the Monte Carlo estimates for the the contrasts $\theta_i = \mu_i - \mu_{i-1}$, where $\mu_i = \alpha_1 y_{i-1} + \alpha_2 y_{i-2} + \cdots + \alpha_{j-1} y_1$ assuming both cases, yi=log(mean.rain.precipitationi) or yi=log(mean.temperaturei), we can detect the consecutive years showing the same annual mean temperatures for each climate station (95% credible interval for θi containing the zero value). From Appendix 1, we discover that the years with not significant differences between the annual mean temperatures and annual mean rain precipitation for two consecutive years are given by:

- Annual mean temperatures: θ_3 (years 1888-1889), θ_{68} (years 1953-1954), θ_{74} (years 1959-1960) and θ_{103} (years 1988-1989). All the other consecutive pairs of years have significant change in the annual mean temperatures (95% credible intervals for the associated contrasts θ does not contain the zero value).
- Annual mean rain precipitations: θ_{16} (years 1901-1902), θ_{41} (years 1926-1037), θ_{69} (years 1954-1955), θ_{103} (years 1988-1989) and θ_{123} (years 2008-2009). All the other consecutive pairs of years have significant change in the annual mean temperatures (95% credible intervals for the associated contrasts θ does not contain the zero value).

Figure 7 shows the graphs of CUSUM (partial sum of consecutive mean temperature diferences and partial sum of consecutive mean rain precipitation diferences) versus time order, from Where we can conclude that

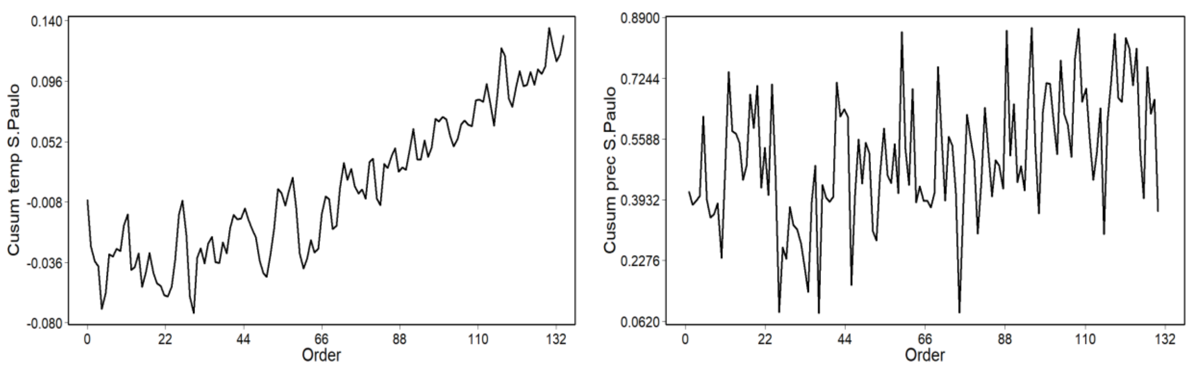

Figure 7 - Graph of CUSUM (partial sum of consecutive annual mean temperature differences and partial sum of consecutive annual mean precipitation differences versus order).

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Figure 4 shows the following behavior for each climate station:

- Annual mean temperature: the graph of CUSUM (partial sum of consecutive mean temperature differences for two consecutive years) show a cyclic behavior (up/down) but in general there is a constant trend in the CUSUM of the estimated diferences from the begining of the follow-up period until the year close to 1946 (θ_{60}); after the year 1946 there is a consecutive increasing in the CUSUM of the estimated diferences of consecutive pairs of years until the end of the follow-up period.This plot shows a consolidated increasing annual mean temperature shift beginnning in the year close to 1946.
- Annual mean rain precipitation: since the model fit for second observation (beginning of the times series) was not good, we use the graph of CUSUM (partial sum of consecutive mean temperature differences for two consecutive years) starting in θ_4 ; the plot of the CUSUM (partial sum of consecutive mean rain precipitation differences for two consecutive years) shows a cyclic behavior (up/down) but in general there is a constant trend in the CUSUM of the estimated diferences from the begining of the follow-up period until the year close to 1965 (θ_{80}); after the year 1965 we observe that the volatities of annual mean precipitations become stable in a value greater than the mean rain precipitation value before the year of 1965. Thus, we can conclude that the annual mean rain precipitations have a increasing shift after the year 1965 (differences close to values 0.1 to 0.2). That is, the annual rain precipitation means are increasing in the last years of the follow-up period of T = 133 years from 1887 to 2019.

CONCLUSION

From the obtained results of this study, we observe that the annual mean temperature started to increase in the year close to 1946 in São Paulo city in the observed period (1887-2019). This increasing in the annual mean temperature could be due to the effect of climate change observed worldwide.

The possible effect of climate change also could be observed in the annual mean rain precipitation, where there is a consistent increasing in the annual mean rain precipitation beginng close to the year 1965, although the great volatilities observed in the follow-up period of 133 years (1887-2019) in São Paulo city.

Climate changes (temperature, rainfall, etc.) have been observed all over the world. As these climate changes can have different effects in diferent locations, the detection of times when changes occur is of great interest to all. The modeling of climate time series has been considered in different ways, as observed in the literature. In this study, we assumed a simple model based on an auto-regressive structure, which in addition to leading to a good fit to the data, it was also possible to detect from the fitted model, significant differences between the annual climate means for two consecutive years and a long follow-up period of 133 years, where it was possible to observe sharp changes in the annual mean temperatures and annual mean rain precipitations in the climate station of São Paulo city using usual CUSUM control charts usually used in industrial statistical control. The obtained results could be easily reproduced for any climate times series data obtained from different locations of the climate station under a Bayesian approach using MCMC methods to generate samples of the joint posterior distribution for the parameters of the proposed model. It is important to point out that the two-by-two year comparisons for the climatic averages in two consecutive years are obtained simultaneously with the simulation of the Gibbs samples.

Considering usual frequentist approaches using separated hypotheses tests to compare two climate means, we would obtain a different p-value for each comparison. That is, the use of a Bayesian approch gives more simplicity in the data analysis.

Other possible great advantage for the use of a Bayesian approach: the use of informative priors obtained from climate experts implying in more accurate inferences. These results can be of great interest in the study of the climatic changes observed throughout the planet.

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Not applicable

DATA AVAILABILITY

Not applicable

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APPENDIX

Appendix 1. Bayesian estimates (posterior means and 95% credible intervals) for the annual mean temperature differences and annual mean precipitation diferences

	Annual mean temperature	Lower 95% Int. credib	Upper 95% Int. credib	Annual mean precipitation	Lower 95% Int. credib	Upper 95% Int. credib
theta[3]	0.02793	-0.03698	0.09149	0.4196	0.03591	0.8053
theta[4]	-0.02764	-0.02978	-0.02553	-0.03468	-0.04615	-0.02311
theta[5]	-0.05073	-0.05128	-0.05021	0.009807	0.007451	0.01217
theta[6]	0.02792	0.02622	0.02974	0.01324	0.01313	0.01334
theta[7]	-0.03243	-0.03378	-0.03112	0.2146	0.1972	0.2327
theta[8]	-0.03823	-0.03839	-0.03808	-0.2254	-0.2662	-0.1847
theta[9]	0.06485	0.06262	0.06721	-0.04771	-0.0686	-0.02661
theta[10]	-0.00487	-0.00644	-0.00334	0.008648	0.006511	0.01079
theta[11]	0.006207	0.005987	0.00644	0.03051	0.0289	0.03221
theta[12]	-0.002928	-0.00313	-0.00272	-0.1483	-0.1645	-0.1326
theta[13]	0.000551	0.000478	0.000629	0.2374	0.2018	0.2738
theta[14]	0.04726	0.04626	0.04833	0.2645	0.2614	0.2677
theta[15]	-0.03288	-0.03469	-0.03111	-0.1595	-0.1961	-0.1227
theta[16]	-0.05625	-0.0568	-0.05573	-0.0062	-0.02442	0.01212
theta[17]	0.06166	0.05911	0.06437	-0.02515	-0.02925	-0.02107
theta[18]	-0.04216	-0.04448	-0.03988	-0.1004	-0.1066	-0.09443
theta[19]	-0.0082	-0.00892	-0.00745	0.03947	0.02644	0.05249
theta[20]	0.03428	0.03335	0.03526	0.1917	0.1803	0.2037
theta[21]	-0.0057	-0.00661	-0.00482	-0.09022	-0.1162	-0.064
theta[22]	-0.02248	-0.02287	-0.0221	0.1142	0.09289	0.1356
theta[23]	0.000774	0.000269	0.001308	-0.2757	-0.3129	-0.2389
theta[24]	-0.005852	-0.00599	-0.00571	0.1075	0.06912	0.1459
theta[25]	-0.006272	-0.00629	-0.00625	-0.1278	-0.1535	-0.1022
theta[26]	0.002032	0.001851	0.002224	0.2998	0.2592	0.3414
theta[27]	0.01795	0.0176	0.01832	-0.2462	-0.2993	-0.1931
theta[28]	0.02405	0.02391	0.02419	-0.3686	-0.3732	-0.3638
theta[29]	0.04165	0.04128	0.04206	0.1743	0.1264	0.2223
theta[30]	-0.01471	-0.01599	-0.01345	-0.03128	-0.05557	-0.00686
theta[31]	-0.03805	-0.0386	-0.03753	0.1403	0.1222	0.1589
theta[32]	-0.06579	-0.06643	-0.06519	-0.04995	-0.0689	-0.03089
theta[33]	0.04705	0.04461	0.04965	-0.009264	-0.01532	-0.00314
theta[34]	0.03747	0.03727	0.03766	-0.0389	-0.0424	-0.03555

theta[35]	-0.02561	-0.02704	-0.0242	-0.06289	-0.06458	-0.06118
theta[36]	0.004185	0.003554	0.004856	-0.06835	-0.06893	-0.06773
theta[37]	0.02539	0.02492	0.02588	0.2429	0.2159	0.2709
theta[38]	-0.01299	-0.01385	-0.01214	0.09854	0.08247	0.1151
theta[39]	-0.03193	-0.03237	-0.03151	-0.3986	-0.4407	-0.3577
theta[40]	0.03536	0.03391	0.03691	0.3455	0.2752	0.4162
theta[41]	-0.004261	-0.00516	-0.00339	-0.03342	-0.07583	0.009227
theta[42]	-0.01373	-0.01396	-0.01352	-0.01151	-0.01904	-0.00390
theta[43]	0.05283	0.05139	0.05435	0.01254	0.01146	0.01367
theta[44]	-0.02832	-0.03014	-0.02653	0.3097	0.2842	0.3363
theta[45]	0.02071	0.01967	0.02182	-0.09217	-0.1305	-0.05357
theta[46]	-0.02341	-0.0244	-0.02245	0.02029	0.005313	0.03522
theta[47]	0.04198	0.04058	0.04346	-0.02211	-0.02777	-0.01641
theta[48]	-0.0635	-0.06588	-0.06118	-0.4536	-0.4917	-0.4171
theta[49]	0.04799	0.0456	0.05054	0.2434	0.1776	0.3092
theta[50]	-0.05595	-0.05828	-0.05368	0.1500	0.1332	0.1672
theta[51]	0.01606	0.01452	0.0177	-0.1193	-0.1406	-0.09801
theta[52]	-0.03347	-0.03457	-0.03239	0.1111	0.08821	0.1341
theta[53]	0.02898	0.02764	0.0304	-0.02847	-0.04366	-0.01318
theta[54]	0.007185	0.006708	0.007651	-0.2108	-0.2253	-0.1971
theta[55]	0.03294	0.03239	0.03353	-0.02536	-0.04332	-0.00721
theta[56]	0.02616	0.02601	0.02631	0.1791	0.1638	0.195
theta[57]	-0.02561	-0.02678	-0.02445	0.124	0.1172	0.1311
theta[58]	-0.001027	-0.00155	-0.00047	-0.1267	-0.1478	-0.1058
theta[59]	0.02385	0.0233	0.02443	-0.02182	-0.03374	-0.00979
theta[60]	-0.00468	-0.00533	-0.00405	0.1059	0.09647	0.1158
theta[61]	-0.0391	-0.0399	-0.03834	-0.1324	-0.1546	-0.1104
theta[62]	-0.03676	-0.03685	-0.03668	0.4347	0.3826	0.4887
theta[63]	0.02161	0.02034	0.02296	-0.316	-0.3884	-0.2434
theta[64]	-0.006967	-0.00760	-0.00634	-0.09657	-0.1254	-0.0676
theta[65]	0.03438	0.0335	0.03532	0.2584	0.2315	0.2863
theta[66]	-0.05209	-0.05405	-0.05019	-0.3055	-0.3585	-0.2527
theta[67]	0.05509	0.05279	0.05754	0.04363	0.006059	0.08111
theta[68]	0.000140	-0.00108	0.001337	-0.03994	-0.05215	-0.02762
theta[69]	0.02586	0.02532	0.02644	0.001539	-0.00371	0.006802
theta[70]	-0.03237	-0.03369	-0.03109	-0.01923	-0.02177	-0.01673
theta[71]	-0.0176	-0.0179	-0.01728	0.03917	0.03377	0.04472
theta[72]	0.02905	0.02803	0.03012	0.3399	0.3148	0.3664
theta[73]	0.03554	0.03538	0.03571	-0.1866	-0.2357	-0.1371

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theta[74]	-0.000139	-0.00082	0.000779	-0.1733	-0.1811	-0.1654
theta[75]	-0.03554	-0.03636	-0.03475	0.1718	0.1428	0.2012
theta[76]	0.0600	0.05794	0.06218	-0.0235	-0.04441	-0.00249
theta[77]	-0.08577	-0.08906	-0.08257	-0.1289	-0.1356	-0.1226
theta[78]	0.07268	0.06929	0.0763	-0.3222	-0.3386	-0.3064
theta[79]	-0.06549	-0.06858	-0.06247	0.2948	0.239	0.3511
theta[80]	0.0513	0.0488	0.05395	0.2391	0.2267	0.2519
theta[81]	0.001542	0.000445	0.002619	-0.06353	-0.08821	-0.03869
theta[82]	0.003042	0.003024	0.003061	-0.05909	-0.06277	-0.05542
theta[83]	-0.06232	-0.06381	-0.06089	-0.1976	-0.2106	-0.1852
theta[84]	0.05782	0.05524	0.06058	0.1374	0.1065	0.1683
theta[85]	0.003202	0.001997	0.004386	0.2015	0.1994	0.2038
theta[86]	-0.007603	-0.00786	-0.00735	-0.1214	-0.1498	-0.093
theta[87]	0.01908	0.01851	0.01968	-0.1171	-0.1213	-0.1128
theta[88]	-0.004668	-0.00520	-0.00414	0.09747	0.07933	0.1158
theta[89]	-0.02929	-0.02986	-0.02875	-0.01472	-0.02692	-0.00246
theta[90]	0.03327	0.03192	0.0347	-0.06174	-0.06427	-0.05926
theta[91]	-0.0324	-0.03387	-0.03096	0.4265	0.3839	0.4705
theta[92]	0.06122	0.05921	0.06334	-0.338	-0.4105	-0.2655
theta[93]	-0.02355	-0.02545	-0.02168	0.139	0.08767	0.1903
theta[94]	-0.03818	-0.03854	-0.03785	-0.2111	-0.2487	-0.1738
theta[95]	0.04504	0.04325	0.04696	0.04437	0.01701	0.07164
theta[96]	-0.01495	-0.01629	-0.01363	-0.06575	-0.07902	-0.05251
theta[97]	-0.01121	-0.01128	-0.01114	0.2477	0.2188	0.2778
theta[98]	0.02937	0.0285	0.0303	0.1913	0.1824	0.2003
theta[99]	0.01761	0.01736	0.01786	-0.3211	-0.3652	-0.2778
theta[100]	-0.02863	-0.02969	-0.0276	-0.1798	-0.1982	-0.1616
theta[101]	0.03584	0.03446	0.03731	0.2733	0.2363	0.3113
theta[102]	-0.03292	-0.03447	-0.03141	0.07789	0.05599	0.1000
theta[103]	0.000443	-0.00027	0.001196	-0.00212	-0.00617	0.001961
theta[104]	-0.01572	-0.01608	-0.01537	-0.1002	-0.1085	-0.09226
theta[105]	0.02844	0.02749	0.02944	-0.08912	-0.0913	-0.08687
theta[106]	-0.004657	-0.00541	-0.00393	0.2526	0.2232	0.2831
theta[107]	0.009554	0.009257	0.009868	-0.145	-0.1834	-0.1062
theta[108]	-0.01563	-0.01619	-0.01507	-0.02938	-0.04459	-0.01404
theta[109]	0.01218	0.01158	0.01281	-0.08553	-0.09268	-0.07869
theta[110]	0.0237	0.02345	0.02397	0.2655	0.2342	0.2981
theta[111]	-0.01526	-0.01614	-0.01439	0.07984	0.05953	0.1004
theta[112]	0.01157	0.01100	0.01218	-0.1964	-0.2182	-0.1751

theta[113]	0.008202	0.008131	0.008272	0.03556	0.0124	0.05865
theta[114]	-0.03732	-0.03836	-0.03632	-0.1364	-0.1547	-0.1184
theta[115]	0.006179	0.005243	0.007173	-0.11	-0.1147	-0.1051
theta[116]	0.04669	0.0458	0.04764	0.07432	0.05888	0.08981
theta[117]	0.02323	0.02272	0.02374	0.119	0.1169	0.1211
theta[118]	-0.03446	-0.03578	-0.03318	-0.3404	-0.3813	-0.3002
theta[119]	-0.03743	-0.03754	-0.03733	0.3081	0.2463	0.3703
theta[120]	0.02554	0.02417	0.02699	0.1034	0.07741	0.1297
theta[121]	0.007962	0.007582	0.008332	0.1287	0.1231	0.1346
theta[122]	0.01762	0.01742	0.01783	-0.1723	-0.1995	-0.1453
theta[123]	-0.04018	-0.0415	-0.03891	-0.01082	-0.02846	0.006945
theta[124]	0.03637	0.03472	0.03812	0.1724	0.1589	0.1865
theta[125]	-0.01241	-0.01349	-0.01134	-0.02909	-0.04846	-0.00961
theta[126]	-0.009834	-0.00988	-0.00978	-0.09844	-0.102	-0.09498
theta[127]	0.0347	0.03374	0.03572	0.09936	0.08167	0.1172
theta[128]	-0.0423	-0.04403	-0.0406	-0.2755	-0.311	-0.2406
theta[129]	0.05805	0.0559	0.06033	-0.1284	-0.1462	-0.111
theta[130]	0.002365	0.00113	0.003579	0.3538	0.3143	0.3948
theta[131]	-0.03229	-0.0331	-0.03151	-0.1259	-0.1728	-0.07864
theta[132]	0.007793	0.006929	0.00871	0.03846	0.01781	0.05907
theta[133]	0.00029	0.000132	0.000446	-0.3013	-0.3343	-0.2691

Appendix 2. Observed and fitted annual mean temperatures and annual mean rain precipitations

Row	Annual mean temp SP.	Annual mean prec SP.	year	Fitted mean temp SP.	Fitted mean prec SP.	Residuals temp SP.	Residuals prec SP.
1	17.633	124.7	1887	17.69	124.46	-0.00322	0.00191
2	18.850	18.850	1888	18.5784	85.970	0.0145129	0.205658
3	18.360	103.8	1889	18.5784	105.214	-0.0118256	-0.013534
4	17.458	105.2	1890	17.9215	104.794	-0.0262020	0.003863
5	17.933	106.6	1891	17.7254	106.166	0.0116426	0.004084
6	17.375	135.7	1892	17.6547	119.821	-0.0159676	0.124447
7	16.725	101.8	1893	17.0816	116.396	-0.0210954	-0.133990
8	17.820	100.2	1894	17.2878	103.028	0.0303214	-0.027832
9	17.750	101.4	1895	17.8143	101.190	-0.0036145	0.002073
10	17.858	104.8	1896	17.7787	102.617	0.0044516	0.021054
11	17.808	88.2	1897	17.8857	96.737	-0.0043522	-0.092393
12	17.817	118.1	1898	17.8678	103.648	-0.0028469	0.130532
13	18.667	153.3	1899	18.2287	131.631	0.0237573	0.152397
14	18.083	123.6	1900	18.3752	135.368	-0.0160277	-0.090949

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15	17.100	126.3	1901	17.6018	126.849	-0.0289215	-0.004340
16	18.158	122.4	1902	17.6370	124.586	0.0291112	-0.017706
17	17.433	109.7	1903	17.8321	116.513	-0.0226350	-0.060251
18	17.283	116.4	1904	17.3744	113.863	-0.0052766	0.022033
19	17.875	143.5	1905	17.5842	128.638	0.0164031	0.109335
20	17.783	126.0	1906	17.8321	132.688	-0.0027571	-0.051718
21	17.392	154.9	1907	17.5666	135.911	-0.0099897	0.070921
22	17.400	104.7	1908	17.4266	122.977	-0.0015298	-0.160901
23	17.300	123.6	1909	17.3918	116.513	-0.0052935	0.059051
24	17.192	104.6	1910	17.2532	112.730	-0.0035558	-0.074856
25	17.225	150.2	1911	17.2360	126.976	-0.0006382	0.167968
26	17.533	108.3	1912	17.3744	124.586	0.0090848	-0.140095
27	17.958	74.5	1913	17.7254	91.469	0.0130357	-0.205201
28	18.717	95.4	1914	18.3752	86.574	0.0184322	0.097079
29	18.458	89.1	1915	18.5784	90.468	-0.0065021	-0.015241
30	17.775	105.4	1916	18.0835	96.737	-0.0172070	0.085763
31	16.650	97.4	1917	17.2360	100.786	-0.0345898	-0.034174
32	17.725	97.4	1918	17.0134	87.710	0.0239060	-0.003174
33	18.092	93.2	1919	17.7609	95.297	0.0184699	-0.022252
34	17.650	87.3	1920	17.9036	90.649	-0.0142642	-0.037650
35	17.717	81.5	1921	17.6900	84.690	0.0015246	-0.038397
36	18167	108.3	1922	17.9574	94.538	0.0116068	0.135905
37	17.942	116.6	1923	18.0654	110.388	-0.0068557	0.054759
38	17.383	73.5	1924	17.7077	92.851	-0.0185073	-0.233715
39	17.992	115.6	1925	17.6900	94.822	0.0169272	0.198136
40	17.925	104.8	1926	17.9753	107.340	-0.0028036	-0.023946
41	17.683	104.8	1927	17.8321	105.742	-0.0083963	-0.008946
42	18.625	106.3	1928	18.1923	106.166	0.0235048	0.001265
43	18.125	150.7	1929	18.7352	125.964	-0.0137078	0.179291
44	18.492	129.6	1930	18.3018	136.729	0.0103382	-0.053547
45	18.075	135.3	1931	18.3201	134.156	-0.0134702	0.008495
46	18.833	131.2	1932	18.4673	133.087	0.0196107	-0.014277
47	17.700	78.8	1933	18.3018	102.412	-0.0334354	-0.262087
48	18.542	111.1	1934	18.1560	97.028	0.0210384	0.135431
49	17.558	125.8	1935	18.0474	115.700	-0.0274903	0.073693
50	17.825	108.1	1936	17.7254	116.396	0.0056020	-0.073943
51	17.250	125.1	1937	17.5666	117.684	-0.0181879	0.061113
52	17.742	118.8	1938	17.5140	121.025	0.0129347	-0.018559
53	17.875	94.2	1939	17.8143	106.272	0.0034031	-0.120580

54	18.467	94.4	1940	18.1741	95.583	0.0159854	-0.012459
55	18.958	115.6	1941	18.7464	104.690	0.0112260	0.099136
56	18.492	129.5	1942	18.6902	120.061	-0.0106618	0.075681
57	18.467	110.5	1943	18.5042	119.224	-0.0020146	-0.075984
58	18.906	110.1	1944	18.7089	111.720	0.0104793	-0.014611
59	18.825	124.2	1945	18.9158	117.566	-0.0048142	0.054893
60	18.112	105.2	1946	18.4673	113.522	-0.0194253	-0.076173
61	17.458	176.0	1947	17.8321	138.103	-0.0212020	0.242484
62	17.825	114.9	1948	17.6194	137.552	0.0116020	0.242484
63	17.708	109.0	1949	17.7609	114.549	-0.0029835	-0.049652
64	18.317	147.1	1950	18.0113	126.976	0.0168296	0.147113
65	17.408	100.0	1951	17.8499	118.866	-0.0250701	-0.172830
66	18.367	110.6	1952	17.8857	107.878	0.0265556	0.024920
67	18.383	104.3	1953	18.3935	106.698	-0.0005737	-0.022729
68	18.858	105.3	1954	18.6342	105.320	0.0119372	-0.000187
69	18.272	102.9	1955	18.5970	104.376	-0.0176302	-0.014242
70	17.950	107.9	1956	18.1741	106.378	-0.0124099	0.014205
71	18.467	157.6	1957	18.2105	129.931	0.0139854	0.193060
72	19.133	121.3	1958	18.7651	134.559	0.0194146	-0.103733
73	19.142	103.2	1959	19.1251	113.409	0.0008849	-0.094331
74	18.483	128.1	1960	18.8781	116.980	-0.0211486	0.090811
75	19.600	121.1	1961	19.0297	123.100	0.025296	-0.015558
76	18.025	105.5	1962	18.7839	113.069	-0.0412403	-0.069289
77	19.342	74.6	1963	18.6715	89.658	0.0352789	-0.183859
78	18.150	109.1	1964	18.7276	91.744	-0.0313294	0.173265
79	19.075	136.0	1965	18.5970	118.866	0.0253786	0.134655
80	19.117	122.9	1966	19.1442	128.252	-0.0014220	-0.042629
81	19.175	116.5	1967	19.1825	121.025	-0.0003927	-0.038109
82	18.033	93.8	1968	18.5970	104.899	-0.0307966	-0.111835
83	19.075	112.8	1969	18.5042	103.648	0.0303786	0.084616
84	19.150	138.3	1970	19.1060	123.224	0.0023027	0.115425
85	19.008	117.3	1971	19.0487	125.336	-0.0021401	-0.066265
86	19.367	105.0	1972	19.2402	112.730	0.0065706	-0.071040
87	19.283	119.0	1973	19.3366	112.618	-0.0027761	0.055123
88	18.733	115.1	1974	18.9917	115.932	-0.0137133	-0.007199
89	19.350	107.8	1975	19.0678	111.944	0.0146924	-0.037722
90	18.750	176.3	1976	19.0297	137.140	0.0291217	-0.197158
91	19.908	112.6	1977	19.3366	137.140	0.0291217	-0.197158
92	19467	139.9	1978	19.6485	127.868	-0.0092793	0.089928

93	18.742	107.0	1979	19.1825	122.119	-0.0232330	-0.132171
94	19.583	116.6	1980	19.1825	113.863	0.0206618	0.023749
95	19.308	107.0	1981	19.4724	111.274	-0.0084805	-0.039171
96	19.092	143.3	1982	19.2209	124.586	-0.0067306	0.139940
97	19.650	171.2	1983	19.3560	153.393	0.0150773	0.109832
98	20.002	116.2	1984	19.8063	139.073	0.0098323	-0.179687
99	19.450	99.8	1985	19.7470	110.609	-0.0151529	-0.102832
100	20.142	138.8	1986	19.8261	119.104	0.0158072	0.153034
101	19.508	145.1	1987	19.7865	138.241	-0.0141754	0.048423
102	19.508	143.9	1988	19.5309	144.460	-0.0011754	-0.003881
103	19.208	128.6	1989	19.3753	136.619	-0.0086731	-0.058293
104	19.750	118.0	1990	19.4919	124.213	0.0131535	-0.051315
105	19.667	158.9	1991	19.7075	137.140	-0.0020579	0.147275
106	19.852	129.6	1992	19.7667	141.034	0.0043048	-0.084547
107	19.551	128.8	1993	19.7075	130.712	-0.0079736	-0.014739
108	19.783	117.0	1994	19.6878	123.100	0.0048230	-0.050826
109	20.254	160.1	1995	20.0855	138.518	0.0083523	0.144799
110	19.958	168.1	1996	20.1056	160.453	-0.0073699	0.046559
111	20.183	133.7	1997	20.0655	149.306	0.0058407	-0.110402
112	20.350	143.5	1998	20.3484	141.599	0.0000809	0.013335
113	19.617	121.8	1999	20.0054	132.026	-0.0196035	-0.080620
114	19.727	109.9	2000	19.6878	117.097	0.0019883	-0.063429
115	20.658	121.2	2001	20.1862	116.048	0.0231027	0.043442
116	21.150	136.9	2002	20.9262	127.996	0.0106399	0.067251
117	20.450	91.6	2003	20.7802	111.052	-0.0160171	-0.192569
118	19.700	137.0	2004	20.1056	115.123	-0.0203814	0.173981
119	20.192	146.0	2005	19.9854	138.518	0.0102865	0.052607
120	20.358	167.5	2006	20.2874	156.022	0.0034740	0.070983
121	20.717	135.3	2007	20.5529	149.456	0.0079546	-0.099505
122	19.917	137.5	2008	20.3077	137.827	-0.0194264	-0.002376
123	20.633	166.8	2009	20.3280	137.827	0.0148917	0.0091795
124	20.392	157.3	2010	20.5323	160.292	-0.0068573	-0.018845
125	20.192	141.8	2011	20.3280	150.506	-0.0067135	-0.059582
126	20.892	160.9	2012	20.5734	152.475	0.0153663	0.053783
127	20.048	115.8	2013	20.4913	136.047	-0.0218706	-0.161135
128	21.217	104.6	2014	30.6146	112.280	0.0288027	-0.070856
129	21.283	158.3	2015	21.2424	129.024	0.0019086	0.204492
130	20.617	129.9	2016	20.9681	139.910	-0.0168840	-0.074235
131	20.767	139.3	2017	20.6972	136.183	0.0033652	0.022630

132	20.775	98.1	2018	20.8010	116.980	-0.0012497	-0.176013
133	21.350	147.7	2019	21.1153	123.594	0.0110517	0.178183

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