Instrument: **SP1 Cooperation**

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FP7 Collaborative Project – Grant Agreement 212492

CLARIS LPB
A Europe-South America Network for Climate Change Assessment and Impact Studies in La Plata Basin

DELIVERABLES

D9.16: A generator of synthetic rainfall series for South/South-East Brazil developed and validated

Due date of deliverable: Month 18

Start date of project: **01/10/2008** Duration: 4 **years**

Organisation name of lead contractor for this deliverable: P12-UFPR

Deliverable No	Deliverable title	WP	Lead beneficiary	Estimated indicative person-months (permanent staff)	Nature	Dissemi nation level	Deliv ery date
D9.16	A generator of synthetic rainfall series for South/South-East Brazil developed and validated	WP9	P12-UFPR	24,62	O	CO	18

TITLE – CLARIS LPB PROJECT: A EUROPE-SOUTH AMERICA NETWORK FOR CLIMATE CHANGE ASSESSMENT AND IMPACT STUDIES IN LA PLATA BASIN WP9: WATER RESOURCES IN LA PLATA BASIN IN THE CONTEXT OF CLIMATE CHANGE: Impact of the climate changes in hydropower

AUTHORS

André Fernandes SANTANA
Cristovão V. S. FERNANDES
Daniel Henrique MARCO DETZEL
Eloy KAVISKI
Heinz Dieter FILL
Marcelo RODRIGUES BESSA
Miriam Rita MORO MINE

RESEARCH ASSISTANTS

Alessandra LEITE BATISTA
Ana Lúcia GOES
Carolina PIANA SERPA
Carolina SEREMETA
Luiz Fernando NASCIMENTO FERREIRA
Sergio Augusto de FREITAS JUNIOR

OBJECTIVE - The purpose of this report is to present the models and results obtained related to deliverable D9.16: "A generator of synthetic rainfall series for South/South-East Brazil developed and validated". The period of this task was from 01/01/2008 to 14/01/2010.

SUMMARY OF THE REPORT

This report presents the activities undertaken to achieve the deliverable D.9.16 referring to models to generate synthetic rainfall series. Activities related to this deliverable correspond to the period from October 01, 2008 to January 14, 2010. The work plan for this deliverable comprised the following activities: 1) Choice of models to generate synthetic rainfall series; 2) Collection and data consistency of rainfall in key stations in South-East Brazil; 3) Checking stationarity of rainfall data; 4) Development and validation of Monthly Seasonal Multivariate Autoregressive Model (SMMAR (1), 5) Development and validation of Annual Multivariate Model with Disaggregation into Monthly Rainfall (MDM), 5) Development and validation of Daily Univariate Model (DUM).

Keywords: generation of synthetic rainfall series, annual generation, monthly generation, daily generation

type of editing:

( ) preliminary (X) final D9.16 ( ) review

SEVENTH FRAMEWORK PROGRAMME

SUMMARY

LIST OF FIGURES

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ABSTRACT

The objective of this research project is to investigate how global climate changes will modify the guaranteed output of a system of interconnected hydropower plants. In particular it is proposed to analyze the performance of the hydropower plants system within the La Plata basin under a set of future climate scenarios. The methodology should be based on Monte Carlo simulations using synthetic streamflow series representing future scenarios of global climate changes. These series should be obtained from synthetic rainfall series using standard rainfall-runoff models at a monthly time scale. A monthly rainfall-runoff model available is Artificial Neural Networks - ANN for the rainfall-runoff transformation. The rainfall series obtained at monthly time scale, need to be generated statistically by defining appropriate stochastic processes to represent the rainfall time series. For generation of synthetic series of monthly rainfall the Monthly Seasonal Multivariate Autoregressive Model is used. However, the suitability of these models will depend on the results of a validation study and the availability of an estimate of their parameters under global climate change from the Global Circulation Model - GCM output. These parameters should be provided by GCM and will be needed at the scale of the main sub-basins, because of the important regional diversity of rainfall pattern within the La Plata basin. This part of the study is supposed to be performed by another group (WP5). Once the synthetic streamflow series are obtained at the principal sub-basin, disaggregation of these series at individual hydropower plant would be necessary. This can be done by means of standard regionalization techniques used by Brazilian energy sector to transpose streamflows from river gauges to hydropower plant sites. Next, streamflow series should be converted to natural energy series also using the method used a long time by Brazilian electric utilities in their power supply studies. The natural energy inflows at each hydropower plant are then combined and natural energy hydrograph method will be used to obtain the guaranteed overall energy output for a given energy shortage probability (risk). For the simulations to be performed it is necessary to have an estimate of future energy demands and how much of these have to be supplied by local plants. Results for several basic climate scenarios should be compared and conclusions about the impact of global climate changes on hydropower generation may be outlined. Models for the natural energy hydrograph method simulation are available both at electric power utilities and at UFPR. Since the CLARIS LPB Project is supposed to be completed within four years this sub-project should be completed at least within the same time. Of course results of GCM models are needed to start the generation of synthetic rainfall series, but the time at this task is performed by others; the suitability of synthetic rainfall series generation models as well as the question of which rainfall-runoff model is best may be analyzed. It is believed that the proposed study gives a quantitative assessment of the impact of future climate change in generation capacity of all the Brazilian scenarios of the La Plata river basin. This evaluation also allows estimating the evolution of the system's failure risk in the long-term horizon and may guide corrective measures in planning the system's expansion. It is intended, firstly, present results for three future scenarios (an optimistic, the most likely and a pessimistic), indicating the percentage variance of the guaranteed energy at a 5% level (criterion adopted by ELETROBRÁS) in relation to values based on historical series of streamflows. Also should be presented the availability of the firm and secondary energy, calculated from the historical and pseudo-historical series of each scenario. The secondary energy can estimate the viable limit of additional thermal generation. It is intended to show, also, the relation between the guaranteed energy and the risk, which will allow estimating the risk's variance for each of the climate scenarios examined. Due to uncertainties about the future evolution of the system and the market for electric power, all analysis will be performed for a static configuration constituted by the power plants in the south southeastern Brazil. The extrapolation of this study's results to configurations including power plants planned for the future and a development of the market is only viable if the hypothesis of similar impacts of climate change for future systems is reasonable. This final report of the Deliverable D9.16 presents the development and validation of the Monthly Seasonal Multivariate Autoregressive Model SMMAR (1) and (also two other models: Annual Multivariate Model with Disaggregation into Monthly Rainfall (ADM) and Daily Univariate Model (DUM).that could be used to obtain the series of pseudo-historic rainfall to evaluate the impact of the climate changes in hydropower.

INTRODUCTION

Global climate changes have recently become headlines in newspaper and magazines as well as at TV news and talk shows. Its possible effects became a major concern all over the world and are, in fact, becoming one important issue for population of many countries.

Scientists have studied global climate changes for at least 20 years, carrying out field surveys, collecting data and developing computer simulation programs which have improved accuracy and reliability on their conclusions. As a result, a huge amount of literature is now available on that issue mostly showing that global climate changes are real.

One particular aspect of these climate changes is their impact on the performance of water resources systems. The objective of this research project is to investigate how global climate changes will modify the guaranteed output of a system of interconnected hydropower plants. In particular it is proposed to analyze the performance of the hydropower plants system within the La Plata basin under a set of future climate scenarios.

The methodology should be based on Monte Carlo simulations using synthetic streamflow series representing future scenarios of global climate changes. These series should be obtained from synthetic rainfall series using standard rainfall-runoff models at a monthly time scale.

A monthly rainfall-runoff model available is the IPHMEN model (Tucci, 1998, (Machado, 2005 and Machado *et al*. 2008) developed at UFRGS/IPH (Universidade Federal do Rio Grande do Sul – Instituto de Pesquisas Hidráulicas). Another possible technique is to use of Artificial Neural Networks - ANN for the rainfall-runoff transformation (Machado, 2005 and Machado *et al*. 2008). Of course, these models need to be calibrated and validated for the main sub-basins of the La Plata basin.

The rainfall series, which are supposed to be obtained also at monthly time scale, need to be generated statistically by defining appropriate stochastic processes to represent the rainfall time series. For generation of synthetic series of monthly rainfall we want to use the Monthly Seasonal Multivariate Autoregressive Model or preliminary generation of annual rainfall by an ARMA(p,q) model (Box & Jenkins, 1976) combined with a monthly disaggregation model based on hydrological scenarios. However the suitability of these models will depend on the results of a validation study and the availability of an estimate of their parameters under global climate change from the Global Circulation Model - GCM output. These parameters should be provided by GCM and will be needed at the scale of the main sub-basins, because of the important regional diversity of rainfall pattern within the La Plata basin. This part of the study is supposed to be performed by another group (WP5).

Once the synthetic streamflow series are obtained at the principal sub-basin, disaggregation of these series at individual hydropower plant would be necessary. This can be done using standard regionalization techniques used by Brazilian energy sector to transpose streamflows from river gauges to hydropower plant sites.

Next, streamflow series should be converted to natural energy series also using the method used a long time by Brazilian electric utilities in their power supply studies. The natural energy inflows at each powerplant are then combined and natural energy hydrograph method (Canambra, 1969) will be used to obtain the guaranteed overall energy output for a given energy shortage probability (risk). Possibly this study could be also applied for sub-systems considering, in particular Brazilian and Argentinean power plants. These systems are not operated at an integrated basis.

For the simulations to be performed it is necessary to have an estimate of future energy demands and how much of these have to be supplied by local plants. Results for several basic climate scenarios should be compared and conclusions about the impact of global climate changes on hydropower generation may be outlined. Models for the natural energy hydrograph method simulation are available both at electric power utilities and at UFPR (Neira, 2005).

Since the CLARIS LPB Project is supposed to be completed within four years this sub-project should be completed at least within the same time. Of course results of GCM models are needed to start the generation of synthetic rainfall series, but the time at this task is performed by others; the suitability of synthetic rainfall series generation models as well as the question of which rainfall-runoff model is best may be analyzed.

It is believed that the proposed study gives a quantitative assessment of the impact of future climate change in generation capacity of all the Brazilian scenarios of the La Plata river basin. This evaluation also allows to estimate the evolution of the system's failure risk in long-term and may guide corrective measures in planning the system's expansion.

It is intended, firstly, present results for three future scenarios (an optimistic, the most likely and a pessimistic), indicating the percentage variance of the guaranteed energy in a level of 5% (criterion adopted by ELETROBRÁS) in relation to values based on historical series of streamflows.

Also should be presented the availability of the firm and secondary energy, calculated from the historical and pseudo-historical series of each scenario. The secondary energy can estimate the viable limit of additional thermal generation (Canambra, 1966).

It is intended to show, also, the relation between the guaranteed energy and the risk, which will allow estimating the risk's variance for each of the climate scenarios examined.

Due to uncertainties about the future evolution of the system and the market for electric power, all analysis will be performed for a static configuration constituted by the power plants (shown in Fig. 3.2 as follows).

The extrapolation of this study's results to configurations including power plants planned for the future and a development of the market is only viable if the hypothesis of similar impacts of climate change for future systems is reasonable. Figure 4.1, as follows, summarizes the main methodology to be aimed in this study.

1. PROJECT OBJECTIVE IN THE FIRST 18 MONTHS

1.1 TEAM'S PARTICIPATION UFPR/DHS IN CLARIS LPB PROJECT – WP9

The CLARIS LPB project aims to study the overall impact of climate change in the La Plate Basin (LPB). It is part of the 7th. Program of the European Community for Research (FP7-ENV-2007-1 - WP-ENV.2007.1.1.5.3). Twenty international universities and research institutions of the European Community and South America are participating of this project. The Federal University of Paraná (UFPR), through the Department of Hydraulic and Sanitation (DHS) has the task of studying the Impact of Climate Change on hydroelectricity.

One of the general objectives of the project is the definition of strategies for adapting the possible scenarios and their hydrological consequences in hydropower in the period 2010-2040.

Figure 1.1 shows a general flow of the project, as presented in the proposal approved in 2007 (Boulanger, 2007) which highlights the main tasks of the UFPR/DHS. Figure 1.1 shows that the project CLARIS-LPB is divided into four sub-projects interrelated and complementary as follows:

1) Activities of management, dissemination and coordination:

WP1: Management;
WP2: Dissemination and coordination.

2) Past and future hydroclimate:

WP3: Improving the description of recent climate variability in LPB;
WP4: Hydroclimate past and future low-frequency variability, trends and shifts;
WP5: Evaluation of regional climate change in the LPB;
WP6: Process and future evolution of extreme climate events in the LPB.

3) Project interface:

WP7: An interface to improve the ability to provide social impacts of climate change.

4) Socio-economic scenarios and adaptation / prevention strategies:

WP8: Changes in soil use, agriculture and socio-economic implications;

WP9: Water resources in the LPB in the context of climate change. A search of UFPR / DHS falls in WP9. (see task 9.6 in Figure 1.1).

1.2 Description of work and role of UFPR participant in WP9.

To investigate how the guaranteed output of a system of interconnected hydropower plants in the Brazilian South/South-East subsystem of La Plata Basin will be modified in the near-future using an ensemble of future hydrological scenarios. This objective corresponds to task 9.6.

The deliverables related to the stages of this task led by UFPR/DHS are:

D9.16 - A generator of synthetic rainfall series for South/Southeast Brazil developed and validated (month 18).

D9.17 - Monthly rainfall-runoff model for South/South-East Brazil validated (month 36).

D9.18 - Brazilian South/Southeast energy subsystem simulation under different climate scenarios (month 42).

D9.19 – Summary and conclusions about changes in firm energy and eventually in the possible changes in the operation strategy of the dams of the Brazilian South/South-East energy subsystem (month 48).

This report presents the models and the results of deliverable D9.16. (a generator of synthetic rainfall series).

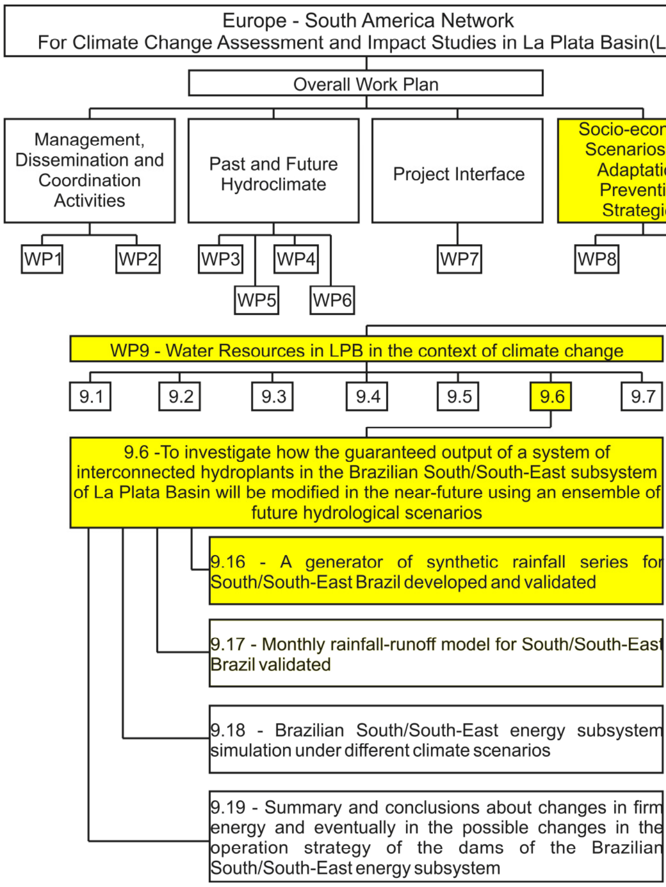


Figure 1.1 - Team's participation UFPR/DHS in CLARIS LPB Project-WP9

2. PUBLICATIONS

In this period we prepared two papers that were accepted for publication in the proceedings of the VIII Brazilian Symposium on Water Resources, in November 2009.

2.1 STATIONARITY VERIFICATION OF HYDROLOGIC SERIES IN THE SOUTH-SOUTHEAST BRAZIL

This publication is not a result of a CLARIS LPB multi-institute but it is a result of a multidisciplinary work.

Authors: Alessandra Leite Batista, Sérgio Augusto de Freitas Júnior, Daniel Henrique Marco Detzel, Miriam Rita Moro Mine, Heinz Dieter Oskar August Fill, Cristóvão Fernandes, Eloy Kaviski

Institute of the authors: Universidade Federal do Paraná – UFPR

Work Package: WP9 - Water resources in La Plata Basin in the context of climate change

Deliverables:

D9.16	A generator of synthetic rainfall series for South/South-East Brazil developed and validated
D9.17	Monthly rainfall-runoff model for South/South-East Brazil validated
D9.18	Brazilian South/South-East energy subsystem simulation under different climate scenarios

Abstract-- This paper aims at determining the stationarity of rainfall and streamflow series in the South and Southeast regions of Brazil. These hydrological series will be used in CLARIS LPB Project to evaluate the guaranteed energy of hydroelectric power plants for various scenarios of climate change. This will be done using synthetic natural energy series of the interconnected system; hence the stationarity appears as a necessary prerequisite. To check the stationarity of rainfall and streamflow data we used the following methods: i) analysis of linear trends in historical series, ii) statistical tests, iii) relationship between streamflow and precipitation, iv) cumulative curves of average annual streamflows in relation of time. These methods allowed us to conclude that within the South region the 1930-2005 series are not stationary.

Key-words: hydrological series, stationarity, tests of hypotheses

2.2 STOCHASTIC GENERATION OF SYNTHETIC PRECIPITATION SERIES ON A DAILY SCALE: review of the main models and methods.

This publication is not a result of a CLARIS LPB multi-institute but it is a result of a multidisciplinary work.

Authors: Daniel Henrique Marco Detzel, Miriam Rita Moro Mine

Institute of the authors: Universidade Federal do Paraná – UFPR

Work Package: WP9 - Water resources in La Plata Basin in the context of climate change

Deliverables:

D9.16	A generator of synthetic rainfall series for South/South-East Brazil developed and validated

Abstract-- Stochastic generation of synthetic precipitation data has been a useful tool for studies, especially the ones with insufficient data. This article presents a review of some of the well-developed models for the generation in a daily scale of time. The analysis also involves methods of multi-site generation, seasonal considerations and a brief summary of what has already been studied on this subject in Brazil. The results of this research may be useful in defining future scenarios of precipitation. These scenarios constitute the pseudo-historical series of precipitation that will be used in determining the energy guaranteed of the hydroelectric system in La Plata Basin.

Key-words: daily precipitation, synthetic series, Monte-Carlo simulation, Markov-chains.

3. BRAZILIAN ELECTRICAL SYSTEM - SEB

According to Bajay (2006) Brazil is the largest economy in Latin America and the 9th largest in the world when measured in terms of Purchasing Power Parity exchange rates. It is 10th largest electrical power consumer in the world and the largest electricity consumer in Latin America. Brazil is, therefore, a very important player in the world energy theater.

With a power generation installed capacity of 100,449 MW in 2007, Brazil is the largest electricity market in South America. The generation mix is 76.6% hydro, 21.3% conventional thermal and 2.1% nuclear (MME, 2008).

There are several large hydropower plants, with seasonal or multi-year storage reservoirs. Brazil has a large hydroelectric potential of 260,093 MW, but as of 2007 only 29.6% in actual operation and 2.2% under construction (MME, 2008).

There are approximately 52.2 million customers, 85% of whom are residential users. The 2007 total electricity consumption was 483.4 TWh, distributed among the industrial users (46.7%), residential users (22.1%), commercial users (14.2%) and others (17.0%)."

In Brazil, the system of production, transmission and distribution of electric energy has multiple owners and is interconnected from the east Pará to Rio Grande do Sul, forming the National Interconnected System – SIN (see figure 3.1).

The SIN consists of the installation of over a hundred agents that includes: generators, transmitters, distributors and free consumers. This organization means that only a small portion (4.2% in 2006) of electrical production capacity of the country is outside of the SIN, in small isolated systems, located mainly in the Amazon region.

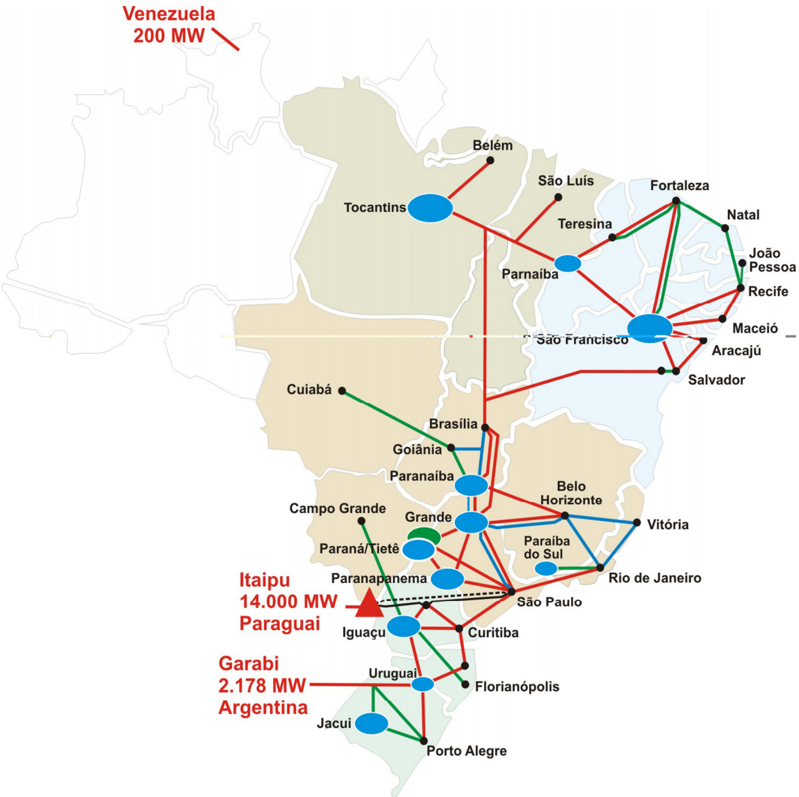


Figure 3.1 - Brazilian integrated system of electricity – SIN – Source: (ONS, 2007)

The National System Operator - ONS is Brazilian governmental agency responsible for the operation of the SIN. Its performance is targeted towards the search for Technical solutions that produce the best outcome for society, respecting the interests of different actors (ONS, 2007).

The South-Southeast interconnected system of Brazil was chosen as a case study of this research, since it is located in *La Plata Basin*. The figure 3.2 shows a schematic diagram of hydroelectric - SIN - South-Southeast system.

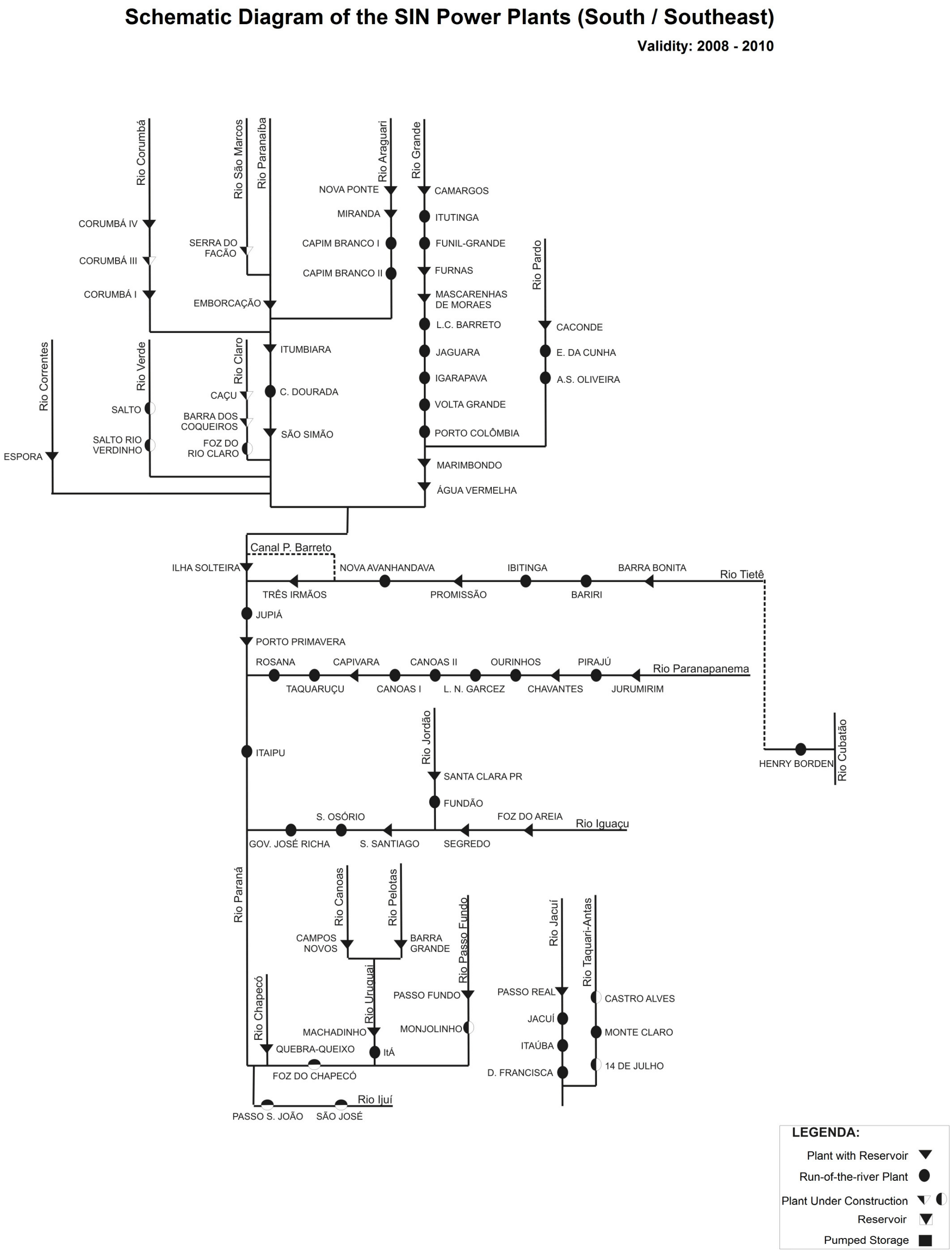


Figure 3.2 - Schematic diagram of hydroelectric - SIN - South-Southeast system

4. METHODOLOGY

The proposed research should contemplate five steps that should be developed sequentially, once the results from each step will be the input data for the next step. However, computer programs needed in the different steps can be tested in advance.

The main study's steps are:

1. Rainfall, streamflow, temperature and hydropower data collection in the basins of interest (major basins that contribute to the La Plata Basin where there are large-scale hydropower plants). These data are constituted mainly of series of streamflows and/or monthly rainfalls over a historical period of at least 50 years and operational data from the hydroelectric power plants required for hydropower simulations (installed capacity, live storage, average net head, average overall efficiency, drainage area and location within the drainage area). The Figure 03 shows a schematic location diagram of each hydropower plant of the sub-system South/Southeast of the Brazilian electrical system.

2. Definition of future climate scenarios based mainly on assumptions of concentration of greenhouse's gases in the atmosphere for the 2010-2040 horizon. These scenarios should be developed by another research group of the CLARIS - LPB project, using global circulation models (GCM) and "downscaling" models, in terms of large basins (> 50.0000 km²) that contribute to the La Plata River Basin .

The relevant variables are the monthly temperature and precipitation. The monthly time scale is the usual scale in hydropower simulations in Brazil (Fortunato *et al*. 1990), Gomide (1986). For the spatial scale there will be streamflow gauge for a drainage area incremental of 100,000 km² and at least one station in each major affluent of the basin where there are hydroelectric plants bigger than 30 MW.

The monthly rainfall and temperatures will be defined for the areas covered by these locations (incremental if there is more than one location in the basin). For historical series, the rainfall and temperatures will be estimated by the method of Thiessen and the future climate scenarios should be provided by the group GCM/downscaling in the form of pseudo-historical series (most likely sequence of future rainfall under the hypothesis of an appropriate scenario) of 50 years, or statistical parameters of the scenarios. In this case should be generated synthetic series of monthly average rainfall with one the models presented in this report.

3. Obtaining a series of streamflows for different scenarios in the representative local of each basin. Initially we should make the choice or development of a rainfall-runoff model in the monthly scale appropriate for large basins (50.000 km^2 to 100.000 km^2) and that includes the temperature as explanatory variable. It is intended, in principle, to use a rainfall-runoff model based in Artificial Neural Networks (ANN) that in the monthly scale, apparently lead to better results than other models based on monthly averages of modeling hydrological processes, such as interception, infiltration, evapotranspiration, retention and superficial and underground runoffs (Machado, 2005, Machado et al., 2008). This type of rainfall-runoff model, based on ANN, should be calibrated and validated in the main basins contributors, using data from the historical period to evaluate its suitability to the purposes of the study.

4. The streamflow series in the representative locations will be transferred to the local plants; in the local plants these series will be converted into natural affluent energy whose total energy is the natural energy of the system. Similarly, the storage volume of the reservoirs will be aggregated into a single reservoir of energy.

This aggregation process is the essence of the so called energy hydrograph method used mainly by the group of studies called Canambra (1966) and Canambra (1969). The energy hydrograph method then allows simulating a system of many interconnected hydroelectric power plant as one equivalent plant that receives incoming energy, variables that vary on time, and counts with a single reservoir of power regulation. As already highlighted by Canambra (1969), this method leads to very accurate results for systems with regulated rivers or without regulation. Fill (1980) showed that in the case of the electric system of the South and Southeast regions of Brazil the error in evaluating the firm energy is less than 5%, which is the magnitude of error in estimating streamflows.

5. Generation of synthetic series of natural affluent energy (and eventually the controllable energy). From the historical and pseudo-historical series correspondent to the future climate scenarios of natural energy, 1000 synthetic series will be generated with equal probabilities using a AR(1) model with lognormal distribution (LP3) for the annual mean energy and disaggregated into monthly natural energy using hydrological scenarios model (Groszewicz et al., 1991). The lognormal model with disaggregated monthly has a long tradition in the Brazilian electric sector (Fortunato *et al.,* 1990, Kelman, 1987) although other models such as PAR (p) (Kelman, 1987) have been tried recently.

The synthetic series should be compared to the historical series, using as a comparing parameter the maximum accumulated deficit as proposed by Neira (2005) and Fill & Neira (2008) in a study of streamflow regulation of the South-Southeast of Brazil.

6. Synthetic series simulation and obtaining guaranteed energy. The synthetic series will be simulated using the energy hydrograph method as described in item 10, obtaining, for each of the 1000 series, the firm energy. These energies will be classified in ascending order and denoted by d_i and with $i = 1,2,...,1000$ and $d_1 \leq d_2 \leq ... \leq d_N$.

The probability of the system to be able to answer a demand equal to or smaller than d_i , which means, the reliability of the system is given by its relative frequency:

$$\Pr(D \leq d_i) = i/1000 \tag{4.1}$$

The risk of failure associated with a demand equal to d_i , will be:

$$\Pr(failure / D = d_i) = 1 - \frac{i}{1000} \tag{4.2}$$

For each scenario and also for the implied conditions in the historical series will be produced diagrams "firm supply by risk." In these graphs, should also be indicated the value of firm energy for each historical series and each one of the pseudo-historical series associated with climate scenarios. Figure 4.1 shows the general flowchart of the method proposed in this research.

5. CHARACTERISTICS OF RIVER BASINS

The main features of the river basins of South-Southeast Brazilian system are presented below.

5.1. Paraná River Basin (60)

Figure 5.1 illustrates the Paraná River basin in the Brazilian area.

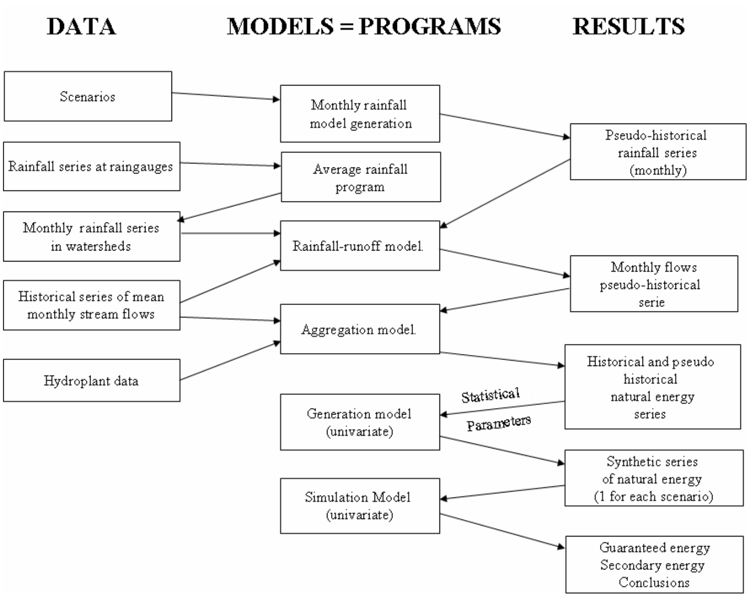


Figure 4.1 – Proposed method

Paraná Hydrographic Region

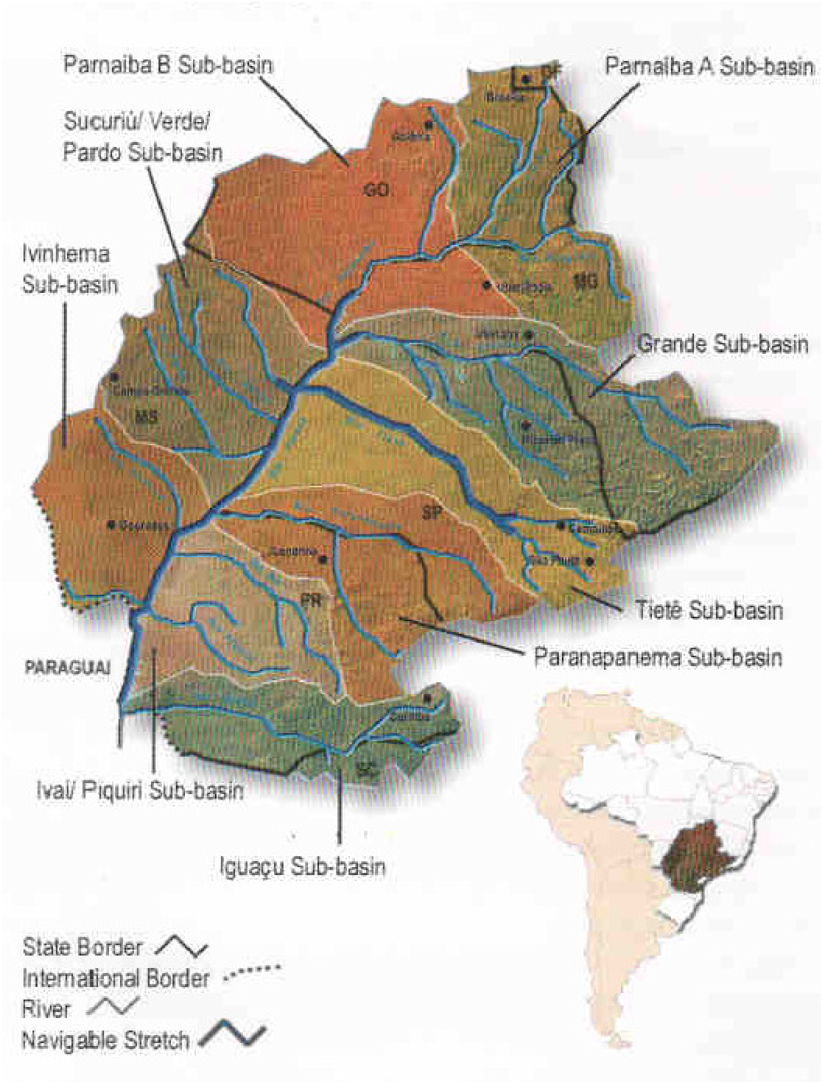
The Paraná hydrographic region is of great importance to the country, as it compiles the highest level of economic development in the country and 32% of the national population.

The following information aims to present an overview of the region regarding the socio-economic aspects, water use and availability and basic sanitation indicators, in addition a summary of the current conflicts regarding the use of water resources and aims for the future is presented.

General Characterization

The Paraná hydrographic region occupies an area of 856,820 km² (10% of national territory) and encompasses the state of São Paulo (25% of the region), Paraná (21%), Mato Grosso do Sul (20%), Minas Gerais (18%), Goiás (14%), Santa Catarina (1.5%) and the Distrito Federal (0.5%). The mean discharge rate in the region is 11,000m³/s (7% of the country's total).

Some 54.5 million people live in the region (32% of the country's population), 90% of whom live in urban areas. The region is home to the most populous city in South America, São Paulo, with its 10.5 million inhabitants. The cities of Brasilia (2 million inhabitants), Curitiba (1.6 million), Goiânia (1.1 million), Campinas (969 thousand), Campo Grande (663 thousand) and Uberlândia (501 thousand) are all also important population centers. The hydrographic region comprises 1,398 local authorities.



Source: ANA (2002a)

Figure 5.1 – The Paraná hydrographic area

Most of the population is concentrated in the sub-basins of the Tietê and Grande rivers, which together account for 63% of the total population. The population density of the hydrographic region is 63.7 inhabitants/km², far higher than the demographic density of the country (19.8 inhabitants/km²).

The region is almost entirely situated in the tropical climate belt, with the exception of small areas in which temperate subtropical variations are recorded. Average annual temperatures of 22°C are recorded, oscillating between 16 and 18°C in the meridian part of the hydrographic region.

The rainfall ranges from 1,300 to 1,900 mm/year, with over 2,000 mm in the *Serra do Mar* highlands, which form the border with the Southeast Hydrographic Coastal region. Average rainfall for the region is 1,509 mm/year. The rainy season occurs between November and February, with the rest of the year witnessing a dry season. The annual evaporation is 1,104mm.

The Paraná Hydrographic Region originally had biomes of the Atlantic Forest and Cerrado (savanna), and five types of plant cover: savanna, Atlantic Forest, Araucária Forest, Deciduous Seasonal Forest and Semi-deciduous Seasonal Forest. The soil usage in the region has gone through many changes during the economic cycles of the country, which has brought about major deforestation.

The agricultural areas occupy an area of 81,555,609 ha, with about 57% being used for pastures, 23% for agriculture, and 20% are native or planted forest areas. The main agricultural activities are cattle farming and orange, soya, sugar cane and coffee cultivation. The industrial zone is the most advanced in the country, and includes the metallurgical, mechanical, chemical and pharmaceutical sectors.

The growth of large urban centers on major rivers, such as São Paulo, Curitiba and Campinas has put great pressure on water resources, as whilst the demand for water increases, the availability falls, owing to the contamination of water by domestic and industrial effluents and urban drainage.

With respect to the socio-economic indicators, the infant mortality rates of the states in the hydrographic region record the following values (per thousand live births): São Paulo (21.37), Santa Catarina (21.73), Distrito Federal (22.24), Paraná (23.69), Mato Grosso do Sul (23.98), Goiás (24.65), Minas Gerais (25.66). The national average is 33.55.

The region accounts for more than 50% of the Gross Domestic Product (GDP) of the country. The GDP per capita (in R$) in the states which make up the region is: Goiás (3,603), Minas Gerais (5,239), Mato Grosso do Sul (5,255), Paraná (6,446), Santa Catarina (6,676), São Paulo (9,210) and Distrito Federal (10,935). With exception of the states of Goiás, Minas Gerais and Mato Grosso do Sul, all the others present a GDP per capita above the national average of R$5,740.

The Human Development Index (HDI) in the states comprised in the region is: Goiás (0.786), Minas Gerais (0.823), Mato Grosso do Sul (0.848), Paraná (0.847), Santa Catarina (0.863), São Paulo (0.868) and Distrito Federal (0.869). Only the states of Goiás and Minas Gerais record HDIs below the national average (0.830).

As for the basic sanitation indicators, the percentage of urban households connected to the sewage collection system ranges fro 7.7% (Mato Grosso do Sul) to 89.7% (Distrito Federal). The percentage of urban households possessing internal plumbing and connected to the water network ranges from 80.1 (Goiás) to 97.8% (São Paulo). The urban sewage treatment percentages range from 5.8% (MG) to 45.9% (DF), with only São Paulo and Distrito Federal presenting values above the national average (20.7%).

Water Availability and Use

The Paraná River is formed by the Grande River, which rises in the Serra da Mantiqueira highlands and runs for 1300 km from east to west, and the Paranaíba River, formed by many tributaries, of which the most northern is the São Bartolomeu, that rises in the Serra dos Pirineus highlands, in the vicinity of Brasília.

The initial course of the upper Paraná runs in a southwesterly direction until it reaches the *Serra do Maracaju* highlands. In this initial stretch, the Paraná River takes in a number of tributaries on both banks, with the most significant of these being the Tietê, Paranapanema and Iguaçu rivers, all in the left bank.

From the confluence of the Paranapanema to the town of Guaira, the Paraná river takes in further smaller tributaries, amongst these are the Ivaí and Piquiri rivers, on the left bank, and the Ivinheima, Amambaí and Iguatemi rivers, on the right bank. The Iguaçu River joins the Paraná River at the point at which the territories of Brazil, Paraguay and Argentina all converge.

The Paraná river runs for 2,570 km to its estuary at the Prata river, which added to the 1,170 km of the Paranaíba river, its main tributary, gives a total of 3,740 km, being the third longest river in the Americas. The Paraná Hydrographic Region is divided up into nine sub-basins: Grande, Iguaçu, Ivaí/ Piquiri, Ivinhema, Paranaíba A, Paranaíba B, Paranapanema, Sucuriú/ Verde/ Pardo and Tietê.

The Paraná River, in Brazilian territory up to the mouth of the Iguaçu River, records a mean discharge rate of 11,000 m³/s (7% of the national total) and a specific discharge rate of 13 l/s/km². With the exception of the Iguaçu sub-basin (21.8 l/s/km²), all the other sub basins record specific discharge rates of between 9 and 16/l/s/ km², indicating that the water availability is relatively well distributed throughout the hydrographic region.

With respect to the groundwaters, metamorphic rocks which gives origin to fractured aquifers, are present in the northern and eastern edges of the Paraná Hydrographic Region, with wells recording discharge rates in the order of 2 to 7 m³/h and an average depth of 120 m. In the remainder of the region, fluviomarine and aeolic sediments associated with basaltic lava predominates. In these sites, the sediments form porous aquifers and possess wells with mean discharge rates in the order of 1 to 15 m³/h and depths of between 100 and 150 m. The Guarani aquifer (839,800 km² in the country) is exceptional within this context, with ground wells that record discharges that can reach 1,000 m³/h and depths which range from 70 to 1,500 m.

The Tietê presents the highest demands arising from irrigation, human and industrial consumption, and the highest demand/ discharge ratio (23.7%). Human demand is 104.2 m³/s, with 55% of this value being concentrated in the sub-basin of the Tietê. Around 90% of the population of the hydrographic region is connected to the water supply network and the average consumption is between 150 and 200 m³/ month/ inhab. Industrial demand is 112.8 m³/s, with the greatest demand being in the sub-basin of the Tietê (54% of the total), especially in the metropolitan area of São Paulo. Irrigation demand is 252.1 m³/s, with the greatest demand being in the sub-basins of the Tietê (206 thousand irrigated hectares) and the Grande River (116 thousand irrigated).

The total irrigated area in the Paraná Hydrographic region is 424,767 ha. Livestock demand is about 43.9 m³/s and has a relatively uniform distribution throughout the hydrographic region, with the highest demand observed in the sub-basin of the Tietê (18% of the total), in most part due to poultry farming activities.

The total water demand is 513.0 m³/s (23% of the demand for the country). With 49% being for irrigation, 22% for industrial use, 20% for human consumption and 9% for livestock watering.

The region boasts the highest installed energy capacity in the country (40,613 MW, 67% of the national total), as well as the greatest demand (75% of national consumption). There are 148 hydroelectric power plants in the region, with the most noteworthy of these being Itaipu, Furnas, Porto Primavera and Marimbondo. There no longer exists the possibility of new large-scale hydroelectric projects on the main rivers, with the current trend being the development of small, hydroelectric power station projects on smaller rivers.

Additionally with respect to river navigability, the Tietê – Paraná waterways is one of the most important, being navigable travel between São Paulo, Goiás, Paraná, Minas Gerais and Mato Grosso do Sul, over a total of 220 municipalities, covering approximately 2,400 km. 5 million tons of cargo was transported on this waterway in 1996. This waterway is particularly important for stimulating the industrialization of the inland areas of the country and integration with the Mercosul member countries.

Industrial and domestic pollution has the greatest impact on water resources in the hydrographic region. The low levels of domestic sewage collection and treatment result in significant pollution burdens, particularly in the vicinities of the main urban centers, thereby affecting the quality of the supply sources. As for the domestic pollution, the urban organic burden potential is 2,666 tons of BOD□/ day (35% of the national total) and is mainly concentrated in the vicinities of the metropolitan region of São Paulo.

Regarding industrial pollution, the concentration of factories in the vicinities of metropolitan regions of São Paulo and Curitiba plays a major role, which does not favor dilution; as they are locate near headwaters.

Events that are considered critical to the water resources are water supply rationing in the city of São Paulo, due to the increase in demand and lack of headwaters offering good quality water. Interruption to the water treatment systems, due to pollution of the headwaters and complaints from the public regarding the bad odor of the water, caused by algae proliferation, is commonplace in the Tietê sub-basin.

Flooding is common in urban areas, due to drainage problems (soils that have become impermeable and river channeling), as often witnessed in the Tietê (São Paulo) and Iguaçu (Curitiba) sub-basins. Floods in rural areas are a result of the strong occupation of river flood plains. Both urban and rural flooding leads to severe economic losses and are a direct result of the significant change of the natural hydrological behavior.

Current Conflicts and Aims for the Future

In 2015, the population in the basin is expected to be 63 million inhabitants. The water availability per capita will be 5,898 m^3/ inhab/ year and the greatest demand will be for irrigation, accounting for 46% of total consumption.

The main issues, in watershed regarding the use of water resources, are supposed to be magnified considered more populous and industrialized areas in the east of the basin. Pollution, as a consequence, will be intensified considering the increase of more demanding activities.

Amongst the main current issues are:

• *The sub-basin of Piracicaba x Alto Tietê*: Some 30m^3/ s are redirected from the sub-basin of Piracicaba for supplying Greater São Paulo, resulting in a shortage of water in the cities along the Piracicaba river (Campinas, Piracicaba, amongst others);

• *Domestic waste water dilution x Public water supply*: The release of domestic effluents into the reservoirs has affected the quality of the water and limit its use for human consumption, particularly in the Greater São Paulo (Guapiranga and Billings reservoirs) and in Distrito Federal.

• *Irrigation x Public water supply*: Conflicts exist between the demands for irrigation and public water supplies in areas with limited availability, especially in the sub-basins of the Piracicaba, Sorocaba, Grande and Turvo rivers (sub-basins of the Tietê and Grande rivers).

• *Hydroelectric Power Generation x Waterway Travel:* Conflicts exist between the need to maintain minimum water volume levels so as to allow waterway travel on the Tietê – Paraná waterway and the operational requirements of the hydroelectric power plants:

• *Industrial Demand x Urban supply:* Issues over the demand from sugar cane and alcohol factories and the public water supply in the basins of Baixo Pardo and Mogi (sub-basin of the Grande River).

Amongst the priority needs and goals to assess better water resources policies are:

• Implementation of treatment systems for domestic sewage in the main urban centers;

• To develop a program for suitable use and management of the soil and control of erosion, preserving the headwaters and preventing the silting up of rivers;

• To rationalize the use of water in irrigation and industry and reduce the losses in supply systems;

• To implement a concession and billing system for water use in the most critical sub-basins;

• To set up a strategy to prevent flooding and to protect vulnerable areas, especially in Greater São Paulo, Campinas, Curitiba and other main urban centers;

• Settle the conflict between the need to maintain minimum water volume levels, so as to allow waterway travel on the Tietê – Paraná waterway, and the operating requirements of the hydroelectric power plants.

5.2. Uruguay River Basin (70)

Figure 5.2 illustrates the Uruguay River basin.

Uruguay Hydrographic Region

The Uruguay Hydrographic Region is of great importance to the country due to its agro-industrial contribution and its hydroelectrical potential. Jointly with the Paraná and Paraguay hydrographic regions it forms the vast La Plata hydrographic region. This report provides an overview of the Uruguay hydrographic region, listing the information under the following main topics: general characterization, socioeconomic data, basic sanitation indicators, water availability and use, summary of current conflicts and desirable scenario. A schematic map shows the region's priority aspects, highlights its problems and opportunities and defines the institutional approach to hydro issues.

General Characterization

The Brazilian section of the Uruguay Hydrographic Region covers 177,494 km² (2.1% of the country) and has a mean discharge of 4,150m³/s. The total area of the Uruguay Basin is 385,000 km², 46% of which is located in Brazilian territory. The Uruguay river is 2,200 km in length, originating from the confluence of the Pelotas and Peixe rivers and running in an east-west direction, dividing the states of Rio Grande do Sul and Santa Catarina. Following its confluence with the Peperi-Guaçu River it swings to the southwest, forming the border between Brazil and Argentina. After the point where it is joined by the Quaraí River, which forms the border between Brazil and Uruguay in the southwest of the state of Rio Grande do Sul it swings south to form the border between Uruguay and Argentina prior to flowing into the River Plate. The hydrographic region encompasses parts of the state of Rio Grande do Sul (74%) and Santa Catarina (26%).

Due to its hydrological characteristics and the principal rivers that form this region it has been divided into seven sub basins, namely: Canoas (15,007 km² - 8% of the region), Pelotas (13,710 km² - 8% of the region), Peixe (12,664 km² - 7% of the region), Capecó (21,137 km² - 12% of the region), Várzea (26,069 km² - 15% of the region), Piratinim/ Ijuí/ Icamaquã (27,718 km² - 16% of the region) and Ibicuí/ Quarai/ Negro (61,189 km² - 16% of the region).

Approximately 3.8 million people live in the Brazilian sector of the Uruguay hydrographic region, with the main population concentrations in the Chapecó (21,0%), Várzea (20,1%) and Ibicuí/ Quaraí/ Negro (14,1%) sub-basins. The urban population represents 68.2% of the total. Population density is 21.6 inhab/ km². The region possesses a total of 337 municipalities of which the following should be highlighted: Lages and Chapecó, in Santa Catarina and Erechim, Ijuí, Uruguaiana, Santana do Livramento and Bagé, in Rio Grande do Sul.

Source: ANA (2002b)

Figure 5.3 – The Uruguay hydrographic region

An overview of the Uruguay hydrographic region may be obtained from the three principal socioeconomic indicators: 1) infant mortality rates (per 1000 births) in the state of Santa Catarina and Rio Grande do Sul stands at 21.73 and 18.11 respectively and are amongst the country's lowest, below the national average of 33.55; 2) per capita GDP in the states of Santa Catarina and Rio Grande do Sul stands at R$ 6,676 and R$ 7,389 respectively, above the national average of R$ 5,740; and 3) the Human Development Index (HDI) – which combines income, health and education indicators – which are high in the basins as they include the state of Santa Catarina (0.863) and Rio Grande do Sul (0.869) the country's highest. Brazil's HDI is currently 0.830.

Basic sanitation indicators are also important when characterizing the hydrographic region. The figures for the number of urban households with internal plumbing and a water supply from a general waste network in the states of Santa Catarina and Rio Grande do Sul stand at 90.7% and 93.1% respectively. The figures for the number of urban households connected to a waste disposal network in these two states are only 9.9% and 17.3% respectively, below the national average of 52.5%. The percentage of treated waste in these states is very low, below the national average of 20.7%.

The region's climate is temperate with rainfall distributed throughout the year, although it is higher in the winter month (May through September). The region's annual precipitation is 1,784 mm and the average annual temperature ranges between 16 and 20° C. Evapotranspirations is about 1,047 mm.

In terms of vegetation, the region originally consisted of Prairie and Brazilian Pine Forest at the headwaters of the Uruguay and Atlantic Forest to the southeast. The region has been intensively deforested and only small pockets of the original vegetation remain. The main changes are a consequence of agricultural expansion, notably the irrigated rice fields of the Campanha region and the soya and wheat fields of the Planalto (tablelands). Small-scale farming enterprises engaged in the rearing of pigs and poultry have developed rapidly in the areas near to the valleys.

The soil in this hydrographic region is predominantly dark red brunizem and litholic (23%) with high rock content in the more salient areas. Small family farms and/ or mixed agricultural and pig or poultry farms predominate in this area. The soil is approximately 20% of the area is dark red or purple latosol and is used for the cultivation of soya, corn and wheat while a little over 15% of the region is composed of glay-humus, used for grazing and irrigation of rice fields. Rice cultivation is the activity that places the greatest demand on the hydrographic region's water resources. Other important soil types in the region are dark brown and purple latosol (10% of the area) and vertisol (10% of the area), the latter also used for grazing and rice cultivation. Soil erosion caused by unsuitable agricultural practices and deforestation is an important problem in the Uruguay hydrographic region.

The region's state parks only represent 0.2% of the total area. Widespread replacement of natural areas with single-crop plantations and cattle farming has turned the few environmental protection areas and forested sections on the margins of its rivers into the main refuge for its wildlife species. The region's ichthyofaune is considered to be very rich, with species such as the lambari, traíra, canivete, pintado, dentudo, piracanjuba and viola, whilst in some areas carnivorous species such as the surubim and dourado are in danger of becoming extinct.

Water Availability and Use

The Uruguay is formed by the confluence of the Pelotas and Canoas rivers. All of its tributaries are perennial. Some of its more important tributaries are the Chapecó and Peixe on its right bank and the Várzea, Piratinim, Ijuí, Ibicuí an its left.
The mean annual discharge of the Uruguay hydrographic region is 4,150 m³/s, which correspond to 2% of the country's available water resources.

The region's hydrological characteristics and its principal rivers were considered when sub-dividing it into 7 basins. The region's rainfall/ discharge ratio is in the order of 41%. Its specific mean discharge is very high (23 l/s/km²), with little variation between sub-regions.

Groundwater addresses the demand of small communities in the region. Fractured aquifers associated with granite and meta-volcanic rocks occur in the extreme south. The discharge from these wells is usually low, in the order of 4 m³/h. Fluviomarine and Aeolian sediments predominate in the region and form porous aquifers, with discharges in the order of 4 to 40 m³/h. Discharge rates can exceed 200 m³/h in the Guarani Aquifer area. Alluvial aquifers are restricted to sections of some rivers and their discharge rates vary widely.

The Uruguay hydrographic region's demand for irrigation is 156.7 m³/s (88.1% of total water demand). Rice farming, primarily in the west of Rio Grande do Sul over some 3,440 km² is the greatest consumer.

Demand for human and livestock consumption predominates in the Pelotas, Canoas, Peixe, Chapecó and Várzea sub-regions. Total human demand for the hydrographic region is 7.8m³/s (4.4% of total demand) and livestock demand is 8.5 m³/s (4.8% of total demand).

Industrial demand in the hydrographic region is 4.7 m³/s (2.6% for/total demand), represented principally by agro-industrial demand associated with the slaughter of animals, sawmills, wood mills and the cellulose industry, all of which are concentrated in the Alto Uruguay region.

Floods are frequent in the region, mainly affecting the communities bordering its main river and some of its tributaries. They may occur at any time of year along the lower, middle and upper reaches of the Uruguay. The urban areas most affected are: Marcelino Ramos, Itaqui, Itá, São Borja, Iraí, and Uruguaiana on the Uruguay and Alegrete on the Ibirapuitã. Although the Uruguay River has a large number of reservoirs, they tend to have limited spare capacity to absorb the excess volume is therefore low.

There are municipalities in the region of the Uruguay River's headwaters that suffer periodically from water rationing due to the irregular nature of the discharge.

The region has a low level of waste water treatment. Discharge of untreated waste is estimated ate 4.3 m³/s, 3.4 m³/s being urban domestic effluent, 1.0 m³/s urban pluvial effluent and 0.9 m³/s domestic rural effluent. Agro-toxic effluent (mainly from rice farming) and waste from pig and poultry farming in the western part of the state of Santa Catarina are another important source of contamination of surface water and groundwater. Untreated domestic organic pollutant is discharged into the region at a rate of 141 ton BOD□/ day, representing 2% of the country's total production.

The Uruguay hydrographic region (in the context of the multiple uses of its water resources) has a great hydroelectric potential with a total production capacity of 40.5 kW/ km² when considering both the Brazilian and Argentinean sides. This is one of the world's highest energy/ km² ratio, representing an absolute potential of 16,500 MW, of which only 3,995 MW (approximately 6% of the energy produced in Brazil) is exploited, having considered both countries present generating facilities. Brazil's current installed hydroelectric generating potential is 1,536 MW, the Passo Fundo (221 MW) and Itá (1,315 MW) being two of the main producers. This represents 38% of total potential installed on the Brazilian side of the hydrographic region and a mere 9% of the basin's total potential. Various smaller hydroelectric facilities of up to 7 MW capacity are scattered throughout the region. The São Marcos dam in the Quaraí sub-region deserves special mention as it is currently the largest construction utilized for irrigation.

River navigation in the region is practically non-existent due to the uneven terrain, significant variations is discharge and silting problems.

The Uruguay rives is navigable all along the stretch from the Uruguay- Argentina border until the dam at Salto Grande, and thereafter, from the lake formed by this dam, to the triple border of Uruguay/ Argentina/ Brazil, at the mouth of the Quaraí River. The Salto Grande dam has lock gates, in the final stages of completion, which means that the river is navigable to the border with Brazil. From there onward, hydroelectric dams are planned, on the Uruguay River, in São Pedro, Garabi, Machadinho and others that, if lock gates be installed, will make the river navigable until close to the Itá dam. The São Pedro dam, the last along this stretch, (approximately 70 m depth) just above Uruguaiana, will flood the lower reaches of the Ibicuí river, which is already navigable along parts of its course. The Ibicuí River is an integral part of the planned waterway that will link the Uruguay River and port of Porto Alegre through the Ibicuí and Jacuí rivers.

Current Conflicts and Aims for the Future

The Uruguay hydrographic region is the focus of some major conflicts involving the use of water:

• Conflicts between rice production and public supply during the summer (November through March) when supplies are scarce, especially on the Santa Maria, Ibicuí and Quaraí rivers. In the Quaraí region, for example, conflicts exist with Uruguayan rice producers. The high demand for irrigation water, especially in the case of rice farming, requires a disciplined approach to its use involving the application of good agricultural and irrigation management practices, and the construction of dams to regulate discharge during periods of greater demand.

• Areas of the Guaçu, das Antas, Chapecó, Irani, Jacutinga, Peixe and Canoas Rivers are the focus of conflict between the discharge of urban, rural (pig and poultry farming) and industrial (cellulose) waste and the supply of the local population.

• The current situation affecting the Uruguay hydrographic region's water resources presents some important challenges.

• It is important to regulate discharges by using dams and rationalizing demands in the municipalities in the region of the Uruguay's headwaters in order to avoid the frequent rationing.

• It is important to introduce a domestic and industrial waste water treatment program, especially in the region's more populated areas in this region.

• Rural producers must adopt waste water treatment plants, and recycling technology to address the problems caused by large-scale production of effluent from pig and poultry operations which contaminate the rivers and aquifers in the western sector of Santa Catarina.

• It is necessary to establish and apply plans to discipline the use and occupation of land in urban areas affected by flooding through the implementation of a real-time warning system in order to reduce risks.

• It is necessary to broaden the scope of the rural expansion program, based upon agro-climatic and the application of suitable agricultural practices to control erosion problems.

6. WORK PROGRESS AND ACHIEVEMENTS DURING THE PERIOD RELATED TO D9.16

This report presents the activities undertaken to achieve the deliverable D.9.16 referring to models to generate synthetic rainfall series. Activities related to this deliverable correspond to the period from 01 October 2008 to January 14, 2010. The work plan for this deliverable comprised the following activities: 1) Choice of models to generate synthetic rainfall series; 2) Collection and data consistency of rainfall in key stations in South-East Brazil; 3) Checking stationarity of rainfall data; 4) Development and validation of Monthly Seasonal Multivariate Autoregressive Model (SMMAR (1), 5) Development and validation of Annual Multivariate Model with Disaggregation into Monthly Rainfall (MDM), 5) Development and validation of Daily Univariate Model (DUM).

These issues are presented in the following items:

7. Rainfall data

8. Generation of synthetic rainfall series

9. Monthly Seasonal Multivariate Autoregressive Model (SMMAR (1))

10 Monthly disaggregation model (MDM)

11. Daily Univariate Model - DUM

7. RAINFALL DATA

7.1 Consistency analysis of rainfall

The rainfall data collection held for the nine stations that constitute the reference points (Figure 7.1 shows the location of rainfall stations) for the generation of synthetic rainfall series in the La Plata basin was based on two data sources: i) National Water Agency (*Agência Nacional de Águas-ANA*), ii) the National Operator of the Electric System (*Operador Nacional do Sistema Elétrico - ONS*). The period of the study was January 1944 to December 2005.

Besides these two sources of data was also used information available in rainfall stations near the key station. These data were used to fill gaps, whose periods are presented in Table 7.1. This table shows the rainfall stations used in the study (name, code), and the stations used to fill in the gaps in main stations and the period where it was filling.

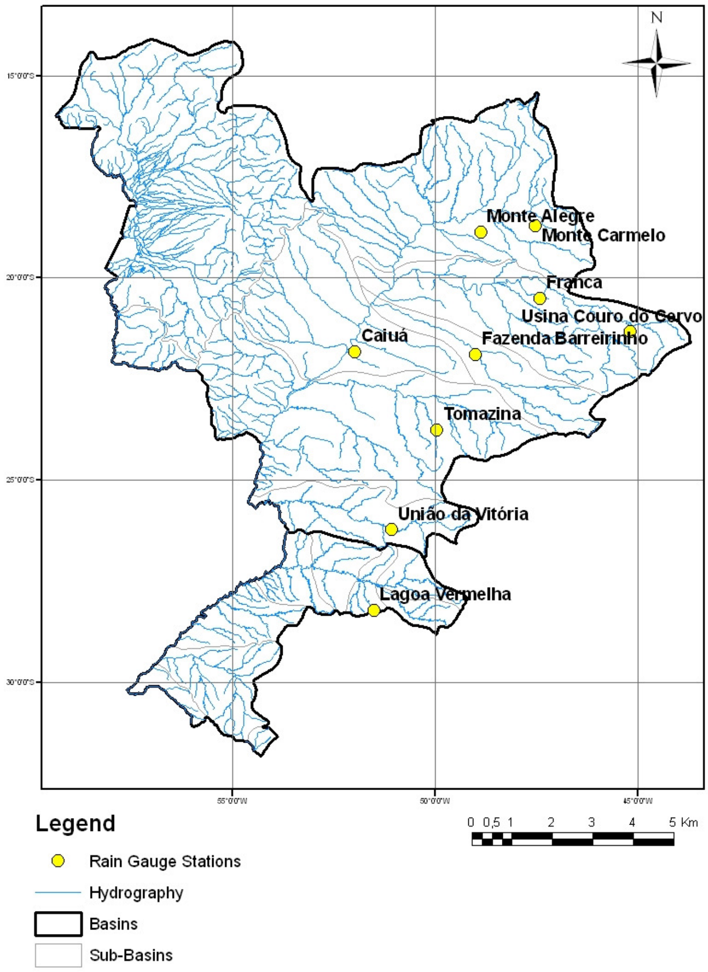


Figure 7.1 – Location of rainfall station

Where possible the collection of rainfall data was obtained with some degree of consistency, where gross errors have been already eliminated. In some stations it was not possible to obtain data preliminary consisted. Then the series were filled with raw data, as detailed in the Table 7.3.

The errors of observation in the raw data can be classified as (Fill & Mine, 1990):

1) Gross errors are human errors (e.g. spillage of water at the time collection, lack of collection on certain days such as weekends and holidays, reading at different times of the predetermined, among other factors), and serious gaps in the records of rainfall (clogging of conduits, etc.). These errors are generally larger than the precision of the equipment and not follow a predetermined pattern.

2) Systematic errors, which are always associated with the equipment. These errors result from lack of calibration, improper installation or changes in the characteristics of rain gages. In this type of error we find the lack of adjustment in the rain gage clock, the non-horizontal surface area, among other factors.

3) Random errors that are errors of observation are within the margin of accuracy of the equipment or the human capacity to observe. As examples of these types of errors we have the evaporation of water rain gage, influence of wind on the amount of rainfall received, etc.

Table 7.1 - Rainfall stations

Station name	Code	Stations used to fill gaps / period completed	Source of data
1) Monte Carmelo	01847000	-	ANA and ONS
2) Monte Alegre de Minas	01848000	Itumbiara (01849004) 01/59 - 12/64	ANA and ONS
3) Usina Couro do Servo	02145007	Carmo da Cachoeira (02145044) 11/05 - 12/05	ANA and ONS
4) Franca	02047017	Franca (02047016), Usina Dourados (02047021) 01/44 – 08/45; 8/00 - 12/05 respectively	ANA and ONS
5) Fazenda Barreirinho	02148128	Reginópolis (02149031) Sítio Esperança (02148044) 11/79 e 02/80; 04/00 - 12/05 respectively	ANA and ONS
6) Tomazina	02349033	-	ANA and ONS
7) União da Vitória	02651000	-	ANA and ONS
8) Lagoa Vermelha	02851014	Clemente Argolo (02751017) 02 - 06/82; 8 - 12/82; 02/83; 4 - 12/83; 9/85 - 12/99; 01 - 08/01	ANA and ONS
9) Caiuá	02151035	Porto Uerê (02152001) 08/00 - 12/05	ANA and ONS

ANA- Agência Nacional de Águas
ONS – Operador Nacional do Sistema Elétrico

Table 7.2 shows the periods for which we used data collected from the National Electric System Operator (ONS), and the periods for which data were collected in the National Water Agency (ANA).

Table 7.2 - Source of rainfall data

Code	Data source	
	ONS	ANA
01847000	01/44 - 12/01	01/02 - 12/05
01848000	01/44 - 12/01	01/02 - 12/05
02145007	01/44 - 12/00	01/01 - 12/05
02047017	01/44 - 07/00	08/00 - 12/05
02148128	01/44 - 08/79; 12/79 - 01/80; 03/80 - 03/00	11/79; 02/80; 04/00 - 12/05
02349033	01/44 - 10/01	11/01 - 12/05
02651000	01/44 - 12/01	01/02 - 12/05
02851014	01/44 - 01/82; 07/82; 01/83; 03/83; 01/84 - 08/85; 01/00 - 12/00; 09/01 - 12/05	02- 06/82; 08/82 - 12/82; 02/83; 4/83 - 12/83; 09/85 - 12/99; 01/01 - 08 - 01
02151035	01/44 - 07/00	08/00 - 12/05

Table 7.3 – Degree of consistency of rainfall data

Station name	Code	Data status	Data period	
			Consisted	Not consisted
1) Monte Carmelo	01847000	Consisted	01/44 - 12/05	Not used
2) Monte Alegre de Minas	01848000	Consisted	01/44 - 12/05	Not used
3) Usina Couro do Cervo	02145007	Consisted	01/44 - 12/05	Not used
4) Franca	02047017	Consisted	01/44 - 12/05	Not used
5) Fazenda Barreirinho	02148128	Not consisted and consisted	01/44 – 12/54; 11/79; 02/80; 04/00 - 12/05	01/55 - 10/79; 12/79 - 01/80; 03/80 - 03/00
6) Tomazina	02349033	Not consisted and consisted	01/44 - 10/01	11/01 - 12/05
7) União da Vitória	02651000	Not consisted and consisted	01/44- 12/01	01/02 - 12/05
8) Lagoa Vermelha	02851014	Consisted	01/44 - 12/05	Not used
9) Caiuá	02151035	Consisted	01/44 - 12/05	Not used

7.2 Checking of stationarity of rainfall series

In general, the consideration of stationarity for a stochastic process brings a concept of statistical equilibrium. For processes that deal with time series, as in many hydrological models, the stationarity appears as a necessary prerequisite for successful reproduction of natural dynamic phenomena through a finite range of data. In developing these models, the researchers involved almost always consider the stationarity of the series as a rule and non-stationarity as an exception. Time series with non-stationary characteristics raise considerably the complexity of the model to be developed, not only in the mathematics involved, but also the physical mechanisms to be considered.

The non-stationarity and lack of representativeness of the rainfall series may occur by climate variability within the sample period (Tucci, 2007). In the context of the CLARIS-LPB project, the presence of non-stationarity in rainfall series invalidates the study. If the statistical moments of the rainfall series vary in time they make impossible to calculate the essential parameters for the development of synthetic rainfall generation models. Even if these models could be built, certainly they would return poor results and not statistically representative.

As a result of the above observations, it was necessary to examine the stationarity of the rainfall series that are being used in CLARIS LPB project. The analysis was done for the key stations shown in Figure 7.1.

To check the stationarity of total annual rainfall series we used the following methods: i) statistical tests of homogeneity of rainfall series: Student's t test and Wilcoxon test, ii) method of cumulative rainfall curve as a function of time.

The latter was used to correct systematic errors or changes from other sources, such as those due to the data series filling.

Statistical tests

A formal way, to verify the homogeneity of random variables, is to apply statistical tests. In the present study, for total annual rainfall series were used the Student's t test (Stevenson, 1981) and Wilcoxon's test (Wilcoxon, 1945; Navid, 2006).

Student's t test

When the population variances are known to be nearly equal, the pooled variance may be used. The pooled variance is given by

$$s_p^2 = \frac{(n_1 - 1)\, s_1^2 + (n_2 - 1)\, s_2^2}{n_1 + n_2 - 2} \qquad (7.1)$$

The test statistic for testing any of the null hypotheses $H_0 : \mu_1 - \mu_2 = 0$, $H_0 : \mu_1 - \mu_2 \leq 0$, or $H_0 : \mu_1 - \mu_2 \geq 0$ is:

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{s_p \sqrt{1/n_1 + 1/n_2}} \qquad (7.2)$$

Under H_0, the test statistic has a student's distribution with $n_1 + n_2 - 2$ degrees of freedom.

Summary

Let $X_1,..., X_{n_x}$ and $Y_1,..., Y_{n_x}$ be samples from *normal* populations with means μ_1 and μ_2 and standard deviations σ_1 and σ_2, respectively. Assume the samples are drawn independently of each other.

If σ_1 and σ_2 are known to be equal, then, to test a null hypothesis of the form $H_0 : \mu_1 - \mu_2 \leq \Delta_0$, $H_0 : \mu_1 - \mu_2 \geq \Delta_0$, or $H_0 : \mu_1 - \mu_2 = \Delta_0$:

- Compute $s_p = \sqrt{\dfrac{(n_1 - 1)\, s_1^2 + (n_2 - 1)\, s_2^2}{n_1 + n_2 - 2}}$
- Compute the test statistic $t = \dfrac{(\bar{x}_1 - \bar{x}_2)}{s_p \sqrt{1/n_1 + 1/n_2}}$
- Compute the *P*- value. The *P*- value is an area under the Student's *t* curve with $n_1 + n_2 - 2$ degrees of freedom, which depends on the alternate hypothesis as follows:

Alternate Hypothesis	***P*- value**
$H_1 : \mu_1 - \mu_2 > \Delta_0$	Area to the right of *t*
$H_1 : \mu_1 - \mu_2 < \Delta_0$	Area to the left of *t*
$H_1 : \mu_1 - \mu_2 \neq \Delta_0$	Sum of the areas in the tails cut off by *t* and -*t*

Distribution-Free Tests

The Student's t tests formally require that samples come from normal populations. Distribution-free tests get their name from the fact that the samples are not required to come from any specific distribution. While distribution-free tests do require assumptions for their validity, these assumptions are somewhat less restrictive than the assumptions needed for the t test. Distribution-free tests are sometimes called *nonparametric tests***.** In case of rainfall, the assumption of normality of the total annual precipitation is acceptable, avoiding any type of data processing.

The Wilcoxon Rank-Sum Test

The Wilcoxon rank-sum test, also called the Mann-Whitney test, can be used to test the difference in population means in certain cases where the populations are not normal. Two assumptions are necessary. First, the populations must be continuous. Second, their probability density functions must be identical in shape and size; the only possible difference between them being their location. To describe the test, let $X_1,...,X_m$ be a random sample from one population and let $Y_1,...,Y_n$ be a random sample from the other. We adopt the notational convention that when the sample sizes are unequal, the smaller sample will be denoted $X_1,...,X_m$. Thus the sample sizes are *m* and *n*, with $m \le n$. Denote the population means by μ_X and μ_Y, respectively.

The test is performed by ordering the $m + n$ values obtained by combining the two samples, and assigning ranks 1, 2, …, $m + n$ to them. The test statistic, denoted by *W*, is the sum of the ranks corresponding to $X_1,...,X_m$. Since the populations are identical with the possible exception of location, it follows that if $\mu_1 < \mu_2$, the values in the *X* sample will tend to be smaller than those in the *Y* sample, so the rank sum *W* will tend to be smaller as well. By similar reasoning, if $\mu_1 > \mu_2$, *W* will tend to be larger.

Large-Sample Approximation

When both sample sizes *m* and *n* are greater than 8, it can be shown by advanced methods that the null distribution of the test statistic *W* is approximately normal with mean $m(m+n+1)/2$ and variance $mn(m+n+1)/12$. In these cases the test is performed by computing the *z*-score of *W*, and then using the normal table to find the P-value. The *z*-score is

$$z = \frac{W - m(m+n+1)/2}{\sqrt{mn(m+n+1)/12}} \qquad (7.3)$$

Verification of the homogeneity of rainfall series

In this section of the report we present the application of tests and the results obtained. The Student's t test and Wilcoxon's test were used to evaluate the homogeneity of the total annual precipitation to the stations listed in Table 7.4. The tests were performed for two samples of each rainfall station. The period of the first sample is from 1944 to 1969 and the second sample is from 1970 to 2005.

The distribution was considered normal (Gaussian) with significance level $\alpha = 0.05$ and 60 freedom degrees. Through the statistics provided above were obtained the following values tabulated t = 2.000, z =- 1.644 for Student's t test and Wilcoxon test respectively. The results obtained for the null hypothesis H_0 are shown in Table 7.4.

The observation of the results in Table 7.4 shows that only the station Usina Couro do Cervo in southeastern Brazil and the station Lagoa Vermelha in southern Brazil may be considered homogeneous.

Cumulative precipitation curves

Models to generate synthetic series of rainfall are defined for stationary time series. Therefore, we used the curves of cumulative rainfall for the correction of such data. This correction was made for the current period based on the relationship between the slopes of the curves adjusted to the accumulated rainfall, plotted as a function of time. Table 7.5 shows the coefficients obtained for the correction of data and the period consisted (corrected) for each key station.

Table 7.4 - Results of rainfall homogeneity tests

Rainfall station	**Student's-t test**		**Wilcoxon test**	
	$T_{calculated}$	**Result of Ho**	$Z_{calculated}$	**Result of Ho**
1. Monte Carmelo	-2,179	Rejected	-2,082	Rejected
2. Monte Alegre de Minas	-2,592	Rejected	-2,738	Rejected
3. Usina Couro do Cervo	-0,740	Accepted	-0,156	Accepted
4. Franca	-2,942	Rejected	-2,710	Rejected
5. Fazenda Barreirinho	-2,611	Rejected	-2,368	Rejected
6. Tomazina	-3,206	Rejected	-3,124	Rejected
7. União da Vitória	-3,102	Rejected	-3,152	Rejected
8. Lagoa Vermelha	-1,710	Accepted	-1,569	Accepted
9. Caiuá	-5,085	Rejected	-4,507	Rejected

Table 7.5 – Rainfall data correction through the cumulative curves

Station	Code	Coefficient 1	Coefficient 2	Coefficient 3	Period 1	Period 2	Period 3
1) Monte Carmelo	01847000	0,378	3,948	0,743	01/1944 – 12/1959	01/1944 – 12/1963	01/0944 – 12/1966
2) Monte Alegre de Minas	01848000	1,135	1,085	-	01/44 – 12/49	01/44 – 12/74	-
3) Usina Couro do Servo	02145007	1,067	-	-	01/44 – 12/79	-	-
4) Franca	02047017	1,231	-	-	01/44 – 12/61	-	-
5) Fazenda Barreirinho	02148128	1,157	-	-	01/44 – 12/56	-	-
6)Tomazina	02349033	0,670	1,353	-	01/44 – 12/47	01/44 – 12/53	-
7) União da Vitória	02651000	1,178	-	-	01/44 – 12/72	-	-
8) Lagoa Vermelha	02851014	1,131	0,842	1,224	01/44 – 12/53	01/44 – 12/59	01/44 – 12/83
9) Caiuá	02151035	0,474	2,696	-	01/44 – 12/66	01/44 – 12/69	-

Figure 7.2 shows the method for the Monte Carmelo rainfall station. The other figures are in the Annex A of this report. Table 7.6 presents the periods of rainfall corrections. Table 7.7 presents the difference between the average rainfall in periods 1 and 2 (Period 1 from 1955 to 1969 and period 2 from 1970 to 2005). The results presented allow verifying an increase in precipitation series after 1970 in all stations, but a more significant increase in the South than in Southeastern Brazil. This variation is very likely to be sampling, but we have no assurance of its permanence, and we may have in the future drought cycles. With a series as short as used in this study, it would be too risky to find any justification for non-stationarity, for example, interdecadal climate variability and others.

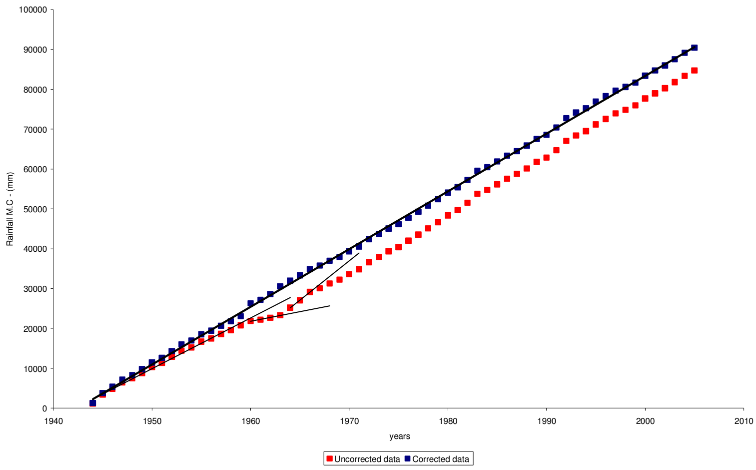


Figure 7.2 - Analysis of the homogeneity of Monte Carmelo station

Table 7.6 - Periods of rainfall corrections

Station	Period 1	Period 2	Period 3	Period 4
Monte Carmelo	1944 - 1959	1960 - 1963	1964 - 1966	1967 - 2005
Monte Alegre de Minas	1944 - 1949	1950 - 1974	1975 - 2005	
Usina Couro do Servo	1944 - 1979	1980 - 2005		
Franca	1944 - 1961	1962 - 2005		
Fazenda Barreirinho	1944 - 1956	1957 - 2005		
Tomazina	1944 - 1947	1948 - 1953	1954 - 2005	
União da Vitória	1944 - 1972	1973 - 2005		
Lagoa Vermelha	1944 - 1953	1954 - 1959	1960 - 1983	1984 - 2005
Caiuá	1944 - 1966	1967 - 1969	1970 - 2005	

Table 7.7 - Behavior of rainfall before and after 70's

Sub-basin	Rainfall station	P_2-P_1 (mm)
Grande	Usina Couro do Cervo	50,53
Grande	Monte Alegre de Minas	96,34
Iguaçu	União da Vitória	271,38
Paranaíba	Monte Alegre de Minas	96,34
Paraná	União da Vitória	271,38
Paranaíba	Monte Carmelo	328,13
Paranapanema	Tomazina	200,18
Tietê	Fazenda Barreirinho	108,82
Uruguai	Lagoa Vermelha	234,38

OBS – (1) period from 1955 to 1969 and
(2) period from 1970 to 2005

8 GENERATION OF SYNTHETIC RAINFALL SERIES

The generation of synthetic rainfall series is only done if the team responsible for providing the scenarios of rainfall (pseudo-historical series) presents only the statistical parameters of the series for each month of the year and location. In this case the pseudo-historical series of rainfall should be generated with one of the models: i) Monthly Seasonal Multivariate Autoregressive Model (SMMAR (1)); ii) Annual Multivariate Model with Disaggregation into Monthly Rainfall (MDM); iii) Daily Univariate Model (DUM).

For generation of synthetic series of monthly rainfall the Seasonal Multivariate Autoregressive Model (SMM) is used. The models (MDM) and (DUM) could be used alongside the SMMAR (1). They are currently being studied and may constitute other options for generating synthetic series of precipitation for the Project CLARIS LPB.

Uncertainty is always an element present when dealing with planning or analysis of water resource systems. It arises because the values of many factors that affect the performance of these systems can not be known certainly. Within those factors, hydrologic variables play an important role and are often treated as random variables or as stochastic processes.

To link the stochastic nature of hydrologic variables such as rainfall, streamflow, temperatures, etc, to the performance of a water resource system, the Monte Carlo approach has often been used successfully. This method is based on the construction of scenarios for rainfall or streamflow sequences (or other inputs) and then by simulation obtains results of the system performance which are linked to the likelihood of each scenario.

Often the scenarios are constructed by so called synthetic series, which are sequences of hydrologic variables generated randomly but preserving the statistical properties of the historic record so that they are statistically indistinguishable from the historic record. Thus the synthetic series represent possible future sequences of the system input and the result of simulations using these series represent possible future performances of the system.

In water resources systems having little storage so that reservoirs refill almost every year, synthetic hydrologic sequences may not be needed if historic sequences of reasonable length are available. In this case any year of historic record provides one scenario of the possible, within year, operation of the system.

However for water resource systems having large amounts of over-year storage (like the Brazilian interconnected electric system) the historic record provides only one time history of how the system would operate from year to year. In this case in order to evaluate the variability of future system performance, synthetic series of the hydrologic input are needed.

Even when the system input are natural streamflows sequences, as it is the case for hydroelectric power systems, often it is useful to generate rainfall sequences and then transform these into streamflows by a rainfall-runoff model. This is particularly done if the purpose of the analysis in to evaluate the impact of climate changes (as it is the goal of the CLARIS LPB project), so that statistical properties of rainfall and streamflow are quite different in the future.

To deal with this challenge, synthetic rainfall generation models have been developed and these models are described in this report.

9 MONTHLY SEASONAL MULTIVARIATE AUTOREGRESSIVE MODEL (SMMAR (1))

The theory of the model is presented below. It is used a multivariate autoregressive seasonal model applied to total monthly rainfall transformed by Box and Cox transformation.

To achieve this goal, the following steps were considered:

(1) Estimation of model parameters;

(2) Generation of synthetic time series;

(3) Analysis of the results.

Related to the first three steps above we developed a computational method, which was prepared in Pascal Language and implemented in Lazarus. This computational method was divided into three modules. These modules are interconnected through files.

The first module aims at applying the method of moments to estimate the parameters of the Box-Cox transformation model. This module prepares a file with the parameters (means, variances and correlation coefficients) for use in the second module.

The second module prepares a file with the synthetic series generated, which can be used by the third module for the analysis of results. The file generated by the second module can be used as an input for other applications to be developed for rainfall-runoff modeling.

The analysis of the results is to verify the conservation properties of the synthetic series compared to historical data used as input data for the first module.

9.1 The model theory

This model deals with seasonal by standardizing rainfall and considers nonstationarity in the correlation structure. Time-varying parameters are required to include seasonal variability in the correlation structure. Most widely used is the seasonal AR (1) (Salas and Pegram, 1977; Salas *et al.,* 1980).

The multivariate seasonal autoregressive model of order 1 will preserve all seasonal means of all variables in the state vector, all seasonal variances, all correlations among all elements of the state vector, and lag-one correlations between adjacent seasons and between all variables. As formulated here, the model will be able to handle normal and *log-normal* variables as well as mixed normal and log-normal or Box-Cox transformation elements in the state vector. The log-normal transformation is a special case of Box-Cox transformation. Mine (1998) used the Box-Cox transformation in rainfall forecasting models.

As the proposed model is valid for stationary processes with marginal normal distribution, the original series of monthly average rainfall should be submitted to a Box-Cox transformation of the first order, with the objective of obtaining data normally distributed. The equations of transformation are presented in Section "Box-Cox Transformations".

The Multivariate Normal Case

Let

$$\left(\overline{X}_{i\,j}-\overline{m}_j\right)=\overline{A}_j\left(\overline{X}_{i,\,j-1}-\overline{m}_{j-1}\right)+\overline{B}_j\,\overline{\varepsilon}_{i\,j} \qquad (9.1)$$

Where $\overline{X}_{i\,j}$ is the state vector $(n\times 1)$ of random variables $x^{\ell}_{i\,j}$, during the year i and season j at location ℓ with mean $\overline{m}_j$.

In detail,

$$\overline{X}_{i\,j}=\begin{bmatrix} x^1_{i\,j} \\ x^2_{i\,j} \\ \vdots \\ x^n_{i\,j} \end{bmatrix} \qquad \text{and} \qquad \overline{m}_j=\begin{bmatrix} m^1_{x_j} \\ m^2_{x_j} \\ \vdots \\ m^n_{x_j} \end{bmatrix}$$

For example, $x^1_{i\,j}$ can be interpreted as the monthly rainfall at station 1 during year i and month j (season) and $m^1_{x_j}$ as the mean value of this variable during the month j.

$\overline{A}_j$ and $\overline{B}_j$ are parameter matrices $(n\times n)$, one for each season. The $(n\times 1)$ vector of standard normal deviates is $\varepsilon_{i\,j}$, for year i and season j.

Notation for Eq. (9.1) is simplified by introducing the zero-mean vector, $\overline{Z}_{i\,j} = \left(\overline{X}_{i\,j} - \overline{m}_j\right)$:

$$\overline{Z}_{i\,j} = \overline{A}_j\,\overline{Z}_{i,\,j-1} + \overline{B}_j\,\overline{\varepsilon}_{i,\,j.} \qquad (9.2)$$

The similarity between the model given by equation (9.2) and the multivariate stationary autoregressive lag-one is obvious; the only difference is the seasonal dependence of $\overline{A}_j$ and $\overline{B}_j$. The lag-zero covariance for season *j* is ${}_j\overline{M}_0$. The covariance matrix between vectors $\overline{Z}_{i\,j}$ and $\overline{Z}_{i,\,j-1}$ is ${}_j\overline{M}_1$.

Following a derivation analogous (Bras and Rodríguez-Iturbe, 1985) to the stationary models AR (1), it should be easy to arrive at the following results:

$$\overline{A}_j = {}_j\overline{M}_1\;{}_{j-1}\overline{M}_0^{-1} \qquad (9.3)$$

$$\overline{B}_j\,\overline{B}_j^T = {}_j\overline{M}_0 - {}_j\overline{M}_1\;{}_{j-1}\overline{M}_0^{-1}\;{}_j\overline{M}_1^T. \qquad (9.4)$$

The decomposition of $\overline{B}_j\overline{B}_j^T$ is accomplished using the procedures described in Bras and Rodríguez-Iturbe, (1985). Since every covariance function is seasonally dependent, so are the resulting parameters.

It is now convenient notationally to redefine the vectors $\overline{Z}_{i\,j}$ and $\overline{Z}_{i,\,j-1}$ as $\overline{Y}$ and $\overline{X}$, respectively. That is, vector $\overline{Y}$, with *n* elements y_i, *i* = 1… *n*, will represent the state vector at season *j;* and vector $\overline{X}$ with elements x_i, *i* = 1… *n*, will represent the state vector in the previous season *j* – 1. The model is now:

$$\overline{Y} = \overline{A}_j\,\overline{X} + \overline{B}_j\,\overline{\varepsilon}_{j\,.} \qquad (9.5)$$

The covariances of interest are now:

$${}_j\overline{M}_0 = \overline{S}_{yy} = E\left[\overline{Y}\,\overline{Y}^T\right]$$

$${}_j\overline{M}_1 = \overline{S}_{yx} = E\left[\overline{Y}\,\overline{X}^T\right]$$

$${}_{j-1}\overline{M}_0 = \overline{S}_{xx} = E\left[\overline{X}\,\overline{X}^T\right]$$

$$\overline{S}_{x\,y} = \overline{S}_{yx}^T$$

Matrices $\overline{S}_{x\,x}, \overline{S}_{x\,y}$, $\overline{S}_{y\,x}$ and $\overline{S}_{yy}$ can be represented in terms of variances, standard deviations, and correlations as

$$\overline{S}_{xx} = \begin{bmatrix} S_{x_1}^2 & r_{x_1\,x_2} S_{x_1} S_{x_2} & \cdots & r_{x_1\,x_n} S_{x_1} S_{x_n} \\ r_{x_2\,x_1} S_{x_2} S_{x_1} & S_{x_2}^2 & & r_{x_2\,x_n} S_{x_2} S_{x_n} \\ \vdots & & \ddots & \\ r_{x_n\,x_1} S_{x_n\,x_1} & r_{x_n\,x_2} S_{x_n} S_{x_2} & \cdots & S_{x_n}^2 \end{bmatrix} \qquad (9.6)$$

$$\overline{S}_{yy} = \begin{bmatrix} S_{y_1}^2 & r_{y_1\,y_2} S_{y_1} S_{y_2} & & r_{y_1\,y_n} S_{y_1} S_{y_n} \\ \vdots & & \ddots & \vdots \\ r_{y_n\,y_1} S_{y_n\,y_1} & r_{y_n\,y_2} S_{y_n} S_{y_2} & \cdots & S_{y_n}^2 \end{bmatrix} \qquad (9.7)$$

$$\overline{S}_{yx} = \begin{bmatrix} r_{y_1\,x_1} S_{x_1} S_{y_1} & r_{y_2\,x_1} S_{x_1} S_{y_2} & \cdots & r_{y_n\,x_1} S_{x_1} S_{y_n} \\ \vdots & \ddots & & \vdots \\ r_{y_1\,x_n} S_{x_n\,y_1} & r_{y_2\,x_n} S_{x_n} S_{y_2} & \cdots & r_{y_n\,x_n} S_{x_n} S_{y_n} \end{bmatrix} \tag{9.8}$$

where S_{x_i} is the standard deviation of variable x_i, $r_{x_i\,x_j}$ is the lag-zero correlation between stations (variables) x_i and x_j, and $r_{y_i\,x_j}$ is the lag-one correlation between variables y_i and x_j,

The estimation of sample covariances should again follow the equations below, to minimize the occurrences of inconsistent (nonpositive definite) $\overline{B}_j \overline{B}_j^T$ matrices.

$$_j\hat{M}_o = \frac{1}{n} \overline{X}_j \overline{X}_j^T \qquad\qquad _j\hat{M}_1 = \frac{1}{n} \overline{X}_j \overline{Y}_j^T$$

The Multivariate Log-Normal Case

Consider the case where the elements of vectors $\overline{X}$ and $\overline{Y}$, x_i and y_i, are random variables following a two-parameter log-normal distribution. Define the variables, $x_i^{'}$ and $y_i^{'}$, as follows:

$$x_i^{'} = \ln(x_i) \tag{9.9}$$

$$y_i^{'} = \ln(y_i) \tag{9.10}$$

Thus, the original variables x_i and y_i are log-normally distributed with means m_{x_i} and m_{y_i}, standard deviations S_{x_i} and S_{y_i}, and the correlation coefficient among them given by $r_{x_i\,y_i}$.

Therefore, the transformed variables $x_i^{'}$ and $y_i^{'}$ are normally distributed with means $m_{x_i^{'}}$ and $m_{y_i^{'}}$, standard deviations $S_{x_i^{'}}$ and $S_{y_i^{'}}$, and the correlation coefficient among them equal to $r_{x_i^{'}\,y_i^{'}}$.

To preserve without bias the statistics of the original variables instead of the statistics of the transformed variables it is necessary to compute parameters of the distribution of $x_i^{'}$ and $y_i^{'}$ based on the parameters of the distribution of the original variables x_i and y_i, using the expressions given by Matalas (1967):

$$m_{x_i} = \exp\,\{S^2_{x_i^{'}}\ /2 + m_{x_i^{'}}\}$$

$$m_{y_i} = \exp\,\{S^2_{y_i^{'}}\ /2 + m_{y_i^{'}}\}$$

$$S^2_{x_i} = \exp\,\{2\left[S^2_{x_i^{'}} + m_{x_i^{'}}\right]\} - \exp\left[S^2_{x_i^{'}} + 2m_{x_i^{'}}\right] \tag{9.11}$$

$$S^2_{y_i} = \exp\,\{2\left[S^2_{y_i^{'}} + m_{y_i^{'}}\right]\} - \exp\left[S^2_{y_i^{'}} + 2m_{y_i^{'}}\right]$$

$$r_{x_i\,y_i} = \frac{\exp\,\{S_{x_i^{'}} S_{y_i^{'}} r_{x_i^{'}\,y_i^{'}}\} - 1}{\exp\,\{S_{x_i^{'}} S_{y_i^{'}}\} - 1}$$

Solving the above system of simultaneous equations for $m_{x_i^{'}}$, $m_{y_i}^{'}$, $S_{x_i^{'}}$, $S_{y_i^{'}}$, and $r_{x_i^{'}\,y_i^{'}}$ yields

$$m_{x_i^{'}} = \ln\,(m_{x_i}) - S^2_{x_i^{'}}\,/2 \tag{9.12}$$

$$S^2_{x'_i} = \ln\left\{\frac{S^2_{x_i}}{m^2_{x_i}}+1\right\} \quad (9.13)$$

$$m_{y'_i} = \ln(m_{y_i}) - S^2_{y'_i}/2 \quad (9.14)$$

$$S^2_{y'_i} = \ln\left\{\frac{S^2_{y_i}}{m^2_{y_i}}+1\right\} \quad (9.15)$$

$$r_{x'_i x'_j} = \frac{\ln\left\{1+r_{x_i y_j}\sqrt{(e^{S_{x'_i}}-1)\,(e^{S_{y'_i}}-1)}\right\}}{S_{x'_i}S_{y'_i}} \quad (9.16)$$

Thus, having the sample variance and correlation coefficient from the historical records, it is possible to compute the values of the transformed variables using Eqs. (9.12) through (9.16).

The parameters of the transformed variables can be used to build the necessary autocovariance and cross-covariance matrices using the definitions given in Eqs. (9.6), (9.7), and (9.8). Generation matrices $\overline{A}_j$ and $\overline{B}_j$ are then available from the previously derived equations.

In order to get the original variables from generated synthetic data, the user must perform the inverse transformation

$$x_i = \exp(x'_i + m_{x'_i})$$

$$y_i = \exp(y'_i + m_{y'_i})$$

Mixture of Normal and Box-Cox Transformation Variables in the Autoregressive Model

Variables such as rainfall are best described by different marginal distributions at each season. For example, the Nile River (Curry and Bras, 1978) exhibits alternating normal and log-normal distributions each month of the year. The multivariate autoregressive model allows the mixing of normal and Box-Cox Transformation variables.

Let x_i and y_i be the original random variables. Assume x_i is Box-Cox Transformation distributed and y_i is normally distributed:

$$x'_i = \ln(x_i)$$

$$x'_i \sim N(m_{x'_i}, S^2_{x'_i})$$

$$y_i \sim N(m_{y_i}, S^2_{y_i})$$

The procedure to obtain the parameters $m_{x'_i}$ and $S^2_{x'_i}$ the log-normal variables was described in Bras and Rodríguez-Iturbe (1985) and made use of Eqs. (9.12) to (9.16). In this case, the problem is to obtain the correlation coefficient between the log-normal and the normal variables while preserving the parameters of the untransformed data. The necessary expression is given by Mejìa *et al*. (1974).

If $r_{x_i y_j}$ is the correlation coefficient among the original variables and $r_{x'_i y'_i}$ the correlation coefficient between the transformed log-normal and the normal variables, the following relationship holds,

$$r_{x_i' y_i} = \frac{r_{x_i y_i}\sqrt{(e^{S^2_{x_i}} - 1)}}{S_{x_i'}} \qquad (9.17)$$

In order to illustrate how to build the required covariance matrices, consider the following example.

Define the random vectors $\overline{X}$ and $\overline{Y}$ with three random variables each,

$$\overline{X} = \begin{bmatrix} x_1 \\ x_2' \\ x_3' \end{bmatrix} \qquad \overline{Y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3' \end{bmatrix} \qquad (9.18)$$

where the random variables $x_1, y_1, \; y_2$ are normally distributed, and $x_2', \; x_3', \; y_3'$ are log-normally distributed. Then the corresponding covariance matrices will be

$$\overline{S}_{xx} = \begin{bmatrix} (S_{X_1})^2 & r_{x_1 x_2'} S_{x_1} S_{x_2'} & r_{x_1 x_3'} S_{x_1} S_{x_3'} \\ r_{x_2' x1} S_{x_2'} S_{x_1} & (S_{x_2'})^2 & r_{x_2' x_3'} S_{x_2'} S_{x_3'} \\ r_{x_3' x_1} S_{x_3'} S_{x_1} & r_{x_3' x_2'} S_{x_3'} S_{x_2'} & (S_{x_3'})^2 \end{bmatrix}$$

$$\overline{S}_{yy} = \begin{bmatrix} (S_{y_1})^2 & r_{y_1 y_2} S_{y_1} S_{y_2} & r_{y_1 y_3'} S_{y_1} S_{y_3'} \\ r_{y_2 y_1} S_{y_2} S_{y_1} & (S_{y_2})^2 & r_{y_2 y_3'} S_{y_2} S_{y_3'} \\ r_{y_3' y_1} S_{y_3'} S_{y_1} & r_{y_3' y_2} S_{y_3'} S_{y_2} & (S_{y_3'})^2 \end{bmatrix} \qquad (9.19)$$

$$\overline{S}_{xy} = \begin{bmatrix} r_{x_1 y_1} S_{x_1} S_{y_1} & r_{x_1 y_2} S_{x_1} S_{y_2} & r_{x_1 y_3'} S_{x_1} S_{y_3'} \\ r_{x_2' y_1} S_{x_2'} S_{y_1} & r_{x_2' y_2} S_{x_2'} S_{y_2} & r_{x_2' y_3'} S_{x'2} S_{y_3'} \\ r_{x_3' y_1} S_{x_3'} S_{y_1} & r_{x_3' y_2} S_{x_3'} S_{y_2} & r_{x_3' y_3'} S_{x_3'} S_{y_3'} \end{bmatrix}$$

The above matrices are again routinely used in the existing expressions to obtain $\overline{A}_j$ and $\overline{B}_j$. The user must remember to add means and perform required inverse transformations at the end of the computations. Since the elements of the sample covariance matrices are now individually evaluated and result from different nonlinear transformations, it is not unusual to obtain inconsistent estimates for the $\overline{B}_j \overline{B}_j^T$ matrix.

Box-Cox Transformations

Transformation to normality by taking logarithms is a property of the log-normal distribution; however, in practice, hydrological data follow a probability distribution that is known to be skew but not necessarily log-normal. A more general transformation, of which the log transform is a particular case, is the family of Box-Cox transformations, defined by

$$z = \begin{cases} (y^{\lambda} - 1)/\lambda \quad when \quad \lambda \quad is \quad non-zero \\ \log y \quad when \quad \lambda \quad is \quad zero \end{cases}$$

where λ is to be estimated from the data. The estimation procedure consists of the following:

i) Assume a range of values for λ: usually values in the range between 2 and -2 are appropriate.

ii) For each value of λ within the range, transform the *y*-sequence of data into *z*-sequence given by the above transformation.

iii) For each value of λ, calculate the maximum of the log-likelihood function, say $\max[\ln L(\lambda)]$.

iv) Select the value of λ for which this quantity is maximized.

Clarke (1994) showed that the value of λ which transforms the data sequence from the Rio Hercílio at Ibirama – Brazil is -0.055; clearly this value does not look very different from zero, and we can in fact test whether it differs significantly from that quantity. To do this, we take the plot of $\ln L(\lambda)$ against λ, and do the following:

i) Draw the (horizontal) tangent to the curve $\ln L(\lambda)$ at the value of λ at which the curve reaches its maximum.

ii) Draw a second horizontal line below this tangent, the perpendicular distance between these two horizontal parallel lines being the $100(1-\alpha)\%$ quantile of the χ^2 distribution with one degree of freedom ($\alpha = 0.05$, from which the 95% quantile of the χ^2 distribution is 3.841, the horizontal distance between the two lines).

iii) Mark the two points where the lower horizontal line cuts the curve $\ln L(\lambda)$; these points define two values of λ, say λ_L , λ_U, which define a $100(1-\alpha)\%$ confidence interval for true value of λ, the parameter of the transformation. If the interval defined by λ_L, λ_U includes zero, corresponding to a log transformation, then the value of λ maximizing $\ln L(\lambda)$ (in the case -0.055) does not differ significantly from this quantity, at the $100\alpha\%$ significance level.

Parameters estimation of the Box-Cox transformation by the method of moments

λ is a parameter that can be estimated by imposing the condition that the skew coefficient of *z* is zero (corresponding to the skew coefficient of the normal distribution).

The equation *Ca*(*Z*)=0 can be solved using the method of simulated annealing (Lee and El-Sharkawi, 2008), estimating λ that minimizes |*Ca*(*Z*)|.

The method of simulated annealing is a technique that has recently received much attention for solving large optimization problems (Mckendall et al., 2006). This method was devised by analogy with the Metropolis algorithm (Metropolis et al., 1953), which was proposed to simulate problems of statistical physics by Monte Carlo method (Newman and Barkema, 1999).

The use of the Metropolis algorithm can be described considering a system whose states are not degenerate with energies *E1* <*E2* <*E3* <... *En*. For the Metropolis algorithm, the objective of the problem is to simulate the evolution of the system in thermal equilibrium which is at temperature *T*. It was initially thought that the system is in state *j* (energy *Ej*). The system may be carried over to any of the other states *f*.

The feasibility of the change of state is analyzed by calculating the increase of energy Δ*E*=*Ej*–*Ef* and the Boltzmann factor exp[–Δ*E*/(*kT*)], and *k* is the Boltzmann constant (1.380658 / 10 ²³ J/K). We generate a uniform random number *p* (0≤*p*≤1) and compare it with the Boltzmann factor: (i) if *p*>exp[–Δ*E*/(*kT*)], the proposal is rejected, the system remaining in state *j*; (ii) if *p*≤exp[–Δ*E*/(*kT*)], the proposal is accepted, and the system will be changed to the state *f*.

As a result, if Δ*E*<0, i.e. the energy of the system is reduced while transiting, the proposal is always accepted, and if Δ*E*>0, the proposal can be accepted with probability *p*, and if it is accepted, it means that the system energy will increase, and this looks a little different from the idea that a system always tends to decrease its energy, which strengthens and adds importance to the Metropolis algorithm.

To make use of the Metropolis algorithm to solve general problems of optimization, should be known the following (Press et al., 1989): (i) description of the possible system configurations; (ii) a random generator to make configuration changes, these changes are options that should be part of the system settings; (iii) an objective function *E* (analogy with energy) whose minimization is the goal of the procedure; (iv) a control parameter (analogy with temperature) and an annealing scheme that the system can be conducted to the lowest value of the objective function.

To solve the equation $Ca(Z)=0$ has been developed a computational method where the objective function was defined as $|Ca(Z)|$. The decision variable is the parameter λ. As initial solution is considered $\lambda = 0$.

The Metropolis algorithm is used to generate a set of points in a space of distributed variables with probability density function estimated by the Boltzmann factor. The parameter kT initially is defined as 0.5, and subsequently reduced by a factor of 0.9 in each of 100 steps considered. Thus, we will generate a sequence of points (generally identified by the vector **λ**) representing a random walk moving through space configured.

The rules under which the random walk is performed in space are the following: (i) to consider that the random walk is at the point λn; (ii) to generate the point $\lambda n+1$ applies an iterative process. The new point can be chosen at random from a range of small δ, around the point λn; (iii) by drafting a possible point λ^*, this solution is accepted or rejected by considering the equation (9.20):

$$r=\exp[-\Delta E/(kT)] \qquad (9.20)$$

and $\Delta E=E(\lambda n)-E(\lambda^*)$, where $E(\lambda n)$ and $E(\lambda^*)$ are the values of the objective function in points λn e λ^*, respectively; (iv) If $r>1$, then the point λ^* is accepted ($\lambda n+1=\lambda^*$), if $r<1$, the point λ^* is accepted with probability r. This is done by comparing r with a number u uniformly distributed in the interval [0,1], accepting λ^* if $u<r$ .When the point λ^* is not accepted the random walk stays in the point λn ($\lambda n+1=\lambda n$) and (v) we generate the point $\lambda n+2$ using the same procedure.

The value of δ must be chosen so that 1/3 to 1/2 of the configurations generated are accepted, otherwise the method becomes inefficient (Koonin and Meredith, 1993). If there is a lot of rejected configurations it means that the value δ is too large, otherwise if δ is very small, there are many configurations accepted but the region explored by the method is small.

Once determined the parameter λ, the parameters *m* e *s*, average and standard deviation of the transformed variable, respectively, can be estimated using the equations (9.21):

$$\frac{1}{n}\sum_{i=1}^{n} y_i = \frac{1}{K}\int_0^{\infty} y^{\lambda}\exp[-\frac{1}{2s^2}(\frac{y^{\lambda}-1}{\lambda}-m)^2]dy,$$
$$\frac{1}{n}\sum_{i=1}^{n} y_i^2 = \frac{1}{K}\int_0^{\infty} y^{\lambda+1}\exp[-\frac{1}{2s^2}(\frac{y^{\lambda}-1}{\lambda}-m)^2]dy, \qquad (9.21)$$

where *K* is determined by:

$$K=\int_0^{\infty} y^{\lambda-1}\exp[-\frac{1}{2s^2}(\frac{y^{\lambda}-1}{\lambda}-m)^2]dy. \qquad (9.22)$$

The system of equations (9.21) must be solved numerically. With the solution obtained the mean and the variance of the variable *y* (precipitation) are preserved.

Analyzing the equations (9.21) we can conclude that there are solutions in the following cases: $\lambda< -1$ and $\lambda>1$.

Computer program

The computer program, in Pascal language, for the implementation of the algorithm below, was developed.

1. ALGORITHM

Sample $\bar{x} \approx N\left(\bar{\mu}, \bar{Q}^{-1}\right)$

To sample $\bar{x} \approx N\left(\bar{\mu}, \bar{Q}^{-1}\right)$, where $\bar{Q} = \bar{L}\bar{L}^T$, we use the following result: If $\bar{z} \approx N\left(\bar{0}, \bar{I}\right)$, then the solution of $\bar{L}^T \bar{x} = \bar{z}$ has covariance matrix $Cov(\bar{x}) = Cov\left(\bar{L}^{-T}\bar{z}\right) = \left(\bar{L}\bar{L}^T\right)^{-1} = \bar{Q}^{-1}$. Hence we obtain Algorithm 1 below. For repeated samples, we do step 1 only once. Step 3 solves the linear system $L^T v = z$ using back substitution, from which we obtain the following result as a by-product, giving some interpretation to the elements of $\bar{L}$.

All letters with a bar above represent vectors or matrices.

Algorithm 1 – Sampling $\bar{x} \approx N\left(\bar{\mu}, \bar{Q}^{-1}\right)$

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1. Compute the Cholesky factorization, $\bar{Q} = \bar{L}\bar{L}^T$
2. Sample $\bar{z} \approx N\left(\bar{0}, \bar{I}\right)$
3. Solve $\bar{L}^T \bar{v} = \bar{z}$
4. Compute $\bar{x} = \bar{\mu} + \bar{v}$
5. Return $\bar{x}$

$\bar{x} = \begin{bmatrix} \bar{y}_i \\ \bar{y}_{i-1} \end{bmatrix}$ where

i= months

$y_{i,j} = \dfrac{P_{i,j}^{\lambda} - 1}{\lambda}$ Box-Cox transformed

$j = 1,\ldots n$

n = number of raingauges

$P_{i,j}$ = valuation of rainfall in months *i* and site *j*.

In the generation of synthetic series of monthly rainfall: $\bar{y}_{i-1}$ are known and $\bar{y}_i$ are the unknowns.

In the generation of synthetic series of monthly rainfall: $\bar{y}_{i-1}$ are known and $\bar{y}_i$ are the unknowns.

9.2 Implementation of SMMAR(1) model

We developed a computational method (to see Annex C) for generating synthetic series of total monthly precipitation. The model used was the multivariate seasonal monthly auto-regressive of order 1 - SMMAR (1), applied to the values of rainfall transformed by Box-Cox transformation.

Model SMMAR (1) was calibrated with the existing monthly rainfall data for the period between jan/1944 and Dec/2005 in nine stations presented in Table 01-B (to see Annex B). Depending on the analysis performed were prepared four versions of the SMMAR (1), which can be used to generate synthetic series of total monthly precipitation for these stations.

The proposed versions for the model SMMAR (1) can be classified according to the parameter of the Box-Cox transformation and covariance matrices between series of total monthly rainfall (between stations for a given month and the previous month).

Model SMMAR (1) can be applied by using the following relationship:

$$y(i)=m(i)+v(i),\ \ i=1,...,k, \qquad (9.23)$$

where $y(i)$ is Box-Cox transformation of the total precipitation in a given month for the site i, in a collection (considered homogeneous) with series of rainfall for n sites; k is the number of sites (series of a given month) with values to be estimated; $n-k$ number of sites with series from the previous month (values considered known); $m(i)$, the average number of $Y(i)$; and $v(i)$ is determined by the expression:

$$v(i)=[z-l(i+1,i)v(i+1)-...-l(n,i)v(n)]/l(i,i),\ \ i=k,...,1, \qquad (9.24)$$

where z is a random number with zero mean and unit variance; $l(i,j)$, with i=1,...,n and j=1,...,i, are elements of a lower triangular matrix obtained by Cholesky factorization of the inverse of the covariance matrix of Y; the values of $v(i)$, for $i=k$+1,...,n, are known, can be initialized or have been determined by the model SMMAR(1) of previous month.

The transformation of Box-Cox variable X, to variable Y, considered normally distributed, is defined by:

$$y=\{\exp[\lambda \ln(x)]-1\}/\lambda,\ \ \text{where } \lambda\neq \qquad (9.25)$$
$$y=\ln(x),\ \ \text{where } \lambda=0,$$

where λ is a parameter that can be estimated by imposing the condition that the skew coefficient of y is zero (corresponding to the skew coefficient of the normal distribution).

Determination of SMMAR (1) parameters

Table 1-B (to see Annex B) presents the parameters of the series of total monthly precipitation transformed by Box-Cox transformation. The values of λ are estimated by the criterion of skew coefficient zero. The equation $Ca(Y)$=0 was solved using the method of simulated annealing (Lee and El-Sharkawi, 2008), estimated λ that minimizes $|Ca(Y)|$. Table 8 presents also the mean and standard deviation of Y, represented by $m(Y)$ and $s(Y)$, respectively, and also the results valid for λ=0 (log transformation). This result is used as the initial solution to the search performed by the method of simulated annealing.

Analyzing the results shown in Table 8, it is found that from 108 results, 100 of them are located in the range $0.16<\lambda<0.95$ and the rest (8 results) are negative and are in the range $-1<\lambda<-0.026$.

To estimate the parameters $m(Y)$ and $s(Y)$ of the normal distribution transformed by Box-Cox transformation, by the method of moments should respect the restrictions: $\lambda<-1$ and $\lambda>1$. All results obtained for λ made it impossible to apply the method of moments, for not comply with these conditions. For this reason it was decided to estimate the parameters $m(Y)$ and $s(Y)$ by applying the method of moments for the normal distribution of rainfall transformed by Box-Cox transformation. The covariance matrices were also estimated in this way. The solution considered, does not preserve the properties of the series of rainfall on the synthetic series generated, but preserves the characteristics of rainfall transformed by Box-Cox transformation.

We decided also to implement the model SMMAR (1) for the log-normal distribution (λ=0), with all parameters estimated by the method of moments. Applying this model the properties of precipitation series are preserved in the synthetic series generated. In the calibration of this version of model SMMAR (1), the inverse of the covariance matrices for the months of June, July, August, September and December resulted in matrices that are not positive definite, making impossible the implementation of Cholesky decomposition (Press *et al*., 1989). Making small changes in rainfall with values equal to zero, as recommended by Fiering (1968), the matrices are no longer inconsistent and were obtained the Cholesky decomposition.

In summary, the model SMMAR (1) was implemented for each month of the year for precipitation transformed by the logarithm and by Box-Cox transformation. Thus, for each model it is necessary a covariance matrix of 18 dimension for each month of the year (9 rainfall stations with the precipitation of the month and previous month). In the calibration phase of the SMMAR (1) model for the rainfall transformed by Box-Cox transformation, the inverse of the covariance matrices did not show inconsistencies.

The analysis was completed to produce two new models SMMAR (1) for the logarithmic and the Box-Cox transformations, developed on homogeneous groups of stations established through principal component analysis (Mardia et al., 1979). This approach was applied in order to reduce the size of the covariance matrices. For each matrix of correlations between total monthly of precipitation (one for each month of the year), with 18 dimension, we applied the principal component analysis. So 26 groups were determined, with dimensions ranging between 2 and 12, and the dimensions to 24 groups are smaller than 10.

The stations belonging to each group, according to the month of the year are listed in Table 2-B (to see Annex B). With the exception of month 3, where there is only one group, for the other months there are at least two groups. For each model SMMAR (1) the calibrations were performed with 26 matrices, with dimensions smaller than 12. By reducing the size of the matrices, we avoid the occurrence of inconsistencies in the implementation of the SMMAR (1) model with the log-normal distribution. However, with the reduction in the size of matrices to relax for the preservation of some covariances of monthly total precipitation (between stations and / or between a lag one monthly) that by the method of principal components analysis can be considered negligible.

9.3 Results of SMMAR(1)

A set of 2000 monthly synthetic series with 62 years (historical series size, in the observation period between 01/1944 and 12/2005) were generated, for each of the 9 rainfall stations used in this project. SMMAR(1) was applied, which considers the Box-Cox transformation for each month of the year.

By definition, the SMMAR(1) generated synthetic series preserve the historical series monthly characteristics and, for this reason, to analyze the generated series quality, significance tests were applied to evaluate the synthetic series annual characteristics.

Evaluated parameters are the annual total long term mean and variance and the 18 dimension correlation matrix, determined between the annual totals series (9 rainfall stations with precipitations in the current and previous years). The table in Annex D, for the three parameters, values of $100-\alpha$ (%) are presented, being α (%) the test significance level. Probabilistic distributions valid to each parameter were used to estimate α.

With the applied tests results, one can verify that: (i) annual totals long term means are preserved in all stations with $\alpha>9\%$ and in 8 stations with $\alpha>16\%$; (ii) annual totals variances are preserved in 4 stations with $\alpha>7\%$, in 1 station with $\alpha>4\%$, in 2 stations with $\alpha>1\%$ and in another 2 station with $\alpha<1\%$; (iii) of 153 calculated correlation coefficients, 130 are preserved with $\alpha>10\%$, 14 are preserved with $\alpha>6\%$, 4 coefficients with $\alpha>1\%$ and for only 5 coefficients, $\alpha<1\%$.

Due the aforementioned results, it is concluded that SMMAR(1) can be considered as totally satisfactory to produce annual and monthly total rainfall synthetic series, for all the stations considered in this work.

1 MONTHLY DISAGGREGATION MODEL (MDM)

This model is based on a monthly time step and is of the disaggregation type generating first annual precipitation and afterwards obtains monthly rainfall by disaggregation preserving the historic within year structure.

Using a monthly time step (i.e. generating monthly precipitation) avoids, within humid regions (like the La Plata Basin), to reproduce sequences of zero rainfall what is a rather complicated procedure. By selecting a disaggregation model one take advantage of the fact that in humid regions annual precipitation has an essentially normal distribution. This has the support of the Central Limit Theorem (annual precipitation is the sum of many independent rainfall events throughout the year) and also has been supported by many statistical tests.

10.1 Description of the model – annual precipitation

It has been assumed that total annual precipitation is not serially correlated, but cross correlation among rainfall stations was considered. Also annual precipitation has been assumed to be normally distributed what is supported both by empirical evidence (Pinto *et al*., 1976; Tucci, 1998; Homberger *et al*., 1998 and also by the Central Limit Theorem if one assumes that different rainfall events (covering several days) throughout the year are independent and there are at least 30 such events per year.

So generation of multisite annual precipitation series is reduced to the generation of multivariate normal distributed random numbers. In order to simplify the analysis, annual precipitation data are standardizing as:

$$x_i = \frac{P_i(t) - \overline{P}_i}{s_i} \qquad (10.1)$$

where:

$x_i(t)$ is the standardized annual precipitation at site *i*;

$P_i(t)$ is the annual precipitation at site *i* and year *t*;

$\overline{P}_i$ is the estimate of the long term mean annual precipitation at site *i*;

s_i is the estimate of the standard deviation of the annual precipitation at site *i*;

n is the number of years in the record.

In case of serially uncorrelated hydrologic variables they may be modeled by the equation using vector notation (Kelman, 1987):

$$\mathbf{x}(t) = \mathbf{B}\mathbf{z}(t) \qquad (10.2)$$

where:

$\mathbf{z}(t)$ is a vector of independent random variables of size k (number of sites);

$\mathbf{x}(t)$ is a vector of k cross-correlated random variables;

$\mathbf{B}$ is a matrix of coefficients.

In this model the variables (annual precipitation) are normally distributed and standardized (see equation 10.1) so that:

$$\begin{aligned} \mathbf{z}(t) &\approx N(0, I) \\ \mathbf{x}(t) &\approx N(0, \Sigma) \end{aligned} \qquad (10.3)$$

The model in equation (10.2) is a particular case of the more general multisite model:

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{z}(t) \quad (10.4)$$

discussed by Loucks *et al.*; (1981) for synthetic streamflow generation where the autocorrelation of the time series may be important.

Estimation of the matrix $\mathbf{B}$ is as follow. Multiplying equation (10.2) by its transpose we obtain:

$$\mathbf{x}(t)\mathbf{x}^T(t) = \mathbf{B}\mathbf{z}(t)\mathbf{z}^T(t)\mathbf{B}^T \quad (10.5)$$

Taking expectations and noting that $E(\mathbf{z}\mathbf{z}^T) = COV(\mathbf{z}) = \mathbf{I}$ results:

$$E(\mathbf{x}\mathbf{x}^T) = COV(\mathbf{x}) = \mathbf{B}\mathbf{B}^T \quad (10.6)$$

But because each $\mathbf{x}_i$ has zero mean and unit variance:

$$COV(\mathbf{x}) = \boldsymbol{\rho}(\mathbf{x}) \quad (10.7)$$

Hence the covariance matrix of $\mathbf{x}$ equals the correlation matrix. A matrix satisfying (10.6) may be used to generate $\mathbf{x}$. For simplicity we have choose the Cholesky decomposition of $\mathbf{BB}^{\mathrm{T}}$ resulting in a known triangular matrix for $\mathbf{B}$ (Kreyszig, 1999).

$$\mathbf{B} = \begin{bmatrix} a_1 & 0 & 0 & \dots \\ b_1 & b_2 & 0 & \dots \\ c_1 & c_2 & c_3 & \dots \\ \dots & \dots & \dots & \dots \end{bmatrix} \quad (10.8)$$

So equation (10.6) combined with equation (10.7) reads as:

$$\begin{bmatrix} a_1 & 0 & 0 & \dots \\ b_1 & b_2 & 0 & \dots \\ c_1 & c_2 & c_3 & \dots \\ \dots & \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} a_1 & b_1 & c_1 & \dots \\ 0 & b_2 & c_2 & \dots \\ 0 & 0 & c_3 & \dots \\ 0 & 0 & 0 & \dots \end{bmatrix} = \begin{bmatrix} a_1^2 & a_1b_1 & a_1c_1 & \dots \\ a_1b_1 & b_1^2+b_2^2 & b_1c_1+b_2c_2 & \dots \\ a_1c_1 & b_1c_1+b_2c_2 & c_1^2+c_2^2+c_3^2 & \dots \\ \dots & \dots & \dots & \dots \end{bmatrix} = \quad (10.9)$$

$$= \mathbf{R} = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \dots \\ \rho_{12} & 1 & \rho_{23} & \dots \\ \rho_{13} & \rho_{23} & 1 & \dots \\ \dots & \dots & .. & \dots \end{bmatrix} \quad (10.10)$$

Solving this system of equation results:

$$\begin{aligned} & a_1^2 = 1 \Rightarrow a_1 = 1 \\ & a_1b_1 = \rho_{12} \Rightarrow b_1 = \rho_{12} \\ & a_1c_1 = \rho_{13} \Rightarrow c_1 = \rho_{13} \\ & \dots\dots\dots\dots\dots\dots\dots\dots \\ & b_1^2 + b_2^2 = 1 \Rightarrow b_2 = \sqrt{1-\rho_{12}^2} \\ & \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \end{aligned} \quad (10.11)$$

Matrix $\mathbf{R}$ may be estimated from the historic record as follows. Organizing the historic record in matrix form:

$$\mathbf{x} = \begin{bmatrix} x_1(1) & x_1(2) & .... & x_1(n) \\ x_2(1) & x_2(2) & ... & x_2(n) \\ ... & ... & ... & ... \\ x_k(1) & x_k(2) & .... & x_k(n) \end{bmatrix} \qquad (10.12)$$

where $\mathbf{X_j}(t)$ denotes the standardized rainfall at site *j* in year *t*.

The product $\mathbf{xx}^\mathrm{T}$ results in:

$$\mathbf{xx}^T = \begin{bmatrix} \sum x_1^2(t) & \sum x_1(t)x_2(t) & .... \\ \sum x_1(t)x_2(t) & \sum x_2^2(t) & .... \\ ..... & ...... & ...... \end{bmatrix} \qquad (10.13)$$

So that

$$\frac{1}{n}\mathbf{xx}^T = \mathrm{cov}(\mathbf{x}) = \hat{\rho}(\mathbf{x}) \qquad (10.14)$$

The model is composed of two modules:

- Module 1 – to estimate parameters, basically mean and standard deviation at each site, matrix $\mathbf{B}$ to generate annual precipitation and hydrologic scenarios (referred later) to disaggregated annual precipitation into monthly precipitation.

- Module 2 – to generate concurrent monthly rainfall series at k sites and each series of length *n*.

The model performs sequentially the following steps:

1. Compute mean and variance at each site;

2. Standardize mean annual precipitation using equation (10.1)

3. Compute $\hat{\rho}(x)$ matrix using equation (10.14)

4. Compute matrix $\mathbf{B}$ using equation (10.11)

5. Compute disaggregation matrices as described in section

6. Generate *k* independent standard normal random number using a build in function of MatLab (random (*k*,*n*)). The results are *n* iid (independent and identically distributed) random vectors of size *k* organized as columns of a $k \times n$ matrix.

7; Transform the iid standard normal vector into cross correlated random vector using equation 10.2.

8. Obtain cross correlated annual precipitation series of length *n* by:

$$P_i(t) = x_i(t)s_i + \overline{P_i} \quad \mathrm{t} = 1,2,...\mathrm{n} \quad \mathrm{e} \quad \mathrm{i} = 1,2,...,\mathrm{k}$$

9. Disaggregate annual precipitation into monthly values using the method of hydrologic scenarios described in the next section.

Steps 1 to 5 are performed in module 1 and steps 6 to 9 in module 2.

10.2 Description of the model – monthly disaggregation

The most classical disaggregation model has been proposed by Valencia & Schaake (1972) extended by Mejia and Rousselle (1976). This model is described in detail in many classical texts (e.g. Loucks *et al.*, 1981; Kelman, 1987); and follows basically the equation:

$$\mathbf{m}(t) = \mathbf{Ax}(t) + \mathbf{Bz}(t) \qquad (10.15)$$

where:

$\mathbf{m}(t) = [m_{1,1}(t), m_{1,2}(t), \ldots m_{1,12}(t), m_{2,1}(t) \ldots, m_{k,12}(t)]^T$ vector $12k \times 1$ of monthly values of interest

$\mathbf{A} = (12k \times k)$ matrix of coefficients

$\mathbf{B} = (12k \times 12k)$ matrix of coefficients

$\mathbf{z}(t) = (12k \times 1)$ vector of iid standard normal variables

$\mathbf{x}(t) = (k \times 1)$ vector of annual values

Estimation of matrices $\mathbf{A}$ and $\mathbf{B}$ is discussed by Loucks *et al*. (1981).

Another disaggregation method is that of the so called hydrologic scenarios, which is used in this section. This method uses disaggregation coefficients computed from the historic record.

For each year of the historic record we may construct a matrix $\mathbf{D}_j$, $(\mathrm{j} = 1,2,\ldots,\mathrm{m})$ (*m* = length of historic record) with size $k \times 12$ (*k* = number of sites), whose elements are:

$$d_{im}(j) = \frac{P_{im}(j)}{P(j)_i} \qquad (10.16)$$

$P_{im}(t)$ precipitation of month *m*, site *i*, year *j*

$P_i(t)$ annual precipitation of site *i* year *j*

Groszewicz *et al.* (1991) have analyzed this disaggregation procedure for monthly streamflows and found that the results are equivalent to the Valencia & Schaake (1972). Therefore in the present model the hydrologic scenarios model has been used to generate series of monthly precipitation.

10.3 Validation of the model – annual precipitation

For the validation of the annual precipitation generation model some statistics of the synthetic series have been compared to those computed from the historic record for selected sites within the La Plata Basin. Table 10.1 lists the sites used in the validation procedure and figure 7.1 shows their geographical location within the La Plata Basin.

It have been generated 1000 series each one 62 year long (the same length as the historic record) and the following statistic have been computed: mean, standard deviation, skew coefficient, number of consecutive years below/above mean, maximum cumulative deficit for 80% of mean and correlation matrix of each synthetic series.

For each of these statistics the maximum, minimum and average value of the 1000 series has been compared and compared to the respective historic record values. The maximum cumulative deficit $D_{\max}$ (Gomide, 1975) has been computed by the following algorithm:

$$d(0) = 0$$

$$d(t) = \max\begin{cases} 0 \\ d(t-1) - P(t) + 0{,}8\overline{P} \end{cases} \quad \text{with} \quad \mathrm{t} = 1,2,\ldots,\mathrm{n} \qquad (10.17)$$

$$\mathrm{D}_{\max} = \max d(t)$$

This statistic has an important effect on flow regulation studies because influences significantly hydropower generation in well regulated systems, such as the Brazilian interconnected system.

All these values are listed on table 10.2 below.

Table 10.1– Sites for model validation

BASIN	CODE	NAME/SITE NUMBER	COORDINATES LAT	LONG	ALTITUDE (m)	PERIOD INITIAL	END
Alto Paranaíba	01847000	Monte Carmelo (1)	-18:43:14	-47:31:28	880	31/12/1941	31/12/2001
Baixo Paranaíba	01848000	Monte Alegre de Minas (2)	-18:52:20	-48:52:10	730	31/01/1941	31/12/2001
Alto Grande	02145007	Usina Couro do Cervo(3)	-21:20:37	-45:10:13	813	01/01/1941	01/12/2000
Baixo Grande	02047017	Franca (4)	-20:31:0	-47:24:0	1020	01/05/1935	01/07/2000
Tietê	02148128	Fazenda Barreirinho (5)	-21:54:0	-49:0:0	450	30/11/1937	31/03/2000
Paranapanema	02349033	Tomazina (6)	-23:46:0	-49:57:0	483	31/07/1937	31/12/2001
Iguaçu	02651000	União da Vitória (7)	-26:13:41	-51:4:49	736	28/02/1938	31/12/2001
Uruguai	02851014	Lagoa Vermelha (8)	-28:13:19	-51:30:45	842	31/01/1931	31/12/2005
Paraná	02151035	Caiuá (9)	-21:50:0	-51:59:0	350	31/01/1942	31/07/2000

Table 10.2 – Comparison of selected statistics for validation

1000 synthetic series				**Historic record**
MEAN				
site	**minimum**	**average**	**maximum**	**Observed**
Site 1	1285.8	1457.7	1639.9	1458.6
Site 2	1404.3	1511.2	1612.3	1512
Site 3	1317.3	1448.1	1584.2	1448.2
Site 4	1556.3	1705.1	1816.3	1705.9
Site 5	1195.2	1302.3	1418.1	1303.4
Site 6	1317.7	1424.9	1527.6	1425.1
Site 7	1662.1	1776.1	1892	1774.2
Site 8	1748.7	1922.5	2130.1	1918.1
Site 9	1150.9	1279.7	1413.2	1278.4
STANDARD DEVIATION				
Site 1	307.6594	409.2315	531.0857	412.253
Site 2	170.5037	234.86	301.6179	235.696
Site 3	264.1306	348.3539	450.7311	349.344
Site 4	230.2892	305.4436	403.3322	305.883
Site 5	172.4308	242.4982	314.8108	244.552
Site 6	178.2483	231.9033	296.6224	233.348
Site 7	243.5975	350.7588	458.5019	351.719
Site 8	377.285	494.4545	657.554	497.521
Site 9	221.317	301.5657	385.8833	302.075
SKEW COEFFICIENT				
Site 1	-1.0599	0.0043	0.8159	1.6096
Site 2	-1.0523	-0.0001	0.9629	0.1819
Site 3	-1.0141	-0.0067	0.9995	1.1001
Site 4	-1.1086	-0.0018	1.0097	0.0775
Site 5	-1.389	-0.0102	1.0382	-0.013
Site 6	-1.0797	0.0002	0.9785	0.2695
Site 7	-1.2794	0.0051	0.8888	0.8228
Site 8	-1.09	-0.0038	1.5296	-0.1655
Site 9	-0.9446	-0.0041	0.9601	0.6718
CONSECUTIVE YEARS BELOW AVERAGE				

Site 1	2	5.255	12	5
Site 2	2	5.385	13	8
Site 3	2	5.381	17	6
Site 4	2	5.223	13	7
Site 5	2	5.297	13	5
Site 6	2	5.386	13	7
Site 7	2	5.347	13	7
Site 8	2	5.303	14	6
Site 9	2	5.343	15	7
CONSECUTIVE YEARS ABOVE AVERAGE				
Site 1	2	5.15	14	5
Site 2	2	5.353	13	3
Site 3	2	5.314	14	4
Site 4	2	5.345	14	5
Site 5	2	5.313	12	4
Site 6	2	5.4	14	6
Site 7	3	5.376	14	5
Site 8	2	5.363	12	4
Site 9	2	5.327	13	6
MAXIMUM CUMULATIVE DEFICIT				
Site 1	290.3	854.1	2884.6	344.7
Site 2	30.2	300.6	1477.1	443.1
Site 3	171.7	638.7	1807.1	421
Site 4	69.6	425.1	1397.8	521.8
Site 5	86.7	345	903	382.6
Site 6	0	284.2	825.8	242
Site 7	31.4	524.7	1307.4	388.3
Site 8	262.5	959.7	2506.1	1310.8
Site 9	156.3	567.4	2746.2	457.3

CORRELATION MATRIX OF HISTORIC RECORD								
1	0.110	0.355	0.266	0.275	0.233	-0.012	-0.224	0.093
0.110	1	0.495	0.509	0.219	0.170	0.081	0.060	0.252
0.355	0.495	1	0.535	0.271	0.194	0.155	-0.001	0.053
0.266	0.509	0.535	1	0.252	0.196	0.259	0.131	0.307
0.275	0.219	0.271	0.252	1	0.452	0.249	0.089	0.261
0.233	0.170	0.194	0.196	0.452	1	0.585	0.363	0.350
-0.012	0.081	0.155	0.259	0.249	0.585	1	0.596	0.442
-0.224	0.060	-0.001	0.131	0.089	0.363	0.596	1	0.185
0.093	0.252	0.053	0.307	0.261	0.350	0.442	0.185	1

We can see from Table 10.2 that for all statistics, except the skew coefficient, the value computed from historic record is well within the range of the values of the synthetic series and in most cases close to the average from 1000 series computed. This shows that the synthetic series reasonably preserve well most of the statistics of the historic record in terms of annual precipitation.

Only for skew coefficient there are two cases were the value computed from historic records are outside of the interval of the synthetic series. This happens at sides 1 and 3 corresponding to locations near the northeastern limit of the basin where, perhaps, the normality assumption does not apply because of a strong dry season (from April to October) so that not enough precipitation events occur throughout the year.

In spite of the fact that the synthetic series show almost no skew (because of the normality assumption) and the historic record is generally skewed, the statistics more related to the proposed usage of the model (analysis of hydropower output) are well represented by the synthetic series.

10.4 Validation of the model – monthly precipitation

The monthly precipitation series obtained by disaggregation of the annual values have been analyzed for the same 9 sites used in the annual validation process.

There have been computed seasonal values for the mean, standard deviation and autocorrelation. The results are shown in Annex E for both the synthetic series and the historic record. For the synthetic series average, maximum and minimum values have been computed and are compared to the historic record.

The statistics in Annex E for the monthly series are well related to the historic values at mean, standard deviation and lag 1 autocorrelation. These statistics are always within the range of synthetic values and in most cases are close to the mean synthetic values. In view of the validation results for both annual and monthly results, it is believed that this model is well suited to generate synthetic series of monthly rainfall series within the La Plata Basin, and particularly for the South-Southeastern region of Brazil. It should be emphasized that arid or semi-arid regions are not well represented by this model because the normality assumption for annual rainfall may not apply. Disaggregation by hydrologic scenarios seems to be well suited at the region of interest (La Plata Basin) producing monthly rainfall series preserving relevant characteristics of the historic series. Also the accumulated maximum deficit, which is an important characteristic for dependable energy simulations, is consistent with the historic record. Annex F presents the complete program written in MATLAB programming language. Annex G shows a sample case of program input and output.

11 DAILY UNIVARIATE MODEL - DUM

This section aims to explain the construction of a daily scale rainfall generator. Apart of monthly and annual scales, series of daily records contain many “zeros”, representing days without rain. This fact brings higher complexity to the model developed. Therefore, researches willing to work with daily scales, structure their generation models in two distinct phases: occurrences determination and calculation of amounts of rain in days considered wet.

The model to be presented refers to a single site simulation and follows a Wilks-type parametric formulation (Wilks, 1998): occurrences are determined with first order and two states Markov chains and amounts are calculated using a three parameters mixed exponential probabilistic distribution. Good results obtained in Wilks’ study are referred to rainfall stations located in the New York State, USA. It is clear that physical and meteorological characteristics of those stations differ to the ones in La Plata Basin. However, as will be shown, the model was able to reproduce quite well the rainfall behavior in the present study area.

Even with the uncertainty about the model response to La Plata Basin climate, it was decided that the main structure of Wilks’ model would no be changed. Yet, tests to determine the optimum order of Markov chain and the adjustment of mixed exponential distribution are found in this text. The computer language chosen to develop the model was Matlab (R13, The Mathworks Inc, 2000, under license).

11.1 Description of the model

As said in the introduction of this item, the model to be used here is a single site Wilks-type model (Wilks, 1998). As a common parametric two part model, occurrences are determined regardless of amounts. Techniques used to achieve this work’s objectives are the subject of the present section.

Precipitation occurrences determination

As a usual method in temporal series evaluation, stochastic processes are applied. We can define stochastic process as a sequence of events governed by probabilistic laws. Markovian models are counted as one efficient stochastic process which main property is that future events of a system rely only on the actual states and never on past ones. In other words, the system has no “memory” that allows it to use past information for current behavior. When applied to discrete time intervals, markovian models are called Markov chains; random variables are represented as $\{X_0, X_1, X_2, ..., X_n\}$, or observations in X state, referred to time $T = \{0,1,2,...,n\}$, respectively.

Clarke and Disney (1979) define the conditioned probability distribution function of a Markov chains as:

$$\Pr\{X_{n+1} = x_{n+1} \mid X_0 = x_0, X_1 = x_1, ..., X_n = x_n\} = \Pr\{X_{n+1} = x_{n+1} \mid X_n = x_n\} \quad (11.1)$$

The element in the right hand of the equation (11.1) is called transition probability. Is denoted by:

$$p_{ij}(n) = \Pr\{X_{n+1} = j \mid X_n = i\}, \qquad n = 0,1,2,... \quad (11.2)$$

Matrix P formed by the elements p_{ij}, is known as transition matrix, or chain matrix:

$$P = (p_{ij}) = \begin{vmatrix} p_{00} & p_{01} & p_{02} & \cdots \\ p_{10} & p_{11} & p_{12} & \cdots \\ \cdots & \cdots & \cdots & p_{nn} \end{vmatrix} \quad (11.3)$$

Which elements respect $0 \le p_{ij} \le 1$ and $\sum_j p_{ij} = 1$.

Equations (11.1), (11.2) and (11.3) summarize the structure of a first order Markov chain. This means that a process governed by these kind of structure takes into account information in times *T=n* and *T=n-1*. It is also possible to have superior Markov chains' orders; a second order process, for example, consider events in times *T=n, T=n-1* and *T=n-2*. Third order Markov chains, in turn, use events in times *T=n, T=n-1, T=n-2* and *T=n-3*. The mechanism for even superior orders is identical; however it is clear that the complexity of the stochastic process grows significantly.

The application of this stochastic process to rainfall occurrences refers to the events of wet/dry days, in the local *k*, day *t*, as such:

$$X_t(k) = \begin{cases} 0, \text{for day } t \text{ dry, in local } k; \\ 1, \text{for day } t \text{ wet, in local } k \end{cases} \quad (11.4)$$

Construction of Markov chain begins with the definition of the transition probabilities:

$$\begin{aligned} &\Pr\{X_t(k) = 1 \mid X_{t-1}(k) = 0\} = p_{10}(k); \\ &\Pr\{X_t(k) = 1 \mid X_{t-1}(k) = 1\} = p_{11}(k) \end{aligned} \quad (11.5)$$

This representation is interpreted as $p_{01}(k)$ indicating a dry day preceded by a wet day and $p_{11}(k)$ indicating a wet day preceded by another wet day. Process continues defining the complementary conditional transition probabilities:

$$\begin{aligned} &p_{00}(k) = 1 - p_{10}(k); \\ &p_{01}(k) = 1 - p_{11}(k) \end{aligned} \quad (11.6)$$

With the definitions in equations (11.5) and (11.6), the transition matrix can be built:

$$P = p_{ij} = \begin{vmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{vmatrix} \quad (11.7)$$

These transition probabilities are calculated counting the elements present in the historical records of the local *k*. Equation (11.8) details it:

$$\begin{cases} p_{00}(k) = \dfrac{N_{00}(k)}{N_{00}(k)+N_{10}(k)} = \dfrac{N_{00}(k)}{N_0(k)} \\ p_{10}(k) = \dfrac{N_{10}(k)}{N_{00}(k)+N_{10}(k)} = \dfrac{N_{10}(k)}{N_0(k)} = 1 - p_{00}(k) \\ p_{11}(k) = \dfrac{N_{11}(k)}{N_{10}(k)+N_{11}(k)} = \dfrac{N_{11}(k)}{N_1(k)} \\ p_{01}(k) = \dfrac{N_{01}(k)}{N_{10}(k)+N_{11}(k)} = \dfrac{N_{01}(k)}{N_1(k)} = 1 - p_{11}(k) \end{cases} \quad (11.8)$$

where the elements N represent the number of wet or dry days, according with the aforementioned convention.

Following Wilks (1998), construction of synthetic series of occurrences are made using the elements p_{10} and p_{11}. Another probability is defined (p_C) which will be used to determine one of the new states of the series. This probability (called critical probability) assumes the values p_{10} and p_{11}.according with the evolution of the process. Uniform random numbers (u) are used to execute comparisons that will define the initial state (first day of the series) and the other states. Figure 11.1 shows the four steps required to the generation of daily scale synthetic occurrences series. First step is executed once and the others are executed as many times as the size of the series to be generated

In order to verify the optimum order of the Markov chain used in this study, two tests are applied: Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978) are common procedures in the literature to this task. Both are likelihood based estimators, applied to the transition probabilities of each series. Wilks (2006, p. 351) defines the likelihood functions for s states, and zero, one and two orders chains as:

$$\begin{cases} L_0 = \sum_{j=0}^{s-1} N_j(k).\ln\left[p_j(k)\right] \\ L_1 = \sum_{i=0}^{s-1}\sum_{j=0}^{s-1} N_{ij}(k).\ln\left[p_{ij}(k)\right] \\ L_2 = \sum_{h=0}^{s-1}\sum_{i=0}^{s-1}\sum_{j=0}^{s-1} N_{hij}(k).\ln\left[p_{hij}(k)\right] \end{cases} \quad (11.9)$$

where N represents the number of days in historical records with transitions i, j or h, and p represents the transition probabilities.

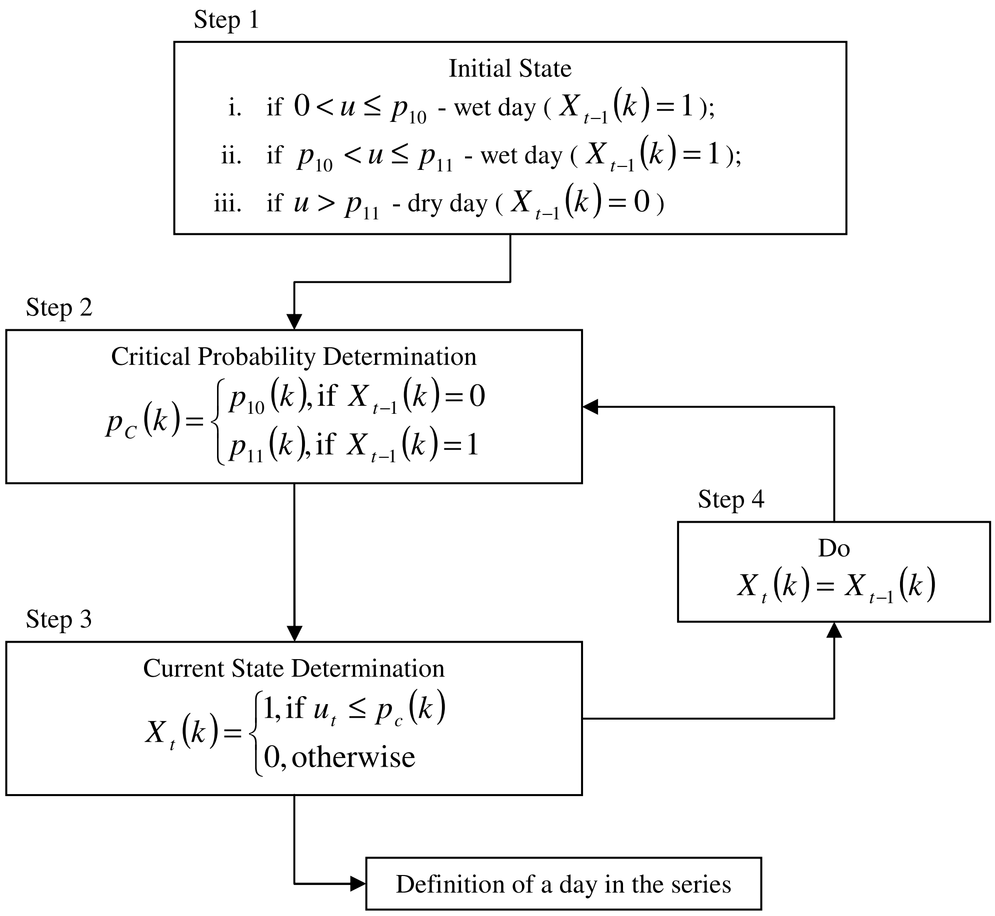


Figure 11.1 – Scheme for rainfall occurrences determination

Physical interpretation of diverse orders chains are the same as first orders'. In a zero order chain, for example, notation N_0 represents the sum of all dry days in the original series. In a second order chain, in turn, notation N_{011} represents the sum of all dry days preceded by two rainy days. This interpretation has obvious extension to the other orders.

Once the parameters are calculated, the criteria can be applied. Optimum order of the model is obtained through an equation that exhibits the goodness of fit and a penalty that increases proportionally with the numbers of parameters to be used. For the Akaike Information Criterion (AIC) (Akaike, 1974), the equation is:

$$AIC(m) = -2L_m + 2s^m(s-1) \tag{11.10}$$

And for the Bayesian Information Criterion (BIC) (Schwarz, 1978):

$$BIC(m) = -2L_m + s^m(\ln n) \tag{11.11}$$

For both equations, m represents the Markov chain's order to be tested, s the number of states and n the size of the sample.

Note that the criteria are similar, differing only on the penalty considered. However, in terms of results, the two estimators can diverge. Katz (1981) analyzed the statistical properties of both criteria when applied to Markov chains. As a conclusion, AIC estimator proved to be biased; in a great number of cases, there was a tendency in overestimate the order of the chain, independently of the size of the sample. Therefore, the author considered AIC inconsistent and strongly recommended the use of BIC estimator.

Nevertheless, further researchers used both criteria in their studies (Deni *et al.*, 2008; Jimoh and Webster, 1996; Gregory *et al.*, 1992). The intention was always to compare the verdicts of the estimators.

In the present work, both tests are also applied, limited to second order chains. As done in the aforementioned studies, a comparison between the two criteria is also intended here.

11.2 Precipitation amounts determination

As in Wilks (1998), the statistical distribution used to determinate the precipitation amounts in rainy days is the three parameters mixed exponential. As attested in Wilks (1998) and Roldán and Woolhiser (1982b) this probabilistic model presented substantially better fits than other distributions.

Mixed exponential density probability function is given by:

$$f_R[r(k)] = \frac{\alpha(k)}{\beta_1(k)}\exp\left[\frac{-r(k)}{\beta_1(k)}\right] + \frac{1-\alpha(k)}{\beta_2(k)}\exp\left[\frac{-r(k)}{\beta_2(k)}\right] \qquad (11.12)$$
$$\beta_1(k) \geq \beta_2(k) > 0, \quad 0 < \alpha(k) \leq 1$$

Accumulated probability function, in turn, is given by:

$$F_R[r(k)] = 1 - \alpha(k)\exp\left[\frac{-r(k)}{\beta_1(k)}\right] - \left\{[1-\alpha(k)]\exp\left[\frac{-r(k)}{\beta_2(k)}\right]\right\} \qquad (11.13)$$

where R represents the random variable, r the value assumed by the random variable (rain amounts) and α, β_1 and β_2 are the parameters. All the unknown variables are related to a specific local k.

From equation (11.12) is easy to see that the mixed distribution can be seen as a sum of two simple exponential distributions (one parameter each), intermediated by a probability factor. In fact, the reduction of this equation to a simple exponential distributions can happen, when $\beta_1 = \beta_2$, $\alpha = 0$ or $\alpha = 1$.

Similarly to the probability density function, statistical properties of the mixed function also depend of the probabilistic parameter α. Thereby, mean and variance are expressed, respectively:

$$\mu = \alpha.\mu_1 + (1-\alpha)\mu_2 \qquad (11.14)$$

$$\sigma^2 = \alpha.\sigma_1^2 + (1-\alpha).\sigma_2^2 + \alpha.(1-\alpha).(\mu_1 - \mu_2)^2 \qquad (11.15)$$

The method for parameters estimation is the Maximum Likelihood, chosen based on successful previous studies found in the literature. Compared to other methods, this is the one that has the best asymptotical properties, suitable for big samples as the ones used in daily scale events studies (Foufoula-Georgiou and Lettenmaier, 1987; Grondona *et al.*; 2000).

Basically the method aims to maximize the likelihood function. Cramér (1974, p. 499) defines it as:

$$L(x_1,\ldots,x_n;\theta,\lambda) = \prod_{i=1}^{n} f(x_i;\theta,\lambda) \qquad (11.16)$$

where $(x_1,\ldots,x_n)$ are the random variables and (θ,λ) the distribution's parameters. To help the deductions and further calculations, it is common to apply natural logarithms to the equations, without any prejudice to the main method. Naturally, in order to maximize the likelihood function, differentiation is required, with respect to the parameters. In equation (11.16), however, two parameters are involved; so a system of partial derivatives must be constructed:

$$\begin{cases} \dfrac{\partial \log L}{\partial \theta} = 0 \\ \dfrac{\partial \log L}{\partial \lambda} = 0 \end{cases} \qquad (1.17)$$

When applied to the mixed exponential distribution though, the Maximum Likelihood method in its traditional formulation (equations 11.16 and 11.17) could not produce straight estimations. The justification is shown below, in the assembly of the likelihood equation:

$$L(r;\alpha,\beta_1,\beta_2)=\prod_{i=1}^{n}\left\{\frac{\alpha(k)}{\beta_1(k)}\exp\left[\frac{-r(k)}{\beta_1(k)}\right]+\frac{1-\alpha(k)}{\beta_2(k)}\exp\left[\frac{-r(k)}{\beta_2(k)}\right]\right\} \tag{1.18}$$

Applying logarithms:

$$\ln L(r;\alpha,\beta_1,\beta_2)=\sum_{i=1}^{n}\ln.\left\{\frac{\alpha(k)}{\beta_1(k)}\exp\left[\frac{-r(k)}{\beta_1(k)}\right]+\frac{1-\alpha(k)}{\beta_2(k)}\exp\left[\frac{-r(k)}{\beta_2(k)}\right]\right\}=$$

$$=\sum_{i=1}^{n}\left\{\ln[\alpha(k)]-\ln[\beta_1(k)]-\frac{r(k)}{\beta_1(k)}+\ln[1-\alpha(k)]-\ln[\beta_2(k)]-\frac{r(k)}{\beta_2(k)}\right\}=$$

$$=n\ln[\alpha(k)]-n\ln[\beta_1(k)]-\frac{\sum_{i-1}^{n}r(k)}{n\beta_1(k)}+n\ln[1-\alpha(k)]-n\ln[\beta_2(k)]-\frac{\sum_{i-1}^{n}r(k)}{n\beta_2(k)} \tag{11.19}$$

Equation (11.19) represents the likelihood function for the mixed exponential distribution. For the estimations of the three parameters, partial derivatives are required. Once deducted, equations are equated to zero to obtain the maximum of the function:

$$\begin{cases}\dfrac{\partial\ln L}{\partial\alpha(k)}=\dfrac{n}{\alpha(k)}+\dfrac{n}{\alpha(k)-1}=\dfrac{[2.\alpha(k)-1].n}{\alpha(k)^2-\alpha(k)}=0\\[2ex]\dfrac{\partial\ln L}{\partial\beta_1(k)}=-\dfrac{n}{\beta_1(k)}+\dfrac{\sum_{i-1}^{n}r(k)}{n\beta_1(k)}=-\dfrac{n\beta_1(k)-\sum_{i-1}^{n}r(k)}{\beta_1^2}=0\\[2ex]\dfrac{\partial\ln L}{\partial\beta_2(k)}=-\dfrac{n}{\beta_2(k)}+\dfrac{\sum_{i-1}^{n}r(k)}{n\beta_2(k)}=-\dfrac{n\beta_2(k)-\sum_{i-1}^{n}r(k)}{\beta_2^2}=0\end{cases} \tag{11.20}$$

Analyzing equations (11.20) it is clear that no results can be produced simply solving the system. Parameters are implicit in the equations, so is necessary to use another method to determinate the estimatives.

The solution found is a technique called EM algorithm, which original paper was written by Dempster, Laird and Rubin (1977). In addiction to estimate the needed variables, this technique is quite convenient, because its formulation was structured so eventual missing values in original series do not interfere in the final result (Wilks, 2006, p. 117). This fact is particularly attractive here since the meteorological stations present in the study have some days without registers.

It is important to say that the EM algorithm was not developed exclusively to estimate parameters of probabilistic distributions. Wilks (2006, p. 117) also reinforce that the expression "algorithm" is not fully appropriate, considering that this term expresses an objective procedure. Instead, this technique is a "conceptual approach that needs to be molded to particular problems". Thus it can be molded to a problem whose objective is the estimations of statistical parameters through the Maximum Likelihood Method.

EM algorithm consists in an iterative procedure with two distinct phases: Expectance and Maximization. The first one, or Expectance, calculates the *n* conditional probabilities attached to the mixed exponential distributions and each one of the observations:

$$P\left(f_{1,2} \mid r_i, k\right) = \frac{\alpha(k).f_1(r_i, \beta_1, k)}{\alpha(k).f_1(r_i, \beta_1, k) + [1-\alpha(k)].f_2(r_i, \beta_2, k)}, \qquad i = 1, 2, \ldots, n \qquad (11.21)$$

Functions f_1 and f_2 refer to both simple exponential distributions contained in the mixed one, which parameters are β_1 and β_2, respectively. The first update of α parameter is then obtained:

$$\alpha^*(k) = \frac{1}{n}\sum_{i=1}^{n} P\left(f_{1,2} \mid r_i, k\right) \qquad (11.22)$$

Second phase, or Maximization, is nothing more than the application of the concept of Maximum Likelihood. The first update of the parameters β_1 and β_2 are calculated:

$$\begin{aligned} \beta_1^*(k) &= \frac{1}{n.\alpha^*(k)} \sum_{i=1}^{n} P\left(f_{1,2} \mid r_i, k\right).r_i(k) \\ \beta_2^*(k) &= \frac{1}{n.[1-\alpha^*(k)]} \sum_{i=1}^{n} \left[1 - P\left(f_{1,2} \mid r_i, k\right)\right].r_i(k) \end{aligned} \qquad (11.23)$$

Implementation of the algorithm is summarized in the initial attributions of values (guesses) to the three parameters α, β_1 and β_2. Equations (11.21) and (11.22) are used to the first update of α; equations (11.26) obtain the update for the means β_1 and β_2. With the new values, the process starts again and continues until convergence.

Still according to Wilks (2006, p. 119) initial guesses of the values do not required accurate precision, because EM algorithm converge independent of them. But, in order to improve the utilization of the model, initial guesses are obtained automatically from Moments Method, another method of estimation, less accurate in terms of asymptotical properties than the exposed here. The formulation is taken directly from the study of Rider (1961):

$$\begin{cases} \alpha(k).\beta_1(k) + [1-\alpha(k)].\beta_2(k) = m_1 \\ \alpha(k).\beta_1^2(k) + [1-\alpha(k)].\beta_2^2(k) = \dfrac{m_2}{2} \\ \alpha(k)\beta_1^3(k) + [1-\alpha(k)].\beta_2^3(k) = \dfrac{m_3}{6} \end{cases} \qquad (11.24)$$

where m_1, m_2 e m_3 represents the first, second and third statistical moments (mean, variance and skew coefficient, respectively). Solving equations (11.24), arrives:

$$6.\left(2.m_1^2 - m_2\right).\beta_j^2(k) + 2.(m_3 - 3.m_1.m_2).\beta_j(k) + 3.m_2 - 2.m_1 m_3 = 0 \qquad (11.25)$$

The two roots of polynomial (11.25) are referred to β_1 and β_2. Value of α is obtained through:

$$\alpha(k) = \frac{[m_1 - \beta_2(k)]}{[\beta_1(k) - \beta_2(k)]} \qquad (11.26)$$

Once the needed parameters for a specific location are estimated, rainfall amounts can be calculated. The objective is now the determination of a random variable $R(k)$ corresponding to the current probabilistic function. Therefore, the method is basically the generation of exponential distributed random variables. Wilks (2006, p. 123) describes this method as the inversion of the cumulated density probabilistic function:

$$F_R(r;\beta)=\int_0^{r(k)}\frac{1}{\beta(k)}\exp\left(-\frac{x}{\beta(k)}\right)=1-\exp\left(-\frac{r(k)}{\beta(k)}\right) \quad (11.27)$$

Note that in the equation (11.27) involves only a simple one parameter exponential distribution. It is important to emphasize that, in the generation of the amount of rain on a specific day, just one of the means β_1 and β_2 is used. So, roughly speaking, the three parameters mixed distribution reduces to a one parameter exponential in the final determination of the amount of rain precipitated.

Wilks (1998) exhibit the result of the inversion method applied to the exponential case. Rainfall amounts are calculated as:

$$r_i(k)=r_{\min}-\beta(k).\ln(v_i) \quad (11.28)$$

where $r_{\min}$ represents the minimal quantity of precipitation for a day to be considered wet and v_i is a uniformly distributed random number, within the interval (0,1]. The choice between the means β_1 and β_2 is done from the generation of another uniform random number (u_i). If $u_i \le \alpha$,, the mean β_1 is picked; if $u_i > \alpha$, the picked mean is β_2.

Generation model is completed with the concatenation of the occurrences and amounts determination, as shows equation (11.29):

$$Y_i(k)=X_i(k).r_i(k) \quad (11.29)$$

where $X_i(k)$ assumes the values 0 or 1, depending of the results of the occurrences process, explained in the last section.

As said in the introduction of this section, despite the choice of the mixed exponential distribution, its performance in the La Plata Basin area is unknown. Therefore, a small analyze of goodness of fit is done, independently of the main study. As in the AIC and BIC criteria application, the results will not imply in changes on the main structure of the model.

As a first approach, verification of the probabilistic fits is not made with application of tests, but simply with visual analyses based on the probabilistic curves. Mixed exponential distribution is compared to the two parameter Gamma distribution, another function widely used for rainfall generation purposes. Its density probabilistic function is written as follows (Wilks, 2006, p. 96):

$$f_X(x)=\frac{(x/\beta)^{\alpha-1}\exp(-x/\beta)}{\beta\Gamma(x)},\quad x,\alpha,\beta>0 \quad (11.30)$$

The distribution parameters (α and β) are calculated with the expressions (Botelho and Morais, 1999):

$$\begin{cases}\alpha=\dfrac{1+\sqrt{1+4A/3}}{4A}\\ \beta=\dfrac{\overline{X}}{\alpha}\end{cases} \quad (11.31)$$

where

$$A=\ln\overline{X}-\frac{1}{n}\sum_{j=1}^{n}\ln x_j \quad (11.32)$$

and $\overline{X}$ represents the precipitated mean in the period, x_j the rainfall amount in the event and n the number of years of the sample.

Two are the graphs constructed: the first one is a traditional comparison between the empirical distributions and its respective adjustments, according to the cited models. The probabilistic classes (or levels) follow the well known Weibull formulation:

$$F_X(i) = \frac{i}{n+1} \tag{11.33}$$

where i represents the current observation and n the total number of elements in the sample. Parsing the constructed theoretical graphs, the best fit will be the one whose curve most approximates the empirical distribution.

The second graph is a direct comparison between probabilities. Also known as P-P plot (Wilks, 2006, p. 114), this representation computes the probabilistic levels (again using equation 11.33) as a function of the analyzed distribution. The result is a graph with axis of the same dimension ($0 < i < 1$), whose best fit as being the one that approaches the 1:1 diagonal line.

After the visual verifications, quality of the adjustments is evaluated formally, through employment of two classical tests: Chi-square (χ^2) and Kolmogorov-Smirnov. Both are widely used in the literature justly to the goodness of fit examination. The tested hypotheses for the tests are:

$$\begin{cases} H_0 = \text{there are no differences between the tested groups} \\ H_1 = \text{there is, at least, one difference between the tested gropus} \end{cases}$$

Chi-square test (χ^2) is based on the separation of the data in classes (or bins) and further comparison among the observed values and expected ones in each class. Its statistic is calculated as shows equation (11.34) (Kite, 1977):

$$\chi^2_{calc} = \sum_{j=1}^{k} \frac{\left(O_j - E_j\right)^2}{O_j} \tag{11.34}$$

Equation (11.34) follows a chi-square distribution with $k-1$ degrees of freedom, where O_j is the number of observed events in each class j and E_j is the number of expected events in the same class, according to the theoretical distribution under test. The verdict is known through the comparison of the calculated value in (11.34) and the tabled value of χ^2 (with significance level α and $k-1$ degrees of freedom). If $\chi^2_{calc} \le \chi^2$, null hypothesis is accepted and the probabilistic model is considered suitable.

The definition of the number of classes used in the test is subjective; Wilks (2006, p. 147) writes that classes with limited number of events may be avoided. In the present work, the number of classes was calculated according to formulation found in Kite (1977, p. 159):

$$Classes = \overline{X} + \left(\frac{\chi^2 . \gamma}{4} - \frac{2}{\gamma}\right) . S \tag{11.35}$$

where $\overline{X}, S$ and γ are, respectively, the mean, state deviation and skew coefficient of the sample; χ^2 is the tabled chi-square value for level of significance P and $8/\gamma^2$ degrees of freedom.

According to Kite (1977, p. 160) and Wilks (2006, p. 146), split the sample in classes, especially when working with continuous probabilistic distribution, can cause an undesirable loss of information. So, authors recommend the application of a second test: Kolmogorov-Smirnov. With a simple formulation, it searches for the highest deviation between the theoretical and empirical distributions. These deviations, or differences, are calculated for each element of the sample through equation (11.36):

$$D_n = máx\left|F_X(i) - F_X(x)\right| \tag{11.36}$$

where $F_X(i)$ is the empirical cumulative density probabilistic function (calculated with equation 11.33), $F_X(x)$ the theoretical cumulative density probabilistic function and D_n is the maximum difference found. When compared to a critical value (D_{crit}) the verdict is known. There are tables to the diverse critical values of D_{crit}; because they are dependent of the number of the elements of the sample (different in each rainfall station), a generic equation proposed by Stephens (1974 *apud* Wilks, 2006, p. 148) is used:

$$D_{crit} = \frac{K_\alpha}{\sqrt{n} + 0{,}12 + 0{,}11.\sqrt{n}} \quad (11.37)$$

where K_α assumes 1.224, 1.358 or 1.628, for the significance levels of 10%, 5% and 1% respectively and n is the number of the elements of the sample. Null hypothesis is accepted if $D_n \leq D_{crit}$.

It is expected that these four analyses, together with the application of the AIC and BIC criteria, provide a better notion of the performance of the generation model used, when applied to the present study area.

11.3 Model validation

When modeling temporal series related to natural phenomena, it is assumed that the system is ruled by a deterministic process. We can say that different events of natural series follow a specific probabilistic distribution, inside the main mechanism.

Thus, working with the synthetic series generation usually implies in producing a large number of them. The entire set of generated series must be able to reproduce the same statistical characteristics of the original ones, used to develop the model. Indistinguishable series are also desirable, or their application on the simulation of distinct scenarios would not make sense.

To validate a model is common the calculation of diverse statistical properties of the generated series and comparison with the same properties of the original records. However, Kelman (1987, p. 363) states that "when a property is used in the determination of a model's parameter, this property is automatically preserved, by construction." So, when validating a model, it is important the analysis of diverse factors, rather related to what this model is proposed to do. In many cases, this verification can be done simply through a visual analysis over the results produced.

In the present section, validation process follows a collection of procedures taken from many studies (Richardson, 1981; Foufoula-Georgiou e Lettenmaier, 1987; Haan, Allen e Street, 1976; Chin, 1977; Harrold, Sharma e Sheather, 2003a and 2003b; Lima, 2004; Liao, Zhang e Chen, 2004). These studies are representative from the validation point of view; techniques used by their respective authors are also employed in many other existent studies.

Firstly, data from the construction of the Markov chains is analyzed. All the parameters of the chain (transition probabilities) and the verdicts of the AIC and BIC tests are computed. Next, total number of dry and wet days in the synthetic series (in terms of means) is compared with the historical ones.

Regarding the amounts precipitated, various calculations are performed. As in the occurrences procedure, all the parameters of the mixed exponential distribution obtained by the two cited methods are computed. Then, long term means and standard deviances are compared, so as total amount and maximum daily precipitation. Confidence intervals for means and standard deviations are also constructed.

In order to formalize the result of the model, two statistical significance tests are made between the original and generated data. Both are executed for means and standard deviations and are formulated as in Martins (2002, p. 210-213). They are summarized in Table 11.1:

Table 11.1 – Formulation of the significance tests applied

Parameters	Hypotheses	Test's variable	Formulation	Conclusion
Means	$H_0 \rightarrow \mu = \mu_0$ $H_1 \rightarrow \mu \neq \mu_0$	t-Student	$t_{cal} = \dfrac{\overline{X} - \mu_0}{s/\sqrt{n}}$	If $-t_{\alpha/2} \leq t_{cal} \leq t_{\alpha/2}$ H_0 is accepted
Standard Deviation	$H_0 \rightarrow \sigma = \sigma_0$ $H_1 \rightarrow \sigma \neq \sigma_0$	Chi-Square	$\chi^2_{cal} = \sqrt{\dfrac{(n-1).s}{\sigma_0}}$	If $\chi^2_{\inf} \leq \chi^2_{cal} \leq \chi^2_{\sup}$ H_0 is accepted

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, $\overline{X}$ is the sample mean, μ_0 are σ_0 the values of the null hypotheses for the mean and standard deviation, respectively, s is the sample standard deviation, n is the sample size, α is the significance level and $t_{\alpha/2}$, $\chi^2_{\inf}$ e $\chi^2_{\sup}$ are the tabled values of the respective variables. It is important to say that, for all the calculations concerning rain amounts, the dry days are ignored.

The last parameter to be calculated in the validation process is the cross correlation coefficient, between the historical and synthetic series. As mentioned in the beginning of this section, it is desirable series that are indistinguishable from each other. Therefore the expected result of this coefficient is as close to zero as possible, characterizing the independence between the series.

11.4 Further analyses

With the generation model properly debugged and validated, new analyses can be performed. In the present section, it was made the option for analyses related to extreme events, or low frequency events. It is important to say that these occurrences are not limited only to high intensity rain, but also to dry periods larger than the usual.

Among the many ways to do extreme events analyses, it was chosen to determine:

- The maximum sequence of consecutive dry or wet days: it is clear, through the method explained in section 11.1, that the precipitation occurrences are determined based on comparisons between transition probabilities and random numbers. It is interesting to know, however, if the model is capable of reproduce sequences of days of the same state, consistent with the original series;

- Total amount by period: in many cases heavy rain distributed in periods superior to one day are very significant. So, total amounts are calculated for periods between one and ten days long. In this case, other than the basic statistics calculated for the generated rain amounts, dry days are not ignored;

- Probability distribution for the sequences of dry days: in order to perform a deeper analysis of the drought periods, the empirical probabilistic distributions for the sequences of dry days of the original and generated series are compared.

With these analyses it is expected a careful examination of the generated series produced by the proposed model.

11.5 Selected rainfall stations

In order to test the model under various climate conditions, it was decided to choose rainfall stations spatially distributed inside the study area. Thus, the total number of stations was fixed in 11. Table 11.2 describes the selected stations and its main characteristics. Figure 11.2, in turn, shows the geographic location of each station.

Another important factor to the definition of the stations was the size of the available historical series. For this work, series with the same length were desirable, which requested a rigorous research among the stations. The larger common period encountered was defined by Caracol (code 02257000) and Caiuá (code 02151035) rainfall stations. So, used series cover the period from 01/12/1969 to 31/12/2009, totalizing 35 years or 12760 days of registers, to each station.

Unfortunately, some of the historical series collected for this study presented some flaws in the registers, corresponding a few days without records. As a common practice in hydrology, it was chosen not to fill this data, because daily scale precipitation provides high levels of variability (occurrences and amounts) even among neighbor stations. However, this fact does not represent problems to the model's application; as saw in section 11.1, the method used is able to do the calculations even with blanks in the series. The only direct consequence is a loss in terms of precision.

Table 11.2 – Selected rainfall stations

#	Station	Code ANA*	Sub-basin (code)	City	Latitude	Longitude	Altitude (m)
MAM	Monte Alegre de Minas	01848000	Parnaíba River (60)	Monte Alegre de Minas	-18°52'20"	-48°52'10"	730.00
UCC	Usina Couro do Cervo	02145007	Grande River (61)	Lavras	-21°20'37"	-45°10'13"	813.00
MM	Monte Mor	02247058	Tietê River (62)	Monte Mor	-22°57'39"	-47°17'45"	560.00
Ca	Caiuá	02151035	Paraná, Pardo and others Rivers (63)	Caiuá	-21°50'00"	-51°59'00"	350.00
To	Tomazina	02349033	Paraná, Paranapanema and others Rivers (64)	Tomazina	-23°46'00"	-49°57'00"	483.00
UV	União da Vitória - 396	02651000	Paraná, Iguaçu and others Rivers (65)	União da Vitória	-26°13'41"	-51°04'49"	736.00
Ta	Taiamã	01655003	Paraguay, São Lourenço and Others Rivers (66)	Santo Antônio do Leverger	-16°43'39"	-55°31'17"	163.00
Co	Caracol	02257000	Paraguay, Apa and Others Rivers (67)	Caracol	-22°01'51"	-57°01'45"	247.00
PM	Passo Marombas	02750009	Canoas (71)	Curitibanos	-27°19'51"	-50°45'03"	829.00
LC	Linha Cescon	02753004	Uruguay, da Várzea and Others Rivers (74)	Sarandi	-27°48'42"	-53°01'40"	350.00
Cq	Cacequi	02954001	Uruguay, Ibicuí and Others Rivers (76)	Cacequi	-29°52'40"	-54°49'25"	100.00

* ANA is the acronym for *Agência Nacional de Águas*, or the Brazilian's Water Agency, government agency which provides the data used in this work.

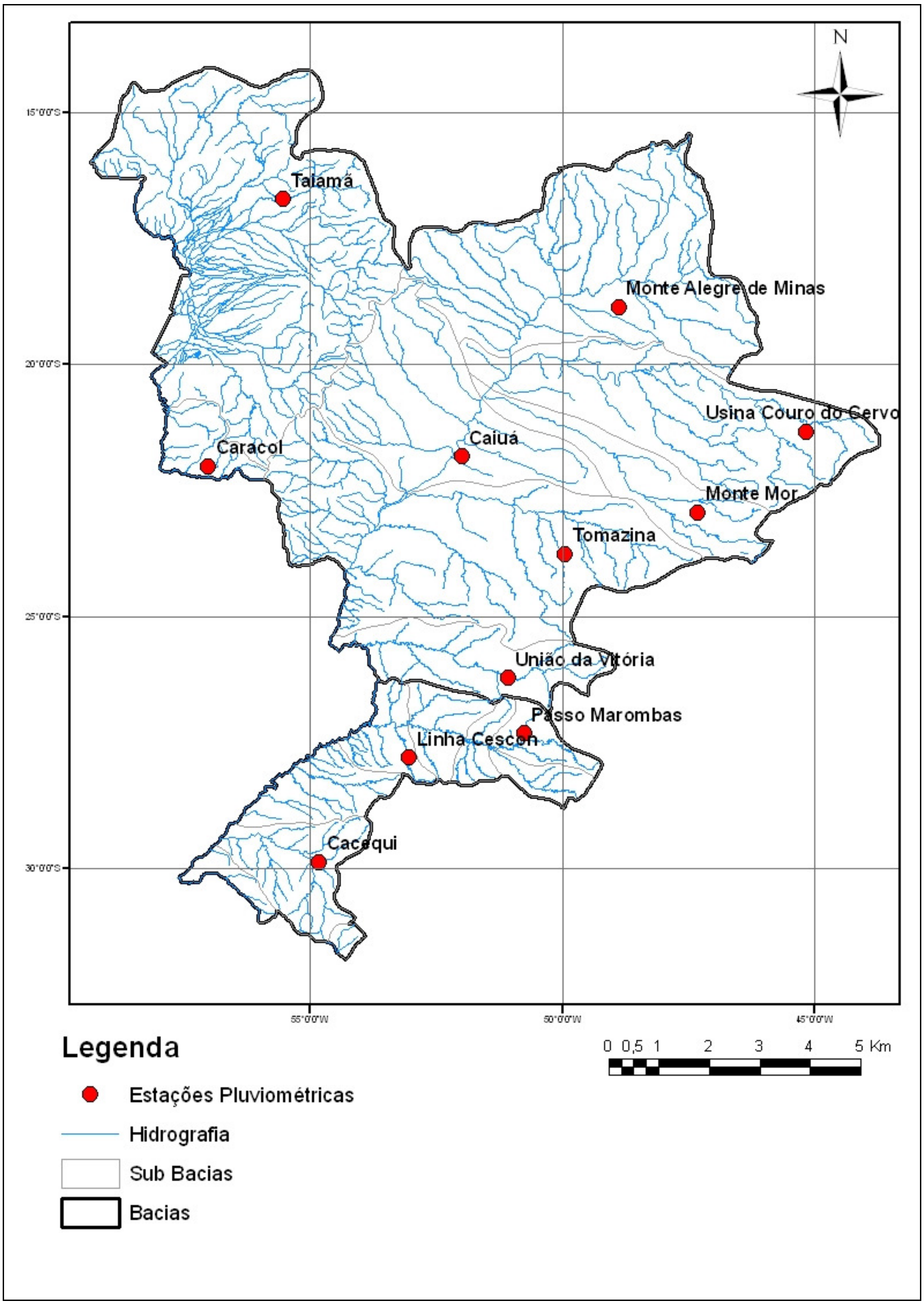


Figure 11.2 – Location of the selected rainfall stations

11.6. Application of the model

To obtain the results proposed in the objectives of this section, some initial considerations were made. The first one refers to seasonality; as in Wilks (1998), Haan, Allen and Street (1976) and Liao, Zhang e Chen (2004), seasonal period is equivalent to one month. Therefore, each year of the historical series is split in months. The series used to run the model are formed grouping all the months with the same name, within a specific station.

Inside every month, stationarity condition was assumed. This consideration brings with it a concept of statistical "equilibrium", since its sample parameters do not vary in time. For processes that work with temporal series, as the one presented here, stationarity appears as a necessary requisite to a good reproduction of dynamic natural phenomena through a finite data interval. Among all parametric models researched to develop this work, stationarity condition was unanimous.

Necessary random numbers to the implementation of the method were generated directly through Matlab software, which offers a generator as a tool. Moler (2004) brings a good description of the methods used by the software to generate these numbers. According to the author, generator's period reaches 2^{1492} before repeating itself. Obviously, in this work is not necessary to generate this quantity of numbers, yet, as a precaution was adopted the renewal of generator's seed before every execution of the model.

Of great importance, it is essential the definition of the minimal amount of rain which classifies a day into wet. Deni, Jemain and Ibrahim (2008) show that these limit values can influence the order of the Markov chains to be used. Here, the limit value is the same as in Wilks (1998), Brissette, Khalili and Leconte (2007) and Katz (1977): 0,3 mm.

Results presented in the following sections are referred to the application of the model as described in section 11.1. In order to give flexibility to the procedure, it was chosen to elaborate four distinct modules, namely:

- Module 1 – "*Ordem_Markov.m*": does the analysis of the optimum order of the Markov's chain to be used in the current rainfall station, based on the AIC and BIC criteria. Also calculates all the transition probabilities needed;
- Module 2 – "*Gerar.m*": from the transition probabilities determined in the first module, generate the series;
- Module 3 – "*Validacao.m*": execute all the statistical calculations relevant to the validation of the generated series in module 2;
- Module 4 – "*Valores_extremos.m*": does the analyses relative the extreme events, as described in section 1.4.

Thus, entirely execution of the procedure exhibited in section 11.1 consists on the application of the four computational modules aforementioned.

Occurrences determination

For occurrences determination, modules 1 and 2 of the program are executed, in sequence. Figures 11.3 and 11.4 exhibit the inputs and outputs of each module.

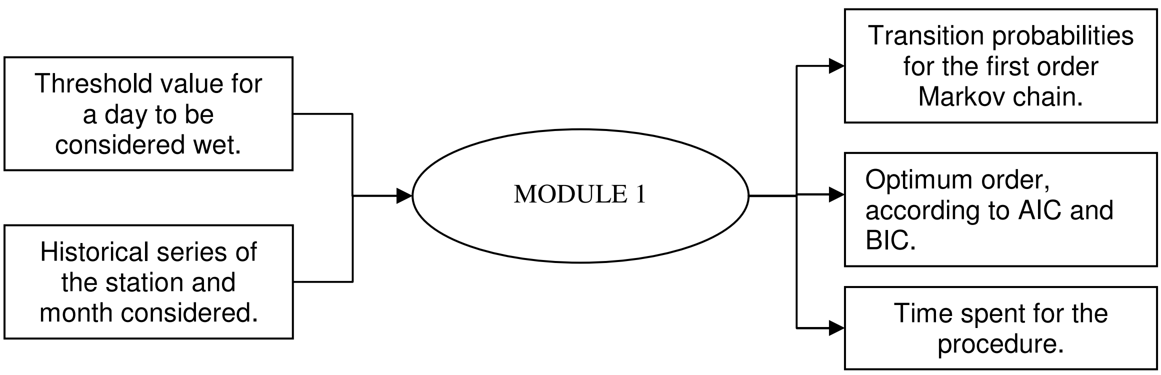


Figure 11.3 - Inputs and outputs for module 1

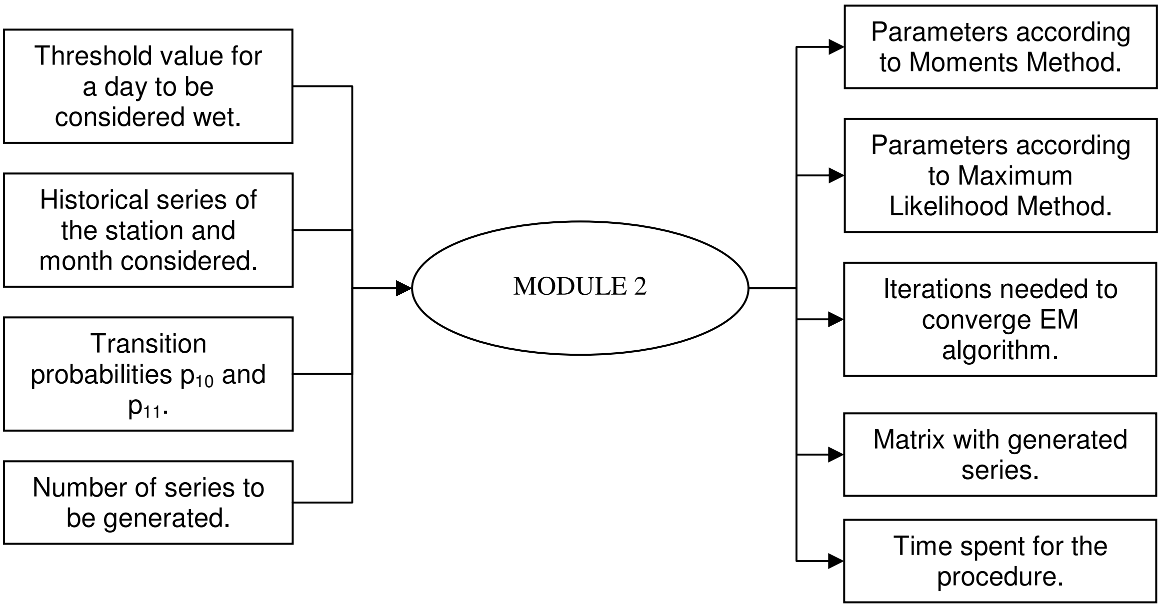


Figure 11.4 – Inputs and outputs for module 2

Complete algorithms can be seen in Annex I. Application of the module 1 to the rainfall stations results, firstly, the calculated transition probabilities between states. Results, for the rainfall stations of Taiamã, União da Vitória – 396 and Cacequi are shown in Table 11.3. Together with the parameters and AIC and BIC criteria, last column of the table exhibits the time spent for the computer to execute this module. For the complete results, see Annex H.

It is interesting to note that the transition probabilities brings with it, intrinsically, information related to the dry or wet periods of each station. It is also possible to foresee the magnitude of these periods over the stations. This finding is clear when comparing the probabilities values in climatologic distinct rainfall stations. It is the case of the three stations in the Table 11.3; variations in the probabilities of wet days after dry days are quite marked in Taiamã, for example, located in the Southeast region of Brazil. In the winter months, these values approach zero, indicating very low probability for occurrence of this type of transition between states. On the other hand, in União da Vitória – 396 and Cacequi, both located in the South region of Brazil, variations among the probabilities are smoother. The numbers confirm the indefinite meteorological behavior of this Brazilian's region.

Table 11.3 – Partial results of the module 1

Stations	Months	Markov chains' parameters				Optimum Order		Time (s)
		p00	p10	p01	p11	AIC	BIC	
Taiamã (Ta)	January	0.6761	0.3239	0.4936	0.5064	2	1	2.34
	February	0.6255	0.3745	0.5611	0.4389	2	0	2.16
	March	0.6952	0.3048	0.5801	0.4199	2	1	2.88
	April	0.8235	0.1765	0.6882	0.3118	1	1	1.44
	May	0.9077	0.0923	0.7429	0.2571	1	1	1.55
	June	0.9605	0.0395	0.7907	0.2093	1	1	1.39
	July	0.9776	0.0224	0.9091	0.0909	1	0	1.39
	August	0.9677	0.0323	0.8788	0.1212	1	0	1.05
	September	0.8849	0.1151	0.8230	0.1770	2	0	3.02
	October	0.8138	0.1862	0.7462	0.2538	2	0	1.47
	November	0.7061	0.2939	0.6689	0.3311	2	0	1.56
	December	0.6727	0.3273	0.5534	0.4466	2	1	1.63
União da Vitória (UV)	January	0.6684	0.3316	0.4012	0.5988	2	2	5.17
	February	0.6424	0.3576	0.3590	0.6410	1	1	2.8
	March	0.6885	0.3115	0.4556	0.5444	2	1	10.64

	April	0.7712	0.2288	0.5160	0.4840	2	1	1.7
	May	0.7958	0.2042	0.5100	0.4900	1	1	3.31
	June	0.7843	0.2157	0.5000	0.5000	1	1	1.83
	July	0.8032	0.1968	0.4916	0.5084	1	1	1.45
	August	0.8273	0.1727	0.4784	0.5216	2	1	1.84
	September	0.7601	0.2399	0.4585	0.5415	2	1	2.03
	October	0.6984	0.3016	0.4903	0.5097	1	1	2.27
	November	0.7231	0.2769	0.4817	0.5183	1	1	1.44
	December	0.6947	0.3053	0.4402	0.5598	1	1	2.66
Cacequi (Ca)	January	0.8228	0.1772	0.6107	0.3893	1	1	1.06
	February	0.7941	0.2059	0.6245	0.3755	1	1	1.38
	March	0.8312	0.1688	0.6372	0.3628	1	1	1.44
	April	0.8157	0.1843	0.6419	0.3581	1	1	1.36
	May	0.8547	0.1453	0.6019	0.3981	1	1	1.59
	June	0.8162	0.1838	0.6368	0.3632	1	1	1.39
	July	0.8053	0.1947	0.6364	0.3636	1	1	1.61
	August	0.8449	0.1551	0.6538	0.3462	1	1	1.28
	September	0.8133	0.1867	0.6398	0.3602	1	1	1.80
	October	0.8173	0.1827	0.6710	0.3290	2	1	1.09
	November	0.8098	0.1902	0.7383	0.2617	1	0	1.44
	December	0.8430	0.1570	0.7202	0.2798	1	1	1.72

Table 11.3 also shows the results of criteria AIC and BIC calculated for the three cases. To a better visualization of the verdicts, a new table was constructed, containing the general accounting of all 11 rainfall stations considered (Table 11.5):

Table 11.4 – Results of AIC and BIC criteria

	Absolute Numbers		Percentages	
	AIC	BIC	AIC	BIC
Optimum Order 0	0	8	0%	6,%
Optimum Order 1	82	119	62%	90%
Optimum Order 2	50	5	38%	4%
Totals	132	132	100%	100%

Both criteria indicate clear preference for the first order. It is noted, however, that the number of indications for each order varies. Theses results are consistent to what Katz (1981) wrote about the difference between the two tests; AIC criterion tends to overestimate the order of the chain to be used. BIC estimator, on the other hand, presents well consistent results, being the criterion recommended by the author for determination of the optimum order of the model. Still, Wilks (1998) emphasizes that, in working with large samples (higher than 1000 elements), the most recommended criterion is BIC.

A particular case occurs mainly in Taiamã station: BIC estimator indicated order zero in half of the cases. This result was predictable, since this station is located in a well defined climate region, where winters are extremely dry. So, model could be structured as a simple binomial distribution (or Bernoulli trials). Though, this kind of consideration is overly simple for modeling a natural phenomenon (Chin, 1977).

With the exposed, first order Markov chains can be considered appropriated for the present rainfall stations.

Amounts determination

To the amounts determination, module 2 is executed. Inputs and outputs of it can be seen in Figure 11.4 the last section. Its first procedure is the estimation of the mixed exponential parameters, using the Moments Method. According to Rider (1961), for parameters different from each other and higher than zero, equations (11.25) and (11.26) produce estimators consistent with the purpose of mixed exponential distribution, i. e., $\beta_1 > 0$, $\beta_2 > 0$ and $0 \le \alpha \le 1$.

However, the application of this method, in many cases, did not produce the predicted results. This fact was not unexpected, because equation (11.25) is a second degree polynomial and its solution allows equal, negative and imaginary parameters. First case does not represent problems, just the exponential distribution, before mixed, falls into a simple exponential. Negative or imaginary parameters, on the other hand, are not admissible, because their physical interpretation is impossible and the continuation of the calculus is jeopardized. Besides, α parameter resulted, in some cases, values higher than the unit, also unacceptable for it is a probability value.

The fact of the Moments Method does not be the most efficient to estimate the needed parameters is sufficient to use it only as a first approach to another method. And, in order to automate the computational program, some adaptations were done, involving the elimination of negative and imaginary values. With this, EM algorithm could be initialized, using the Moments Method estimations as first guesses of the iterative process.

Table 11.5 exhibit the results of parameters determined with the Moments Method (with the adaptations) and with the Maximum Likelihood Method (EM algorithm), and the number of iterations needed as long as the total computational time consumed. It is noteworthy that this time accounts the complete execution of module 2, not only the parameters' determination. Again, complete results for all rainfall stations considered are presented in Annex H.

Table 11.5 – Parameters for the mixed exponential distribution

Stations	Months	Initial Estimative (Moments Method)			Definitive Estimative (Maximum Likelihood Method)				Time (s)
		α	β_1	β_2	α	β_1	β_2	Interactions	
Taiamã (Ta)	January	0.6261	15.4457	10.2971	0.6551	20.3954	14.9604	34	424.27
	February	0.8015	16.3589	10.9059	0.7304	20.0071	11.4894	270	407.03
	March	0.3095	9.0300	6.0200	0.4167	15.8028	15.7048	31	398.06
	April	0.7890	12.3652	8.2435	0.7868	14.8260	8.4555	34	341.97
	May	0.3868	10.2522	6.8348	0.4817	15.8225	15.5329	40	458.84
	June	0.1012	18.9742	12.6495	0.3175	20.4806	8.0682	106	421.24
	July	0.5807	11.8996	7.9331	0.6359	16.6537	11.4624	25	426.09
	August	0.5325	30.1074	20.0716	0.4458	23.8105	7.4249	26	275.09
	September	0.5516	9.8076	6.5384	0.6054	13.9985	10.1163	33	407.99
	October	0.5531	11.5241	7.6827	0.6022	15.8689	12.7520	40	431.22
	November	0.8890	18.6151	12.4100	0.4440	23.8675	13.1849	676	522.31
	December	0.6877	16.6852	11.1234	0.7067	20.9375	15.0491	32	532.25
União da Vitória (UV)	January	0.8780	19.2202	14.9177	0.7220	14.3633	2.7946	35	484.17
	February	0.1725	19.2262	12.8175	0.7211	15.0506	3.0992	201	367.20
	March	0.0755	28.3299	11.6885	0.6710	14.4279	2.3020	140	651.75
	April	0.1107	44.3132	16.6399	0.5912	20.9941	2.8951	41	530.31
	May	0.0018	136.6367	16.7489	0.7069	22.7334	1.6738	98	361.84
	June	0.1259	37.0422	17.8447	0.6542	22.3745	2.4445	79	365.33
	July	0.3075	30.4399	18.7901	0.7354	19.9383	2.2093	151	358.44
	August	0.0427	44.7434	15.4274	0.7006	19.5974	1.5722	91	351.00
	September	0.2002	21.2012	14.1341	0.7825	18.9682	3.3158	260	470.53
	October	0.7427	16.4942	10.9961	0.8004	18.3960	1.8350	63	402.84
	November	0.3203	16.6238	11.0825	0.7728	15.8738	2.6299	138	451.03
	December	0.2313	22.7089	15.1393	0.7321	16.7494	4.2339	350	476.09

Cacequi (Cq)	January	0.7184	22.8955	12.8955	0.7111	23.7393	11.0708	23	370.02
	February	0.7833	22.2782	12.2782	0.7769	22.6942	11.1268	24	333.83
	March	0.7896	18.085	8.085	0.8642	20.7791	20.5682	47	359.76
	April	0.538	28.6819	18.6819	0.1402	44.3039	20.762	686	348.39
	May	0.7946	20.7955	10.7955	0.9016	25.3388	5.4378	85	359.28
	June	0.5591	24.0198	14.0198	0.1694	32.9451	16.893	980	359.88
	July	0.7469	16.135	6.135	0.8538	19.5343	19.4621	25	369.66
	August	0.1955	24.6995	14.6995	0.8526	19.0027	3.0877	573	366.36
	September	0.9847	21.8923	11.8923	0.8864	23.6261	7.0198	138	369.61
	October	0.6902	18.0912	8.0912	0.8002	22.602	22.4987	32	479.19
	November	0.7591	18.456	8.456	0.8268	21.6673	21.4512	37	389.56
	December	0.9084	18.6868	8.6868	0.9258	19.7232	19.3831	38	341.39

Note that the parameters vary considerably, even inside one station. These differences are influenced, not only by the rainfall regime in a specific station, but also by the intensity of individual precipitations. This is because the application of EM algorithm involves all the rainy days of the historical series, making the presence of stronger rains an important influence factor over the calculation of the parameters.

Even with the commented variations, it is clear the inter-relation among the parameters. There is a tendency of compensation between the form parameters (β_1 and β_2), i. e., the variation of one mean is followed by the other. In his article, Wilks (1998) used ratios between the parameters as indicators of the degree of differentiation that mixed exponential distribution is able to provide, with respect to rainfall intensity. In other words, when represented by two means, mixed exponential distribution is rigorous in considering different intensity events. In his study, the ratio (β_1/β_2), evaluated for all months and all stations, resulted a mean value of 4.8; here, the same value was 3.4.

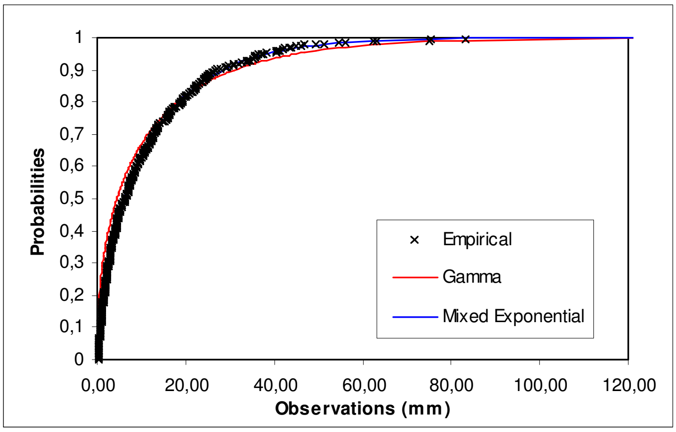
Regarding the probability parameter (α), Wilks (1998) also calculated some basic statistics, finding a mean value of 0.60. In the present section, the mean value found was 0.66. Yet, this parameter presented a large variability, even inside months with the same names. The researcher also determined standard deviances of α between rainfall stations, given a specific month, finding values between 0.1 and 0.2. Here, same calculation was made and the mean value of 0.17 was found.

The proximity of results suggests that some climatic characteristics related with the rainfall regime in New York State (location where Wilks applied the model) are quite close to the region considered here. The minor value for the ratio between means can be a direct influence of rainfall stations located in climatologic undefined regions, like the ones located in the South region of Brazil.

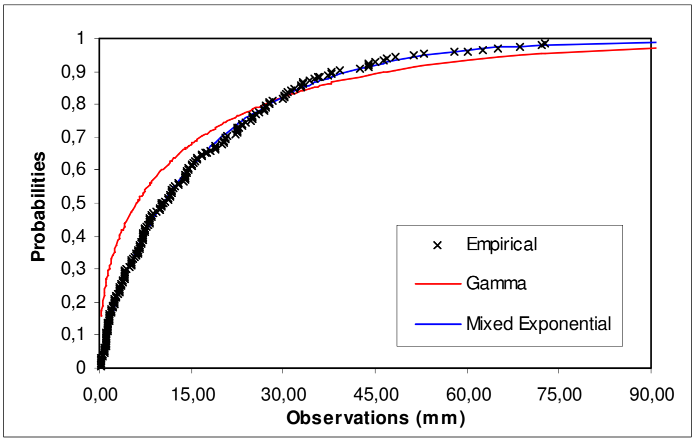
For the precipitated amounts, other analyses were elaborated, in order to verify the quality of the adjustment provided by the mixed exponential to the observed data. These analyses, however, were limited only to the three rainfall stations cited above. Inside each station, three distinct rainfall behaviors were sought: a marked rain period (União da Vitória – 396 station, in Januaries), an intermediate period (Cacequi station, in Augusts) and a drought period (Taiamã station, in Julys). As alternate probabilistic distribution, two parameters gamma was adopted, the most widespread distribution in rainfall modeling.

The first verification comes from visual analyses through the construction of graphs. Initially a comparison of both probabilistic models with empirical distribution is made. After, P-P plots are constructed (Wilks, 2006, p. 114). They are expressed in figures 11.5 and 11.6, respectively.

In the comparison of the theoretical with the empirical distributions (Figure 11.5) note that the adjustment of gamma distribution gets worse as the number of rainy days decreases. Mixed exponential, though, seems to follow the observed values regardless the sample size. Another interesting fact to be noted is the graph's region containing the minor intensity observations. Gamma distribution is relatively insensible to these values. In Taiamã's case (Figure 11.5-C), adjustment presents a large discontinuity on the beginning of the interval. However, mixed exponential distribution is able to represent quite well the inferior limit of the sample. P-P plots showed in Figure 11.6 demonstrate, again, a significantly better adjustment of mixed exponential distribution over gamma distribution. As in the previous graphs, quality of the adjustments tends to get worse as sample size decreases. In physical terms, the driest period used, the probabilistic models have more difficulty in reproducing observed data.



(A)



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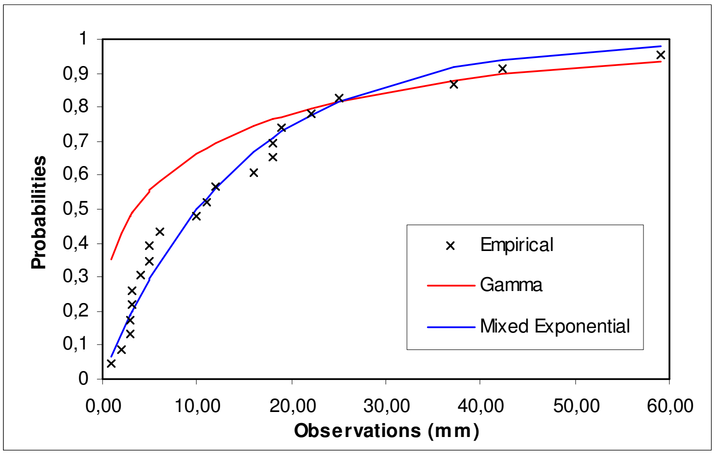

(C)

Figure 11.5 – Comparison between empirical and adjusted distributions (a) União da Vitória (januaries) (b) Cacequi (Augusts) (c) Taiamã (Julys)

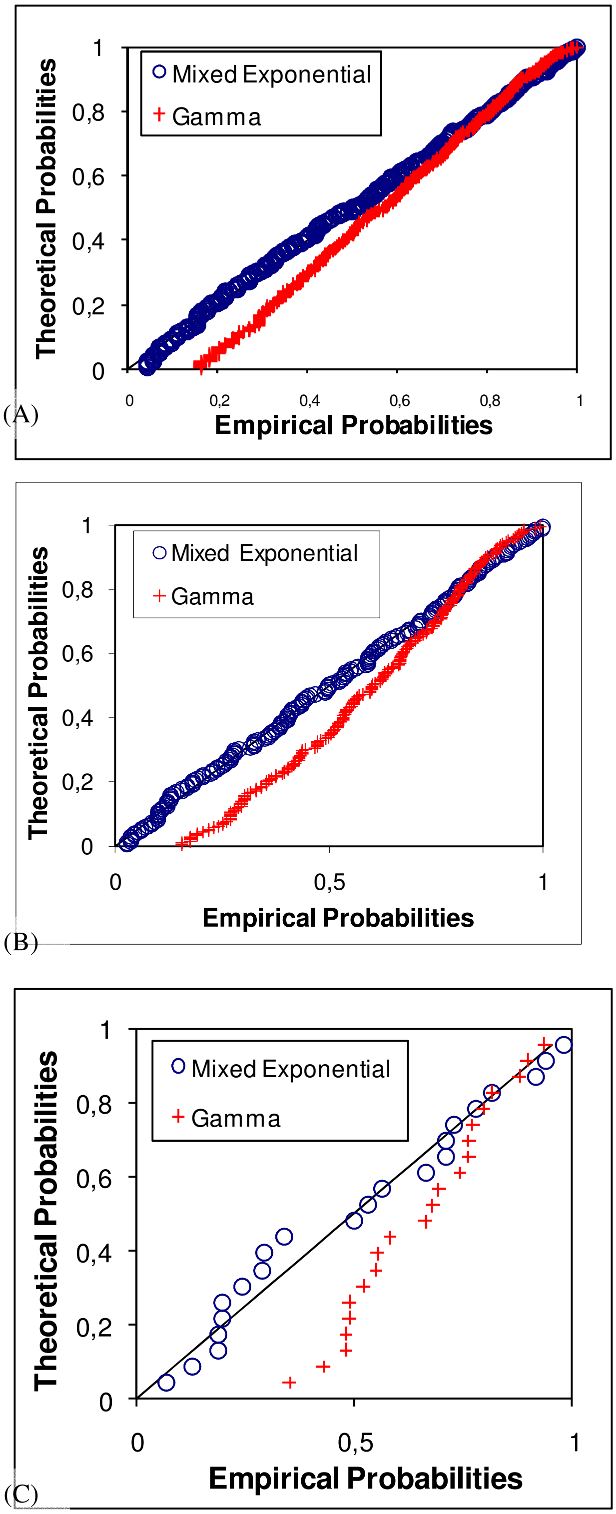

Figure 11.6 – P-P plots (a) União da Vitória (Januaries)
(b) Cacequi (Augusts) (c) Taiamã (Julys)

Table 11.6 (a) – Chi-square test for União da Vitória – 396 (januaries)

	Classes					Totals
	0 - 24.8	24.8 - 49.6	49.6 - 74.3	74.3 - 99.1	99.1 - 124.2	
# Observed	431	51	6	2	1	491
Gamma:						
Probability	0.86	0.10	0.03	0.01	0.003	1.00
# Expected	423.06	48.32	13.40	4.16	1.37	490.31
Test's statistics	0.15	0.15	4.08	1.12	0.10	5.60
Mixed Exponential:						
Probability	0.87	0.11	0.02	0.00	0.001	1.00
# Expected	427.83	51.92	9.24	1.65	0.29	490.94
Test's statistics	0.02	0.02	1.14	0.08	1.69	2.94
				Tabled Value (P=95% - 4 GL):		9.49

Table 11.6 (b) – Chi-square test for Cacequi (Augusts)

	Classes					Totals
	0 - 27.1	27.1 - 54.3	54.3 – 81.4	81.4 – 108.6	108.6 – 136.0	
# Observed	164	35	7	1	1	208
Gamma:						
Probability	0.80	0.12	0.04	0.02	0.01	0.99
# Expected	166.78	24.74	9.28	3.92	1.76	206.48
Test's statistics	0.05	4.25	0.56	2.17	0.33	7.36
Mixed Exponential:						
Probability	0.80	0.16	0.04	0.01	0.002	1.00
# Expected	165.48	32.33	7.75	1.86	0.45	207.86
Test's statistics	0.01	0.22	0.07	0.40	0.68	1.38
				Tabled Value (P=95% - 4 GL):		9.49

Table 11.6 (c) – Chi-square Test for Cacequi (Julys)

	Classes					Totals
	0 – 11.6	11.6 – 23.2	23.2 – 34.8	34.8 – 46.4	46.4 – 59.0	
# Observed	12	6	2	1	1	22
Gamma:						
Probability	0.69	0.12	0.06	0.04	0.03	0.94
# Expected	15.15	2.56	1.39	0.87	0.62	20.59
Test's statistics	0.65	4.61	0.27	0.02	0.24	5.79
Mixed Exponential:						
Probability	0.55	0.24	0.11	0.05	0.03	0.98
# Expected	12.12	5.35	2.42	1.11	0.55	21.55
Test's statistics	0.001	0.08	0.07	0.01	0.37	0.53
				Tabled Value (P=95% - 4 GL):		9.49

Second section of verifications are referred to the application of Chi-square (χ^2) and Kolmogorov-Smirnov tests. In Chi-square's case, definition of the number of classes to be used follows equation (11.35). Significance level adopted was 5%, which resulted in five classes. This number was equally adopted for the three considered stations. Therefore, the number of degrees of freedom used was four ($k-1$ degrees of freedom, where k is the number of classes of the test). Table 11.6 exhibit procedures and test's verdict.

To the Kolmogorov-Smirnov test, the same significance level was used (5%), making that K_α in equation (11.37) assumed 1.358. It is important to emphasize that this equation is employed to determinate the critical value from the test (D_{crit}). Verdict can be seen in Table 11.7.

Note that for Chi-square test, null hypothesis was accepted for the three considered cases and for both probabilistic distributions under analysis. However, performance of mixed exponential distribution is superior to the gamma distribution, because it presented calculated statistics farthest than tabled value.

Table 11.7 – Kolmogorov-Smirnov test application

Station (Months)	Maximum Observed Distances		Critical Distances (equation 1.37)
	Gamma	Mixed Exponential	
União da Vitória (Januaries)	0.16	0.04	0.06
Cacequi (Augusts)	0.19	0.03	0.09
Taiamã (Julys)	0.35	0.10	0.28

On the other hand, Table 11.7 shows that gamma distribution was rejected for the three cases. Accounting all the elements for the needed calculation, it was perceived that the maximum observed distances were located at the initial portion of the sample, i. e., at the minor intensity rains. This fact is consistent with the discontinuity presented on the initial part of curves in figures 11.6 and 11.7. It is evident, thus, that gamma distribution has a serious issue in represent this kind of event. For the mixed exponential distribution, as in other cases, null hypothesis was accepted in all cases. To the present study, expressly superior performance of mixed exponential distribution allows to affirm that the generation model adopted is prudent.

Validation of the model

To validate the generated series, module 3 of the computational program is executed. Figure 11.7 shows a scheme for the inputs and outputs of this module. Complete algorithm can be visualized in Annex I.

It is known that application of Monte Carlo Method requires generation of a large set of synthetic series, in order to obtain distinct results and enable the creation of scenerios. Kelman (1987, p. 354) states that a sufficient number of synthetic series is one that allows a good proximity with the theoretical probability. Thus, in this section, a number of 1000 series was adopted as pattern, for each month and each rainfall station.

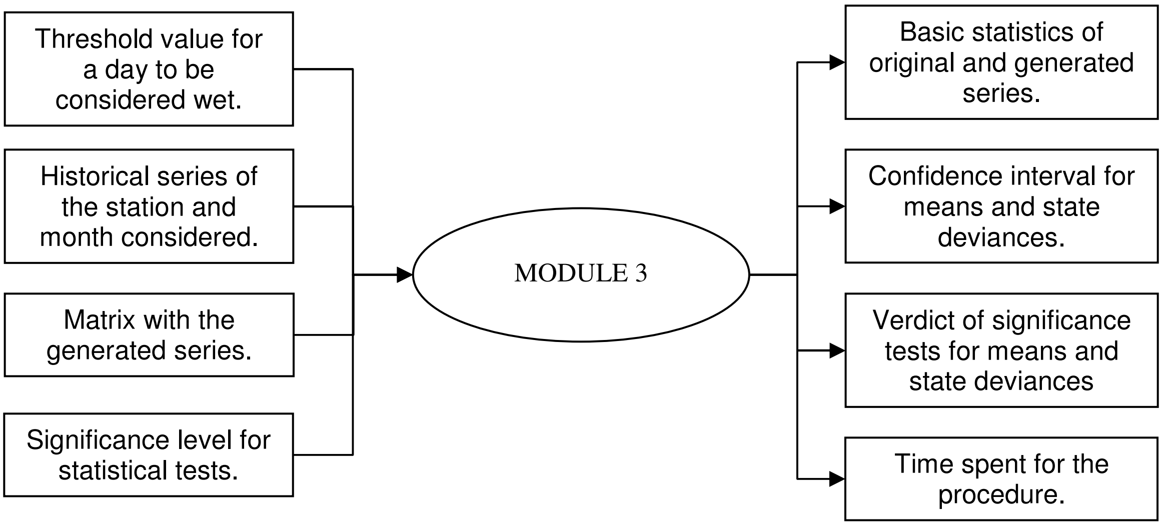

Figure 11.7 – Inputs and outputs for module 3

That means that, for every station, approximately $12x10^6$ days were generated, sufficient quantity to validate the model. Verification is made through comparisons of statistics between original and synthetic series. All calculation done for the synthetic series is referred to the mean of the 1000 generated series. Tables 11.8 and 11.9 exhibit results obtained for the three rainfall stations considered. Last column of Table 11.9 also shows the total time spent for the procedure. Results for the other stations are presented in Annex H.

Table 11.8 – Results for validation of the model – part 1

Stations	Months	Mean (mm)		St. Deviance (mm)		Total Amount (mm)		Daily Maximum (mm)		Wet Days		Dry Days	
		Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic
Taiamã (Ta)	January	18.5	18.8	19.0	18.5	7278.7	7377.5	137.0	121.9	393	393	599	599
	February	17.7	18.0	18.6	18.5	6375.3	6492.9	130.0	123.6	360	362	542	540
	March	15.8	16.0	14.7	15.7	5211.8	5300.7	96.0	100.9	331	332	630	629
	April	13.5	13.7	14.1	13.9	2504.9	2569.0	87.0	82.7	186	187	731	730
	May	15.7	15.9	15.1	15.4	1645.4	1687.6	72.1	81.4	105	106	856	855
	June	12.0	12.2	14.0	13.9	516.4	541.4	66.0	66.3	43	44	887	886
	July	14.8	15.0	15.0	14.5	324.8	349.1	59.0	57.3	22	23	939	938
	August	14.7	15.0	17.8	17.8	486.0	506.0	80.0	79.3	33	34	928	927
	September	12.5	12.7	12.6	12.6	1408.5	1452.0	60.0	68.9	113	114	817	816
	October	14.6	14.9	14.8	14.8	2881.6	2967.6	100.0	88.7	197	199	795	793
	November	17.9	18.1	19.3	19.3	5252.4	5312.1	124.0	130.7	293	293	667	667
	December	19.2	19.4	19.9	19.5	6838.9	6930.0	157.0	128.6	356	357	605	604
União da Vitória (UV)	January	11.1	11.4	13.7	13.4	5469.8	5577.7	124.2	93.0	491	490	594	595
	February	11.7	12.0	13.7	13.9	5774.0	5900.7	81.2	96.8	493	493	495	495
	March	10.4	10.7	13.1	13.1	4464.8	4561.5	99.8	90.7	428	427	626	627
	April	12.4	12.7	15.2	15.7	3871.0	3965.6	68.1	100.6	312	314	908	906
	May	16.5	16.9	22.2	21.0	4958.3	5122.5	154.6	131.8	300	303	754	751
	June	15.4	15.8	19.3	20.5	4721.1	4858.1	87.9	132.1	306	307	714	713
	July	15.2	15.5	18.8	18.8	4516.6	4632.9	121.4	119.2	297	299	747	745
	August	14.2	14.5	18.0	18.3	3940.5	4043.9	110.0	114.7	278	280	776	774
	September	15.6	15.8	17.7	17.9	5426.7	5539.9	112.0	117.0	349	351	671	669
	October	15.1	15.3	16.4	17.6	6212.8	6315.7	87.4	116.8	412	413	673	672
	November	12.9	13.1	14.5	15.0	4911.5	5028.4	84.4	99.4	382	383	668	667
	December	13.4	13.6	15.8	15.5	5931.2	6052.9	156.2	107.3	443	444	642	641
Cacequi (Cq)	January	20.1	20.3	21.3	21.5	4899.3	4968.0	116.0	136.5	244	244	841	841
	February	20.1	20.5	21.1	21.2	4927.3	5013.7	114.3	132.9	245	245	743	743
	March	20.8	21.0	19.4	20.6	4689.4	4774.3	98.6	124.7	226	227	859	858
	April	24.1	24.3	26.5	26.5	5510.1	5561.6	203.7	183.4	229	229	792	792
	May	23.4	23.7	22.9	24.7	4933.3	4995.9	106.2	148.2	211	211	874	874
	June	19.6	19.9	21.3	21.2	4589.0	4676.0	137.6	143.1	234	235	816	815
Cacequi (Cq)	July	19.5	19.8	17.2	19.5	4939.3	5053.3	107.8	120.4	253	255	832	830
	August	16.7	16.9	18.8	18.4	3464.1	3511.8	136.0	109.5	208	208	877	877
	September	21.7	22.0	22.2	22.9	5130.5	5220.7	135.0	141.0	236	237	814	813
	October	22.6	22.8	20.6	22.5	5215.9	5313.3	138.8	137.2	231	233	854	852
	November	21.6	21.9	20.3	21.5	4628.8	4723.1	115.8	128.3	214	216	836	834
	December	19.7	20.0	19.1	19.7	3801.1	3882.2	135.6	116.3	193	194	892	891

Table 11.9 – Results for validation of the model – part 2

Stations	Months	Cross Correlation	Mean Test	Standard Deviance Test	Conf. Int. – Mean Inferior	Conf. Int. – Mean Superior	Conf. Int. – St. Deviance Inferior	Conf. Int. – St. Deviance Superior	Time (s)
Taiamã (Ta)	January	0.002	Accepted	Accepted	16.1	21.0	17.4	20.9	16.53
	February	-0.001	Accepted	Accepted	15.2	20.2	17.0	20.6	19.53
	March	-0.001	Accepted	Accepted	13.7	17.8	13.3	16.3	18.72
	April	0.000	Accepted	Accepted	10.8	16.1	12.5	16.3	21.59
	May	0.001	Accepted	Accepted	11.9	19.5	12.8	18.4	30.91
	June	0.001	Accepted	Accepted	6.5	17.5	10.9	19.3	25.48
	July	0.000	Accepted	Accepted	6.5	23.0	10.7	24.3	30.94
	August	0.000	Accepted	Accepted	6.7	22.7	13.4	25.9	18.22
	September	0.000	Accepted	Accepted	9.4	15.5	10.8	15.2	21.36
	October	-0.002	Accepted	Accepted	11.9	17.3	13.1	17.0	22.00
	November	-0.001	Accepted	Accepted	15.0	20.8	17.5	21.6	29.47
	December	-0.001	Accepted	Accepted	16.5	21.9	18.1	22.0	22.20
União da Vitória (UV)	January	0.002	Accepted	Accepted	9.6	12.7	12.6	14.9	19.72
	February	0.000	Accepted	Accepted	10.1	13.3	12.7	14.9	16.34
	March	-0.001	Accepted	Accepted	8.8	12.1	12.1	14.4	30.98
	April	0.001	Accepted	Accepted	10.2	14.6	13.8	16.9	23.80
	May	-0.002	Accepted	Accepted	13.2	19.8	20.1	24.8	19.05
	June	0.002	Accepted	Accepted	12.6	18.3	17.5	21.5	17.14
	July	-0.001	Accepted	Accepted	12.4	18.0	17.0	21.0	16.44
União da Vitória (UV)	August	0.002	Accepted	Accepted	11.4	17.0	16.2	20.2	22.23
	September	0.001	Accepted	Accepted	13.1	18.0	16.1	19.6	23.02
	October	0.000	Accepted	Accepted	13.0	17.2	15.1	18.0	28.30
	November	-0.001	Accepted	Accepted	11.0	14.8	13.2	15.9	29.17
	December	0.000	Accepted	Accepted	11.5	15.3	14.5	17.3	21.13
Cacequi (cq)	January	0.000	Accepted	Accepted	16.6	23.6	19.1	24.1	17.73
	February	0.000	Accepted	Accepted	16.6	23.6	18.9	23.8	15.25
	March	-0.001	Accepted	Accepted	17.4	24.1	17.3	22.1	18.84
	April	0.000	Accepted	Accepted	19.5	28.6	23.7	30.1	15.63
	May	-0.001	Accepted	Accepted	19.3	27.4	20.3	26.2	16.47
	June	0.002	Accepted	Accepted	16.0	23.2	19.0	24.1	17.52
	July	0.001	Accepted	Accepted	16.8	22.3	15.4	19.4	18.97
	August	0.001	Accepted	Accepted	13.3	20.0	16.7	21.5	17.78
	September	-0.001	Accepted	Accepted	18.0	25.5	19.9	25.2	16.55
	October	-0.001	Accepted	Accepted	19.1	26.1	18.4	23.4	23.86
	November	-0.001	Accepted	Accepted	18.1	25.2	18.0	23.1	21.91
	December	-0.001	Accepted	Accepted	16.2	23.2	16.8	21.9	17.16

Based on a visual analysis, it is observed that the model attended well its objectives. The larger difference between means was 0.5 mm (station Monte Mor, Julys), whereas for standard deviation the maximum difference was 1.2 mm (station Linha Cescon, Aprils). Coincidentally, larger discrepancies between the series were found on the driest months of the year. This fact is perfectly justified, because with less rainy days, the model has less information for determinate the parameters, what reflex directly in its precision. Good results in term of means and standard deviances were confirmed by statistical significance tests: both had 100% of acceptance, for a 99% significance level.

For total amounts synthetic series registered an absolute mean error of 82.7 mm and an absolute maximum error of 179.7 mm (station Usina Couro do Cervo, Decembers). Assuming that this mean error was uniformly distributed among the 35 yeas of the series, it would result in approximately 2.4 mm per month and 28.3 mm per year. Starting from the assumption that mean precipitation on the selected stations reached 1500.0 annually, it is evident that this error is practically negligible.

The setback of the model appears on determination of daily maximums. Even if some results can be considered acceptable, absolute medium error for this parameter was 13.7 mm and absolute maximum error was 52.8 (station Caracol, Decembers). This magnitude is elevated, in terms of maximum daily precipitation, what appoint a difficulty of the model in represent extreme events. Further comments and results related to extreme events are presented on next section.

Regarding the number of wet and dry days, it can be said that application of Markov chains produced an excellent result. Absolute mean error was 1 day, while absolute maximum error was 3 days (station Monte Mor, Septembers and Station União da Vitória, Mays). These numbers, when compared to the size of the sample, are quite low. In many cases, model was able to reproduce exactly the same quantity of wet and dry days present in original series. Another parameter that was adequately reproduced was cross correlation. In all cases, correlations between original and synthetic series resulted practically null values. As written in section 1, indistinguishable series are extremely wanted, considering the generation of various scenarios. In turn, confidence intervals, for both the means and standard deviations at a level of significance of 1%, had total acceptation.

With the exposed, the model is considered suitable and well structured. So, extra analyses can be made; next section is dedicated to extreme events analyses, related with the synthetic series generated.

Further analyses

For the extreme events analyses, module 4 of the computational program is executed. Like the other modules, a schematic figure is constructed to indicate inputs and outputs of this module. It can be seen in Figure 11.8.

As well as the other modules, module 4 was executed for all stations and months of the study. For determination of total amounts per period, however, both wet and dry days were included. Total amounts for 1 day of duration are the same of daily maximum precipitation calculated in module 3.

Table 11.10 exhibits the results obtained with the application of module 4 for the three stations considered. Other results are exposed in Annex H. Again, last column of the table refers to the computation time spent.

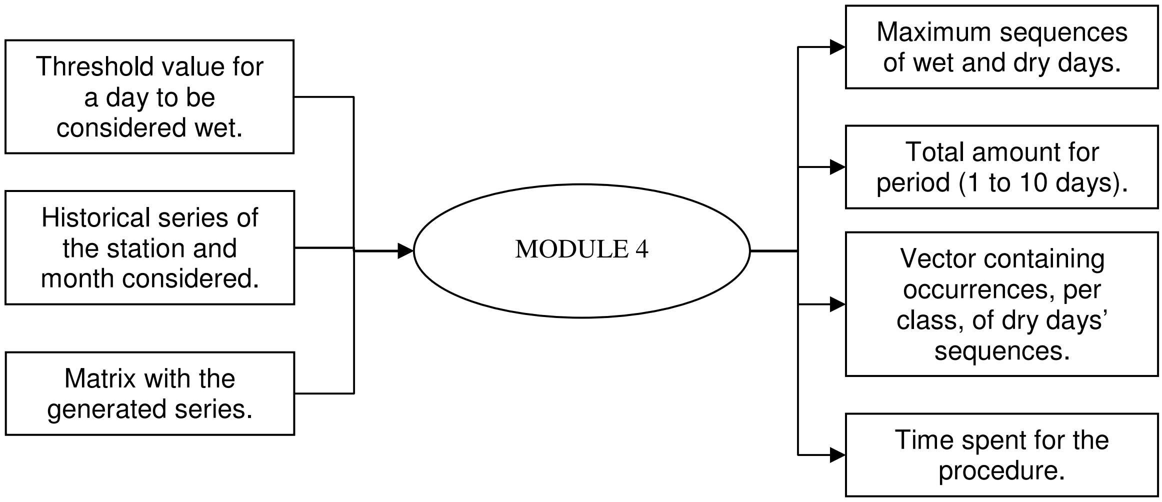

Figure 11.8 – Inputs and outputs for module 4

Table 11.10 – Extreme events analyses

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Taiamã (Ta)	January	O	14	13	A	137.0	159.0	175.0	177.0	179.0	201.0	201.0	214.0	236.0	244.0	478.83
					M	7.3	14.7	22.0	29.4	36.8	44.1	51.5	58.9	66.4	73.8	
		S	15	9	A	121.9	149.0	169.3	187.7	203.9	219.1	233.8	247.6	260.5	273.7	
					M	7.4	14.9	22.3	29.8	37.2	44.6	52.1	59.5	66.9	74.4	
	February	O	11	10	A	130.0	140.0	148.0	223.0	223.0	223.0	242.0	242.0	278.0	363.0	450.91
					M	7.1	14.2	21.2	28.3	35.5	42.6	49.7	56.9	64.0	71.1	
		S	13	8	A	123.6	146.7	164.8	180.9	196.7	211.0	224.3	236.6	249.2	262.0	
					M	7.2	14.4	21.6	28.8	36.0	43.2	50.4	57.6	64.8	72.0	
	March	O	21	7	A	96.0	100.1	144.2	153.1	153.1	153.1	153.1	164.0	192.2	195.4	462.22
					M	5.4	10.8	16.3	21.7	27.2	32.6	38.1	43.5	49.0	54.5	
		S	16	7	A	100.9	121.1	137.7	151.1	163.0	174.5	185.7	196.3	206.7	216.7	
					M	5.5	11.0	16.5	22.1	27.6	33.1	38.6	44.1	49.6	55.2	
	April	O	24	5	A	87.0	89.0	93.0	106.0	108.0	117.0	130.0	130.0	136.0	136.0	480.08
					M	2.7	5.5	8.2	11.0	13.7	16.5	19.2	22.0	24.7	27.5	
		S	29	5	A	82.7	96.2	105.4	113.6	120.8	127.6	133.9	140.3	145.9	151.3	
					M	2.8	5.6	8.4	11.2	14.0	16.8	19.6	22.4	25.2	28.0	
	May	O	44	4	A	72.1	78.7	84.6	87.3	87.3	87.3	87.3	100.0	110.0	110.0	470.16
					M	1.7	3.4	5.1	6.8	8.5	10.2	11.9	13.5	15.2	16.9	
		S	52	4	A	81.4	94.7	103.0	108.7	114.1	119.0	123.3	127.0	130.8	134.9	
					M	1.8	3.5	5.3	7.0	8.8	10.5	12.3	14.0	15.8	17.5	
	June	O	98	3	A	66.0	66.0	66.0	81.0	81.0	82.0	95.0	95.0	97.0	97.0	424.55
					M	0.6	1.1	1.7	2.2	2.8	3.3	3.9	4.5	5.0	5.6	
		S	103	3	A	66.3	72.9	75.7	77.4	79.2	80.3	81.6	82.5	83.9	85.5	
					M	0.6	1.2	1.7	2.3	2.9	3.5	4.1	4.7	5.2	5.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Taiamã (Ta)	July	O	222	2	A	59.0	59.0	59.0	59.0	61.0	61.0	61.0	61.0	61.0	61.0	428.11
					M	0.3	0.7	1.0	1.4	1.7	2.0	2.4	2.7	3.1	3.4	
		S	158	2	A	57.3	60.3	61.5	62.4	63.3	64.0	64.8	65.7	66.5	67.2	
					M	0.4	0.7	1.1	1.5	1.8	2.2	2.5	2.9	3.3	3.6	
	August	O	113	2	A	80.0	80.0	80.0	80.0	80.0	94.0	94.0	94.0	94.0	94.0	451.81
					M	0.5	1.0	1.5	2.0	2.5	3.1	3.5	4.0	4.5	5.0	
		S	122	2	A	79.3	83.4	85.0	86.3	87.3	88.6	89.6	90.7	92.1	93.6	
					M	0.5	1.1	1.6	2.1	2.6	3.2	3.7	4.2	4.7	5.3	
	September	O	47	4	A	60.0	60.0	60.0	60.0	60.0	70.0	74.0	74.0	74.0	74.0	394.28
					M	1.5	3.0	4.5	6.0	7.5	9.0	10.5	11.9	13.4	14.9	
		S	42	4	A	68.9	77.3	82.1	86.4	91.1	95.3	99.2	102.6	106.0	108.8	
					M	1.6	3.1	4.7	6.2	7.8	9.4	10.9	12.5	14.1	15.6	
	October	O	36	5	A	100.0	100.0	100.0	103.0	105.0	105.0	105.0	122.0	122.0	127.0	480.97
					M	2.9	5.8	8.7	11.6	14.5	17.3	20.2	23.1	25.9	28.8	
		S	28	5	A	88.7	102.1	111.2	120.3	127.5	133.8	140.5	147.1	153.0	158.8	
					M	3.0	6.0	9.0	12.0	15.0	17.9	20.9	23.9	26.9	29.9	
	November	O	24	7	A	124.0	204.4	211.8	216.1	221.1	225.4	230.2	230.2	237.7	237.7	435.03
					M	5.5	11.0	16.4	21.9	27.3	32.8	38.2	43.7	49.2	54.6	
		S	17	6	A	130.7	148.3	163.2	176.8	189.1	200.7	211.9	222.2	232.1	241.5	
					M	5.5	11.1	16.6	22.1	27.7	33.2	38.7	44.3	49.8	55.3	
	December	O	24	12	A	157.0	201.0	226.0	246.0	271.0	291.0	315.0	355.0	375.0	400.0	451.91
					M	7.1	14.2	21.3	28.5	35.5	42.7	49.8	56.9	64.0	71.2	
		S	15	8	A	128.6	154.2	175.0	192.6	207.9	222.8	236.9	251.3	264.5	276.3	
					M	7.2	14.4	21.6	28.8	36.1	43.3	50.5	57.7	64.9	72.1	
União da Vitória (UV)	January	O	19	19	A	124.2	159.7	163.5	164.1	167.5	209.5	222.3	222.9	234.9	236.4	532.89
					M	5.0	10.1	15.2	20.2	25.3	30.3	35.4	40.4	45.4	50.4	
		S	15	12	A	93.0	111.7	126.7	139.2	151.5	162.3	172.7	182.6	191.9	201.5	
					M	5.1	10.3	15.4	20.6	25.7	30.8	36.0	41.1	46.3	51.4	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
União da Vitória (UV)	February	O	14	15	A	81.2	112.8	154.4	162.0	162.0	162.0	165.4	175.0	212.0	219.6	327.63
					M	5.8	11.7	17.6	23.4	29.3	35.2	41.1	46.9	52.8	58.7	
		S	13	14	A	96.8	117.0	134.0	149.0	162.1	174.1	186.4	197.6	208.6	219.1	
					M	6.0	11.9	17.9	23.9	29.9	35.8	41.8	47.8	53.7	59.7	
	March	O	15	11	A	99.8	127.3	127.3	149.2	154.4	154.4	154.4	158.7	168.9	177.6	329.73
					M	4.2	8.5	12.7	17.0	21.2	25.5	29.8	34.1	38.3	42.6	
		S	16	10	A	90.7	107.7	120.9	132.2	142.1	152.0	160.9	169.5	177.4	185.1	
					M	4.3	8.7	13.0	17.3	21.6	26.0	30.3	34.6	39.0	43.3	
	April	O	37	9	A	68.1	125.4	132.8	147.4	153.5	197.4	199.6	199.6	203.8	215.0	325.17
					M	3.8	7.6	11.4	15.2	18.9	22.6	26.3	30.0	33.7	37.4	
		S	22	8	A	100.6	119.9	134.8	146.0	155.7	165.8	174.8	183.3	190.8	198.5	
					M	3.9	7.8	11.7	15.5	19.4	23.3	27.2	31.1	35.0	38.9	
	May	O	27	7	A	154.6	214.2	261.1	261.1	261.1	261.3	311.3	340.3	340.3	340.3	468.05
					M	4.7	9.4	14.2	18.9	23.6	28.4	33.1	37.9	42.7	47.4	
		S	25	8	A	131.8	156.2	174.7	189.4	203.2	215.1	226.6	236.9	247.9	258.2	
					M	4.9	9.7	14.6	19.4	24.3	29.2	34.0	38.9	43.8	48.6	
	June	O	23	8	A	87.9	144.0	184.2	188.4	197.4	197.4	197.4	205.8	205.8	205.8	831.20
					M	4.6	9.3	13.9	18.6	23.3	27.9	32.6	37.3	42.0	46.7	
		S	24	9	A	132.1	156.1	172.8	187.1	200.0	211.7	223.0	235.4	245.2	254.3	
					M	4.8	9.5	14.3	19.0	23.8	28.6	33.3	38.1	42.9	47.6	
	July	O	27	9	A	121.4	192.0	269.8	326.8	345.4	378.1	396.7	414.9	421.3	435.3	518.03
					M	4.3	8.7	13.0	17.4	21.8	26.1	30.5	34.9	39.3	43.6	
		S	26	9	A	119.2	142.3	160.2	174.3	186.3	197.1	207.1	217.4	226.9	235.8	
					M	4.4	8.9	13.3	17.7	22.2	26.6	31.0	35.5	39.9	44.3	
	August	O	24	10	A	110.0	149.1	191.5	231.9	236.1	236.1	241.5	245.7	246.1	246.6	520.25
					M	3.7	7.5	11.3	15.0	18.8	22.6	26.3	30.1	33.9	37.7	
		S	30	9	A	114.7	136.0	152.0	166.0	177.8	188.8	197.6	206.6	214.7	223.3	
					M	3.8	7.7	11.5	15.3	19.2	23.0	26.8	30.7	34.5	38.3	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
União da Vitória (UV)	September	O	17	15	A	112.0	146.3	152.5	170.6	207.5	222.8	244.4	260.3	268.3	298.4	466.36
					M	5.3	10.7	16.0	21.4	26.7	32.0	37.4	42.7	48.1	53.4	
		S	21	10	A	117.0	141.8	160.6	175.7	189.5	202.1	214.7	225.9	237.2	248.0	
					M	5.4	10.9	16.3	21.7	27.2	32.6	38.0	43.4	48.9	54.3	
	October	O	18	11	A	87.4	122.1	122.1	127.0	155.2	180.4	195.4	205.3	239.7	239.7	513.91
					M	5.7	11.5	17.2	23.0	28.8	34.5	40.3	46.0	51.7	57.5	
		S	17	9	A	116.8	140.0	158.0	173.2	186.2	199.1	212.2	224.4	235.4	246.4	
					M	5.8	11.6	17.5	23.3	29.1	34.9	40.7	46.5	52.4	58.2	
	November	O	18	8	A	84.4	115.2	144.4	155.8	166.7	178.1	186.6	187.1	187.2	195.1	488.67
					M	4.7	9.4	14.1	18.8	23.5	28.2	32.9	37.5	42.2	46.8	
		S	19	9	A	99.4	119.0	133.8	147.0	159.2	170.3	180.3	189.9	199.6	208.8	
					M	4.8	9.6	14.4	19.2	23.9	28.7	33.5	38.3	43.1	47.9	
	December	O	14	13	A	156.2	156.7	198.3	202.1	202.6	203.1	203.3	207.3	245.1	263.9	524.19
					M	5.5	10.9	16.4	21.9	27.3	32.8	38.3	43.8	49.3	54.8	
		S	16	11	A	107.3	128.6	145.4	159.2	171.9	183.7	195.2	206.2	217.1	227.2	
					M	5.6	11.2	16.7	22.3	27.9	33.5	39.0	44.6	50.2	55.8	
Cacequi (Cq)	January	O	27	9	A	116.0	210.0	255.0	255.0	255.0	286.4	286.4	286.4	286.4	286.4	208.53
					M	4.5	9.0	13.5	18.0	22.5	27.0	31.5	36.0	40.4	44.9	
		S	29	6	A	136.5	159.3	175.5	188.4	200.9	212.8	223.3	233.4	243.8	252.5	
					M	4.6	9.2	13.7	18.3	22.9	27.5	32.0	36.6	41.2	45.8	
	February	O	21	8	A	114.3	156.2	239.0	255.2	255.2	255.2	255.2	255.2	255.2	255.2	194.88
					M	5.0	10.0	15.0	20.0	25.0	30.0	35.0	39.9	44.9	49.8	
		S	25	6	A	132.9	156.9	173.3	187.4	200.8	212.8	223.7	235.1	245.4	254.5	
					M	5.1	10.1	15.2	20.3	25.4	30.5	35.5	40.6	45.7	50.8	
	March	O	29	9	A	98.6	120.0	120.0	127.0	151.0	151.0	160.0	198.0	222.0	222.0	208.89
					M	4.3	8.7	13.0	17.3	21.7	26.1	30.4	34.8	39.2	43.6	
		S	30	6	A	124.7	148.5	164.7	177.9	189.8	201.3	212.0	221.4	231.0	240.4	
					M	4.4	8.8	13.2	17.6	22.0	26.4	30.8	35.2	39.6	44.0	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
	April	O	30	7	A	203.7	261.5	312.4	312.4	312.4	317.7	324.5	350.0	358.5	359.7	195.99
					M	5.4	10.7	16.1	21.4	26.7	32.1	37.5	42.8	48.2	53.6	
		S	27	6	A	183.4	206.1	224.1	237.8	251.0	263.8	275.7	287.2	298.4	309.1	
					M	5.4	10.9	16.3	21.8	27.2	32.7	38.1	43.6	49.0	54.5	
	May	O	30	5	A	106.2	131.2	176.2	184.6	189.2	233.2	233.2	234.5	247.3	262.0	207.95
					M	4.5	9.1	13.7	18.2	22.8	27.3	31.9	36.5	41.1	45.7	
		S	35	6	A	148.2	175.8	195.8	211.7	225.1	236.6	248.2	259.2	269.9	279.8	
					M	4.6	9.2	13.8	18.4	23.0	27.6	32.2	36.8	41.4	46.0	
	June	O	21	5	A	137.6	179.2	191.6	191.6	195.5	197.3	197.3	208.8	217.7	231.5	201.86
					M	4.4	8.8	13.1	17.5	21.9	26.4	30.8	35.2	39.6	44.1	
		S	28	6	A	143.1	162.9	177.2	188.7	200.3	211.3	221.0	230.7	239.9	248.7	
					M	4.5	8.9	13.4	17.8	22.3	26.7	31.2	35.6	40.1	44.5	
Cacequi (Cq)	July	O	25	8	A	107.8	108.4	122.6	145.8	150.1	153.3	170.4	179.9	179.9	202.1	208.41
					M	4.6	9.1	13.7	18.3	22.8	27.4	32.0	36.6	41.2	45.8	
		S	27	6	A	120.4	142.2	158.3	172.4	184.6	196.6	206.7	217.1	226.5	235.5	
					M	4.7	9.3	14.0	18.6	23.3	27.9	32.6	37.2	41.9	46.6	
	August	O	34	7	A	136.0	152.0	152.0	152.0	152.2	167.4	167.4	167.4	167.4	181.4	208.56
					M	3.2	6.4	9.5	12.7	15.9	19.1	22.3	25.5	28.6	31.8	
		S	33	6	A	109.5	128.0	140.4	151.1	159.9	168.4	176.0	183.3	190.4	197.5	
					M	3.2	6.5	9.7	12.9	16.2	19.4	22.7	25.9	29.1	32.4	
	September	O	21	5	A	135.0	165.5	178.8	183.6	190.1	207.1	207.1	207.1	265.8	265.8	202.13
					M	4.9	9.8	14.7	19.6	24.5	29.5	34.4	39.3	44.3	49.3	
		S	27	6	A	141.0	165.3	183.6	197.9	210.6	222.6	234.0	244.9	256.5	266.6	
					M	5.0	9.9	14.9	19.9	24.9	29.8	34.8	39.8	44.8	49.7	
	October	O	33	7	A	138.8	140.0	147.8	160.7	177.9	212.1	228.3	228.3	245.8	258.1	208.08
					M	4.8	9.6	14.4	19.3	24.1	29.0	33.7	38.5	43.2	48.0	
		S	28	6	A	137.2	161.3	178.3	192.3	204.5	216.4	226.8	237.1	247.4	256.6	
					M	4.9	9.8	14.7	19.6	24.5	29.4	34.3	39.2	44.1	49.0	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

conclusion

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Cacequi (Cq)	November	O	30	5	A	115.8	158.2	160.0	161.4	178.4	182.8	182.8	199.4	229.8	272.2	202.39
					M	4.4	8.8	13.3	17.7	22.1	26.5	30.8	35.1	39.4	43.8	
		S	27	5	A	128.3	147.3	162.8	174.3	186.6	197.6	207.2	217.1	225.4	233.8	
					M	4.5	9.0	13.5	18.0	22.5	27.0	31.5	36.0	40.5	45.0	
	December	O	25	3	A	135.6	135.6	154.0	154.0	208.7	208.7	208.7	208.7	237.9	237.9	208.75
					M	3.5	7.0	10.5	14.1	17.6	21.1	24.6	28.1	31.7	35.2	
		S	33	5	A	116.3	134.6	148.1	158.1	167.6	176.6	184.5	193.1	200.6	208.0	
					M	3.6	7.2	10.7	14.3	17.9	21.5	25.0	28.6	32.2	35.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

Regarding the total amount per period, it was chosen to present results in two ways: absolute terms and mean terms. The option was made from the initial analysis of the absolute terms. Model revealed some difficulty in reproducing accumulated amounts events per period (or class). However these errors, which in some cases resulted in elevated values, did no consist with the obtained results on the validation of the model. For this reason, calculation in mean terms was included. Table 11.11 shows the magnitude of mean errors obtained, in both terms considered.

Table 11.11 – Mean errors for total amounts per period

Term	Errors in Total amounts (mm) per class (days)									
	1	2	3	4	5	6	7	8	9	10
Absolute	13.7	20.3	25.6	27.6	29.6	32.5	34.6	34.5	35.1	36.8
Mean	0.1	0.2	0.2	0.3	0.4	0.4	0.5	0.6	0.7	0.7

Note that the errors, in mean terms, have low magnitude, i. e., model kept its good performance previously presented. Therefore, it is understood that obtaining a good reproduction of total amounts in absolute term could be prejudiced by two reasons: first, theoretical, is related with sample variability present in the generated series. A bias analysis for the estimators was not made, so it is not clear the degree of reliability of them. Second, physical, is related to great intensity of some events found in historical series. Still knowing that some synthetic series were able to reproduce them, results are expressed as means of the 1000 generated series. Thus, when comparing these mean values there is an undesirable loss of information.

In the case of maximum sequences of events in a same state, it can be said that the model had a good performance, mainly for wet days. Mean error for this was only 1 day. For droughts, minor precision was obtained that results a mean error of 6 days. However, analyzing the results, one can note that this means was strongly influenced by periods of extreme droughts. As an example, Taiamã station, in Julys, had 222 dry days in sequence, corresponding to approximately 23% of the sample. Mean of synthetic series indicated 158 days in sequence, without rain. Even that there is a tendency in reproducing this large dry period, error was 64 days. It is understood that, for cases like that, 35 years of historical records are insufficient to the application of the model.

Last requirement to be evaluated in this section is the distribution of empirical probabilities for the drought periods. Once again, the curves were drawn for only three stations, the same used previously. The only difference is that the distributions were estimated for two groups of months in each station: Januaries and Julys, representing low and high rainfall periods, respectively. As exception, for Taiamã, in Julys, it was not possible to drawn the probabilistic curve, because of its extreme quantity of dry days. Figure 11.9 shows the graphs obtained.

The analysis over Figure 11.9 clarifies that the model showed a good performance. It is noteworthy that, for Taiamã's station in Julys, a larger historical sample would be necessary to proper modeling.

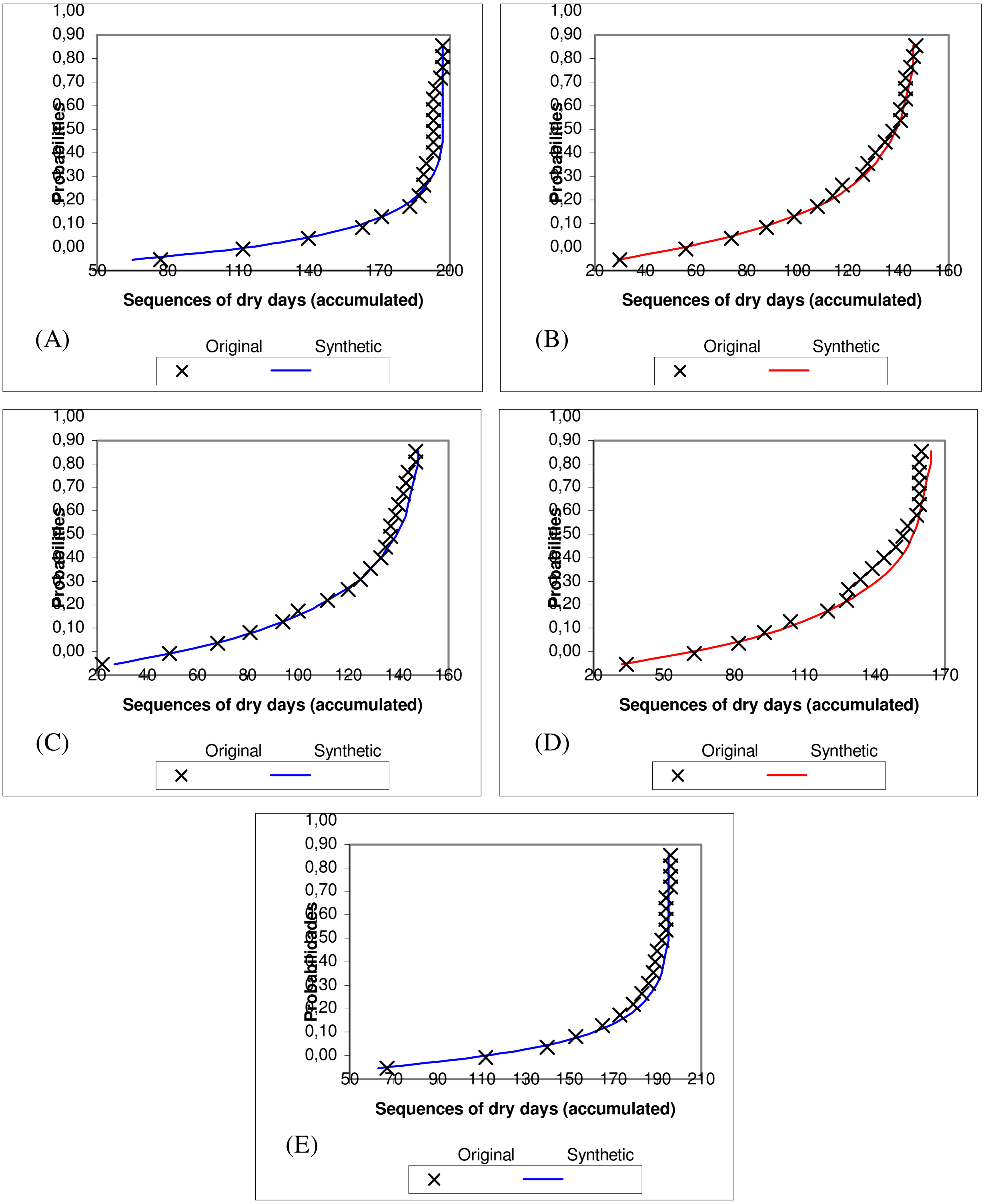

Figure 11.9 – Empirical distributions for sequences of dry days (A) União da Vitória, Januaries (B) União da Vitória, Julys (C) Cacequi, Januaries (D) Cacequi, Julys (E) Taiamã, Januaries

CONCLUSIONS

With respect to SMMAR91) Model with the applied tests results, we can verify that: (i) annual totals long term means are preserved in all stations with α>9% and in 8 stations with α>16%; (ii) annual totals variances are preserved in 4 stations with α>7%, in 1 station with α>4%, in 2 stations with α>1% and in another 2 station with α<1%; (iii) of 153 calculated correlation coefficients, 130 are preserved with α >10%, 14 are preserved with α>6%, 4 coefficients with α>1% and for only 5 coefficients, α<1%.

Due the aforementioned results, it is concluded that SMMAR(1) can be considered as totally satisfactory to produce annual and monthly total rainfall synthetic series, for all the stations considered in this work.

With respect to the model to generate synthetic series of annual rainfall (MDM Model) with monthly disagregagtion it was observed that all statistics, except the skew coefficient, the value computed from historic record is well within the range of the values of the synthetic series and in most cases close to the average from 1,000 series computed. This shows that the synthetic series reasonably preserve well most of the statistics of the historic record in terms of annual precipitation.

Only for skew coefficient there are two cases were the value computed from historic records are outside of the interval of the synthetic series. This happens at sides 1 and 3 corresponding to locations near the northeastern limit of the basin where, perhaps, the normality assumption does not apply because of a strong dry season (from April to October) so that not enough precipitation events occur throughout the year.

In spite of the fact that the synthetic series show almost no skew (because of the normality assumption) and the historic record is generally skewed, the statistics more related to the proposed usage of the model (analysis of hydropower output) are well represented by the synthetic series.

Regarding DUM Model for daily generation of synthetic series proposed in the present work, it is predominantly parametric, and strongly based in statistical concepts, employing information taken from historical series. As a basis reference, univariate (single site) part of Wilks (1998) article was used. Initially developed and applied in New York State, USA, model presented very good results, what led the author to credit this performance to the use of three parameter mixed exponential probabilistic distribution, underused until then.

As assumption for this work, alterations in Wilks' model were not made, just for analysis of its performance in a climatologic distinct region. In evaluating the results, it was clear that the model repeated its good performance.

However, the construction of the model imposed some challenges, mainly related to the mixed exponential distribution. First one appeared in the estimation of the three required parameters; such as the used of this distribution has limited bibliography, extensive research around the appropriate method was needed. In the following, came the doubt about the quality of adjustment that this distribution was able to provide for the data group of the wanted study area. So, four were the analyses to evaluate this questions. Comparing with two parameters gamma distribution (most used for generation of synthetic series of precipitation), mixed exponential was superior in all cases. This fact, together with application of AIC and BIC criteria to determine the optimum order of the markovian chains used, provided an extra reliability to the application of the model.

Another difficulty found in developing this work is related with the historical data used. Among the 11 rainfall stations considered, only a few had the complete 35 yeas of registers. Great majority has misses that varies from soma days to months with black data. Fortunately, the way the model was structured, the flaws in registers did not prevent its execution, but definitely reflected on the precision of presented results. However, even with the large volume of information obtained with 35 years of daily data, it was clear that they were insufficient to a good representation in some rainfall stations, rather in extreme events analyses.

Regarding the objectives proposed in this work, it is concluded that they were successfully reached. Therefore, one can say that the employed model is appropriate to generate synthetic series of precipitation, on a daily scale basis.

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ANNEX A - HOMOGENEITY ANALYSIS OF RAINFALL STATIONS

Figure 01 A - Homogeneity Analysis of Monte Carmelo station

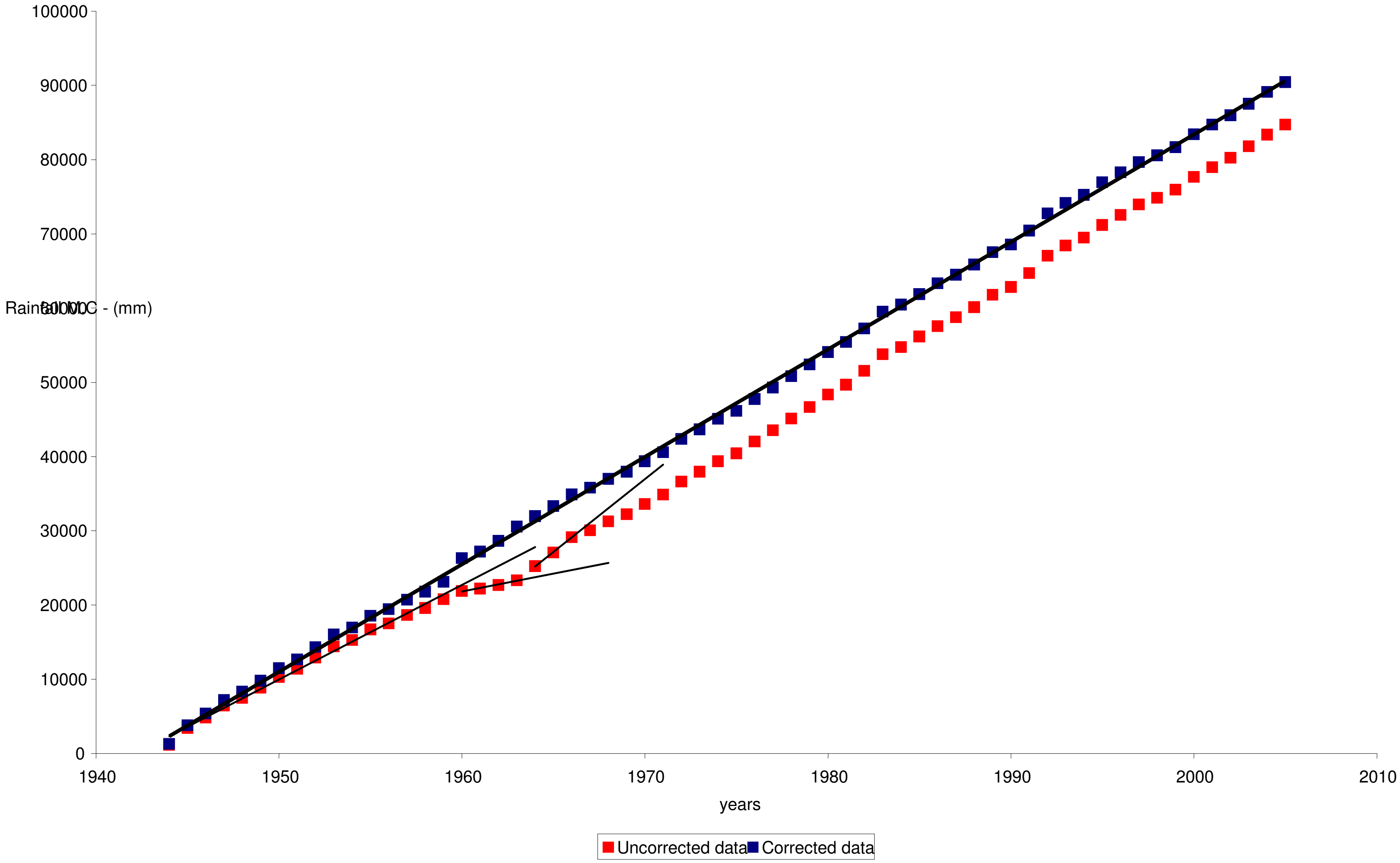


Figure 02 A - Homogeneity Analysis of Monte Alegre de Minas station

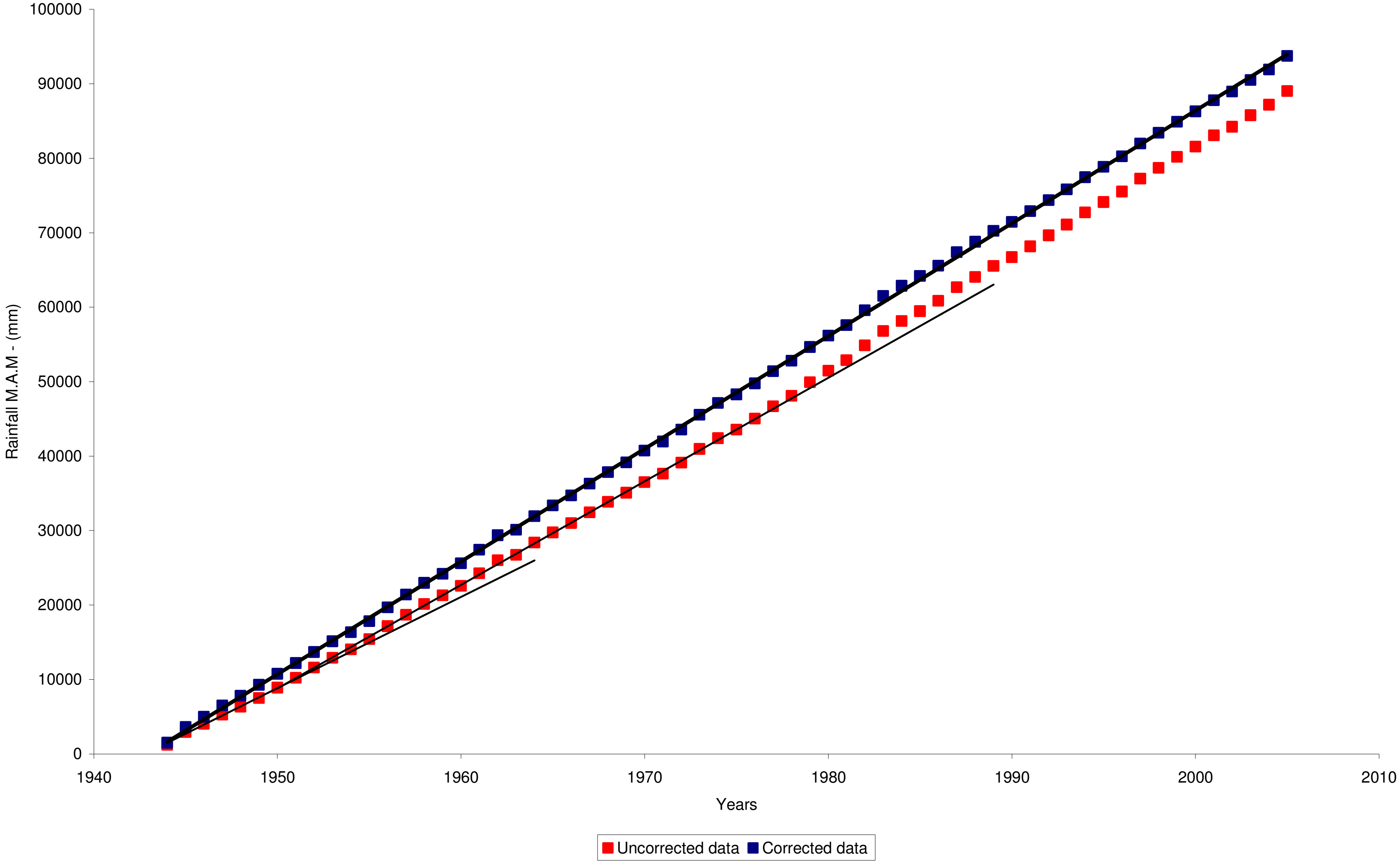


Figure 03 A - Homogeneity Analysis of Usina Couro do Servo station

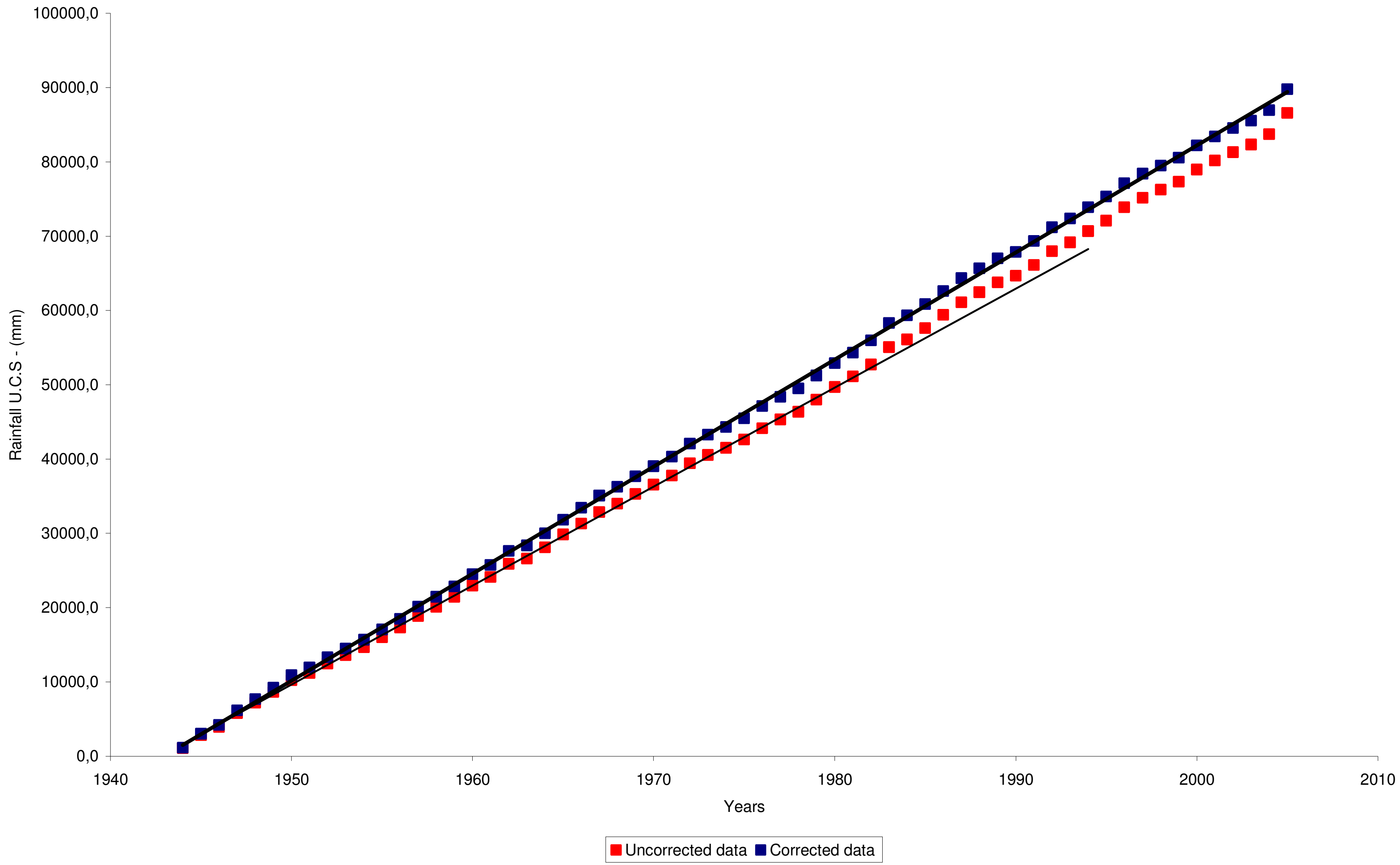


Figure 04 A - Homogeneity Analysis of Franca station

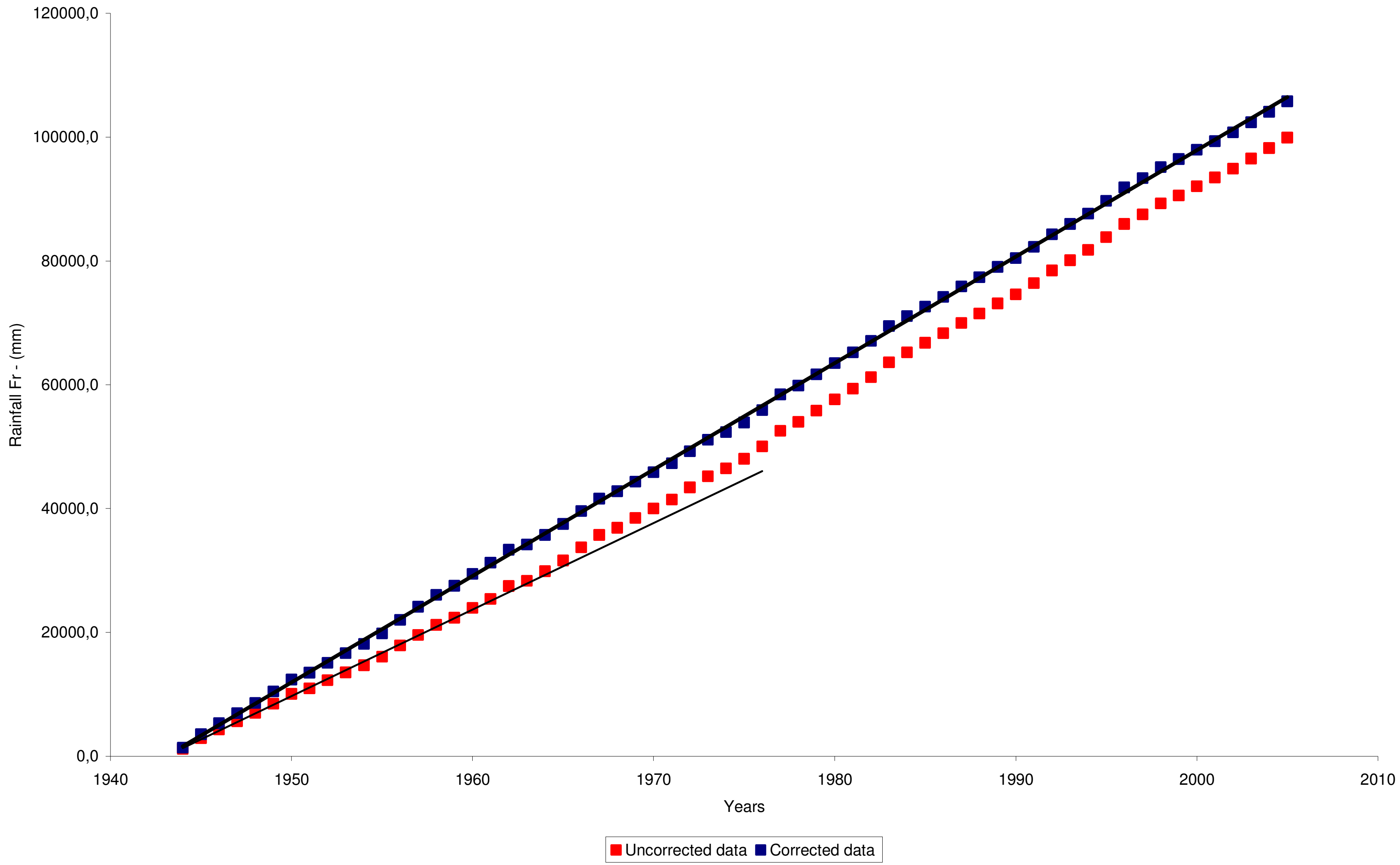


Figure 05 A - Homogeneity Analysis of Fazenda Barreirinho station

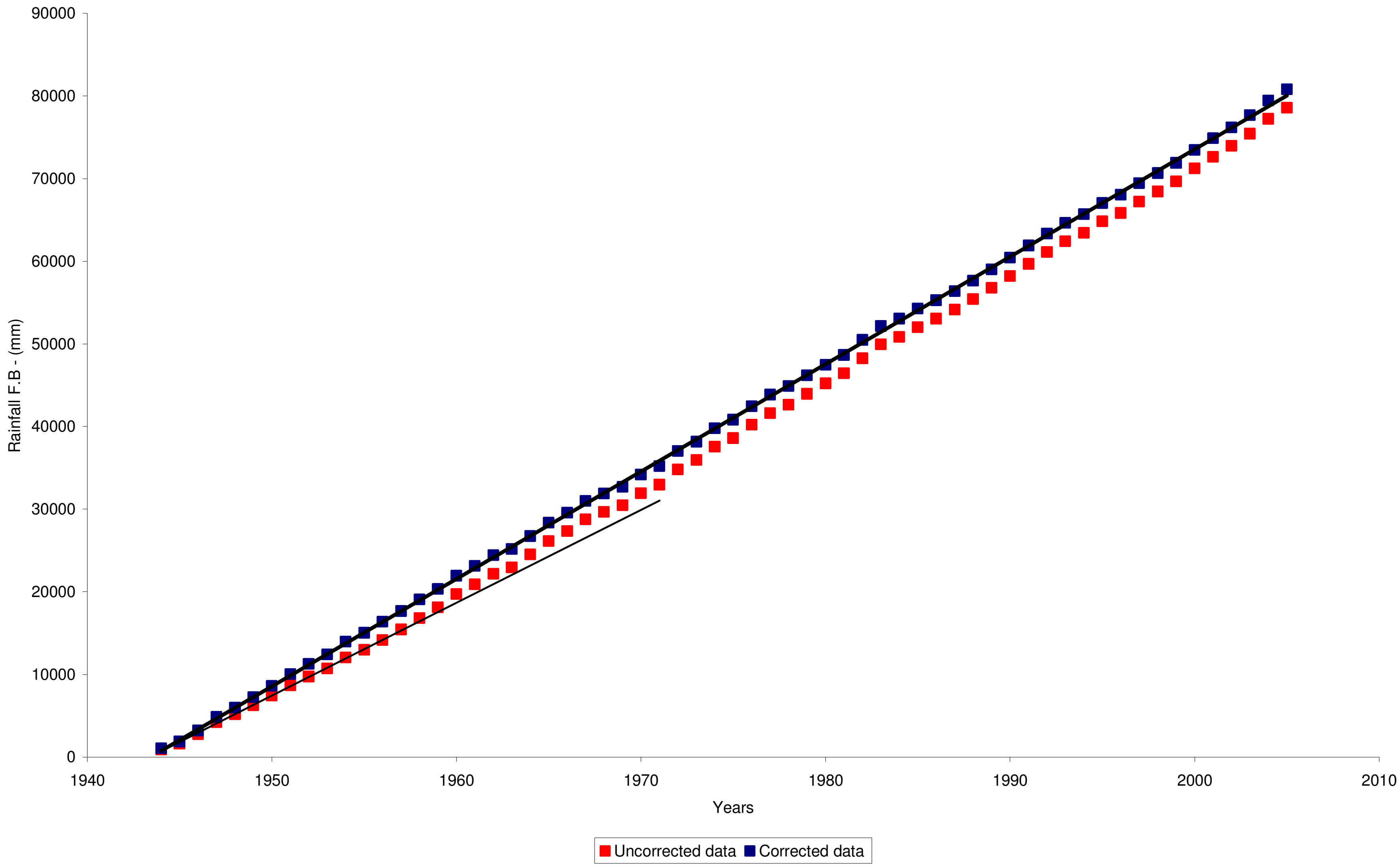


Figure 06 A - Homogeneity Analysis of Tomazina station

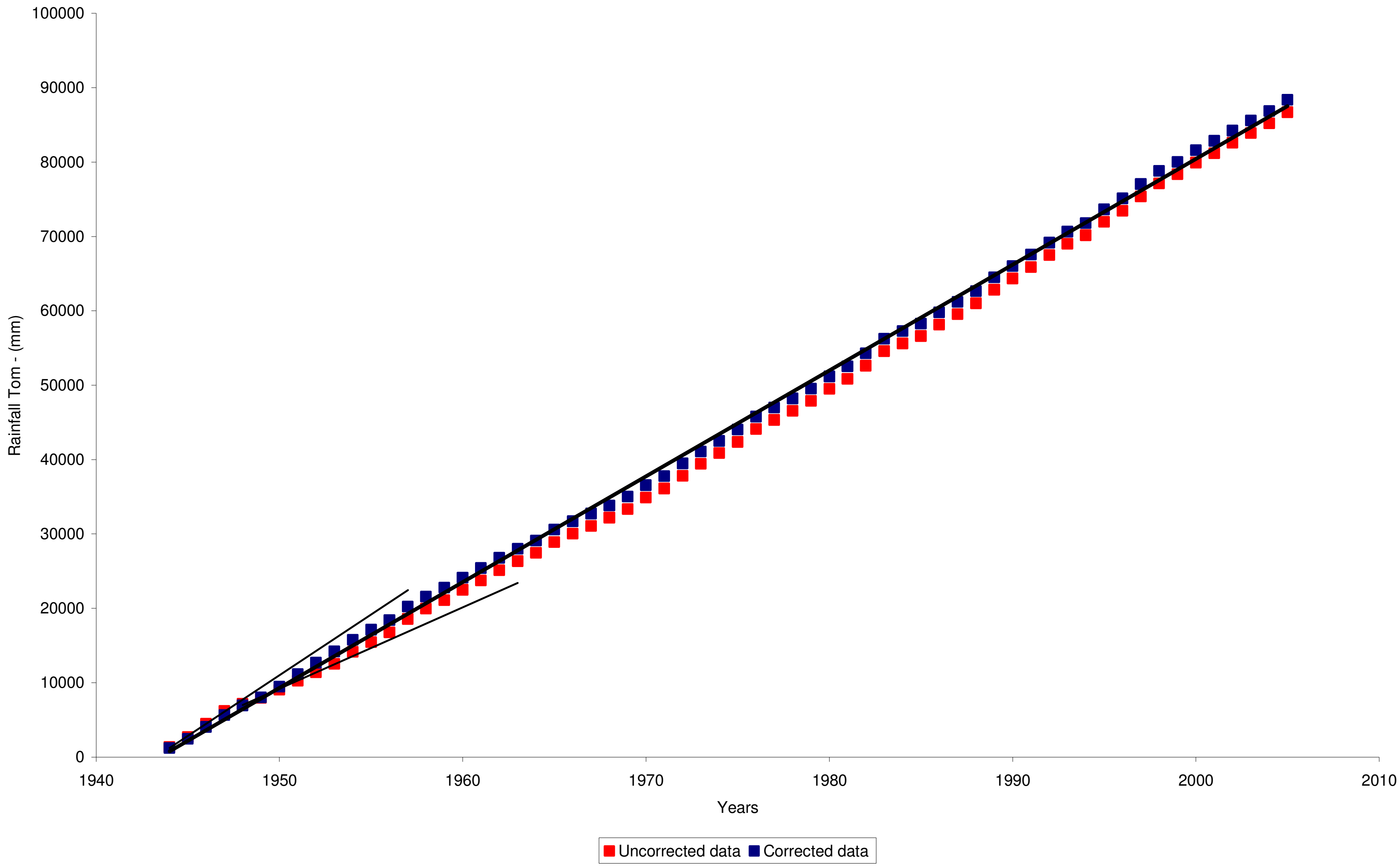


Figure 07 A - Homogeneity Analysis of União da Vitória station

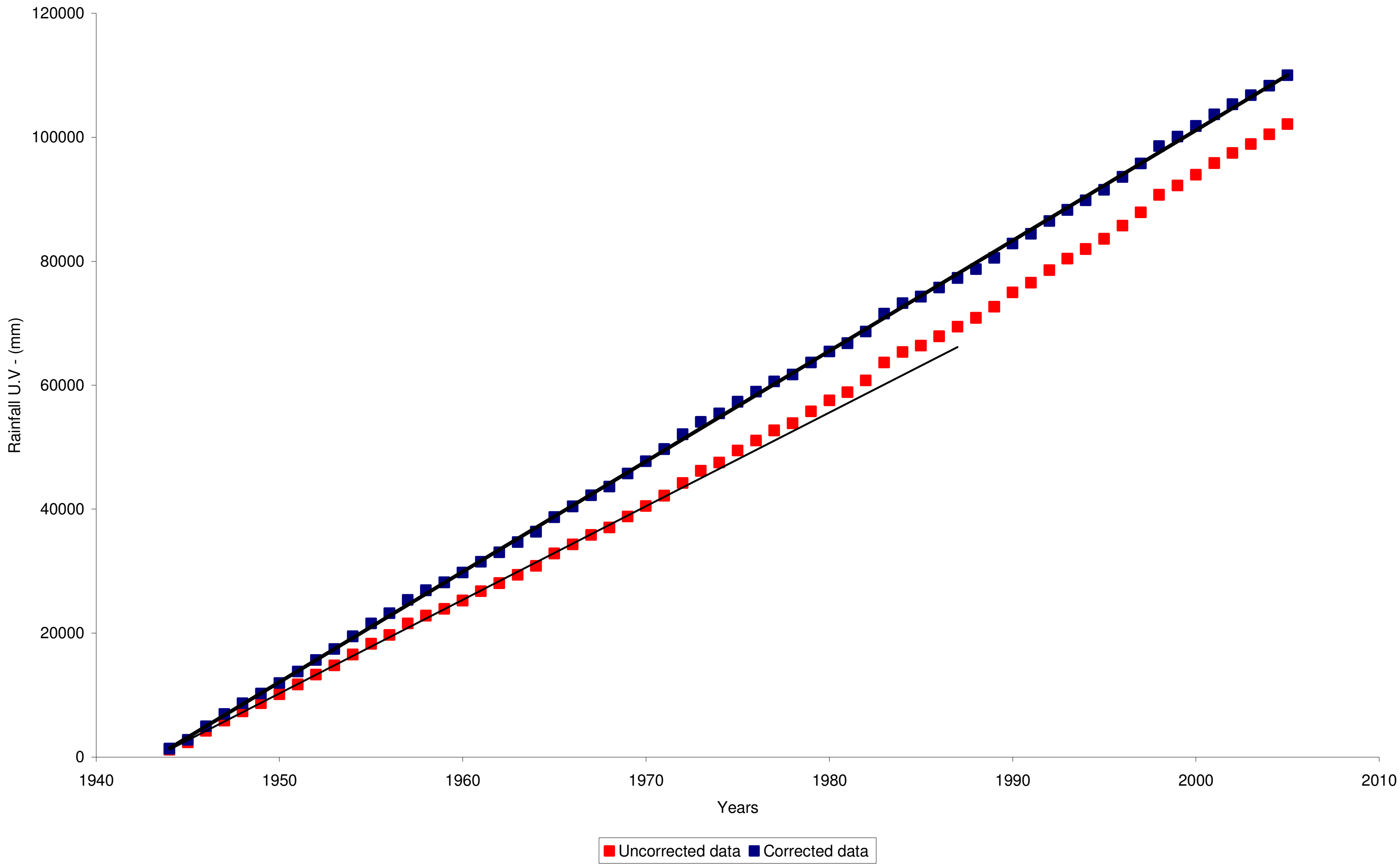


Figure 08 A - Homogeneity Analysis of Lagoa Vermelha station

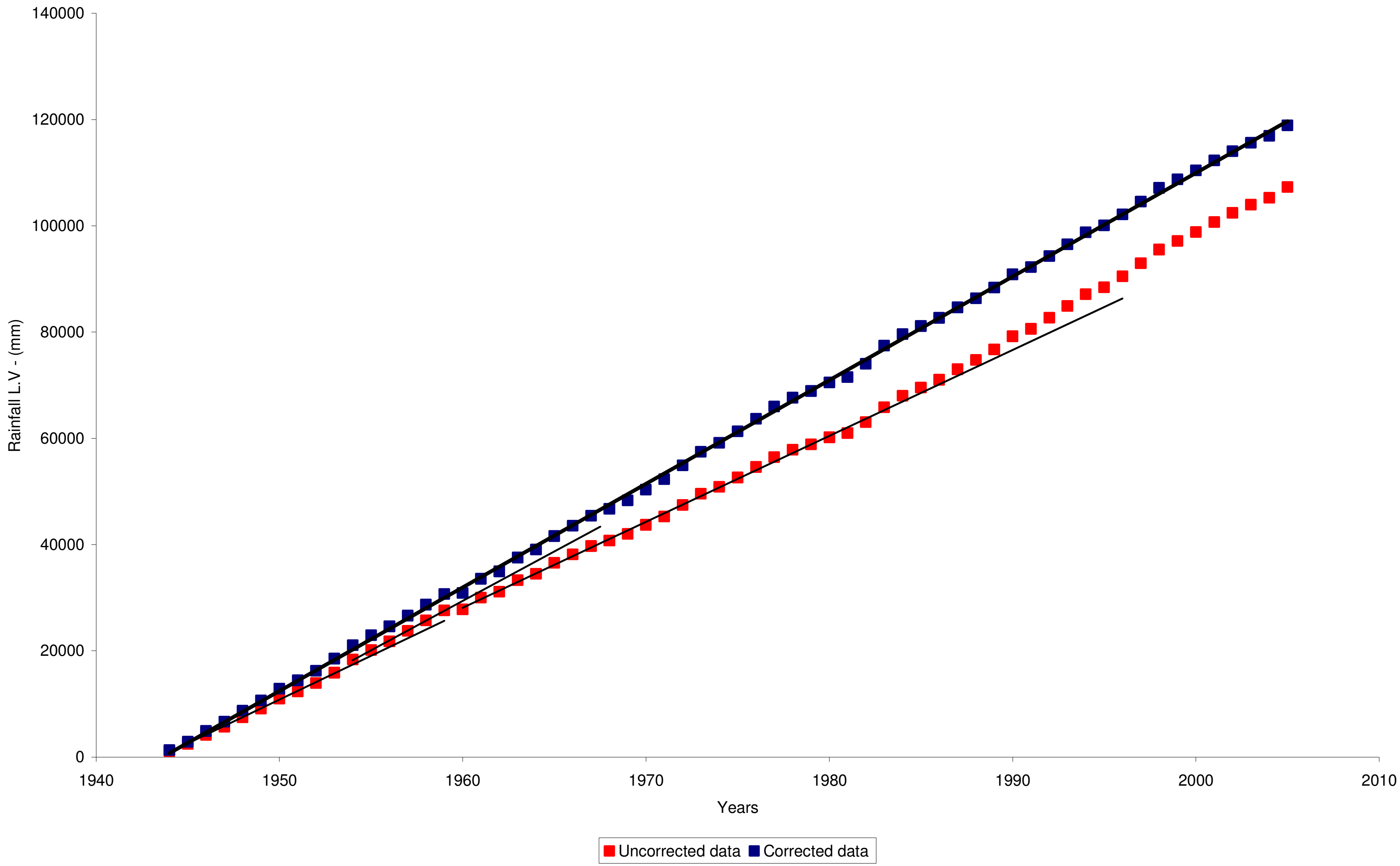
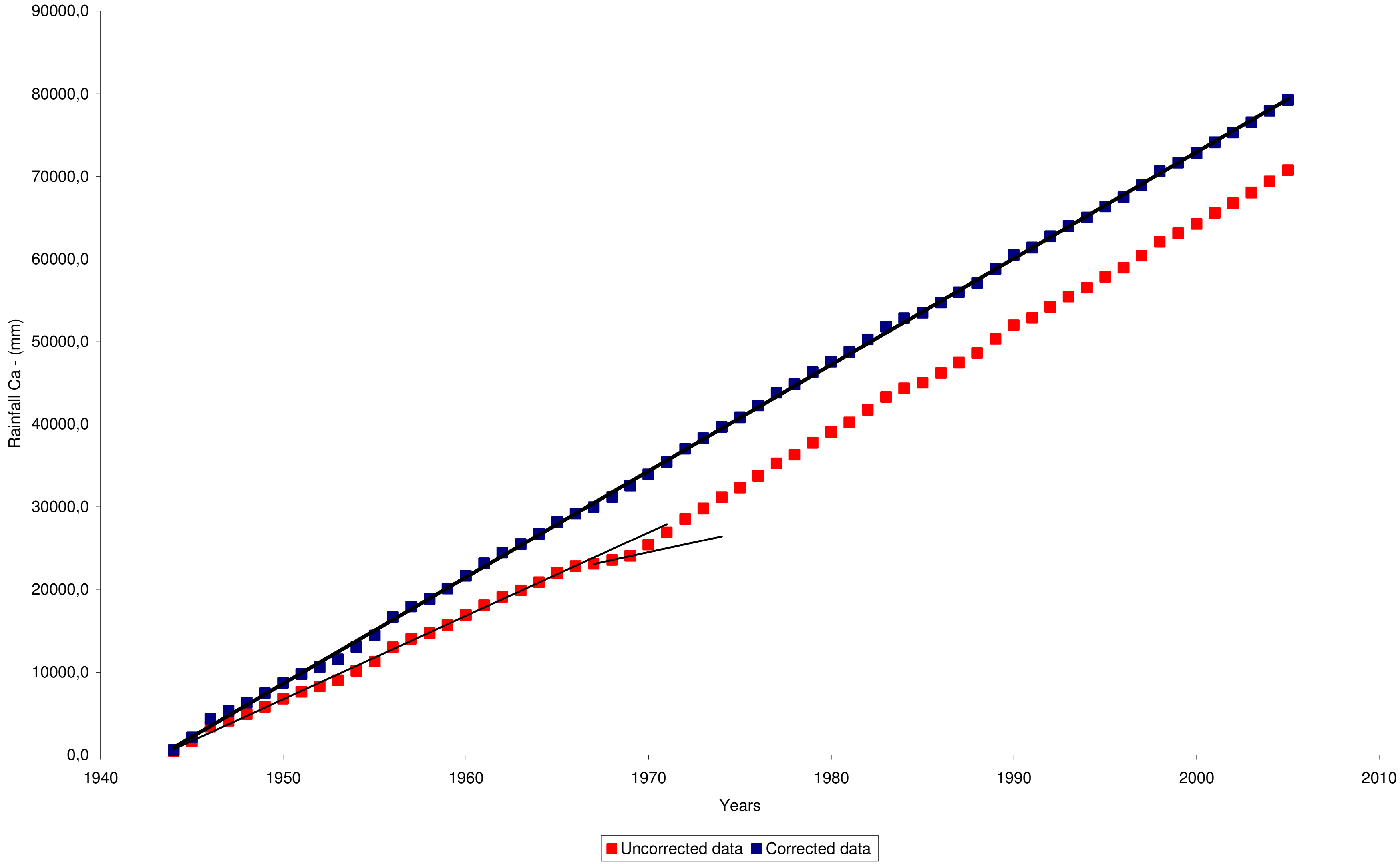


Figure 09 A - Homogeneity Analysis of Caiuá station



ANNEX B – SMMAR(1) MODELS PARAMETERS

Table 1-B. Rainfall stations

No.	Code	Station name	UF	Lat. (°)	Lat. (′)	Lon. (°)	Lon. (′)
1	01847000	Monte Carmelo	MG	18	45	47	41
2	01848000	Monte Alegre de Minas	MG	18	52	48	52
3	02145007	Usina Couro do Cervo	MG	21	21	45	11
4	02047017	Cidade Nova (Nsa. de Fátima)	SP	20	32	47	25
5	02148128	Fazenda Barreirinho	SP	21	56	48	59
6	02349033	Tomazina	PR	23	46	49	57
7	02651000	União da Vitória	PR	26	14	51	04
8	02851014	Lagoa Vermelha	RS	28	12	51	32
9	02151035	Caiuá (Prefeitura)	SP	21	50	51	59

No – The serial number of the station identified in each row.

Table 2-B. Parameters of monthly precipitation series transformed by Box-Cox transformation

Code	month	λ	$\lvert Ca(Y) \rvert$	$m(Y)$	$s(Y)$
01847000	1	0.00000	6.3193631	5.3591914	1.6810386
	1	0.48006	0.0000003	28.6545841	9.3283242
	2	0.00000	3.8003748	4.6785903	2.5839242
	2	0.64714	0.0014031	45.9523510	21.5397898
	3	0.00000	4.4852159	4.6658914	2.1508731
	3	0.57746	0.0004896	31.3212112	13.3816521
	4	0.00000	3.7073282	3.6349454	1.9143349
	4	0.42487	0.0007465	10.6621798	5.1817213
	5	0.00000	1.5343964	1.7575320	3.2212574
	5	0.41603	0.0018576	5.6066785	4.7450398
	6	0.00000	0.2262411	-1.0531803	3.4107114
	6	-0.25212	0.0002761	-3.1388346	4.7582482
	7	0.00000	0.2059275	-1.0786298	3.5316721
	7	-0.99998	0.0021301	-42.0235259	42.4924775
	8	0.00000	0.2091887	-1.0275615	3.3557425
	8	-0.78416	0.0009373	-16.7857507	17.6634299
	9	0.00000	1.9423432	2.5305656	2.5945008
	9	0.41813	0.0010437	7.2099954	5.3497176
	10	0.00000	5.7898144	4.4893401	1.4754069
	10	0.53298	0.0000636	21.4053940	7.7560704
	11	0.00000	6.3088619	4.9780441	1.5642311
	11	0.54555	0.0005524	29.6912422	9.9716734
	12	0.00000	6.8107417	5.3302936	1.5727230
	12	0.73122	0.0000000	78.7685372	26.2411257
01848000	1	0.00000	0.1753265	5.5922758	0.4227961
	1	0.17891	0.0002059	9.6553223	1.1463879
	2	0.00000	1.5181980	5.2294748	0.5608233
	2	0.73307	0.0006379	66.3221740	22.7099020
	3	0.00000	0.9772095	5.1447487	0.5416552
	3	0.73473	0.0003084	62.5888865	21.7857792
	4	0.00000	4.5793995	4.0195059	1.5059406
	4	0.45984	0.0011206	13.4205243	5.5172024
	5	0.00000	2.4408504	2.8931033	2.0012204
	5	0.38226	0.0017718	6.8568754	4.2440594
	6	0.00000	0.4756464	0.1019037	3.5342913
	6	0.21174	0.0011120	1.3812622	3.5186333

Table 2-B. Parameters of monthly precipitation series transformed by Box-Cox transformation (continuation)

Código	mês	λ	$\|Ca(Y)\|$	$m(Y)$	$s(Y)$
01848000	7	0.00000	0.1854423	-0.8879974	3.5010046
	7	-0.26620	0.0001308	-3.1259952	4.8790913
	8	0.00000	0.1654474	-0.8815186	3.7079036
	8	-0.69419	0.0009675	-14.7909724	15.8809220
	9	0.00000	1.8569123	2.5244401	2.8028788
	9	0.68845	0.0001480	15.8818885	11.4773894
	10	0.00000	0.8947556	4.7933898	0.6201512
	10	0.61510	0.0004930	31.4741870	11.0091200
	11	0.00000	0.2104654	5.2577356	0.4151129
	11	0.18049	0.0001326	8.8108244	1.0681381
	12	0.00000	0.3959906	5.5005179	0.3357042
	12	0.43771	0.0002744	23.3623684	3.6773036
02145007	1	0.00000	0.7939622	5.4658395	0.5205543
	1	0.73957	0.0002432	80.9925459	27.8112563
	2	0.00000	1.0375728	5.1714402	0.6256668
	2	0.94629	0.0001807	161.5697044	74.0054484
	3	0.00000	0.3786985	5.0279647	0.4611139
	3	0.22473	0.0005213	9.3974898	1.4129929
	4	0.00000	0.7288412	3.9763651	0.7119627
	4	0.27845	0.0007107	7.4816820	2.0774381
	5	0.00000	2.8892567	3.1127197	1.8055760
	5	0.42467	0.0005142	8.1462773	4.6228276
	6	0.00000	0.9282854	0.9797539	3.3510725
	6	0.35973	0.0012626	3.5476208	4.1994594
	7	0.00000	0.5310610	0.2717302	3.5819510
	7	0.27498	0.0009602	2.0544592	3.7917253
	8	0.00000	0.8704639	0.6725076	3.3369703
	8	0.26867	0.0016651	2.2723683	3.5192176
	9	0.00000	2.2550996	2.8570837	2.9070181
	9	0.44843	0.0003661	9.6472047	6.2851084
	10	0.00000	1.6339190	4.5845864	0.6066376
	10	0.82386	0.0005342	57.3403249	22.4535997
	11	0.00000	0.3892138	5.1598744	0.5202428
	11	-0.07093	0.0024517	4.3144085	0.3593200
	12	0.00000	0.3294423	5.5341656	0.5204580
	12	-0.07432	0.0018218	4.5305938	0.3437005

Table 2-B. Parameters of monthly precipitation series transformed by Box-Cox transformation (continuation)

Código	mês	λ	$\|Ca(Y)\|$	$m(Y)$	$s(Y)$
02047017	1	0.00000	0.4704109	5.6742153	0.3145951
	1	0.50804	0.0004413	33.6333942	5.5167937
	2	0.00000	1.5814941	5.3616210	0.5894325
	2	0.70024	0.0002750	64.0476462	21.9436204
	3	0.00000	0.2817746	5.1976949	0.4261962
	3	0.25599	0.0002089	10.9595779	1.6007873
	4	0.00000	1.1533972	4.2698831	0.7650122
	4	0.53208	0.0007927	17.7054710	6.7299154
	5	0.00000	2.8768950	3.3223912	1.9237069
	5	0.46545	0.0010290	10.4032704	5.9205103
	6	0.00000	1.0180254	1.2379181	3.3483264
	6	0.43549	0.0009819	4.9787016	5.0749409
	7	0.00000	0.7227835	0.8060160	3.2322944
	7	0.27361	0.0009327	2.4984319	3.7692804
	8	0.00000	0.6277689	0.5555025	3.4693575
	8	0.26219	0.0000320	2.2637539	3.8274115
	9	0.00000	2.3160155	3.1347227	2.6569359
	9	0.47594	0.0016308	11.5601102	7.4166882
	10	0.00000	0.0803321	5.0135921	0.5422401
	10	-0.02600	0.0014848	4.6972089	0.4758227
	11	0.00000	0.0991230	5.3301104	0.3720823
	11	0.16221	0.0001722	8.4975534	0.8822845
	12	0.00000	1.1476025	5.5827235	0.3888637
	12	0.68922	0.0006235	68.8399548	16.8742550
02148128	1	0.00000	1.2204017	5.3185487	0.5697242
	1	0.75070	0.0006482	76.7160355	27.5473191
	2	0.00000	0.3664328	5.1910183	0.5211695
	2	0.29610	0.0000179	12.5145348	2.3922283
	3	0.00000	0.6779136	4.7476186	0.6007072
	3	0.22144	0.0004402	8.5177250	1.6786485
	4	0.00000	2.9750010	3.4677870	1.9990186
	4	0.52598	0.0005282	13.5485112	7.6660096
	5	0.00000	2.7725588	3.2525331	2.3393663
	5	0.43432	0.0014061	9.9401590	5.7883694
	6	0.00000	1.8030332	2.3609901	2.9062443
	6	0.45425	0.0013332	7.8436180	5.9644596

Table 2-B. Parameters of monthly precipitation series transformed by Box-Cox transformation (continuation)

Código	mês	λ	$\|Ca(Y)\|$	$m(Y)$	$s(Y)$
02148128	7	0.00000	1.1258860	1.3088111	3.2533419
	7	0.25730	0.0013771	3.1243175	3.8500790
	8	0.00000	0.7002651	0.7764920	3.6733226
	8	0.31937	0.0003672	3.3395713	4.5134601
	9	0.00000	2.9101109	3.5218831	1.6241391
	9	0.53818	0.0006193	13.5205286	7.5171690
	10	0.00000	0.6827180	4.6228252	0.5080807
	10	0.45869	0.0000018	16.4653470	4.0713800
	11	0.00000	2.9910594	4.6443596	0.7793047
	11	0.46593	0.0008633	17.4990229	5.3623484
	12	0.00000	0.3609473	5.2389825	0.4425860
	12	0.24912	0.0006214	10.8799972	1.6159719
02349033	1	0.00000	0.8687163	5.2297989	0.4991876
	1	0.40489	0.0007280	18.4563690	3.9705013
	2	0.00000	1.0651076	4.9389560	0.6368417
	2	0.61304	0.0002098	34.3836669	11.9747227
	3	0.00000	0.4312758	4.8179579	0.5101651
	3	0.33564	0.0003464	12.2480855	2.5254368
	4	0.00000	4.0805393	4.0219770	1.5603311
	4	0.55432	0.0013323	18.3083335	8.5415844
	5	0.00000	4.1721175	4.0777901	1.5637542
	5	0.36109	0.0000278	10.4996667	4.4619860
	6	0.00000	3.5942491	3.9111886	1.6032879
	6	0.53266	0.0007556	16.3961947	8.2304521
	7	0.00000	2.6070115	3.1953205	2.6289860
	7	0.42902	0.0016806	10.1059024	6.0722322
	8	0.00000	2.2424340	2.9983272	2.4056283
	8	0.49915	0.0007184	10.9198886	7.2952277
	9	0.00000	0.7933689	4.3277630	0.8451059
	9	0.41050	0.0006757	12.7724119	4.7050246
	10	0.00000	0.5357068	4.8272263	0.5426527
	10	0.35739	0.0005416	13.1974226	2.9732509
	11	0.00000	5.7983097	4.4272541	1.4227794
	11	0.63788	0.0014011	29.2246667	11.0567593
	12	0.00000	0.5312498	4.9972513	0.4641911
	12	0.42220	0.0003848	17.5303454	3.7367352

Table 2-B. Parameters of monthly precipitation series transformed by Box-Cox transformation (continuation)

Código	mês	λ	$\|Ca(Y)\|$	$m(Y)$	$s(Y)$
02651000	1	0.00000	0.7516299	5.0128195	0.4869063
	1	0.59393	0.0003467	32.6861829	9.0902604
	2	0.00000	1.3813989	5.0098117	0.5443110
	2	0.75642	0.0006896	61.4958436	21.1934531
	3	0.00000	0.4015388	4.8122560	0.5092985
	3	0.35739	0.0003818	13.0800819	2.7982247
	4	0.00000	1.4078514	4.5114858	0.8331502
	4	0.25919	0.0025304	8.8324127	2.4729241
	5	0.00000	0.6139751	4.5986909	0.8777231
	5	0.34097	0.0002747	11.7395781	4.0412321
	6	0.00000	1.4879697	4.7124545	0.7615037
	6	0.75362	0.0003390	51.2601242	22.4660299
	7	0.00000	1.1025503	4.5775322	0.8234431
	7	0.28347	0.0008226	9.7150704	2.8183906
	8	0.00000	0.9700424	4.4356991	0.8714486
	8	0.39740	0.0001174	12.9618170	4.6988000
	9	0.00000	0.5924168	4.9311198	0.6300077
	9	0.42774	0.0002286	17.6045996	5.0147367
	10	0.00000	0.2073749	5.1461723	0.4549040
	10	0.23552	0.0004370	10.1032111	1.5212350
	11	0.00000	1.2768009	4.8134080	0.6192899
	11	0.60029	0.0001640	30.1428801	9.9969486
	12	0.00000	0.4111784	4.9875093	0.5096694
	12	0.26799	0.0007472	10.6014210	1.9131710
02851014	1	0.00000	0.3258201	5.0892034	0.5586145
	1	0.26347	0.0003940	10.8673700	2.1124446
	2	0.00000	0.8576770	4.9585953	0.6054312
	2	0.69591	0.0000580	47.5659980	17.7129300
	3	0.00000	0.7285735	4.7277383	0.6011620
	3	0.38301	0.0007957	13.7612622	3.5296268
	4	0.00000	2.5125156	4.5534647	1.0480337
	4	0.58274	0.0010005	25.9695410	11.2616981
	5	0.00000	1.7485729	4.6572528	0.9723334
	5	0.57063	0.0011224	26.3323640	11.2729290
	6	0.00000	4.0265446	4.7733954	0.9815585
	6	0.59688	0.0010862	30.3816832	11.3352283

Table 2-B. Parameters of monthly precipitation series transformed by Box-Cox transformation (continuation)

Código	mês	λ	$\|Ca(Y)\|$	$m(Y)$	$s(Y)$
02851014	7	0.00000	2.0565471	4.8370566	0.7852480
	7	0.26433	0.0004039	10.0668090	2.5197407
	8	0.00000	2.3310016	4.7654682	1.0785475
	8	0.58277	0.0002468	29.8632256	13.0869683
	9	0.00000	0.6688609	5.1842776	0.5271007
	9	0.47112	0.0002019	23.0120516	5.8265301
	10	0.00000	0.3162138	5.2247693	0.4938536
	10	0.25580	0.0003613	11.0857437	1.8615558
	11	0.00000	1.2218026	4.7724376	0.6697018
	11	0.45449	0.0009718	17.8668996	5.3645505
	12	0.00000	2.3103425	4.9054255	0.7156520
	12	0.52567	0.0008263	24.6138382	7.7051466
02151035	1	0.00000	0.6990493	5.1480648	0.6682859
	1	0.32011	0.0002626	13.4670902	3.3546958
	2	0.00000	1.4010966	4.8505431	0.7902558
	2	0.46173	0.0001886	19.3675350	6.5662689
	3	0.00000	5.6605243	4.4472543	1.4398229
	3	0.61482	0.0005643	27.5749161	10.9018058
	4	0.00000	3.5000138	3.7191048	2.0161320
	4	0.47826	0.0005328	13.3031936	6.6783173
	5	0.00000	3.4216159	3.7547099	2.0521026
	5	0.44351	0.0003388	12.3710038	6.3841895
	6	0.00000	1.9556380	2.5803525	2.9891089
	6	0.37394	0.0003638	7.1836276	5.3687370
	7	0.00000	1.2378174	1.6225202	3.4506018
	7	0.31183	0.0011648	4.4845765	4.6251858
	8	0.00000	0.9123537	1.1515099	3.5862459
	8	0.30156	0.0012410	3.6834336	4.5150313
	9	0.00000	3.1725336	3.5391103	1.9444038
	9	0.45785	0.0008233	11.4204088	6.2659440
	10	0.00000	0.7821386	4.6034639	0.7872810
	10	0.34833	0.0009268	11.9087561	3.7288197
	11	0.00000	5.0419424	4.3987564	1.6532838
	11	0.33466	0.0000005	11.1419696	4.1197519
	12	0.00000	0.6386761	4.9415570	0.6965183
	12	0.28352	0.0010627	11.0611505	2.7387925

Table 3-B. Groups established by analysis of the principal components between of monthly rainfall

Mês	Ns	Número identificador das séries de precipitações mensais (Ni)
1	8	1 2 3 4 5 8 10 14
1	3	6 7 9
2	7	2 3 8 10 11 15 18
2	8	1 4 5 6 7 9 12 14
3	12	1 2 3 4 5 6 7 8 9 10 11 12
4	5	2 7 8 9 10
4	6	1 3 4 5 6 15
5	7	2 5 6 12 14 15 16
5	2	9 10
5	4	1 3 4 18
5	5	7 8 11 13 17
6	6	1 2 3 4 10 12
6	8	5 6 7 8 9 11 13 14
7	9	1 2 3 4 5 6 7 14 16
7	3	9 11 18
7	6	8 10 12 13 15 17
8	8	1 3 5 6 7 8 9 10
8	10	2 4 11 12 13 14 15 16 17 18
9	8	1 6 7 9 10 11 12 13
9	6	3 4 14 15 16 18
9	4	2 5 8 17
10	9	1 2 3 4 5 6 7 8 9
11	9	1 6 7 8 9 12 13 14 15
11	6	2 3 4 5 10 11
12	7	2 3 6 7 8 9 10
12	6	1 4 5 15 17 18

Obs.: Ns – Number of series of monthly precipitation in homogeneous group
Ni – Identification number of the rainfall series, when
Ni≤9 corresponds to the serial number (No) of rainfall station from table 1-B (No = Ni), when Ni> 9, identifies the monthly series in the previous month (lag 1) of the station with serial number No = Ni - 9.

Annex C - GER_PREC Program Listing

Author – Eloy KAVISKI

```
program ger_prec;
{ Geração de séries sintéticas de precipitações totais mensais }
  type
    vetd  = array[1..13]       of double;
    veti  = array[1..52]       of integer;
    vet20 = array[1..20]       of single;
    mat   = array[1..20,1..20] of double;
    mat1  = array[1..10,0..12] of double;

  var
    nl,
    modelo   : integer;
    l        : array[1..30] of ^mat;
    dec      : array[1..30] of vetd;
    ec       : array[1..30] of veti absolute dec;
    print    : text;
    pbin     : file of mat1;
    narqs,
    nbin,
    prec_mes,
    param_bc,
    lista_es : string;
    narqsc   : byte absolute narqs;
    uest,np  : veti;
    codest   : array[1..50] of longint;
    nest,
    nano,
    nser,mes,
    i,j      : integer;
    vger,
    miny,
    lamb,
    uslamb,
    prec,
    medl,
    med,
    meds,
    dpds     : ^mat1;
    medy,
    puam12   : vet20;

    function ran3:real;

      var
        i,ii,k : integer;
        aux    : real;
        mj,mk  : longint;

      const
        mbig   : longint = 1000000000;
        seed   : longint =  161803398;
        mz     : longint =          0;
        fac    : double  =     1.0e-9;
        idum   : byte    =          0;
        next   : byte    =          0;
        nextp  : byte    =          0;
        ma     : array[1..55] of longint = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
                                            0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
                                            0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
                                            0,0,0,0,0,0,0,0,0,0);

      begin

        if idum = 0
          then
            begin
              mj := (seed + idum) mod mbig;
              ma[55]  := mj;
              mk      := 1;
              for i := 1 to 54 do
                begin
                  ii      := 21*i mod 55;
                  ma[ii]  := mk;
                  mk      := mj - mk;
                  if mk < mz
```

```
                    then
                      mk := mk + mbig;
                  mj := ma[ii];
                  end;

              for k := 1 to 4 do
                for i := 1 to 55 do
                  begin
                    ma[i] := ma[i] - ma[1+((i+30) mod 55)];
                    if ma[i] < mz
                      then
                        ma[i] := ma[i] + mbig;
                    end;
              idum  := 10;
              next  :=  0;
              nextp := 31;
              end;

        repeat
          next := next + 1;
          if next > 55
            then
              next := 1;
          nextp := nextp + 1;
          if nextp > 55
            then
              nextp := 1;
          mj := ma[next] - ma[nextp];
          if mj < mz
            then
              mj := mj + mbig;
          ma[next] := mj;
          aux      := mj*fac;
          until (aux > 1.0e-8) and (aux < 0.99999999);

        ran3 := aux;

        end;

    function norbm:double;
{   Geração de números normais com média 0 e variância 1. }
      var
        r  : double;
      const
        v1 : double  =  0.0;
        v2 : double  =  0.0;
        f  : double  =  0.0;
        t  : boolean = true;

      begin

        if t
          then
            begin
              repeat
                v1 := 2.0*ran3 - 1.0;
                v2 := 2.0*ran3 - 1.0;
                r  := v1*v1 + v2*v2;
                until (r < 1.0) and (r > 0.0);
              f     := sqrt(-2.0*ln(r)/r);
              norbm := v1*f;
              t     := false;
              end
          else
            begin
              norbm := v2*f;
              t     := true;
              end;
        end;

procedure lerest;
{
  Lista de estações usadas para eliminar estações.
  Os códigos das estações eliminadas devem ser zerados.
}
  var
    arq : text;
    n   : integer;

  begin

    assign(arq,lista_es);
    reset (arq);

    n := 0;
```

```
    repeat
      n := n + 1;
      readln(arq,codest[n],uest[n]);
      until eof(arq);

    close(arq);

    nest := n;

    writeln(nest);
    end;

procedure lerparam;

  var
    i,j  : integer;
    cas,
    medy,
    dpdy : double;
    a    : text;

  begin

    assign(a,param_bc);
    reset (a);

    repeat
      readln(a,i,j);
      readln(a,i,j,miny^[i,j],lamb^[i,j],cas,medy,dpdy);
      uslamb^[i,j] := 1.0e0/lamb^[i,j];
      until eof(a);
    close(a);
    end;

procedure lerprec;

  var
    a      : text;
    s      : string;
    p      : vet20;
    i,j,i1,
    n,ne   : integer;
    rc     : word;

procedure conver(i2:integer);

  var
    j,rc : integer;

  begin

    ne := ne + 1;
    if uest[ne] = 0
      then
        exit;

    n := n + 1;
    j := i2 - i1;
    if (j > 0) and (s[i1] <> '#')
      then
        val(copy(s,i1,j),puam12[n],rc);

    end;

  begin

    assign(a,prec_mes);
    reset (a);

    readln(a,s);

    repeat

      readln(a,s);

      n  := 0;
      ne := 0;
      i1 := 8;
      for i := 8 to length(s) do
        if ord(s[i]) = 9
          then
            begin
              conver(i);
              i1 := i + 1;
              end;
```

```
      conver(length(s)+1);

      until eof(a);

    close(a);
    end;

procedure lerbin;

  var
    i,j : integer;
    bin : file of double;

  begin

    assign(bin,nbin);
    reset (bin);

    nl := 0;
    repeat

      nl := nl + 1;

      new(l[nl]);

      for j := 1 to 13 do
        read(bin,dec[nl,j]);

      j := ec[nl,52];  { n. de estações por mês=ec[nl,51] }

      while ec[nl,j] > nest do
        j := j - 1;

      np[nl] := j;
      for j := np[nl]+1 to ec[nl,52] do
        ec[nl,j] := ec[nl,j] - nest;

      for j := 1 to ec[nl,52] do
        read(bin,medl^[nl,j]);

      for i := 1 to ec[nl,52] do
        for j := 1 to ec[nl,52] do
          read(bin,l[nl]^[i,j]);

      if ec[nl,51] = 12
        then
          for j := 1 to np[nl] do
            medy[ec[nl,j]] := medl^[nl,j];

      until eof(bin);

    close(bin);
    end;

procedure series12;

  var
    i,j,
    ser,
    ano : integer;

procedure gerar;

  var
    i,
    j,n : integer;
    s   : extended;

  begin

    for i := 1 to nest do
      vger^[i,0] := vger^[i,12];

    for n := 1 to nl do
      for i := np[n] downto 1 do
        begin
          s := norbm;
          for j := i+1 to ec[n,52] do
            s := s - l[n]^[j,i]*vger^[ec[n,j],ec[n,51]-1];
          vger^[ec[n,i],ec[n,51]] := s/l[n]^[i,i];
          prec^[ec[n,i],ec[n,51]] := exp(medl^[ec[n,i],ec[n,51]] +
                                        vger^[ec[n,i],ec[n,51]]);
          end;
    end;
```

```
  begin

    for i := 1 to nest do
      for j := 1 to 12 do
        begin
          meds^[i,j] := 0.0e0;
          dpds^[i,j] := 0.0e0;
          end;
    for i := 1 to nest do
      vger^[i,12] := ln(puam12[i]) - medy[i];
    for ser := 1 to nser do
      begin

        for i := 1 to 12 do
          for j := 1 to nest do
            med^[i,j] := 0.0e0;

        for ano := 1 to nano do
          begin

            gerar;

            for i := 1 to nest do
              for j := 1 to 12 do
                med^[i,j] := prec^[i,j];

            write(pbin,prec^);

            end;

        for i := 1 to nest do
          for j := 1 to 12 do
            begin
              med^ [i,j] := med^[i,j]/nano;
              meds^[i,j] := meds^[i,j] + med^[i,j];
              dpds^[i,j] := dpds^[i,j] + med^[i,j]*med^[i,j];
              end;
        end;
    end;

procedure series34;

  var
    i,j,
    ser,
    ano : integer;

procedure gerar;

  var
    i,
    j,n : integer;
    aux : double;
    s   : extended;

  begin

    for i := 1 to nest do
      vger^[i,0] := vger^[i,12];

    for n := 1 to nl do
      for i := np[n] downto 1 do
        begin
          s := norbm;
          for j := i+1 to ec[n,52] do
            s := s - l[n]^[j,i]*vger^[ec[n,j],ec[n,51]-1];
          vger^[ec[n,i],ec[n,51]] := s/l[n]^[i,i];

          aux := medl^[ec[n,i],ec[n,51]] + vger^[ec[n,i],ec[n,51]];
          aux := ln(lamb^[ec[n,i],ec[n,51]]*aux + 1.0e0);

          prec^[ec[n,i],ec[n,51]] := exp(uslamb^[ec[n,i],ec[n,51]]*aux);
          end;
    end;

  begin

    for i := 1 to nest do
      for j := 1 to 12 do
        begin
          meds^[i,j] := 0.0e0;
          dpds^[i,j] := 0.0e0;
          end;
```

```
    for i := 1 to nest do
      vger^[i,12] := uslamb^[i,12]*(exp(lamb^[i,12]*ln(puam12[i])) - 1.0e0) - medy[i];

    for ser := 1 to nser do
      begin

        for i := 1 to nest do
          for j := 1 to 12 do
            med^[i,j] := 0.0e0;

        for ano := 1 to nano do
          begin

            gerar;

            for i := 1 to nest do
              for j := 1 to 12 do
                med^[i,j] := med^[i,j] + prec^[i,j];

            write(pbin,prec^);

            end;

        for i := 1 to 12 do
          for j := 1 to nest do
            begin
              med^ [i,j] := med^[i,j]/nano;
              meds^[i,j] := meds^[i,j] + med^[i,j];
              dpds^[i,j] := dpds^[i,j] + med^[i,j]*med^[i,j];
              end;
        end;
    end;

  begin

    writeln('ger_prec - dez/2009');
    writeln;
    writeln('Modelos: 1 - Ln/mês');
    writeln('         2 - Ln/grupo');
    writeln('         3 - BC/mês');
    writeln('         4 - BC/grupo');
    writeln;
    write('Escolher o modelo: ');
    read(modelo);

    case modelo of
      1 : nbin := 'prclaris.bin';
      2 : nbin := 'prclari1.bin';
      3 : nbin := 'prclari2.bin';
      4 : nbin := 'prclari3.bin';
      else
        begin
          writeln;
          writeln('*** Modelo inválido.');
          halt;
          end;
      end;

    writeln;
    write('Número de séries: ');
    read(nser);
    writeln;
    write('Número de anos/série: ');
    read(nano);
    writeln;
    write('Arquivo de saída: ');

    narqsc := 0;
    repeat
      narqsc := narqsc + 1;
      narqs[narqsc] := readkey;
      write(narqs[narqsc]);
      until ord(narqs[narqsc]) = 13;

    narqs[narqsc] := '.';

    new(vger);
    new(miny);
    new(lamb);
    new(uslamb);
    new(prec);
    new(medl);
    new(med);
    new(meds);
    new(dpds);
```

```
lista_es := 'prclaris.lst';   { Relação de estações          }
prec_mes := 'prclaris.txt';   { Precipitações totais mensais }
param_bc := 'lambca04.txt';   { Parâmetros - modelo Box-Cox  }

lerest;
lerparam;
lerprec;

assign (print,narqs+'txt');
rewrite(print);

assign (pbin,narqs+'bin');
rewrite(pbin);

if modelo < 3
  then
    series12
  else
    series34;

close(print);
close(pbin);
end.
```

ANNEX D – VALIDATION OF SMMAR (1) MODEL

Table 1. Applied tests Results.

Type par.	Order Number	Station A	Station B	Parameter value	100-α (%)
med	1	1	0	1461.570489	76.58
var	1	1	0	169419.873935	92.90
med	2	2	0	1515.315903	90.77
var	2	2	0	54853.929212	95.64
med	3	3	0	1483.179999	79.34
var	3	3	0	258161.410766	99.90
med	4	4	0	1710.912786	78.65
var	4	4	0	92036.314219	99.39
med	5	5	0	1307.359345	77.17
var	5	5	0	58842.704784	91.47
med	6	6	0	1428.238689	70.33
var	6	6	0	53846.152034	69.84
med	7	7	0	1780.928195	65.65
var	7	7	0	120867.255861	99.80
med	8	8	0	1957.716722	67.91
var	8	8	0	193348.397761	99.95
med	9	9	0	1290.045246	83.56
var	9	9	0	82778.900638	55.36
cor	1	2	1	0.099192	20.90
cor	2	3	1	0.222375	46.97
cor	3	3	2	0.428221	58.45
cor	4	4	1	0.261139	83.46
cor	5	4	2	0.514310	78.08
cor	6	4	3	0.354970	3.31
cor	7	5	1	0.270424	89.53
cor	8	5	2	0.211369	62.17
cor	9	5	3	0.190441	48.29
cor	10	5	4	0.239694	39.66
cor	11	6	1	0.228727	92.34
cor	12	6	2	0.164898	69.17
cor	13	6	3	0.144960	54.40
cor	14	6	4	0.185292	46.51
cor	15	6	5	0.444469	59.47
cor	16	7	1	-0.021104	53.94
cor	17	7	2	0.082175	75.81
cor	18	7	3	0.076762	66.65
cor	19	7	4	0.244876	88.32
cor	20	7	5	0.233935	58.45

Type par.	Order Number	Station A	Station B	Parameter value	100-α (%)
cor	21	7	6	0.578717	84.45
cor	22	8	1	0.027888	80.61
cor	23	8	2	0.040055	86.38
cor	24	8	3	0.022761	69.29
cor	25	8	4	0.177137	91.52
cor	26	8	5	0.158116	61.42
cor	27	8	6	0.376658	75.39
cor	28	8	7	0.616476	77.03
cor	29	9	1	0.079570	78.39
cor	30	9	2	0.253193	83.02
cor	31	9	3	0.025509	38.75
cor	32	9	4	0.283776	62.44
cor	33	9	5	0.235550	21.04
cor	34	9	6	0.336053	18.60
cor	35	9	7	0.420260	84.06
cor	36	9	8	0.230676	72.16
cor	37	10	1	-0.137257	22.21
cor	38	10	2	0.094954	78.47
cor	39	10	3	-0.037381	41.77
cor	40	10	4	0.077332	76.97
cor	41	10	5	-0.026534	37.30
cor	42	10	6	-0.012625	49.13
cor	43	10	7	0.226694	95.47
cor	44	10	8	0.335764	99.41
cor	45	10	9	0.247001	91.34
cor	46	11	1	-0.092683	29.69
cor	47	11	2	-0.130746	20.09
cor	48	11	3	-0.130135	23.33
cor	49	11	4	-0.013214	49.50
cor	50	11	5	-0.219384	4.59
cor	51	11	6	0.118464	77.46
cor	52	11	7	0.173820	89.88
cor	53	11	8	0.180617	89.20
cor	54	11	9	0.142097	82.29
cor	55	11	10	0.107754	22.90
cor	56	12	1	-0.136695	29.24
cor	57	12	2	-0.048960	44.61
cor	58	12	3	-0.089675	30.13

Table 1. Applied tests Results (continuation).

Type par.	Order Number	Station A	Station B	Parameter value	100-α (%)
cor	59	12	4	0.050471	55.93
cor	60	12	5	-0.254836	0.62
cor	61	12	6	0.009083	35.73
cor	62	12	7	0.119851	77.23
cor	63	12	8	0.319599	97.77
cor	64	12	9	0.042589	51.87
cor	65	12	10	0.436736	95.48
cor	66	12	11	0.483219	77.64
cor	67	13	1	-0.148155	16.04
cor	68	13	2	-0.008565	45.34
cor	69	13	3	-0.109371	13.77
cor	70	13	4	0.075094	62.84
cor	71	13	5	-0.175476	4.62
cor	72	13	6	-0.014457	28.24
cor	73	13	7	-0.079510	20.75
cor	74	13	8	0.204162	92.95
cor	75	13	9	-0.056503	17.56
cor	76	13	10	0.265508	84.87
cor	77	13	11	0.520647	80.06
cor	78	13	12	0.630252	85.93
cor	79	14	1	-0.035924	41.60
cor	80	14	2	-0.013859	55.64
cor	81	14	3	0.157488	89.98
cor	82	14	4	0.100028	75.57
cor	83	14	5	-0.093030	25.07
cor	84	14	6	-0.002700	57.56
cor	85	14	7	0.178081	92.45
cor	86	14	8	0.336955	99.79
cor	87	14	9	-0.164696	11.96
cor	88	14	10	0.276340	90.67
cor	89	14	11	0.207724	60.75
cor	90	14	12	0.298580	80.62
cor	91	14	13	0.252489	43.64
cor	92	15	1	-0.190348	8.77
cor	93	15	2	-0.018996	51.38
cor	94	15	3	-0.209397	8.50
cor	95	15	4	0.061501	71.26
cor	96	15	5	-0.021853	50.96

Table 1. Applied tests Results (continuation).

Type par.	Order Number	Station A	Station B	Parameter value	100-α (%)
cor	97	15	6	0.162075	92.80
cor	98	15	7	0.296692	99.29
cor	99	15	8	0.364310	99.83
cor	100	15	9	-0.048551	47.79
cor	101	15	10	0.234998	93.24
cor	102	15	11	0.158892	67.39
cor	103	15	12	0.201405	69.90
cor	104	15	13	0.196917	50.08
cor	105	15	14	0.451187	61.44
cor	106	16	1	-0.302710	0.78
cor	107	16	2	-0.010763	42.88
cor	108	16	3	-0.208844	6.60
cor	109	16	4	-0.044301	43.40
cor	110	16	5	-0.024611	50.23
cor	111	16	6	-0.066604	37.25
cor	112	16	7	0.113281	85.86
cor	113	16	8	0.154688	91.09
cor	114	16	9	-0.215251	6.02
cor	115	16	10	-0.013895	56.02
cor	116	16	11	0.089670	77.78
cor	117	16	12	0.204622	92.15
cor	118	16	13	0.259174	90.00
cor	119	16	14	0.250027	64.66
cor	120	16	15	0.587481	87.28
cor	121	17	1	-0.197520	8.44
cor	122	17	2	0.020009	61.74
cor	123	17	3	-0.265765	3.08
cor	124	17	4	0.026940	65.32
cor	125	17	5	0.019867	60.22
cor	126	17	6	-0.172521	11.26
cor	127	17	7	-0.044420	38.61
cor	128	17	8	0.093853	82.08
cor	129	17	9	-0.123886	16.67
cor	130	17	10	0.038217	82.38
cor	131	17	11	0.036319	84.59
cor	132	17	12	0.038582	73.74
cor	133	17	13	0.196110	93.54
cor	134	17	14	0.176737	67.80

Table 1. Applied tests Results (continuation).

Type par.	Order Number	Station A	Station B	Parameter value	100-α (%)
cor	135	17	15	0.387084	79.10
cor	136	17	16	0.628003	81.30
cor	137	18	1	-0.138499	18.22
cor	138	18	2	0.009958	47.08
cor	139	18	3	-0.000986	52.16
cor	140	18	4	0.118118	79.11
cor	141	18	5	0.152307	91.48
cor	142	18	6	0.216403	98.59
cor	143	18	7	0.318870	99.73
cor	144	18	8	0.194925	93.41
cor	145	18	9	0.075722	77.58
cor	146	18	10	0.093963	82.04
cor	147	18	11	0.239258	80.32
cor	148	18	12	0.044326	44.36
cor	149	18	13	0.307509	70.24
cor	150	18	14	0.260600	28.13
cor	151	18	15	0.349667	22.24
cor	152	18	16	0.443500	88.29
cor	153	18	17	0.270674	82.17

Annex F - MDM Program Listing

```
function  valida
  %Realiza testes de validação para o algoritmo de geração de series
  %sintéticas de chuvas anuais com desagregação em mensais. A entrada de
  %dados ocorre de maneira automática, sendo que o usuário deve informar a
  %quantidade de anos e postos observados. Todos os dados de saída estarão
  %listados ao termino do programa.
  clear all
  clc
  tic;%Inicia a contagem do tempo de execução do algoritmo.
  series=1000;%Quantidade de series sintéticas.
  [M,P]=leitura;%Arquivo contendo as precipitações observadas M=mensais e P=anuais.
  [a,b]=size(P);%a=numero de linhas(anos observados) e b=numero de colunas(postos).
  u=b*b;%Artifício para calcular matrizes de correlações mensais.
  [m,n]=size(M);%m=numero de linhas(meses observados) e b=numero de colunas(postos).
  Mm=mean(M);%Calcula a media mensal de cada posto.
  T=matriz_postos(M,a,b);%Matrizes mensais referentes por postos.
  Mm1=mean(T); %Calcula as medias de cada mês por posto. Por exemplo, a media dos meses de
janeiro do
  %posto 1.
  for i=1:b
    M1(i,:)=Mm1(:,:,i);%Matriz com as medias mensais por posto.
  end
  Pm=mean(P); %Calcula as medias de cada posto.
  Defict=def_acum(P,Pm,a,b); %Calcula o Maximo do déficit de acumulação anual.
  Defi=def_acum(M,Mm,m,n);%Calcula o Maximo do déficit de acumulação mensal.
  S=std(P); %Calcula o desvio padrão de cada posto.
  Sm=std(T);%Calcula o desvio padrão de cada mês por posto.
  for i=1:b
    Sm1(i,:)=Sm(:,:,i);%Matriz com os desvios padrão por posto.
  end
  A3=skewness(P); %Calcula o coeficiente de assimetria.
  A3m=skewness(M);%Calcula o coeficiente de assimetria de cada mês por posto.
  R=corrcoef(P); %Calcula a matriz de correlação anual.
  for i=1:b
    Rm(:,:,i)=corrcoef(T(:,:,i));%Matriz das correlações mensais de cada posto.
  end
  R1=Rm(:,:,1);%Matriz das correlações mensais do posto 1.
  R2=Rm(:,:,2);
  R3=Rm(:,:,3);
  R4=Rm(:,:,4);
  R5=Rm(:,:,5);
  R6=Rm(:,:,6);
  R7=Rm(:,:,7);
  R8=Rm(:,:,8);
  R9=Rm(:,:,9);%Matriz das correlações mensais do posto 9.
  Infe=runinf(P,Pm,a,b);%Numero Maximo de valores consecutivos abaixo da media anual.
  Infem=runinf(M,Mm,m,n);%Numero Maximo de valores consecutivos abaixo da media mensal.
```

```
  Supe=runsup(P,Pm,a,b);%Numero Maximo de valores consecutivos acima da media anual.
  Supem=runsup(M,Mm,m,n);%Numero Maximo de valores consecutivos acima da media
mensal.
  B=chol(R); %Faz a decomposição cholesky.
  D=desa_men(M,P,a,b); %Matrizes de coeficientes de desagregação.
  for k=1:series %Gerar 1000 series.
      Z=randn(b,a); %Matriz de números aleatórios.
      X=B'*Z; %Geração da matriz das variáveis aleatórias.
      Xt=X'; %Artifício para resolução simplificada.
      for j=1:b
         G(:,j)=[S(j)*Xt(:,j)]+[Pm(j)]; %Transforma as variáveis normais padrão em precipitação
sintética anual.
      end
      Mgs=gera_men(D,G,a,b);%Precipitação sintética mensal.
      Gm=mean(G); %Calcula as medias anuais de cada posto.
      Tg=matriz_postos(Mgs,a,b);%Separa as precipitações sintéticas mensais por posto.
      Mme1=mean(Tg);%Calcula as medias geradas de cada mês por posto.
      Mme=mean(Mgs);%Calcula as medias mensais de cada posto.
      Gc=corrcoef(G); %Matriz de correlação das series sintéticas anuais.
      Matco(k,:)=reshape(Gc,1,u);%Guarda as correlações na linha da matriz Matco.
      Me(k,:)=Gm; %Guarda as medias anuais em uma matriz.
      De(k,:)=std(G); %Guarda os desvios padrão das series sintéticas numa matriz.
      Med(k,:,:)=mean(Tg); %Calcula as medias geradas de cada mês por posto e as guarda numa
matriz.
      Dem(k,:,:)=std(Tg); %Guarda os desvio padrão de cada mês por posto.
      for i=1:9
         Med(k,:,i)=Mme1(:,:,i); %Guarda as medias de cada mês por posto.
         Dem(k,:,i)=std(Tg(:,:,i)); %Guarda os desvio padrão de cada mês por posto.
      end
      A(k,:)=skewness(G); %Guarda os coeficiente de assimetria anual numa matriz.
      Am(k,:)=skewness(Mgs);%Guarda os coeficientes de assimetria mensais.
      rinf(k,:)=runinf(G,Gm,a,b); %Run if - Maximo de precipitações consecutivas abaixo da
media anual.
      rinfm(k,:)=runinf(Mgs,Mme,m,n);%Run if - Maximo de precipitações consecutivas abaixo da
media
      %mensal.
      rsup(k,:)=runsup(G,Gm,a,b); %Run sup - Maximo de precipitações consecutivas acima da
media anual.
      rsupm(k,:)=runsup(Mgs,Mme,m,n);%Run sup - Maximo de precipitações consecutivas acima
da media
      %mensal.
      Defa(k,:)=def_acum(G,Gm,a,b); %Maximo déficit de acumulação para 80 por cento da media
anual.
      Defam(k,:)=def_acum(Mgs,Mme,m,n);%Deficit de acumulação mensal.
      for i=1:9
          Rm(:,:,i)=corrcoef(Tg(:,:,i));%Matriz das correlações de cada posto.
      end
      C1(k,:)=reshape(Rm(:,:,1),1,144);%Guarda a matriz de correlação mensal do posto 1 na linha
k.
      C2(k,:)=reshape(Rm(:,:,2),1,144);
      C3(k,:)=reshape(Rm(:,:,3),1,144);
      C4(k,:)=reshape(Rm(:,:,4),1,144);
```

```
    C5(k,:)=reshape(Rm(:,:,5),1,144);
    C6(k,:)=reshape(Rm(:,:,6),1,144);
    C7(k,:)=reshape(Rm(:,:,7),1,144);
    C8(k,:)=reshape(Rm(:,:,8),1,144);
    C9(k,:)=reshape(Rm(:,:,9),1,144);
  end
  %====================
  %Testes de validação.
  %====================
  Mg=[(min(Me))',(mean(Me))',(max(Me))']; %Matriz com as medias das series sintéticas anuais.
  Mg1=[min(Med(:,:,1));mean(Med(:,:,1));max(Med(:,:,1))]; %Matriz com as medias mensais
sintéticas do
  %posto 1.
  Mg2=[min(Med(:,:,2));mean(Med(:,:,2));max(Med(:,:,2))];
  Mg3=[min(Med(:,:,3));mean(Med(:,:,3));max(Med(:,:,3))];
  Mg4=[min(Med(:,:,4));mean(Med(:,:,4));max(Med(:,:,4))];
  Mg5=[min(Med(:,:,5));mean(Med(:,:,5));max(Med(:,:,5))];
  Mg6=[min(Med(:,:,6));mean(Med(:,:,6));max(Med(:,:,6))];
  Mg7=[min(Med(:,:,7));mean(Med(:,:,7));max(Med(:,:,7))];
  Mg8=[min(Med(:,:,8));mean(Med(:,:,8));max(Med(:,:,8))];
  Mg9=[min(Med(:,:,9));mean(Med(:,:,9));max(Med(:,:,9))];
  %Matriz composta por todas as medias mensais.
Mprint=[M1(1,:);Mg1;M1(2,:);Mg2;M1(3,:);Mg3;M1(4,:);Mg4;M1(5,:);Mg5;M1(6,:);Mg6;M1(7,
:);Mg7;M1(8,:);Mg8;M1(9,:);Mg9];
  Deg=[(min(De))',(mean(De))',(max(De))']; %Matriz com os desvios padrão das series sintéticas
anuais.
  Degm1=[min(Dem(:,:,1));mean(Dem(:,:,1));max(Dem(:,:,1))];%Desvio padrão mensal do posto
1.
  Degm2=[min(Dem(:,:,2));mean(Dem(:,:,2));max(Dem(:,:,2))];
  Degm3=[min(Dem(:,:,3));mean(Dem(:,:,3));max(Dem(:,:,3))];
  Degm4=[min(Dem(:,:,4));mean(Dem(:,:,4));max(Dem(:,:,4))];
  Degm5=[min(Dem(:,:,5));mean(Dem(:,:,5));max(Dem(:,:,5))];
  Degm6=[min(Dem(:,:,6));mean(Dem(:,:,6));max(Dem(:,:,6))];
  Degm7=[min(Dem(:,:,7));mean(Dem(:,:,7));max(Dem(:,:,7))];
  Degm8=[min(Dem(:,:,8));mean(Dem(:,:,8));max(Dem(:,:,8))];
  Degm9=[min(Dem(:,:,9));mean(Dem(:,:,9));max(Dem(:,:,9))];
  %Matriz composta por todos os desvios padrão mensais.

Sprint=[Sm1(1,:);Degm1;Sm1(2,:);Degm2;Sm1(3,:);Degm3;Sm1(4,:);Degm4;Sm1(5,:);Degm5;S
m1(6,:);Degm6;Sm1(7,:);Degm7;Sm1(8,:);Degm8;Sm1(9,:);Degm9];
  Ag=[(min(A))',(mean(A))',(max(A))']; %Matriz com os coeficientes de assimetria anual.
  Agm=[(min(Am))',(mean(Am))',(max(Am))'];%Matriz com os coeficientes de assimetria
mensal.
  Rig=[(min(rinf))',(mean(rinf))',(max(rinf))']; %Run if - Maximo de precipitações consecutivas
abaixo da
  % media anual.
  Rigm=[(min(rinfm))',(mean(rinfm))',(max(rinfm))'];%Run if - Maximo de precipitações
consecutivas abaixo da media mensal.
  Rsg=[(min(rsup))',(mean(rsup))',(max(rsup))']; %Run sup - Maximo de precipitações
consecutivas acima da media anual.
  Rsgm=[(min(rsupm))',(mean(rsupm))',(max(rsupm))'];%Run sup - Maximo de precipitações
consecutivas acima da media mensal.
```

```
Defag=[(min(Defa))',(mean(Defa))',(max(Defa))']; %Matriz com os déficit de acumulação anuais.
Defagm=[(min(Defam))',(mean(Defam))',(max(Defam))']; %Matriz com os déficit de acumulação mensais.
Mat1=reshape(min(Matco),b,b);%Matriz mínima das correlações anuais.
Mat2=reshape(mean(Matco),b,b);
Mat3=reshape(max(Matco),b,b);
Rming1=reshape(min(C1),12,12);%Matriz das correlações mi ninas mensais do posto 1.
Rmedg1=reshape(mean(C1),12,12);
Rmaxg1=reshape(max(C1),12,12);
Rming2=reshape(min(C2),12,12);
Rmedg2=reshape(mean(C2),12,12);
Rmaxg2=reshape(max(C2),12,12);
Rming3=reshape(min(C3),12,12);
Rmedg3=reshape(mean(C3),12,12);
Rmaxg3=reshape(max(C3),12,12);
Rming4=reshape(min(C4),12,12);
Rmedg4=reshape(mean(C4),12,12);
Rmaxg4=reshape(max(C4),12,12);
Rming5=reshape(min(C5),12,12);
Rmedg5=reshape(mean(C5),12,12);
Rmaxg5=reshape(max(C5),12,12);
Rming6=reshape(min(C6),12,12);
Rmedg6=reshape(mean(C6),12,12);
Rmaxg6=reshape(max(C6),12,12);
Rming7=reshape(min(C7),12,12);
Rmedg7=reshape(mean(C7),12,12);
Rmaxg7=reshape(max(C7),12,12);
Rming8=reshape(min(C8),12,12);
Rmedg8=reshape(mean(C8),12,12);
Rmaxg8=reshape(max(C8),12,12);
Rming9=reshape(min(C9),12,12);
Rmedg9=reshape(mean(C9),12,12);
Rmaxg9=reshape(max(C9),12,12);%Matriz das correlações máximas mensais do posto 9.

%===================================================================
%Dados de saída salvos em arquivos de planilha eletrônica do Excel.

%===================================================================
%Matriz com as medias mensais de todos os postos, tanto observadas como as geradas.
wk1write('C:\Documents and Settings\User\Desktop\med_mensais2.xls',[Mprint]);
%Medias mensais sintéticas do posto 1.
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint1.xls',[Mg1]);
%Medias mensais sintéticas do posto 2.
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint2.xls',[Mg2]);
%Medias mensais sintéticas do posto 3.
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint3.xls',[Mg3]);
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint4.xls',[Mg4]);
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint5.xls',[Mg5]);
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint6.xls',[Mg6]);
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint7.xls',[Mg7]);
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint8.xls',[Mg8]);
```

```
%Medias mensais sintéticas do posto 9.
wk1write('C:\Documents and Settings\User\Desktop\med_mensais_sint9.xls',[Mg9]);
%Medias anuais observadas de todos os postos.
wk1write('C:\Documents and Settings\User\Desktop\med_anuais.xls',[Pm]);
%Medias anuais sintéticas de todos os postos.
wk1write('C:\Documents and Settings\User\Desktop\med_anuais_sint.xls',[Mg]);
%Desvios padrão anuais das series observadas.
wk1write('C:\Documents and Settings\User\Desktop\des_pad_anuais.xls',[S]);
%Desvios padrão anuais das series sintéticas.
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_anuais.xls',[Deg]);
%Matriz com todos os desvios padrão mensais das series observadas e sintéticas.
wk1write('C:\Documents and Settings\User\Desktop\des_pad_mensais2.xls',[Sprint]);
%Desvios padrão mensais sintéticas do posto 1.
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais1.xls',[Degm1]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais2.xls',[Degm2]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais3.xls',[Degm3]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais4.xls',[Degm4]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais5.xls',[Degm5]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais6.xls',[Degm6]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais7.xls',[Degm7]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais8.xls',[Degm8]);
wk1write('C:\Documents and Settings\User\Desktop\des_pad_sint_mensais9.xls',[Degm9]);
%Coeficiente de assimetria da serie anual observada.
wk1write('C:\Documents and Settings\User\Desktop\coef_ass_anuais.xls',[A3]);
%Coeficiente de assimetria da serie anual sintética.
wk1write('C:\Documents and Settings\User\Desktop\coef_ass_sint_anuais.xls',[Ag]);
%Coeficiente de assimetria da serie mensal observada.
wk1write('C:\Documents and Settings\User\Desktop\coef_ass_mensais.xls',[A3m']);
%Coeficiente de assimetria da serie mensal sintética.
wk1write('C:\Documents and Settings\User\Desktop\coef_ass_mensais_sint.xls',[Agm]);
%Run inf - série anual observada.
wk1write('C:\Documents and Settings\User\Desktop\run_inf_anuais.xls',[Infe']);
%Run inf - serie anual sintética.
wk1write('C:\Documents and Settings\User\Desktop\run_inf_sint_anuais.xls',[Rig]);
%Run inf - serie mensal observada.
wk1write('C:\Documents and Settings\User\Desktop\run_inf_mensais.xls',[Infem']);
%Run inf - serie mensal sintética.
wk1write('C:\Documents and Settings\User\Desktop\run_inf_sint_mensais.xls',[Rigm]);
%Run sup - serie anual observada.
wk1write('C:\Documents and Settings\User\Desktop\run_sup_anuais.xls',[Supe']);
%Run sup - serie anual sintética.
wk1write('C:\Documents and Settings\User\Desktop\run_sup_sint_anuais.xls',[Rsg]);
%Run sup - serie mensal observada.
wk1write('C:\Documents and Settings\User\Desktop\run_sup_mensais.xls',[Supem']);
%Run sup - serie mensal sintética.
wk1write('C:\Documents and Settings\User\Desktop\run_sup_sint_mensais.xls',[Rsgm]);
%Deficit de acumulação anual observada.
wk1write('C:\Documents and Settings\User\Desktop\def_acum_an.xls',[Defict']);
%Deficit de acumulação anual sintética.
wk1write('C:\Documents and Settings\User\Desktop\def_acum_an_sint.xls',[Defag]);
%Deficit de acumulação mensal observada.
wk1write('C:\Documents and Settings\User\Desktop\def_acum_mensais.xls',[Defi']);
```

```
%Deficit de acumulação mensal sintética.
wk1write('C:\Documents and Settings\User\Desktop\def_acum_sint_mensais.xls',[Defagm]);
%Matriz das correlações anuais observadas.
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_anuais.xls',[R]);
%Matriz das correlações mínima anuais sintéticas.
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_anuais.xls',[Mat1]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_anuais.xls',[Mat2]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_anuais.xls',[Mat3]);
%Matriz das correlações mensais do posto 1.
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais1.xls',[R1]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais2.xls',[R2]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais3.xls',[R3]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais4.xls',[R4]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais5.xls',[R5]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais6.xls',[R6]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais7.xls',[R7]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais8.xls',[R8]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_mensais9.xls',[R9]);
%Matriz das correlações mínimas mensais sintéticas do posto 1.
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais1.xls',[Rming1]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais1.xls',[Rmedg1]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais1.xls',[Rmaxg1]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais2.xls',[Rming2]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais2.xls',[Rmedg2]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais2.xls',[Rmaxg2]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais3.xls',[Rming3]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais3.xls',[Rmedg3]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais3.xls',[Rmaxg3]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais4.xls',[Rming4]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais4.xls',[Rmedg4]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais4.xls',[Rmaxg4]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais5.xls',[Rming5]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais5.xls',[Rmedg5]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais5.xls',[Rmaxg5]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais6.xls',[Rming6]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais6.xls',[Rmedg6]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais6.xls',[Rmaxg6]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais7.xls',[Rming7]);
wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais7.xls',[Rmedg7]);
```

```
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais7.xls',[Rmaxg7]);
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais8.xls',[Rming8]);
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais8.xls',[Rmedg8]);
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais8.xls',[Rmaxg8]);
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_min_mensais9.xls',[Rming9]);
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_med_mensais9.xls',[Rmedg9]);
  %Matriz das correlações máximas mensais sintéticas do posto 9.
  wk1write('C:\Documents and Settings\User\Desktop\matriz_corr_max_mensais9.xls',[Rmaxg9]);
end
fprintf('O tempo de processamento total foi de (segundos): 51.2f\n',toc); %Calcula o tempo de execução do algoritmo.

function [M,P]=leitura
%Realiza a leitura do arquivo salvo como planilha do excel no desktop.
%C:\Documents and Settings\User\Desktop\anuais.xls: caminho onde se
%encontra o arquivo. Para descobrir o caminho clicar com o botao direito do
%mouse no arquivo e clicar em propriedades.
%xlsread = le arquivo de planilha eletronica.
    P = xlsread('C:\Documents and Settings\User\Desktop\anuais.xls'); %Arquivo com os dados observados de precipitaçoes anuais.
    M = xlsread('C:\Documents and Settings\User\Desktop\mensais.xls'); %Arquivo com os dados observados de precipitaçoes mensais.

function X=def_acum(G,Gm,a,b)
 %E o maximo de periodos (anuais, mensais) consecutivos com valores abaixo
 %de 80% da media. Esses valores sao utilizados no planejameto de
 %reservatorios de usinas hidreletricas.
 rimax=zeros(1,b);%Inicializa o vetor com o deficit minimo para cada posto.
 soma=0;
 for j=1:b
    for i=1:a
       if (G(i,j)-0.8*Gm(j)<0)%Se for 80% menor que a media.
          soma=soma+G(i,j)-0.8*Gm(j);%Guarda a acumulaçao por posto.
       elseif (abs(soma) > rimax(j))
          rimax(j)=abs(soma);
          soma=0;
       else
          soma=0;
       end
    end
 end
X=rimax;

function [D]=desa_men(M,P,a,b)
   %Cria as matrizes com os coeficientes de desagregaçao, a quantidade de
   %matrizes depende da quantidade de anos observados.
   for k=1:a
```

```
    for j=1:b
       w=1;
       for i=(k-1)*12 +1:(k-1)*12+12
          A(w,j)=M(i,j)/P(k,j); %Calcula a matriz de coeficientes de desagregaçao.
          w=w+1;
       end
    end
    D(:,:,k)=A; %Guarda as matrizes de desagregaçao em forma de fichario
 End

function  [Mg]=gera_men(D,G,a,b)
    %Desagrega series sinteticas anuais em mensais. Entrada: D=matriz de
    %desagregaçao, G=serie sintetica anual, a=numero de anos e b=numero de
    %postos observados.
    for t=1:a
       U=rand;%Numero randomico entre 0 e 1.
       f=fix(a*U)+1; %Sorteia uma matriz de desagregaçao.
       Daf=D(:,:,f); %Matriz sorteada.
       for j=1:b
          w=(t-1)*12+1;%Artificio utilizado para mudar linha da matriz de precipitaçao mensal.
          for i=1:12
            Mg(w,j)=G(t,j)*Daf(i,j); %Desagrega anuais em mensais.
            w=w+1;
          end
       end
    end

function [G,Mgs]=gera_sinteticas
  %Algoritmo para gerar serie sintetica anual com desagregaçao em mensal.
  clear all%Apaga lixo da memoria.
  clc%Limpa tela.
  [M,P]=leitura;%Arquivo com dados observados de precipitaçoes mensais e anuais.
  a=input('Entre com a quantidade de anos observados: ');
  b=input('Entre com a quantidade de postos pluviometricos: ');
  Pm=mean(P); %Calcula as medias de cada posto.
  S=std(P); %Calcula o desvio padrao de cada posto.
  R=corrcoef(P); %Calcula a matriz de correlaçao.
  B=chol(R); %Faz a decomposiçao cholesky.
  D=desa_men(M,P,a,b); %Gera as matrizes de coeficientes de desagragaçao.
  T=matriz_postos(M,a,b);%Matrizes mensais referentes por postos.
  for i=1:b
     Rm(:,:,i)=corrcoef(T(:,:,i));%Matriz das correlaçoes mensais de cada posto.
  end

  Z=randn(b,a); %Matriz de numeros aleatorios.
  X=B'*Z; %Geraçao da matriz das variaveis aleatorias.
  Xt=X'; %Artificio para resoluçao simplificada.
  for j=1:b
     G(:,j)=[S(j)*Xt(:,j)]+[Pm(j)]; %Transforma as variaveis normais padrao em precipitaçao
sintetica anual.
  end
  Mgs=gera_men(D,G,a,b);%Desagrega anuais em mensis.
```

```
  %Salva os dados gerados em arquivos do excel.
  %wk1write('C:\Documents and Settings\Claris\Desktop\sint_anuais.xls',G);
  %wk1write('C:\Documents and Settings\Claris\Desktop\sint_mensais.xls',Mgs);
End

function [D]=matriz_postos(M,a,b)
  %O objetivo e separar os dados observados por posto, assim teremos todos
  %os janeiros, fevereiros, ..., dezembros de um local. Essas tabelas
  %serao uteis no calculo das matrizes de correlaçoes.
  c=a*12-12;
  for j=1:b %Numero de postos.
    for k=1:12 %Numero de meses.
      for i=k:12:c+k %Separa os meses.Ex: 1,13,25,...,732; 2,14,...,733;3,15,...,734;...
        A(ceil(i/12),k)=M(i,j); %Guarda os meses de cada posto numa matriz.
      end
    end
    D(:,:,j)=A;% Guarda cada matriz num fichario.
  End

function X=runinf(G,Gm,a,b)
 %Calcula X o numero maximo de precipitaçoes consecutivas abaixo da media,
 %para cada posto pluviometrico. Entrada: G=matriz com as
 %precipitaçoes(mensais ou anuais, sinteticas ou observadas), Gm=vetor
 %contendo as medias por posto, a=numero de anos observados e b=numero de
 %postos.
 aux=0;
 rimax=zeros(1,b);%Inicializa o vetor com valores minimos.
 for j=1:b
    for i=1:a
      if (G(i,j) < Gm(j))
         aux=aux+1;
      elseif (aux > rimax(j))
         rimax(j)=aux;
         aux=0;
      else
         aux=0;
      end
    end
 end
X=rimax;

function X=runsup(G,Gm,a,b)
 %Calcula X o numero maximo de precipitaçoes consecutivas
 %acima da media, para cada posto pluviometrico. Entrada: G=matriz com as
 %precipitaçoes(mensais ou anuais, sinteticas ou observadas), Gm=vetor
 %contendo as medias por posto, a=numero de anos observados e b=numero de
 %postos.
 aux=0;
 rsmax=zeros(1,b);
 for j=1:b
    for i=1:a
      if (G(i,j) > Gm(j))
```

```
            aux=aux+1;
        elseif (aux > rsmax(j))
            rsmax(j)=aux;
            aux=0;
        else
            aux=0;
        end
    end
  end
X=rsmax;
```

ANNEX G – INPUT/OUTPUT FILES OF THE PROGRAM – MDM MODEL

The files containing the data of observed annual and monthly rainfall enter the program with **xls** format. The function **"function valida"** includes the input data automatically. The User should inform the path where the file is stored and add to the "**reading function**". In this case it was used the path: C: \ Documents and Settings \ User \ Desktop \ anuais.xls through the command: P = xlsread ('C: \ Documents and Settings \ User \ Desktop \ anuais.xls');

The **"function [G, Mgs] = gera_sinteticas"** generates only just one synthetic series of annual precipitations disagreggated into monthly values. Besides the input data mentioned above, the User may choose the number of years and sites.

Annual precipitations

For this example the format of the spreadsheet used is as follows.

1279,56	1519,91	1152,92	1403,04	1062,98	1234,49	1361,39	1323,19	565,34
2508,48	2121,86	1860,88	2149,54	824,96	1207,35	1412,4	1555,72	1541,63
1576,35	1344,77	1205,65	1778,45	1318,6	1609,8	2206,33	2022,77	2268,92
1816,41	1524,1	1958,11	1589,72	1663,93	1588,19	1945,11	1756,05	934,56
1125	1307,18	1509,62	1666,3	1113,34	1308,22	1754,58	2070,02	1007,4
1499,07	1454,22	1526,49	1853,92	1284,68	1067,69	1555,92	1938,06	1133,12
1650,52	1479,21	1706,22	1937,63	1341,17	1476,2	1732,54	2208,4	1250,26

The columns indicate the rainfall stations and lines the observed years. All files will follow the same layout.

	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9
1944	1279,56	1519,91	1152,92	1403,04	1062,98	1234,49	1361,39	1323,19	565,34
1945	2508,48	2121,86	1860,88	2149,54	824,96	1207,35	1412,4	1555,72	1541,63
1946	1576,35	1344,77	1205,65	1778,45	1318,6	1609,8	2206,33	2022,77	2268,92
1947	1816,41	1524,1	1958,11	1589,72	1663,93	1588,19	1945,11	1756,05	934,56
1948	1125	1307,18	1509,62	1666,3	1113,34	1308,22	1754,58	2070,02	1007,4
1949	1499,07	1454,22	1526,49	1853,92	1284,68	1067,69	1555,92	1938,06	1133,12
1950	1650,52	1479,21	1706,22	1937,63	1341,17	1476,2	1732,54	2208,4	1250,26

Monthly Precipitations

294,02	170,58	223,07	276,21	135,45	198,82	241,08	154,24	45,58
212,74	205,95	248,47	226,49	292,31	268,36	125,6	197,88	25,86
146,79	261,78	201,08	285,86	209,54	114,39	166,37	107,34	85,77
193,87	219,88	45,25	112,15	60,78	30,5	87,19	42,94	14,47
0	9,12	1,28	12,09	0,23	93,87	17,44	15,75	47,37
0	3,2	1,28	0	2,32	89,7	56,32	214,45	5,38
0	0	0,43	0	0,58	15,62	26,75	68,72	10,75
0	0	0	0	0	7,63	105,34	68,6	0
3,44	1,73	2,99	0	1,74	56,83	31,46	60,09	29,57
154,23	212,48	64,25	158,32	153,39	50,84	98,27	216,2	47,75
109,37	231,09	189,56	214,88	147,03	193,37	257,69	173,26	177,44

This is like values are stored.

	Site 1	**Site 2**	**Site 3**	**Site 4**	**Site 5**	**Site 6**	**Site 7**	**Site 8**	**Site 9**
jan/44	294,02	170,58	223,07	276,21	135,45	198,82	241,08	154,24	45,58
feb/44	212,74	205,95	248,47	226,49	292,31	268,36	125,6	197,88	25,86
mar/44	146,79	261,78	201,08	285,86	209,54	114,39	166,37	107,34	85,77
apr/44	193,87	219,88	45,25	112,15	60,78	30,5	87,19	42,94	14,47
may/44	0	9,12	1,28	12,09	0,23	93,87	17,44	15,75	47,37
jun/44	0	3,2	1,28	0	2,32	89,7	56,32	214,45	5,38
jul/44	0	0	0,43	0	0,58	15,62	26,75	68,72	10,75
aug/44	0	0	0	0	0	7,63	105,34	68,6	0
sept/44	3,44	1,73	2,99	0	1,74	56,83	31,46	60,09	29,57
oct/44	154,23	212,48	64,25	158,32	153,39	50,84	98,27	216,2	47,75
nov/44	109,37	231,09	189,56	214,88	147,03	193,37	257,69	173,26	177,44
dec/44	165,11	204,1	175,25	117,03	59,62	114,57	147,87	3,73	75,4

Comments on the construction of files for the program:

1. All files of the input data should be saved in **xls format**, another extension may cause error because the reading functions used by Matlab.

2. The data file in the **xls format** should contain only the data in a matrix form, excluding

therefore the rows and columns of the nomenclature;

3. Errors will happen when there are blank cells within text files, or space between the data recorded with the space bar and if the data is not saved in the first cell of the Excel spreadsheet.

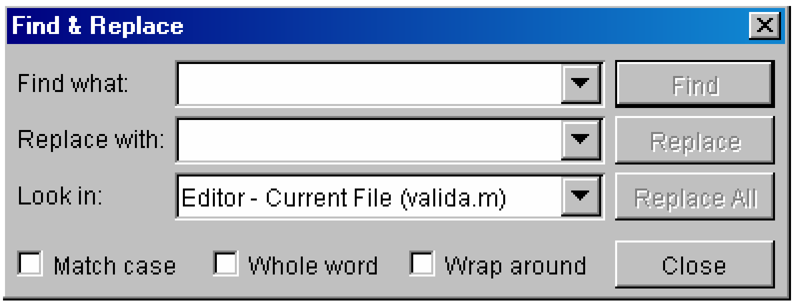
Running the program.

To run the program you must have the software Matlab. In this project the version 6.0.0.88 - R12, 2000 The Mathworks Inc is used under license. Install a version lower than the R12 may cause error.

Step 1: Save the file. m. In the directory where you installed Matlab, there is a folder with the name of **work**. All the files **.m** should be saved in this folder.

Step 2: Path of the input file. Enter the path of the input files in "read-function" as specified above.

Step 3: Retrace the path of the file to the output data. Inside Matlab open the file **"function validates"** then go **to "edit"** and then "**Find and Replace"** (or press CTRL + F). Will open the following window:



In the **"Find what"** spot type the old path, **C:** \ **Documents and Settings** \ **User** \ **Desktop** and in the **"Replace with"** type the new location where the files will be saved. The same procedure must be done in the **"function [G, Mgs] = gera_sinteticas**.

Step 4: function valida. This program runs automatically, the user just need to run previous procedures. At the end of a message will appear with the computer time for this task.

Step 5: function [G, Mgs] = gera_sinteticas. The user can check the output format of a series of synthetic annual precipitation with monthly disaggregation. The execution can be made using different values for the rainfall stations and the observed years.

Output data.

The results will be provided in **.xls format** automatically saved in the directory chosen by the user. Below some files will be mentioned.

- **med_anuais.xls**: Contains the average of the historical annual series.
- **med_anuais_sint.xls**: Contains the average annual synthetic series.
- **des_pad_anuais.xls**: Contains the standard deviations of the historical annual series.
- **des_pad_sint_anuais.xls**: Contains the standard deviations of the annual synthetic series.
- **med_mensais2.xls:** Contains the average of the series by stations, both synthetic and observed.
- **des_pad_mensais2.xls:** Contains the standard deviations by stations, both synthetic and observed.

Some disaggregation arrays verification testing

Monthly precipitation of year 1944									
	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9
January	294,02	170,58	223,07	276,21	135,45	198,82	241,08	154,24	45,58
February	212,74	205,95	248,47	226,49	292,31	268,36	125,6	197,88	25,86
March	146,79	261,78	201,08	285,86	209,54	114,39	166,37	107,34	85,77
April	193,87	219,88	45,25	112,15	60,78	30,5	87,19	42,94	14,47
May	0	9,12	1,28	12,09	0,23	93,87	17,44	15,75	47,37
June	0	3,2	1,28	0	2,32	89,7	56,32	214,45	5,38
July	0	0	0,43	0	0,58	15,62	26,75	68,72	10,75
August	0	0	0	0	0	7,63	105,34	68,6	0
September	3,44	1,73	2,99	0	1,74	56,83	31,46	60,09	29,57
October	154,23	212,48	64,25	158,32	153,39	50,84	98,27	216,2	47,75
November	109,37	231,09	189,56	214,88	147,03	193,37	257,69	173,26	177,44
December	165,11	204,1	175,25	117,03	59,62	114,57	147,87	3,73	75,4
TOTAL	**1279,6**	**1519,9**	**1152,9**	**1403**	**1063**	**1234,5**	**1361,4**	**1323,2**	**565,34**

Annual precipitation of year 1944								
Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9
1279,6	1519,9	1152,9	1403	1063	1234,5	1361,4	1323,2	565,3

Matrix of disaggregation coefficients - D1								
0,2298	0,1122	0,1935	0,1969	0,1274	0,1611	0,1771	0,1166	0,0806
0,1663	0,1355	0,2155	0,1614	0,275	0,2174	0,0923	0,1495	0,0457
0,1147	0,1722	0,1744	0,2037	0,1971	0,0927	0,1222	0,0811	0,1517
0,1515	0,1447	0,0392	0,0799	0,0572	0,0247	0,064	0,0325	0,0256
0	0,006	0,0011	0,0086	0,0002	0,076	0,0128	0,0119	0,0838
0	0,0021	0,0011	0	0,0022	0,0727	0,0414	0,1621	0,0095
0	0	0,0004	0	0,0005	0,0127	0,0196	0,0519	0,019
0	0	0	0	0	0,0062	0,0774	0,0518	0
0,0027	0,0011	0,0026	0	0,0016	0,046	0,0231	0,0454	0,0523
0,1205	0,1398	0,0557	0,1128	0,1443	0,0412	0,0722	0,1634	0,0845
0,0855	0,152	0,1644	0,1532	0,1383	0,1566	0,1893	0,1309	0,3139
0,129	0,1343	0,152	0,0834	0,0561	0,0928	0,1086	0,0028	0,1334

Monthly precipitation of year 1945									
	Station 1	**Station 2**	**Station 3**	**Station 4**	**Station 5**	**Station 6**	**Station 7**	**Station 8**	**Station 9**
January	388,4	405,24	281,13	380,41	133,13	132,55	93,32	168,71	200,35
February	441,14	256,11	292,87	321,17	63,79	253,29	228	85,29	255,27
March	241,72	262,15	170,56	269,98	126,19	87,15	84,48	143,39	126,23
April	306,56	126,95	85,39	94,68	15,05	58,37	81,65	98,36	108,69
May	12,55	37,1	26,9	0,86	2,32	30,5	26,04	15,17	52,62
June	0,22	11,09	17,5	0,73	14,24	145,26	99,45	155,99	196,77
July	0	0	1,71	2,57	5,09	62,64	159,89	223,2	47,11
August	0	0	0	4,52	1,16	18,16	78	141,64	11,14
September	2,11	20,71	35,44	17,36	28,94	67,18	95,32	182,83	72,84
October	81,61	239,1	77,06	153,64	94,93	115,3	105,69	64,87	35,08
November	383,73	450,97	284,12	385,58	57,65	98,96	211,38	79,92	114,96
December	650,44	312,44	588,2	518,05	282,47	137,99	149,17	196,36	320,57
TOTAL	**2508,5**	**2121,9**	**1860,9**	**2149,6**	**824,96**	**1207,4**	**1412,4**	**1555,7**	**1541,6**

Annual precipitation of year 1945								
Station 1	**Station 2**	**Station 3**	**Station 4**	**Station 5**	**Station 6**	**Station 7**	**Station 8**	**Station 9**
2508,5	2121,9	1860,9	2149,5	824,96	1207,4	1412,4	1555,7	1541,6

Matrix of disaggregation coefficients - D2								
0,1548	0,191	0,1511	0,177	0,1614	0,1098	0,0661	0,1084	0,13
0,1759	0,1207	0,1574	0,1494	0,0773	0,2098	0,1614	0,0548	0,1656
0,0964	0,1235	0,0917	0,1256	0,153	0,0722	0,0598	0,0922	0,0819
0,1222	0,0598	0,0459	0,044	0,0182	0,0483	0,0578	0,0632	0,0705
0,005	0,0175	0,0145	0,0004	0,0028	0,0253	0,0184	0,0098	0,0341
0,0001	0,0052	0,0094	0,0003	0,0173	0,1203	0,0704	0,1003	0,1276
0	0	0,0009	0,0012	0,0062	0,0519	0,1132	0,1435	0,0306
0	0	0	0,0021	0,0014	0,015	0,0552	0,091	0,0072
0,0008	0,0098	0,019	0,0081	0,0351	0,0556	0,0675	0,1175	0,0472
0,0325	0,1127	0,0414	0,0715	0,1151	0,0955	0,0748	0,0417	0,0228
0,153	0,2125	0,1527	0,1794	0,0699	0,082	0,1497	0,0514	0,0746
0,2593	0,1472	0,3161	0,241	0,3424	0,1143	0,1056	0,1262	0,2079

Monthly precipitation of year 1986									
	Station 1	**Station 2**	**Station 3**	**Station 4**	**Station 5**	**Station 6**	**Station 7**	**Station 8**	**Station 9**
January	245,5	195,6	304,9	373,3	81,4	129,7	160,9	117,3	166
February	192,2	201,8	232	129,4	237,7	180	233,5	97,8	151,9
March	165,5	129,5	120,9	160	116,8	167,9	122,6	68,8	126,3
April	35,6	21,7	69,5	49,2	15,4	132,7	122,7	299	86,2
May	28,6	28,4	106,1	147,5	94,7	209,9	156,5	168,6	114,4
June	0,2	0	3,2	0,5	0	1,2	24,9	55,1	0
July	19,2	59,2	81,7	72,9	26,7	13	30,6	54,4	8,7
August	52,2	83,1	134,1	109,5	129,1	147,4	140,7	121,1	144,5
September	61,1	37,2	30,1	39,9	16,6	61,4	134,2	170,7	49,6
October	105	129,4	37,8	68,7	46,1	97,2	119,9	109	27,6
November	81,3	149,3	174,7	98,7	66,2	201,6	118,9	193,1	74,1
December	452,4	358	465,3	314,8	189,8	172,3	111	53,8	251,7
TOTAL	**1438,8**	**1393,2**	**1760,3**	**1564,4**	**1020,5**	**1514,3**	**1476,4**	**1508,7**	**1201**

Annual precipitation of year 1986								
Station 1	**Station 2**	**Station 3**	**Station 4**	**Station 5**	**Station 6**	**Station 7**	**Station 8**	**Station 9**
1438,8	1393,2	1760,3	1564,4	1020,5	1514,3	1476,4	1508,7	1201

Matrix of disaggregation coefficients - D3								
0,1706	0,1404	0,1732	0,2386	0,0798	0,0857	0,109	0,0777	0,1382
0,1336	0,1448	0,1318	0,0827	0,2329	0,1189	0,1582	0,0648	0,1265
0,115	0,093	0,0687	0,1023	0,1145	0,1109	0,083	0,0456	0,1052
0,0247	0,0156	0,0395	0,0314	0,0151	0,0876	0,0831	0,1982	0,0718
0,0199	0,0204	0,0603	0,0943	0,0928	0,1386	0,106	0,1118	0,0953
0,0001	0	0,0018	0,0003	0	0,0008	0,0169	0,0365	0
0,0133	0,0425	0,0464	0,0466	0,0262	0,0086	0,0207	0,0361	0,0072
0,0363	0,0596	0,0762	0,07	0,1265	0,0973	0,0953	0,0803	0,1203
0,0425	0,0267	0,0171	0,0255	0,0163	0,0405	0,0909	0,1131	0,0413
0,073	0,0929	0,0215	0,0439	0,0452	0,0642	0,0812	0,0722	0,023
0,0565	0,1072	0,0992	0,0631	0,0649	0,1331	0,0805	0,128	0,0617
0,3144	0,257	0,2643	0,2012	0,186	0,1138	0,0752	0,0357	0,2096

ANNEX H - COMPLETE RESULTS OBTAINED- DUM MODEL

In this first Annex, complete results of the application of the four modules of the computational model developed, for the 11 rainfall selected stations, are presented. Results already showed previously are repeated in the section.

Four are the tables presented: table A-1.1, to module 1; table A-1.2 to module 2; tables A-1.3 and A-1.4, to module 3 and table A-1.5 to module 4 of the computational program.

TABLE A-1.1 – COMPLETE RESULTS FOR MODULE 1

Stations	Months	Markov Chain's Parameters				Optimum Order		Time (s)
		p00	p10	p01	p11	AIC	BIC	
Monte Alegre de Minas (MAM)	January	0.5711	0.4289	0.3026	0.6974	2	2	1.72
	February	0.6169	0.3831	0.3365	0.6635	2	1	1.25
	March	0.6408	0.3592	0.3926	0.6074	2	1	1.61
	April	0.7891	0.2109	0.5404	0.4596	1	1	2.00
	May	0.8974	0.1026	0.7090	0.2910	2	1	1.69
	June	0.9511	0.0489	0.7797	0.2203	1	1	1.84
	July	0.9661	0.0339	0.6471	0.3529	2	1	3.91
	August	0.9502	0.0498	0.6761	0.3239	2	2	1.75
	September	0.8468	0.1532	0.6000	0.4000	2	1	1.64
	October	0.7239	0.2761	0.5513	0.4487	2	1	1.22
	November	0.6499	0.3501	0.3794	0.6206	1	1	1.06
	December	0.4743	0.5257	0.3130	0.6870	2	1	1.97
Usina Couro do Cervo (UCC)	January	0.6574	0.3426	0.3358	0.6642	1	1	0.13
	February	0.7305	0.2695	0.3561	0.6439	2	1	1.05
	March	0.7511	0.2489	0.4365	0.5635	2	1	1.16
	April	0.8729	0.1271	0.6215	0.3785	1	1	1.13
	May	0.9061	0.0939	0.6423	0.3577	2	1	1.11
	June	0.9406	0.0594	0.7051	0.2949	1	1	1.72
	July	0.9511	0.0489	0.6528	0.3472	1	1	0.97
	August	0.9391	0.0609	0.6988	0.3012	2	1	2.30
	September	0.8634	0.1366	0.6404	0.3596	1	1	1.64
	October	0.7587	0.2413	0.5954	0.4046	1	1	1.16
	November	0.7037	0.2963	0.4586	0.5414	1	1	1.13
	December	0.6306	0.3694	0.3191	0.6809	2	1	2.05

continue

Stations	Months	Markov Chain's Parameters				Optimum Order		Time (s)
		p00	p10	p01	p11	AIC	BIC	
Monte Mor (MM)	January	0.6696	0.3304	0.4034	0.5966	2	1	2.42
	February	0.6784	0.3216	0.4216	0.5784	2	1	1.88
	March	0.7689	0.2311	0.4629	0.5371	1	1	4.36
	April	0.8599	0.1401	0.6270	0.3730	2	1	2.08
	May	0.8447	0.1553	0.6019	0.3981	2	1	2.14
	June	0.8903	0.1097	0.6026	0.3974	1	1	1.89
	July	0.9284	0.0716	0.5981	0.4019	1	1	2.56
	August	0.9197	0.0803	0.5680	0.4320	2	1	2.62
	September	0.8359	0.1641	0.5122	0.4878	1	1	2.05
	October	0.7966	0.2034	0.5455	0.4545	2	1	1.78
	November	0.7664	0.2336	0.4803	0.5197	2	1	1.72
	December	0.6909	0.3091	0.3881	0.6119	1	1	2.23
Caiuá (Ca)	January	0.7085	0.2915	0.4157	0.5843	2	1	1.61
	February	0.6797	0.3203	0.5603	0.4397	2	1	2.53
	March	0.7686	0.2314	0.5762	0.4238	2	2	2.61
	April	0.8613	0.1387	0.6486	0.3514	1	1	2.06
	May	0.8434	0.1566	0.6054	0.3946	1	1	3.09
	June	0.8854	0.1146	0.6375	0.3625	1	1	3.66
	July	0.9165	0.0835	0.6957	0.3043	2	1	2.13
	August	0.9155	0.0845	0.7043	0.2957	2	2	7.33
	September	0.8200	0.1800	0.5720	0.4280	1	1	7.84
	October	0.8088	0.1912	0.6452	0.3548	1	1	1.76
	November	0.7723	0.2277	0.5719	0.4281	1	1	1.64
	December	0.7302	0.2698	0.4458	0.5542	2	1	3.97
Tomazina (To)	January	0.6896	0.3104	0.3783	0.6217	2	1	4.05
	February	0.6721	0.3279	0.4100	0.5900	1	1	2.02
	March	0.7472	0.2528	0.4878	0.5122	1	1	2.20
	April	0.8534	0.1466	0.5782	0.4218	1	1	2.13
	May	0.8465	0.1535	0.5060	0.4940	1	1	2.42
	June	0.8506	0.1494	0.5591	0.4409	1	1	2.47
	July	0.8804	0.1196	0.5879	0.4121	1	1	2.23
	August	0.8880	0.1120	0.5464	0.4536	2	1	2.58
	September	0.8061	0.1939	0.5000	0.5000	1	1	2.22
	October	0.7520	0.2480	0.5650	0.4350	1	1	2.03
	November	0.7529	0.2471	0.5705	0.4295	1	1	1.64
	December	0.6946	0.3054	0.4262	0.5738	1	1	2.05

continue

Stations	Months	Markov Chain's Parameters				Optimum Order		Time (s)
		p00	p10	p01	p11	AIC	BIC	
União da Vitória (UV)	January	0.6684	0.3316	0.4012	0.5988	2	2	5.17
	February	0.6424	0.3576	0.3590	0.6410	1	1	2.80
	March	0.6885	0.3115	0.4556	0.5444	2	1	10.64
	April	0.7712	0.2288	0.5160	0.4840	2	1	1.70
	May	0.7958	0.2042	0.5100	0.4900	1	1	3.31
	June	0.7843	0.2157	0.5000	0.5000	1	1	1.83
	July	0.8032	0.1968	0.4916	0.5084	1	1	1.45
	August	0.8273	0.1727	0.4784	0.5216	2	1	1.84
	September	0.7601	0.2399	0.4585	0.5415	2	1	2.03
	October	0.6984	0.3016	0.4903	0.5097	1	1	2.27
	November	0.7231	0.2769	0.4817	0.5183	1	1	1.44
	December	0.6947	0.3053	0.4402	0.5598	1	1	2.66
Taiamã (Ta)	January	0.6761	0.3239	0.4936	0.5064	2	1	2.34
	February	0.6255	0.3745	0.5611	0.4389	2	0	2.16
	March	0.6952	0.3048	0.5801	0.4199	2	1	2.88
	April	0.8235	0.1765	0.6882	0.3118	1	1	1.44
	May	0.9077	0.0923	0.7429	0.2571	1	1	1.55
	June	0.9605	0.0395	0.7907	0.2093	1	1	1.39
	July	0.9776	0.0224	0.9091	0.0909	1	0	1.39
	August	0.9677	0.0323	0.8788	0.1212	1	0	1.05
	September	0.8849	0.1151	0.8230	0.1770	2	0	3.02
	October	0.8138	0.1862	0.7462	0.2538	2	0	1.47
	November	0.7061	0.2939	0.6689	0.3311	2	0	1.56
	December	0.6727	0.3273	0.5534	0.4466	2	1	1.63
Caracol (Co)	January	0.7905	0.2095	0.5882	0.4118	1	1	1.73
	February	0.7443	0.2557	0.5795	0.4205	1	1	1.41
	March	0.8137	0.1863	0.6438	0.3563	1	1	1.67
	April	0.8639	0.1361	0.6667	0.3333	1	1	1.72
	May	0.8685	0.1315	0.6299	0.3701	1	1	1.78
	June	0.8610	0.1390	0.6308	0.3692	1	1	1.63
	July	0.9193	0.0807	0.7067	0.2933	1	1	1.63
	August	0.9143	0.0857	0.7397	0.2603	1	1	1.61
	September	0.8488	0.1512	0.6508	0.3492	1	1	2.11
	October	0.8086	0.1914	0.6883	0.3117	1	1	1.72
	November	0.7808	0.2192	0.6890	0.3110	1	0	1.56
	December	0.7921	0.2079	0.6270	0.3730	1	1	1.59

continue

conclusion

Stations	Months	Markov Chain's Parameters				Optimum Order		Time (s)
		p00	p10	p01	p11	AIC	BIC	
Passo Marom-bas (PM)	January	0.7319	0.2681	0.4401	0.5599	1	1	1.25
	February	0.7023	0.2977	0.3929	0.6071	1	1	1.92
	March	0.7747	0.2253	0.5475	0.4525	1	1	1.97
	April	0.8272	0.1728	0.5391	0.4609	1	1	2.91
	May	0.8307	0.1693	0.5578	0.4422	1	1	2.09
	June	0.7982	0.2018	0.5480	0.4520	1	1	2.42
	July	0.8246	0.1754	0.4982	0.5018	1	1	1.70
	August	0.8288	0.1712	0.5055	0.4945	1	1	1.78
	September	0.7843	0.2157	0.4845	0.5155	2	1	1.69
	October	0.7411	0.2589	0.5339	0.4661	2	1	1.11
	November	0.7394	0.2606	0.5476	0.4524	1	1	2.00
	December	0.7390	0.2610	0.5322	0.4678	2	1	1.70
Linha Cescon (LC)	January	0.8063	0.1937	0.531	0.469	1	1	1.17
	February	0.7697	0.2303	0.5766	0.4234	1	1	1.36
	March	0.8457	0.1543	0.6927	0.3073	1	1	1.22
	April	0.8538	0.1462	0.608	0.392	1	1	1.34
	May	0.8412	0.1588	0.6364	0.3636	1	1	1.50
	June	0.8213	0.1787	0.5726	0.4274	2	1	1.39
	July	0.8225	0.1775	0.6076	0.3924	1	1	1.59
	August	0.8402	0.1598	0.5746	0.4254	2	1	2.38
	September	0.8206	0.1794	0.5657	0.4343	1	1	1.70
	October	0.7968	0.2032	0.6007	0.3993	2	1	1.70
	November	0.8262	0.1738	0.6905	0.3095	2	1	1.69
	December	0.8182	0.1818	0.6872	0.3128	2	1	1.28
Cacequi (Cq)	January	0.8228	0.1772	0.6107	0.3893	1	1	1.06
	February	0.7941	0.2059	0.6245	0.3755	1	1	1.38
	March	0.8312	0.1688	0.6372	0.3628	1	1	1.44
	April	0.8157	0.1843	0.6419	0.3581	1	1	1.36
	May	0.8547	0.1453	0.6019	0.3981	1	1	1.59
	June	0.8162	0.1838	0.6368	0.3632	1	1	1.39
	July	0.8053	0.1947	0.6364	0.3636	1	1	1.61
	August	0.8449	0.1551	0.6538	0.3462	1	1	1.28
	September	0.8133	0.1867	0.6398	0.3602	1	1	1.80
	October	0.8173	0.1827	0.671	0.329	2	1	1.09
	November	0.8098	0.1902	0.7383	0.2617	1	0	1.44
	December	0.843	0.157	0.7202	0.2798	1	1	1.72

TABLE A-1.2 – COMPLETE RELATION OF MIXED EXPONENTIAL DISTRIBUTION'S PARAMETERS

Stations	Months	Initial Estimative (Moments Method)			Definitive Estimative (Maximum Likelihood Method)				Time (s)
		α	β_1	β_2	α	β_1	β_2	Iterations	
Monte Alegre de Minas (MAM)	January	0.2242	24.0937	14.0937	0.7870	19.7252	3.8348	227	438.91
	February	0.0483	22.0793	12.0793	0.7218	15.9006	3.9268	299	676.28
	March	0.5469	28.0253	18.0253	0.6532	17.3360	3.5672	102	583.42
	April	0.0387	35.5706	11.8853	0.6543	15.5151	2.3830	108	448.22
	May	0.0079	49.0332	9.7401	0.6903	12.7771	1.9979	196	349.47
	June	0.0016	88.2501	9.5562	0.5314	15.6896	2.3534	86	305.70
	July	0.1095	19.4693	9.4693	0.6498	11.7750	2.0808	81	315.83
	August	0.3750	13.9469	3.9469	0.4134	8.1917	7.3896	36	318.39
	September	0.0540	19.1819	9.1819	0.6266	11.9002	3.1932	192	320.42
	October	0.4024	26.9157	16.9157	0.6455	17.7244	4.1155	166	346.39
	November	0.3254	27.6999	17.6999	0.6941	18.9315	4.2894	232	365.25
	December	0.0531	23.7742	13.7742	0.7093	17.2019	3.6003	199	413.77
Usina Couro do Cervo (UCC)	January	0.3051	23.0860	13.0860	0.7103	19.9321	6.8351	317	410.67
	February	0.5383	19.6757	9.6757	0.5397	18.4698	11.0615	24	364.64
	March	0.4151	20.3841	10.3841	0.5613	18.9566	8.8815	271	370.39
	April	0.1055	23.6061	13.6061	0.0230	65.7074	11.2979	32	417.52
	May	0.2284	19.7832	9.7832	0.0790	27.7756	10.7251	217	334.61
	June	0.3932	16.3952	6.3952	0.4000	13.5056	8.2120	18	309.06
	July	0.2827	21.7588	11.7588	0.4210	14.1695	5.1289	147	317.84
	August	0.2749	15.9068	5.9068	0.2538	12.7964	7.2518	46	317.81
	September	0.6964	16.1921	6.1921	0.7388	13.2587	12.8812	70	324.19
	October	0.4690	17.4563	7.4563	0.6057	14.8112	8.0572	331	353.03
	November	0.5697	19.2554	9.2554	0.5725	18.0514	10.8026	24	353.78
	December	0.6308	19.4633	9.4633	0.6404	18.5324	10.8577	26	394.47
Monte Mor (MM)	January	0.4756	29.6038	19.7359	0.7974	18.2330	2.5077	187	536.17
	February	0.3407	26.8610	17.9073	0.8272	17.4522	2.4581	519	488.70
	March	0.0786	21.3776	14.2517	0.6559	18.6255	4.3477	171	425.28
	April	0.4506	16.5978	6.5978	0.4475	13.0318	9.6333	68	445.17
	May	0.0258	16.3140	10.8760	0.7254	14.5097	2.0741	212	446.89
	June	0.5187	13.5313	9.0208	0.6721	15.5322	3.2226	98	396.50
	July	0.0743	14.6422	9.7615	0.4386	14.5045	5.6849	329	446.84
	August	0.4586	6.6110	4.4073	0.4758	9.3495	9.1925	26	441.01
	September	0.2749	17.8397	11.8932	0.6466	14.1462	3.1912	119	469.34
	October	0.7719	13.9281	9.2854	0.4866	16.8923	9.0814	388	511.05
	November	0.8148	12.1329	8.0886	0.8598	14.4486	4.5489	268	464.30
	December	0.6563	12.1152	8.0768	0.6829	16.1220	10.1732	15	502.67

continue

Stations	Months	Initial Estimative (Moments Method)			Definitive Estimative (Maximum Likelihood Method)			Iterations	Time (s)
		α	β_1	β_2	α	β_1	β_2		
Caiuá (Ca)	January	0.6554	17.9379	11.9586	0.5516	20.0947	10.6925	335	519.91
	February	0.3112	20.4463	13.6309	0.7074	19.7385	6.1217	231	624.91
	March	0.0525	23.9897	13.9897	0.7375	17.8196	5.2356	597	647.48
	April	0.3492	18.7432	12.4954	0.7530	18.0032	4.5506	178	438.50
	May	0.7292	12.5303	8.3535	0.8370	16.1420	3.5158	109	465.22
	June	0.2999	19.3255	12.8837	0.6563	14.7940	3.6277	135	444.00
	July	0.0316	39.6446	12.3998	0.6339	16.4762	3.0072	133	488.95
	August	0.5312	22.7556	15.1704	0.5585	16.8269	3.9711	70	377.31
	September	0.3615	15.7208	10.4805	0.7033	15.3714	5.2845	399	533.28
	October	0.9121	14.7859	9.8572	0.8681	16.9867	3.9139	39	568.34
	November	0.0841	40.6620	17.3433	0.2308	29.5078	11.1453	392	570.89
	December	0.3295	18.9987	12.6658	0.6478	19.2153	6.5467	212	473.36
Tomazina (To)	January	0.1350	36.4671	17.9347	0.5621	22.9191	5.8326	152	646.11
	February	0.0453	41.8690	14.7042	0.4293	21.8774	7.1611	260	587.70
	March	0.6288	27.1558	18.1038	0.5320	18.4045	5.6196	23	460.92
	April	0.8115	14.9484	9.9656	0.8314	16.2018	3.2478	105	417.28
	May	0.4940	19.8013	13.2009	0.6973	20.0444	4.8389	130	427.49
	June	0.6758	12.5557	8.3705	0.8439	16.4361	4.4701	192	461.34
	July	0.2406	22.8205	15.2137	0.6319	18.7132	4.2496	90	460.69
	August	0.0770	17.5262	11.6841	0.7306	15.4979	3.0394	189	389.92
	September	0.7713	12.8364	8.5576	0.7730	16.2577	6.8002	53	377.19
	October	0.6946	15.2442	10.1628	0.8465	15.5422	3.5331	268	386.36
	November	0.7886	13.6713	9.1142	0.7798	15.1979	3.9239	149	353.27
	December	0.5738	12.7929	8.5286	0.8362	16.4654	3.5261	126	428.75
União da Vitória (UV)	January	0.8780	19.2202	14.9177	0.7220	14.3633	2.7946	35	484.17
	February	0.1725	19.2262	12.8175	0.7211	15.0506	3.0992	201	367.20
	March	0.0755	28.3299	11.6885	0.6710	14.4279	2.3020	140	651.75
	April	0.1107	44.3132	16.6399	0.5912	20.9941	2.8951	138	530.31
	May	0.0018	136.6367	16.7489	0.7069	22.7334	1.6738	98	361.84
	June	0.1259	37.0422	17.8447	0.6542	22.3745	2.4445	79	365.33
	July	0.3075	30.4399	18.7901	0.7354	19.9383	2.2093	151	358.44
	August	0.0427	44.7434	15.4274	0.7006	19.5974	1.5722	91	351.00
	September	0.2002	21.2012	14.1341	0.7825	18.9682	3.3158	260	470.53
	October	0.7427	16.4942	10.9961	0.8004	18.3960	1.8350	63	402.84
	November	0.3203	16.6238	11.0825	0.7728	15.8738	2.6299	138	451.03
	December	0.2313	22.7089	15.1393	0.7321	16.7494	4.2339	350	476.09

continue

Stations	Months	Initial Estimative (Moments Method)			Definitive Estimative (Maximum Likelihood Method)				Time (s)
		α	β_1	β_2	α	β_1	β_2	Iterations	
Taiamã (Ta)	January	0.6261	15.4457	10.2971	0.6551	20.3954	14.9604	34	424.27
	February	0.8015	16.3589	10.9059	0.7304	20.0071	11.4894	270	407.03
	March	0.3095	9.03	6.02	0.4167	15.8028	15.7048	31	398.06
	April	0.789	12.3652	8.2435	0.7868	14.826	8.4555	34	341.97
	May	0.3868	10.2522	6.8348	0.4817	15.8225	15.5329	40	458.84
	June	0.1012	18.9742	12.6495	0.3175	20.4806	8.0682	106	421.24
	July	0.5807	11.8996	7.9331	0.6359	16.6537	11.4624	25	426.09
	August	0.5325	30.1074	20.0716	0.4458	23.8105	7.4249	26	275.09
	September	0.5516	9.8076	6.5384	0.6054	13.9985	10.1163	33	407.99
	October	0.5531	11.5241	7.6827	0.6022	15.8689	12.752	40	431.22
	November	0.889	18.6151	12.41	0.444	23.8675	13.1849	676	522.31
	December	0.6877	16.6852	11.1234	0.7067	20.9375	15.0491	32	532.25
Caracol (Co)	January	0.8841	18.3285	8.3285	0.8775	18.7486	5.8872	32	378.39
	February	0.0897	25.2831	15.2831	0.8525	18.5271	2.6426	459	251.78
	March	0.5719	35.5579	25.5579	0.2044	38.5009	15.0541	293	272.06
	April	0.7527	19.849	9.849	0.9004	25.2258	4.282	67	267.05
	May	0.1666	42.0195	21.9644	0.5831	27.6795	5.9644	119	241.06
	June	0.2392	20.558	10.558	0.7344	16.6871	2.6457	106	273.49
	July	0.1865	26.8697	14.5011	0.4614	19.2616	6.166	199	233.67
	August	0.194	26.9637	16.9637	0.747	19.1259	2.9263	118	227.33
	September	0.7109	16.2832	6.2832	0.7751	13.4801	13.1205	95	220.02
	October	0.779	21.4664	11.4664	0.8345	22.1628	4.6209	69	234.92
	November	0.8286	20.6873	10.6873	0.8654	22.9203	21.7139	81	230.22
	December	0.6516	19.6181	9.6181	0.7868	25.0017	24.8541	48	246.01
Passo Marom-bas (PM)	January	0.7433	15.9388	5.9388	0.7784	13.4202	13.2033	51	460.39
	February	0.523	17.8226	7.8226	0.5294	15.6589	10.1206	30	551.17
	March	0.423	17.8619	7.8619	0.6729	14.7039	6.7181	333	416.86
	April	0.5641	18.9921	8.9921	0.8515	16.4792	4.0462	176	376.55
	May	0.4826	21.4819	11.4819	0.6489	20.2897	8.9493	254	454.47
	June	0.5181	19.6048	9.6048	0.6704	17.9859	8.2757	265	606.94
	July	0.0096	26.0481	16.0481	0.1675	32.2483	12.9042	168	498.69
	August	0.5599	20.212	10.212	0.5595	18.9883	11.7756	27	390.47
	September	0.7098	17.8416	7.8416	0.8814	16.1668	5.8237	254	481.70
	October	0.791	18.2732	8.2732	0.8855	17.5377	5.7109	151	710.19
	November	0.6715	17.0618	7.0618	0.7066	14.9026	11.0648	58	499.20
	December	0.8122	16.891	6.891	0.8371	15.0825	14.6586	65	601.97

continue

conclusion

Stations	Months	Initial Estimative (Moments Method)			Definitive Estimative (Maximum Likelihood Method)				Time (s)
		α	β_1	β_2	α	β_1	β_2	Iterations	
Taiamã (Ta)	January	0.6261	15.4457	10.2971	0.6551	20.3954	14.9604	34	424.27
	February	0.8015	16.3589	10.9059	0.7304	20.0071	11.4894	270	407.03
	March	0.3095	9.03	6.02	0.4167	15.8028	15.7048	31	398.06
	April	0.789	12.3652	8.2435	0.7868	14.826	8.4555	34	341.97
	May	0.3868	10.2522	6.8348	0.4817	15.8225	15.5329	40	458.84
	June	0.1012	18.9742	12.6495	0.3175	20.4806	8.0682	106	421.24
	July	0.5807	11.8996	7.9331	0.6359	16.6537	11.4624	25	426.09
	August	0.5325	30.1074	20.0716	0.4458	23.8105	7.4249	26	275.09
	September	0.5516	9.8076	6.5384	0.6054	13.9985	10.1163	33	407.99
	October	0.5531	11.5241	7.6827	0.6022	15.8689	12.752	40	431.22
	November	0.889	18.6151	12.41	0.444	23.8675	13.1849	676	522.31
	December	0.6877	16.6852	11.1234	0.7067	20.9375	15.0491	32	532.25
Caracol (Co)	January	0.8841	18.3285	8.3285	0.8775	18.7486	5.8872	32	378.39
	February	0.0897	25.2831	15.2831	0.8525	18.5271	2.6426	459	251.78
	March	0.5719	35.5579	25.5579	0.2044	38.5009	15.0541	293	272.06
	April	0.7527	19.849	9.849	0.9004	25.2258	4.282	67	267.05
	May	0.1666	42.0195	21.9644	0.5831	27.6795	5.9644	119	241.06
	June	0.2392	20.558	10.558	0.7344	16.6871	2.6457	106	273.49
	July	0.1865	26.8697	14.5011	0.4614	19.2616	6.166	199	233.67
	August	0.194	26.9637	16.9637	0.747	19.1259	2.9263	118	227.33
	September	0.7109	16.2832	6.2832	0.7751	13.4801	13.1205	95	220.02
	October	0.779	21.4664	11.4664	0.8345	22.1628	4.6209	69	234.92
	November	0.8286	20.6873	10.6873	0.8654	22.9203	21.7139	81	230.22
	December	0.6516	19.6181	9.6181	0.7868	25.0017	24.8541	48	246.01

TABLE A-1.3 – COMPLETE RESULTS FOR THE VALIDATION OF THE MODEL – PART 1

Stations	Months	Mean (mm)		St. Deviance (mm)		Total Amount (mm)		Daily Maximum (mm)		Wet Days		Dry Days	
		Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic
Monte Alegre de Minas (MAM)	January	16.3	16.6	18.4	18.7	10095.6	10241.5	143.4	133.0	618	618	436	436
	February	12.6	12.8	14.4	14.6	6608.0	6716.7	104.0	103.7	526	525	442	441
	March	12.6	12.8	15.3	15.5	6491.5	6633.3	100.8	110.3	517	518	568	567
	April	11.0	11.2	14.0	14.1	3125.8	3219.7	83.4	91.1	285	286	735	734
	May	9.4	9.7	12.4	11.7	1263.6	1314.3	69.0	65.3	134	135	936	935
	June	9.4	9.8	14.2	13.1	556.5	580.4	85.2	63.9	59	59	961	961
	July	8.4	8.6	9.9	10.3	427.1	455.3	40.4	48.0	51	53	1003	1001
	August	7.7	8.0	7.8	7.7	546.5	579.5	34.1	37.9	71	73	983	981
	September	8.6	8.9	10.1	10.4	1728.3	1790.5	52.6	64.9	200	202	790	788
	October	12.9	13.2	15.5	15.8	4396.2	4483.9	84.7	106.7	341	341	681	681
	November	14.5	14.7	17.2	17.2	6587.3	6703.5	102.0	120.8	456	457	497	496
	December	13.2	13.5	15.4	15.9	8250.4	8419.0	110.0	115.2	623	622	369	370
Usina Couro do Cervo (UCC)	January	16.1	16.4	18.0	18.2	8843.3	8983.0	147.4	131.8	548	548	537	537
	February	15.1	15.3	16.0	16.0	6385.0	6530.1	128.8	112.6	424	426	564	562
	March	14.5	14.8	15.8	16.1	5726.9	5842.8	87.1	113.2	394	394	691	691
	April	12.6	12.7	14.7	16.0	2221.6	2270.7	122.3	134.8	177	178	873	872
	May	12.1	12.3	13.4	13.4	1653.2	1697.6	99.0	87.5	137	138	948	947
	June	10.3	10.5	10.9	10.7	805.5	830.5	56.1	55.5	78	79	942	941
	July	8.9	9.2	10.8	10.7	643.1	685.4	55.0	57.5	72	74	982	980
	August	8.7	8.9	9.3	9.1	718.4	744.4	58.0	48.0	83	83	969	969
	September	13.2	13.4	13.0	13.1	2341.7	2387.7	65.4	76.4	178	178	842	842
	October	12.2	12.4	12.8	13.0	3692.6	3779.5	68.0	86.6	304	304	750	750
	November	15.0	15.2	15.7	15.7	5965.9	6099.9	110.2	109.1	399	401	621	619
	December	15.8	16.0	16.5	16.6	8895.3	9075.0	125.3	119.4	564	566	490	488
Monte Mor (MM)	January	15.0	15.3	18.1	17.4	7085.3	7197.2	138.4	117.9	471	470	575	576
	February	14.9	15.1	17.7	16.7	6061.6	6173.3	130.2	110.4	408	408	538	538
	March	13.7	13.9	15.9	16.6	4792.0	4885.0	94.4	110.6	350	350	701	701
	April	11.1	11.4	11.6	11.9	2054.2	2131.7	72.6	69.4	185	187	835	833
	May	11.0	11.4	12.7	13.4	2269.3	2358.9	67.2	79.3	206	207	805	804
	June	11.4	11.8	12.6	13.8	1715.4	1801.8	60.0	77.5	151	153	839	837

continue

Stations	Months	Mean (mm)		St. Deviance (mm)		Total Amount (mm)		Daily Maximum (mm)		Wet Days		Dry Days	
		Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic
Monte Mor (MM)	July	9.4	9.9	10.9	11.3	1005.7	1071.5	52.0	59.8	107	108	908	907
	August	9.2	9.5	9.1	9.7	1151.6	1201.7	45.6	52.5	125	126	897	896
	September	10.3	10.5	12.1	12.6	2523.6	2614.7	84.4	79.7	246	249	774	771
	October	12.9	13.2	14.0	14.1	3680.6	3762.5	86.0	94.9	286	286	767	767
	November	13.1	13.3	13.7	13.9	3967.9	4046.5	101.3	88.2	304	304	625	625
	December	14.2	14.5	14.7	14.7	6232.8	6340.8	98.2	99.1	438	438	550	550
Caiuá (Ca)	January	15.9	16.1	17.4	17.2	6874.9	6991.5	144.2	123.3	433	434	621	620
	February	15.8	16.0	17.7	18.0	5481.6	5596.2	141.2	120.4	348	349	612	611
	March	14.5	14.8	16.7	16.5	4383.4	4478.8	114.3	107.5	302	302	752	752
	April	14.7	15.0	16.5	16.8	2715.3	2787.6	109.3	99.0	185	186	865	864
	May	14.1	14.3	14.7	14.0	3140.1	3185.9	70.3	84.1	223	222	862	863
	June	11.0	11.2	13.0	13.1	1752.3	1787.6	67.6	76.8	160	160	890	890
	July	11.5	11.8	14.8	14.6	1327.1	1374.5	80.0	81.2	115	117	970	968
	August	11.1	11.4	13.5	14.1	1281.2	1329.0	65.4	79.7	115	117	970	968
	September	12.4	12.6	13.9	13.9	3093.7	3180.4	81.9	87.4	250	252	800	798
	October	15.3	15.5	16.2	16.5	3784.7	3865.3	102.6	101.4	248	249	837	836
	November	15.4	15.6	19.3	18.7	4599.2	4667.8	160.7	141.3	299	299	751	751
	December	14.8	15.1	16.6	17.0	5856.8	5984.5	111.2	118.2	397	398	656	655
Tomazina (To)	January	15.4	15.7	19.3	19.5	7546.6	7665.0	163.0	142.2	489	488	596	597
	February	13.5	13.7	17.1	16.9	5915.3	6020.1	138.5	127.9	439	439	549	549
	March	12.4	12.7	15.2	15.4	4580.1	4677.4	89.0	108.7	369	369	712	712
	April	14.0	14.3	15.2	15.5	2955.9	3031.5	81.0	92.1	211	212	839	838
	May	15.4	15.7	17.3	18.1	3874.0	3962.6	93.2	113.8	251	253	834	832
	June	14.6	14.8	15.1	15.6	3203.9	3295.6	73.6	94.9	220	222	830	828
	July	13.4	13.6	15.8	16.4	2435.8	2500.3	94.2	99.7	182	183	903	902
	August	12.1	12.5	13.9	14.4	2220.5	2310.0	71.2	86.0	183	185	902	900
	September	14.1	14.4	14.8	15.0	4118.8	4225.2	84.6	96.1	292	294	758	756
	October	13.7	14.0	15.0	14.9	4532.1	4623.8	94.0	94.0	331	331	754	754
	November	12.7	13.0	13.8	14.2	3786.9	3892.0	69.6	89.8	298	300	692	690
	December	14.3	14.6	15.0	15.7	6123.2	6247.3	85.6	105.6	427	428	596	595

continue

Stations	Months	Mean (mm)		St. Deviance (mm)		Total Amount (mm)		Daily Maximum (mm)		Wet Days		Dry Days	
		Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic
União da Vitória (UV)	January	11.1	11.4	13.7	13.4	5469.8	5577.7	124.2	93.0	491	490	594	595
	February	11.7	12.0	13.7	13.9	5774.0	5900.7	81.2	96.8	493	493	495	495
	March	10.4	10.7	13.1	13.1	4464.8	4561.5	99.8	90.7	428	427	626	627
	April	12.4	12.7	15.2	15.7	3871.0	3965.6	68.1	100.6	312	314	908	906
	May	16.5	16.9	22.2	21.0	4958.3	5122.5	154.6	131.8	300	303	754	751
	June	15.4	15.8	19.3	20.5	4721.1	4858.1	87.9	132.1	306	307	714	713
	July	15.2	15.5	18.8	18.8	4516.6	4632.9	121.4	119.2	297	299	747	745
	August	14.2	14.5	18.0	18.3	3940.5	4043.9	110.0	114.7	278	280	776	774
	September	15.6	15.8	17.7	17.9	5426.7	5539.9	112.0	117.0	349	351	671	669
	October	15.1	15.3	16.4	17.6	6212.8	6315.7	87.4	116.8	412	413	673	672
	November	12.9	13.1	14.5	15.0	4911.5	5028.4	84.4	99.4	382	383	668	667
	December	13.4	13.6	15.8	15.5	5931.2	6052.9	156.2	107.3	443	444	642	641
Taiamã (Ta)	January	18.5	18.8	19.0	18.5	7278.7	7377.5	137.0	121.9	393	393	599	599
	February	17.7	18.0	18.6	18.5	6375.3	6492.9	130.0	123.6	360	362	542	540
	March	15.8	16.0	14.7	15.7	5211.8	5300.7	96.0	100.9	331	332	630	629
	April	13.5	13.7	14.1	13.9	2504.9	2569.0	87.0	82.7	186	187	731	730
	May	15.7	15.9	15.1	15.4	1645.4	1687.6	72.1	81.4	105	106	856	855
	June	12.0	12.2	14.0	13.9	516.4	541.4	66.0	66.3	43	44	887	886
	July	14.8	15.0	15.0	14.5	324.8	349.1	59.0	57.3	22	23	939	938
	August	14.7	15.0	17.8	17.8	486.0	506.0	80.0	79.3	33	34	928	927
	September	12.5	12.7	12.6	12.6	1408.5	1452.0	60.0	68.9	113	114	817	816
	October	14.6	14.9	14.8	14.8	2881.6	2967.6	100.0	88.7	197	199	795	793
	November	17.9	18.1	19.3	19.3	5252.4	5312.1	124.0	130.7	293	293	667	667
	December	19.2	19.4	19.9	19.5	6838.9	6930.0	157.0	128.6	356	357	605	604
Caracol (Co)	January	17.2	17.4	17.0	18.1	3210.6	3262.5	72.0	107.3	187	187	525	525
	February	16.2	16.4	18.5	17.9	3155.2	3208.6	128.0	105.3	195	196	442	441
	March	19.8	20.0	23.8	23.6	3174.3	3218.5	160.0	158.9	160	161	553	552
	April	23.1	23.4	22.2	24.6	2706.8	2728.1	112.0	132.5	117	117	573	573
	May	18.6	18.9	23.2	23.9	2365.1	2440.1	120.0	136.3	127	129	616	614
	June	13.0	13.3	14.4	15.5	1683.5	1717.3	86.0	85.7	130	129	590	591

continue

Stations	Months	Mean (mm)		St. Deviance (mm)		Total Amount (mm)		Daily Maximum (mm)		Wet Days		Dry Days	
		Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic
Caracol (Co)	July	12.2	12.5	15.2	15.1	914.6	951.2	78.8	81.0	75	76	669	668
	August	15.0	15.4	17.7	17.9	1096.7	1126.6	101.0	88.4	73	73	630	630
	September	13.4	13.6	13.2	13.3	1687.4	1744.4	61.8	72.6	126	128	549	547
	October	19.3	19.4	20.1	21.1	2965.5	3014.4	93.0	120.4	154	155	559	558
	November	22.8	22.9	22.4	22.6	3731.9	3786.7	118.6	129.7	164	165	520	519
	December	25.0	25.1	23.3	24.8	4618.6	4649.5	92.0	144.8	185	185	558	558
Passo Marom-bas (PM)	January	13.4	13.7	13.0	13.4	5469.2	5608.5	106.6	89.2	409	410	675	674
	February	13.1	13.3	13.6	13.6	5547.3	5665.1	88.7	95.2	425	425	561	561
	March	12.1	12.3	12.9	13.1	3821.0	3882.6	74.2	86.4	316	316	768	768
	April	14.6	14.9	15.4	15.9	3746.1	3791.7	94.8	98.7	256	254	793	795
	May	16.3	16.5	17.6	17.8	4093.3	4164.2	104.2	114.3	251	252	833	832
	June	14.8	15.1	15.7	16.1	4154.7	4269.6	80.2	104.9	281	283	768	766
	July	16.1	16.3	18.6	18.8	4536.4	4616.7	128.6	142.4	281	282	804	803
	August	15.8	16.1	16.8	16.5	4316.5	4390.9	117.3	106.1	273	274	812	811
	September	14.9	15.2	15.1	15.7	4810.7	4914.0	99.8	102.4	322	324	728	726
	October	16.2	16.5	16.3	17.0	5728.9	5830.2	91.6	112.1	354	354	730	730
	November	13.8	14.1	13.9	14.0	4628.9	4748.4	80.2	90.5	336	338	710	708
	December	15.0	15.3	14.7	15.0	5359.8	5457.8	93.5	97.3	357	357	728	728
Linha Cescon (LC)	January	20.3	20.6	18.8	20.2	5873.5	5959.5	119.0	126.6	290	290	795	795
	February	20.1	20.3	16.7	17.0	5501.9	5560.0	103.8	123.7	274	274	686	686
	March	19.7	20.0	17.4	19.5	3784.2	3838.9	87.2	114.3	192	192	862	862
	April	23.0	23.2	20.0	22.9	4580.3	4602.4	113.0	136.2	199	198	821	822
	May	25.4	25.7	28.3	28.4	5310.2	5398.6	176.0	185.3	209	211	844	842
	June	22.1	22.3	21.4	22.0	5314.3	5393.9	120.0	134.5	241	242	778	777
	July	22.2	22.4	20.3	22.0	5269.2	5335.0	103.2	133.2	237	238	817	816
	August	21.3	21.5	18.8	21.2	4850.4	4940.6	144.0	128.8	228	229	826	825
	September	21.9	22.1	21.0	21.8	5497.0	5590.4	132.8	133.1	251	253	797	795
	October	24.3	24.5	21.6	24.2	6630.7	6725.0	134.0	150.5	273	274	812	811
	November	22.8	23.1	18.6	18.2	4786.7	4880.4	156.2	134.8	210	211	840	839
	December	23.7	23.9	20.7	23.6	5371.3	5429.0	129.2	143.1	227	227	858	858

continue

conclusion

Stations	Months	Mean (mm)		St. Deviance (mm)		Total Amount (mm)		Daily Maximum (mm)		Wet Days		Dry Days	
		Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic	Original	Synthetic
Cacequi (Cq)	January	20.1	20.3	21.3	21.5	4899.3	4968.0	116.0	136.5	244	244	841	841
	February	20.1	20.5	21.1	21.2	4927.3	5013.7	114.3	132.9	245	245	743	743
	March	20.8	21.0	19.4	20.6	4689.4	4774.3	98.6	124.7	226	227	859	858
	April	24.1	24.3	26.5	26.5	5510.1	5561.6	203.7	183.4	229	229	792	792
	May	23.4	23.7	22.9	24.7	4933.3	4995.9	106.2	148.2	211	211	874	874
	June	19.6	19.9	21.3	21.2	4589.0	4676.0	137.6	143.1	234	235	816	815
	July	19.5	19.8	17.2	19.5	4939.3	5053.3	107.8	120.4	253	255	832	830
	August	16.7	16.9	18.8	18.4	3464.1	3511.8	136.0	109.5	208	208	877	877
	September	21.7	22.0	22.2	22.9	5130.5	5220.7	135.0	141.0	236	237	814	813
	October	22.6	22.8	20.6	22.5	5215.9	5313.3	138.8	137.2	231	233	854	852
	November	21.6	21.9	20.3	21.5	4628.8	4723.1	115.8	128.3	214	216	836	834
	December	19.7	20.0	19.1	19.7	3801.1	3882.2	135.6	116.3	193	194	892	891

TABLE A-1.4 – COMPLETE RESULTS FOR THE VALIDATION OF THE MODEL – PART 2

Stations	Months	Cross Correlation	Mean Test	Standard Deviance Test	Conf. Int. – Mean		Conf. Int. – St. Deviance		Time (s)
					Inferior	Superior	Inferior	Superior	
Monte Alegre de Minas (MAM)	January	0.0004	Accepted	Accepted	14.4	18.2	17.1	19.8	35.88
	February	0.0002	Accepted	Accepted	10.9	14.2	13.4	15.7	25.84
	March	-0.0004	Accepted	Accepted	10.8	14.3	14.2	16.6	26.25
	April	-0.0009	Accepted	Accepted	8.8	13.1	12.6	15.7	20.77
	May	0.0005	Accepted	Accepted	6.7	12.2	10.7	14.7	18.41
	June	0.0004	Accepted	Accepted	4.7	14.2	11.5	18.6	16.00
	July	0.0011	Accepted	Accepted	4.8	11.9	7.8	13.2	16.67
	August	-0.0005	Accepted	Accepted	5.3	10.1	6.4	9.9	16.61
	September	-0.0021	Accepted	Accepted	6.8	10.5	8.9	11.6	15.55
	October	0.0021	Accepted	Accepted	10.7	15.1	14.1	17.2	15.56
	November	0.0002	Accepted	Accepted	12.4	16.5	15.9	18.8	16.89
	December	-0.0004	Accepted	Accepted	11.7	14.8	14.3	16.6	15.53
Usina Couro do Cervo (UCC)	January	-0.0011	Accepted	Accepted	14.2	18.1	16.7	19.5	17.02
	February	-0.0023	Accepted	Accepted	13.1	17.1	14.7	17.5	15.45
	March	-0.0006	Accepted	Accepted	12.5	16.6	14.4	17.4	16.81
	April	0.0003	Accepted	Accepted	9.7	15.4	12.9	17.0	17.59
	May	-0.001	Accepted	Accepted	9.1	15.0	11.6	15.9	16.88
	June	0.0001	Accepted	Accepted	7.2	13.5	9.0	13.7	21.45
	July	0.0008	Accepted	Accepted	5.7	12.2	8.8	13.7	16.95
	August	0.0006	Accepted	Accepted	6.0	11.3	7.7	11.6	17.25
	September	-0.0014	Accepted	Accepted	10.7	15.7	11.4	15.0	16.17
	October	-0.0001	Accepted	Accepted	10.3	14.0	11.5	14.2	15.52
	November	-0.0015	Accepted	Accepted	12.9	17.0	14.4	17.3	16.06
	December	0.0002	Accepted	Accepted	14.0	17.6	15.3	17.8	15.72
Monte Mor (MM)	January	0.0003	Accepted	Accepted	12.9	17.2	16.7	19.8	26.66
	February	0.0005	Accepted	Accepted	12.6	17.1	16.2	19.4	23.23
	March	-0.0013	Accepted	Accepted	11.5	15.9	14.5	17.6	28.00
	April	0.0000	Accepted	Accepted	8.9	13.3	10.2	13.4	28.77
	May	-0.0011	Accepted	Accepted	8.7	13.3	11.3	14.5	23.31
	June	-0.0004	Accepted	Accepted	8.7	14.0	10.9	14.8	20.64
	July	0.0016	Accepted	Accepted	6.7	12.1	9.3	13.2	21.13
	August	-0.0006	Accepted	Accepted	7.1	11.3	7.8	10.9	24.55
	September	0.0003	Accepted	Accepted	8.3	12.3	10.9	13.7	21.53
	October	0.0007	Accepted	Accepted	10.7	15.0	12.6	15.7	28.72
	November	0.0006	Accepted	Accepted	11.0	15.1	12.4	15.3	22.39
	December	0.0005	Accepted	Accepted	12.4	16.0	13.5	16.1	20.30

continue

Stations	Months	Cross Correlation	Mean Test	Standard Deviance Test	Conf. Int. – Mean		Conf. Int. – St. Deviance		Time (s)
					Inferior	Superior	Inferior	Superior	
Caiuá (Ca)	January	0.0004	Accepted	Accepted	13.7	18.0	16.0	19.1	26.20
	February	-0.0018	Accepted	Accepted	13.3	18.2	16.2	19.6	25.92
	March	0.0003	Accepted	Accepted	12.1	17.0	15.1	18.6	20.75
	April	-0.0008	Accepted	Accepted	11.6	17.8	14.5	19.0	24.05
	May	-0.002	Accepted	Accepted	11.6	16.6	13.1	16.7	21.64
	June	0.0014	Accepted	Accepted	8.3	13.6	11.3	15.1	22.88
	July	0.0007	Accepted	Accepted	8.0	15.1	12.6	17.8	20.80
	August	-0.0006	Accepted	Accepted	7.9	14.4	11.5	16.2	19.13
	September	-0.0007	Accepted	Accepted	10.1	14.6	12.4	15.7	26.75
	October	0.0005	Accepted	Accepted	12.6	17.9	14.5	18.3	37.72
	November	0.0005	Accepted	Accepted	12.5	18.3	17.5	21.6	35.84
	December	0.0000	Accepted	Accepted	12.6	16.9	15.2	18.2	25.28
Tomazina (To)	January	-0.0014	Accepted	Accepted	13.2	17.7	17.8	21.0	28.22
	February	0.0024	Accepted	Accepted	11.4	15.6	15.8	18.8	12.41
	March	0.0008	Accepted	Accepted	10.4	14.4	13.8	16.7	23.56
	April	-0.0012	Accepted	Accepted	11.3	16.7	13.5	17.3	21.05
	May	0.0004	Accepted	Accepted	12.6	18.3	15.5	19.6	22.81
	June	-0.0008	Accepted	Accepted	12.0	17.2	13.4	17.2	24.48
	July	-0.0001	Accepted	Accepted	10.4	16.4	13.9	18.2	24.39
	August	0.0003	Accepted	Accepted	9.5	14.8	12.3	16.1	18.41
	September	-0.0004	Accepted	Accepted	11.9	16.3	13.3	16.5	16.25
	October	-0.0001	Accepted	Accepted	11.6	15.8	13.6	16.6	17.38
	November	0.0005	Accepted	Accepted	10.7	14.8	12.5	15.4	21.52
	December	0.0006	Accepted	Accepted	12.5	16.2	13.7	16.4	19.30
União da Vitória (UV)	January	0.0017	Accepted	Accepted	9.6	12.7	12.6	14.9	19.72
	February	0.0002	Accepted	Accepted	10.1	13.3	12.7	14.9	16.34
	March	-0.0013	Accepted	Accepted	8.8	12.1	12.1	14.4	30.98
	April	0.0012	Accepted	Accepted	10.2	14.6	13.8	16.9	23.80
	May	-0.0018	Accepted	Accepted	13.2	19.8	20.1	24.8	19.05
	June	0.0016	Accepted	Accepted	12.6	18.3	17.5	21.5	17.14
	July	-0.0007	Accepted	Accepted	12.4	18.0	17.0	21.0	16.44
	August	0.0015	Accepted	Accepted	11.4	17.0	16.2	20.2	22.23
	September	0.0011	Accepted	Accepted	13.1	18.0	16.1	19.6	23.02
	October	0.0001	Accepted	Accepted	13.0	17.2	15.1	18.0	28.30
	November	-0.0006	Accepted	Accepted	11.0	14.8	13.2	15.9	29.17
	December	-0.0003	Accepted	Accepted	11.5	15.3	14.5	17.3	21.13

continue

Stations	Months	Cross Correlation	Mean Test	Standard Deviance Test	Conf. Int. – Mean		Conf. Int. – St. Deviance		Time (s)
					Inferior	Superior	Inferior	Superior	
Taiamã (Ta)	January	0.0015	Accepted	Accepted	16.1	21.0	17.4	20.9	16.53
	February	-0.0007	Accepted	Accepted	15.2	20.2	17.0	20.6	19.53
	March	-0.0006	Accepted	Accepted	13.7	17.8	13.3	16.3	18.72
	April	-0.0003	Accepted	Accepted	10.8	16.1	12.5	16.3	21.59
	May	0.0013	Accepted	Accepted	11.9	19.5	12.8	18.4	30.91
	June	0.0013	Accepted	Accepted	6.5	17.5	10.9	19.3	25.48
	July	0.0002	Accepted	Accepted	6.5	23.0	10.7	24.3	30.94
	August	-0.0002	Accepted	Accepted	6.7	22.7	13.4	25.9	18.22
	September	0.0002	Accepted	Accepted	9.4	15.5	10.8	15.2	21.36
	October	-0.0015	Accepted	Accepted	11.9	17.3	13.1	17.0	22.00
	November	-0.0005	Accepted	Accepted	15.0	20.8	17.5	21.6	29.47
	December	-0.0011	Accepted	Accepted	16.5	21.9	18.1	22.0	22.20
Caracol (Co)	January	0.0017	Accepted	Accepted	14.0	20.4	15.0	19.6	16.08
	February	0.0013	Accepted	Accepted	12.8	19.6	16.4	21.3	11.36
	March	-0.0019	Accepted	Accepted	15.0	24.7	24.7	27.8	13.64
	April	0.0023	Accepted	Accepted	17.9	28.4	19.0	26.6	13.55
	May	0.0018	Accepted	Accepted	13.3	23.9	19.9	27.6	13.55
	June	0.0009	Accepted	Accepted	9.7	16.2	12.4	17.1	13.31
	July	0.0018	Accepted	Accepted	7.7	16.7	12.5	19.1	12.47
	August	-0.0018	Accepted	Accepted	9.7	20.4	14.5	22.4	11.33
	September	-0.001	Accepted	Accepted	10.4	16.4	11.3	15.7	11.47
	October	-0.0021	Accepted	Accepted	15.1	23.4	17.5	23.5	11.27
	November	-0.0006	Accepted	Accepted	18.3	27.3	19.6	26.1	11.48
	December	0.0014	Accepted	Accepted	20.6	29.4	20.5	26.9	11.30
Passo Marom-bas (PM)	January	-0.0013	Accepted	Accepted	11.7	15.0	11.9	14.3	14.25
	February	0.0005	Accepted	Accepted	11.4	14.8	12.5	14.9	24.47
	March	-0.0004	Accepted	Accepted	10.2	14.0	11.7	14.3	19.52
	April	0	Accepted	Accepted	12.2	17.1	13.8	17.3	17.17
	May	-0.001	Accepted	Accepted	13.4	19.2	15.8	19.9	19.63
	June	-0.0011	Accepted	Accepted	12.4	17.2	14.2	17.6	25.80
	July	-0.0003	Accepted	Accepted	13.3	19.0	16.8	20.9	28.94
	August	-0.0004	Accepted	Accepted	13.2	18.4	15.1	18.9	30.70
	September	-0.0004	Accepted	Accepted	12.8	17.1	13.7	16.8	25.80
	October	-0.0002	Accepted	Accepted	14.0	18.4	14.8	18.0	29.72
	November	0.0014	Accepted	Accepted	11.8	15.7	12.6	15.4	35.25
	December	-0.0008	Accepted	Accepted	13.0	17.0	13.4	16.3	36.52

continue

SEVENTH FRAMEWORK PROGRAMME

conclusion

Stations	Months	Cross Correlation	Mean Test	Standard Deviance Test	Conf. Int. – Mean		Conf. Int. – St. Deviance		Time (s)
					Inferior	Superior	Inferior	Superior	
Linha Cescon (LC)	January	-0.001	Accepted	Accepted	17.4	23.1	17.0	21.1	18.98
	February	0.0009	Accepted	Accepted	17.5	22.7	15.0	18.8	17.86
	March	0.0003	Accepted	Accepted	16.5	22.9	15.3	20.0	24.25
	April	0.0018	Accepted	Accepted	19.4	26.7	17.7	23.0	23.92
	May	0.0008	Accepted	Accepted	20.4	30.5	25.1	32.4	26.45
	June	-0.0002	Accepted	Accepted	18.5	25.6	19.1	24.2	18.66
	July	0.0001	Accepted	Accepted	18.8	25.6	18.1	23.0	27.56
	August	0.0011	Accepted	Accepted	18.1	24.5	16.7	21.3	22.00
	September	-0.0001	Accepted	Accepted	18.5	25.3	18.8	23.7	23.92
	October	-0.0004	Accepted	Accepted	20.9	27.7	19.4	24.2	20.81
	November	0.0005	Accepted	Accepted	19.5	26.1	16.5	21.3	19.58
	December	0.0009	Accepted	Accepted	20.1	27.2	18.5	23.5	17.17
Cacequi (Cq)	January	0.0001	Accepted	Accepted	16.6	23.6	19.1	24.1	17.73
	February	0.0002	Accepted	Accepted	16.6	23.6	18.9	23.8	15.25
	March	-0.0006	Accepted	Accepted	17.4	24.1	17.3	22.1	18.84
	April	0.0001	Accepted	Accepted	19.5	28.6	23.7	30.1	15.63
	May	-0.0008	Accepted	Accepted	19.3	27.4	20.3	26.2	16.47
	June	0.0018	Accepted	Accepted	16.0	23.2	19.0	24.1	17.52
	July	0.0009	Accepted	Accepted	16.8	22.3	15.4	19.4	18.97
	August	0.0013	Accepted	Accepted	13.3	20.0	16.7	21.5	17.78
	September	-0.0009	Accepted	Accepted	18.0	25.5	19.9	25.2	16.55
	October	-0.0008	Accepted	Accepted	19.1	26.1	18.4	23.4	23.86
	November	-0.0005	Accepted	Accepted	18.1	25.2	18.0	23.1	21.91
	December	-0.0012	Accepted	Accepted	16.2	23.2	16.8	21.9	17.16

TABLE A-1.5 – COMPLETE RESULTS FOR EXTREME EVENTS ANALYSES

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Monte Alegre de Minas (MAM)	January	O	10	17	A	143.4	177.2	189.2	227.2	234.2	239.2	249.2	310.4	322.4	357.1	497.55
					M	9.6	19.2	28.8	38.4	48.0	57.6	67.2	76.8	86.4	96.0	
		S	11	17	A	133.0	164.7	189.3	211.1	231.6	251.0	269.5	286.8	303.3	319.4	
					M	9.7	19.4	29.2	38.9	48.6	58.3	68.0	77.7	87.4	97.2	
	February	O	17	17	A	104.0	201.0	235.8	245.7	280.5	290.0	313.6	327.0	342.6	360.1	440.31
					M	6.7	13.4	20.1	26.8	33.6	40.3	47.1	53.9	60.6	67.3	
		S	12	14	A	103.7	125.9	144.2	160.5	174.9	188.8	202.1	214.3	226.0	236.9	
					M	6.8	13.6	20.4	27.2	34.0	40.8	47.6	54.4	61.2	68.0	
	March	O	19	16	A	100.8	110.8	127.7	160.4	169.3	169.3	201.4	202.1	221.7	257.9	432.26
					M	6.0	12.0	18.0	24.0	30.0	36.1	42.1	48.0	54.1	60.1	
		S	14	12	A	110.3	132.7	149.6	164.3	177.9	190.0	202.2	213.5	224.2	235.0	
					M	6.1	12.2	18.3	24.5	30.6	36.7	42.8	48.9	55.0	61.2	
	April	O	22	6	A	83.4	98.9	120.2	125.9	144.3	151.1	171.3	183.1	196.5	205.5	443.69
					M	3.1	6.1	9.2	12.3	15.3	18.4	21.5	24.5	27.6	30.7	
		S	24	8	A	91.1	106.6	117.0	126.6	134.7	142.1	149.9	156.9	163.4	169.6	
					M	3.2	6.3	9.5	12.6	15.8	18.9	22.1	25.3	28.4	31.6	
	May	O	70	4	A	69.0	111.1	113.1	113.1	114.0	136.5	150.0	150.0	159.2	160.8	487.45
					M	1.2	2.4	3.6	4.7	5.9	7.1	8.3	9.5	10.7	11.9	
		S	48	5	A	65.3	74.1	79.7	83.9	87.4	90.9	94.1	97.4	100.1	102.9	
					M	1.2	2.5	3.7	4.9	6.1	7.4	8.6	9.8	11.1	12.3	
	June	O	91	2	A	85.2	85.2	85.2	85.2	85.2	85.2	85.2	85.2	86.2	86.2	455.34
					M	0.5	1.1	1.6	2.2	2.7	3.3	3.8	4.4	4.9	5.5	
		S	90	3	A	63.9	69.6	71.9	73.7	75.1	76.4	77.8	79.4	80.8	82.4	
					M	0.6	1.1	1.7	2.3	2.8	3.4	4.0	4.5	5.1	5.7	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Monte Alegre de Minas (MAM)	July	O	135	4	A	40.4	45.2	46.8	46.8	46.8	53.4	69.2	69.2	69.2	72.2	439.5
					M	0.4	0.8	1.2	1.6	2.0	2.4	2.9	3.3	3.7	4.1	
		S	121	5	A	48.0	55.2	59.3	61.8	63.5	64.6	66.1	67.2	68.5	69.4	
					M	0.4	0.9	1.3	1.7	2.2	2.6	3.0	3.5	3.9	4.3	
	August	O	79	4	A	34.1	42.1	52.5	56.3	66.5	68.0	68.0	68.0	68.0	69.7	432.66
					M	0.5	1.0	1.6	2.1	2.6	3.1	3.7	4.2	4.7	5.2	
		S	87	4	A	37.9	44.7	49.0	51.9	53.9	55.8	57.3	58.9	60.3	61.7	
					M	0.5	1.1	1.6	2.2	2.7	3.3	3.8	4.4	4.9	5.5	
	September	O	48	6	A	52.6	54.9	95.2	99.9	99.9	142.5	142.5	144.8	144.8	144.8	373.25
					M	1.7	3.5	5.2	7.0	8.7	10.5	12.2	14.0	15.7	17.5	
		S	33	6	A	64.9	75.4	82.3	87.8	92.8	97.3	101.7	105.8	109.9	113.6	
					M	1.8	3.6	5.4	7.2	9.0	10.9	12.7	14.5	16.3	18.1	
	October	O	23	6	A	84.7	116.8	135.6	148.7	156.5	162.8	177.8	205.8	205.8	227.2	480.77
					M	4.3	8.6	12.9	17.2	21.5	25.7	30.0	34.3	38.6	42.9	
		S	19	8	A	106.7	124.2	137.7	149.2	160.1	169.8	179.6	188.9	196.4	204.3	
					M	4.4	8.8	13.2	17.5	21.9	26.3	30.7	35.1	39.5	43.9	
	November	O	13	10	A	102.0	141.9	141.9	156.4	186.7	202.0	218.0	226.6	233.1	237.2	404.48
					M	6.9	13.8	20.8	27.7	34.6	41.5	48.4	55.3	62.2	69.1	
		S	14	13	A	120.8	145.6	164.6	182.1	197.4	212.4	226.3	239.7	252.4	264.6	
					M	7.0	14.1	21.1	28.1	35.2	42.2	49.2	56.3	63.3	70.3	
	December	O	7	15	A	110.0	118.4	147.5	169.5	189.2	196.9	218.9	240.7	255.6	269.6	418.55
					M	8.3	16.7	25.0	33.4	41.7	50.1	58.5	66.9	75.3	83.8	
		S	8	16	A	115.2	140.1	160.8	178.7	195.0	211.0	225.9	240.5	254.1	267.2	
					M	8.5	17.0	25.5	33.9	42.4	50.9	59.4	67.9	76.4	84.9	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Usina Couro do Cervo (UCC)	January	O	21	17	A	147.4	194.7	231.7	252.9	265.1	322.8	333.8	363.3	413.4	430.7	550.56
					M	8.2	16.3	24.4	32.5	40.6	48.7	56.8	64.9	73.0	81.1	
		S	14	15	A	131.8	160.0	181.9	201.9	220.1	237.0	253.6	268.6	283.1	297.5	
					M	8.3	16.6	24.8	33.1	41.4	49.7	57.9	66.2	74.5	82.8	
	February	O	19	15	A	128.8	184.3	198.8	234.8	280.0	333.0	337.0	348.0	348.0	357.0	439.58
					M	6.5	12.9	19.4	25.9	32.4	38.9	45.5	52.0	58.6	65.1	
		S	18	13	A	112.6	137.7	156.8	174.9	190.3	204.6	218.7	231.1	244.0	255.5	
					M	6.6	13.2	19.8	26.4	33.0	39.6	46.2	52.9	59.5	66.1	
	March	O	26	8	A	87.1	113.0	133.4	135.7	135.7	144.6	160.3	174.7	190.7	190.7	469.38
					M	5.3	10.6	15.8	21.1	26.4	31.7	37.0	42.3	47.6	53.0	
		S	20	11	A	113.2	135.6	152.3	166.3	179.2	191.3	203.1	214.0	224.9	235.0	
					M	5.4	10.8	16.2	21.5	26.9	32.3	37.7	43.1	48.5	53.8	
	April	O	31	7	A	122.3	136.4	165.8	166.1	168.3	170.7	170.7	170.7	174.2	188.5	546.16
					M	2.1	4.2	6.4	8.5	10.6	12.7	14.8	16.9	19.1	21.1	
		S	39	6	A	134.8	145.1	152.4	157.9	163.1	167.7	171.8	176.1	180.0	184.3	
					M	2.2	4.3	6.5	8.6	10.8	13.0	15.1	17.3	19.5	21.6	
	May	O	47	5	A	99.0	117.1	136.3	138.4	156.7	156.7	160.8	160.8	160.8	162.9	576.11
					M	1.5	3.1	4.6	6.1	7.6	9.2	10.7	12.3	13.8	15.4	
		S	52	5	A	87.5	98.2	105.2	110.8	115.1	118.8	122.6	126.3	130.0	133.1	
					M	1.6	3.1	4.7	6.3	7.8	9.4	11.0	12.5	14.1	15.7	
	June	O	72	4	A	56.1	76.5	76.5	90.4	98.4	98.4	103.4	103.4	103.4	106.7	629.11
					M	0.8	1.6	2.4	3.2	4.0	4.7	5.5	6.3	7.1	7.9	
		S	77	4	A	55.5	63.6	68.5	71.7	74.6	76.9	79.0	81.0	82.8	84.4	
					M	0.8	1.6	2.4	3.3	4.1	4.9	5.7	6.5	7.3	8.1	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Usina Couro do Cervo (UCC)	July	O	80	4	A	55.0	77.6	94.4	95.7	95.7	98.6	99.9	99.9	99.9	99.9	590.36
					M	0.6	1.2	1.8	2.4	3.1	3.7	4.3	4.9	5.5	6.2	
		S	88	5	A	57.5	65.3	69.4	72.2	74.4	76.3	77.9	79.6	81.1	82.5	
					M	0.7	1.3	1.9	2.6	3.2	3.9	4.5	5.2	5.8	6.5	
	August	O	77	5	A	58.0	64.2	76.2	77.2	81.6	81.6	81.6	98.4	99.4	103.8	529.22
					M	0.7	1.4	2.1	2.7	3.4	4.1	4.7	5.4	6.0	6.7	
		S	76	4	A	48.0	55.1	59.0	61.9	64.2	66.1	68.0	70.0	71.7	73.3	
					M	0.7	1.4	2.1	2.8	3.5	4.2	4.9	5.7	6.4	7.1	
	September	O	49	5	A	65.4	122.4	128.6	131.8	138.0	138.0	159.9	171.0	171.0	180.4	599.58
					M	2.3	4.6	6.9	9.2	11.5	13.8	16.2	18.5	20.8	23.2	
		S	37	6	A	76.4	90.3	100.2	107.8	114.5	120.6	126.6	132.3	137.8	142.9	
					M	2.3	4.7	7.0	9.4	11.7	14.0	16.4	18.7	21.1	23.4	
	October	O	19	6	A	68.0	83.4	113.6	130.9	130.9	168.0	168.0	168.0	173.3	199.0	420.92
					M	3.5	7.0	10.5	14.0	17.5	21.0	24.5	28.0	31.5	35.0	
		S	21	7	A	86.6	101.2	112.0	121.8	130.6	138.4	145.9	153.0	160.0	166.5	
					M	3.6	7.2	10.8	14.3	17.9	21.5	25.1	28.7	32.3	35.9	
	November	O	15	11	A	110.2	124.5	138.8	146.3	161.4	167.5	175.7	196.1	208.5	214.7	369.55
					M	5.8	11.7	17.6	23.4	29.2	35.1	41.0	46.8	52.7	58.6	
		S	17	10	A	109.1	131.2	148.7	163.7	177.3	190.0	203.0	215.4	226.4	236.9	
					M	6.0	12.0	17.9	23.9	29.9	35.9	41.9	47.8	53.8	59.8	
	December	O	10	18	A	125.3	150.7	181.7	207.1	236.0	261.4	268.7	282.7	292.0	298.3	349.02
					M	8.4	16.9	25.4	33.8	42.3	50.8	59.3	67.8	76.3	84.8	
		S	13	15	A	119.4	147.1	169.1	189.2	207.4	224.2	241.1	256.8	271.9	285.8	
					M	8.6	17.2	25.8	34.4	43.0	51.7	60.3	68.9	77.5	86.1	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Monte Mor (MM)	January	O	12	12	A	138.4	164.8	183.4	204.7	211.1	211.6	213.3	215.9	228.7	298.2	324.55
					M	6.8	13.5	20.3	27.0	33.7	40.4	47.1	53.7	60.4	67.0	
		S	15	12	A	117.9	143.9	164.2	181.2	196.9	212.2	226.8	240.1	252.8	265.5	
					M	6.9	13.8	20.6	27.5	34.4	41.3	48.2	55.1	61.9	68.8	
	February	O	15	15	A	130.2	158.6	224.2	303.8	328.6	367.8	381.4	395.6	407.8	416.4	318.33
					M	6.4	12.8	19.3	25.7	32.2	38.7	45.2	51.7	58.2	64.7	
		S	15	11	A	110.4	135.3	154.2	169.8	184.8	198.5	211.7	223.8	236.2	247.9	
					M	6.5	13.1	19.6	26.1	32.6	39.1	45.7	52.2	58.7	65.2	
	March	O	20	9	A	94.4	112.2	156.7	156.9	159.2	165.9	176.0	201.1	232.9	239.6	392.06
					M	4.6	9.1	13.7	18.2	22.8	27.4	31.9	36.5	41.1	45.7	
		S	22	10	A	110.6	132.2	148.5	162.4	174.3	184.9	194.7	205.2	215.1	225.3	
					M	4.6	9.3	13.9	18.6	23.2	27.9	32.5	37.2	41.8	46.5	
	April	O	48	6	A	72.6	83.9	84.3	84.4	90.1	90.1	109.1	109.1	109.2	109.2	341.16
					M	2.0	4.1	6.1	8.1	10.2	12.2	14.2	16.2	18.2	20.2	
		S	36	6	A	69.4	81.9	90.7	97.7	103.5	108.7	114.0	118.4	122.8	127.1	
					M	2.1	4.2	6.3	8.4	10.4	12.5	14.6	16.7	18.8	20.9	
	May	O	33	6	A	67.2	98.7	101.5	101.5	114.0	129.3	142.3	149.3	149.3	157.6	335
					M	2.3	4.5	6.8	9.1	11.3	13.6	15.9	18.2	20.5	22.8	
		S	32	6	A	79.3	93.6	102.3	109.8	116.4	122.5	128.0	133.1	138.5	143.4	
					M	2.3	4.7	7.0	9.3	11.7	14.0	16.3	18.7	21.0	23.3	
	June	O	53	11	A	60.0	79.6	112.2	132.2	142.2	174.5	200.7	201.1	220.3	220.8	324.27
					M	1.8	3.5	5.2	7.0	8.7	10.5	12.2	14.0	15.7	17.5	
		S	44	6	A	77.5	91.4	99.8	106.2	111.6	117.5	121.9	126.1	130.4	134.3	
					M	1.8	3.6	5.5	7.3	9.1	10.9	12.7	14.6	16.4	18.2	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Monte Mor (MM)	July	O	54	6	A	52.0	73.0	87.6	90.6	112.8	123.7	123.7	123.8	123.9	124.0	345.67
					M	1.0	2.0	3.0	4.0	5.1	6.1	7.1	8.1	9.1	10.2	
		S	64	6	A	59.8	70.4	77.4	82.4	86.3	89.5	92.5	95.5	98.4	100.5	
					M	1.1	2.1	3.2	4.2	5.3	6.3	7.4	8.4	9.5	10.6	
	August	O	76	7	A	45.6	78.1	103.0	105.7	110.4	110.7	112.2	120.8	123.5	147.8	337.31
					M	1.1	2.3	3.4	4.5	5.7	6.8	8.0	9.1	10.2	11.3	
		S	59	6	A	52.5	63.6	70.6	76.1	80.4	84.7	88.1	91.3	94.0	96.7	
					M	1.2	2.4	3.5	4.7	5.9	7.0	8.2	9.4	10.6	11.7	
	September	O	49	8	A	84.4	121.0	121.0	123.0	135.0	136.6	136.6	144.3	144.3	151.8	337.22
					M	2.5	5.0	7.4	9.9	12.4	14.9	17.4	19.9	22.5	25.0	
		S	31	8	A	79.7	94.2	104.6	113.0	120.1	126.9	133.0	139.1	144.7	150.3	
					M	2.6	5.1	7.7	10.3	12.8	15.4	17.9	20.5	23.1	25.6	
	October	O	24	6	A	86.0	86.9	90.9	116.5	116.5	116.5	116.5	152.0	152.0	187.8	444.84
					M	3.5	7.0	10.5	14.0	17.4	20.9	24.4	27.8	31.3	34.8	
		S	26	8	A	94.9	110.7	123.1	133.1	142.5	150.9	158.3	165.4	172.4	179.2	
					M	3.6	7.1	10.7	14.3	17.9	21.4	25.0	28.6	32.1	35.7	
	November	O	17	9	A	101.3	109.2	109.3	115.9	129.6	132.0	136.0	136.0	145.6	159.3	394.56
					M	4.3	8.6	12.8	17.1	21.4	25.7	30.0	34.3	38.6	42.8	
		S	21	9	A	88.2	107.3	121.1	134.3	145.0	155.6	165.4	174.5	183.2	191.9	
					M	4.4	8.7	13.1	17.4	21.8	26.1	30.5	34.8	39.2	43.6	
	December	O	21	15	A	98.2	108.8	120.4	136.6	142.3	162.5	171.3	185.1	189.0	201.6	409.41
					M	6.3	12.6	18.9	25.2	31.5	37.8	44.2	50.5	56.8	63.2	
		S	16	12	A	99.1	123.7	142.0	157.9	171.9	185.5	198.3	210.1	221.5	233.1	
					M	6.4	12.8	19.3	25.7	32.1	38.5	44.9	51.3	57.8	64.2	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Caiuá (Ca)	January	O	17	10	A	144.2	163.0	192.9	225.0	254.8	286.0	286.0	286.0	286.0	286.0	421.36
					M	6.5	13.1	19.6	26.1	32.7	39.1	45.6	52.0	58.4	64.9	
		S	17	11	A	123.3	148.6	167.6	184.6	199.5	213.3	226.7	240.2	251.8	263.0	
					M	6.6	13.3	19.9	26.5	33.2	39.8	46.4	53.1	59.7	66.3	
	February	O	26	10	A	141.2	187.1	206.0	243.8	252.4	260.1	260.1	260.1	260.1	271.2	455.75
					M	5.7	11.4	17.2	22.9	28.7	34.4	40.2	45.9	51.6	57.3	
		S	16	8	A	120.4	140.6	157.4	172.2	185.6	197.7	209.5	220.9	232.0	242.8	
					M	5.8	11.7	17.5	23.3	29.2	35.0	40.8	46.6	52.5	58.3	
	March	O	22	17	A	114.3	155.6	170.9	171.0	248.9	264.2	285.3	300.6	300.6	300.6	387.59
					M	4.2	8.3	12.5	16.7	20.9	25.1	29.3	33.5	37.7	41.9	
		S	22	7	A	107.5	127.5	141.1	153.7	164.4	174.8	183.4	191.7	200.0	208.6	
					M	4.2	8.5	12.7	17.0	21.2	25.5	29.7	34.0	38.3	42.5	
	April	O	39	5	A	109.3	117.4	132.6	132.6	146.0	146.0	146.0	151.3	163.1	163.1	389.38
					M	2.6	5.2	7.8	10.4	13.0	15.6	18.2	20.8	23.4	26.1	
		S	37	6	A	99.0	115.0	125.7	133.8	140.7	147.8	153.8	159.5	165.8	172.1	
					M	2.7	5.3	8.0	10.6	13.3	15.9	18.6	21.2	23.9	26.5	
	May	O	46	7	A	70.3	128.8	128.8	128.8	136.0	136.0	136.0	136.0	136.0	143.1	412.25
					M	2.9	5.8	8.7	11.6	14.5	17.4	20.4	23.3	26.2	29.1	
		S	33	6	A	84.1	100.7	112.5	122.3	130.5	138.3	145.5	152.5	158.8	165.0	
					M	2.9	5.9	8.8	11.7	14.7	17.6	20.5	23.5	26.4	29.4	
	June	O	62	6	A	67.6	75.4	94.7	126.6	126.6	126.6	143.8	143.8	162.3	192.4	396.13
					M	1.7	3.3	5.0	6.7	8.4	10.1	11.7	13.4	15.1	16.8	
		S	43	6	A	76.8	88.2	95.1	101.5	106.6	111.5	115.6	119.6	123.5	127.2	
					M	1.7	3.4	5.1	6.8	8.5	10.2	11.9	13.6	15.3	17.0	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Caiuá (Ca)	July	O	71	4	A	80.0	83.6	93.0	99.0	99.0	119.4	119.4	137.5	146.6	146.6	486.78
					M	1.2	2.4	3.7	4.9	6.1	7.4	8.6	9.9	11.1	12.3	
		S	58	5	A	81.2	91.5	97.8	102.6	106.3	110.1	113.3	116.4	119.4	122.3	
					M	1.3	2.5	3.8	5.1	6.3	7.6	8.9	10.1	11.4	12.7	
	August	O	78	5	A	65.4	90.0	100.5	101.6	113.9	117.3	120.9	130.8	134.4	134.4	462.28
					M	1.2	2.4	3.6	4.7	5.9	7.1	8.3	9.5	10.7	11.9	
		S	58	5	A	79.7	88.9	94.0	98.7	102.4	105.8	109.0	112.2	114.9	117.4	
					M	1.2	2.4	3.7	4.9	6.1	7.3	8.6	9.8	11.0	12.2	
	September	O	28	8	A	81.9	106.0	134.7	135.2	136.2	143.1	151.3	156.4	166.6	180.9	426.81
					M	2.9	5.9	8.9	11.8	14.8	17.7	20.7	23.6	26.6	29.5	
		S	28	7	A	87.4	103.2	115.2	124.7	133.3	141.1	147.6	154.6	160.9	166.9	
					M	3.0	6.1	9.1	12.1	15.1	18.2	21.2	24.2	27.3	30.3	
	October	O	38	6	A	102.6	132.5	179.6	179.6	181.6	181.6	181.6	192.4	192.4	194.4	482.58
					M	3.5	7.0	10.5	14.0	17.5	21.0	24.5	28.0	31.5	35.0	
		S	27	6	A	101.4	119.2	132.3	142.6	151.3	159.9	168.1	176.3	183.7	190.8	
					M	3.6	7.1	10.7	14.2	17.8	21.4	24.9	28.5	32.1	35.6	
	November	O	18	6	A	160.7	161.9	170.6	179.9	228.1	228.1	228.1	247.3	259.4	276.0	471.97
					M	4.4	8.7	13.1	17.4	21.7	25.9	30.2	34.5	38.8	43.1	
		S	22	7	A	141.3	158.1	170.8	182.5	192.9	202.5	212.1	220.6	228.9	237.2	
					M	4.4	8.9	13.3	17.8	22.2	26.7	31.1	35.6	40.0	44.5	
	December	O	18	12	A	111.2	172.8	197.6	222.3	237.7	237.7	237.7	237.7	237.7	237.7	399.11
					M	5.6	11.1	16.7	22.3	27.9	33.5	39.1	44.7	50.4	56.0	
		S	19	10	A	118.1	141.2	160.2	175.5	189.7	201.9	214.1	225.3	236.3	246.6	
					M	5.7	11.4	17.0	22.7	28.4	34.1	39.8	45.5	51.1	56.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Tomazina (To)	January	O	23	17	A	163.0	225.6	267.0	303.8	332.0	345.4	353.0	369.8	406.6	420.0	333.17
					M	7.0	13.9	20.9	27.9	34.8	41.7	48.7	55.6	62.5	69.4	
		S	16	13	A	142.2	169.3	189.7	208.2	224.9	240.3	254.8	268.1	282.3	295.9	
					M	7.1	14.1	21.2	28.3	35.3	42.4	49.4	56.5	63.6	70.6	
	February	O	18	10	A	138.5	209.5	235.0	243.7	256.8	274.2	275.4	283.0	283.0	283.0	272.25
					M	6.0	12.0	18.0	24.0	30.0	36.1	42.1	48.2	54.2	60.3	
		S	15	11	A	127.9	148.3	165.5	181.0	194.9	208.2	220.2	231.8	242.5	252.9	
					M	6.1	12.2	18.3	24.4	30.5	36.6	42.7	48.7	54.8	60.9	
	March	O	18	9	A	89.0	130.6	133.0	133.1	133.1	153.8	163.0	178.5	184.7	196.3	299.31
					M	4.2	8.5	12.7	17.0	21.2	25.5	29.7	34.0	38.3	42.6	
		S	20	9	A	108.6	125.7	139.8	151.6	162.6	172.2	181.5	189.9	199.0	207.7	
					M	4.3	8.7	13.0	17.3	21.6	26.0	30.3	34.6	38.9	43.3	
	April	O	30	6	A	81.0	126.2	128.0	128.0	129.3	132.0	136.8	136.8	136.8	136.8	290.36
					M	2.8	5.6	8.4	11.3	14.1	16.9	19.7	22.5	25.3	28.1	
		S	35	7	A	92.1	109.7	122.2	131.7	139.9	147.4	154.8	162.2	168.4	174.3	
					M	2.9	5.8	8.7	11.5	14.4	17.3	20.2	23.1	26.0	28.9	
	May	O	44	9	A	93.2	131.0	131.0	170.8	173.0	174.4	178.4	181.6	183.8	185.2	317.42
					M	3.6	7.2	10.7	14.3	17.9	21.5	25.1	28.8	32.3	35.9	
		S	33	8	A	113.8	135.3	151.2	164.1	175.4	185.7	195.3	204.2	212.0	219.8	
					M	3.7	7.3	11.0	14.6	18.3	21.9	25.6	29.2	32.9	36.5	
	June	O	52	6	A	73.6	107.8	129.0	135.0	135.0	137.0	157.0	169.6	191.0	195.6	300.73
					M	3.1	6.1	9.1	12.2	15.2	18.2	21.3	24.3	27.4	30.5	
		S	34	7	A	94.9	113.3	126.7	137.7	146.8	154.9	162.9	170.6	178.1	184.9	
					M	3.1	6.3	9.4	12.5	15.7	18.8	22.0	25.1	28.2	31.4	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Tomazina (To)	July	O	44	7	A	94.2	115.8	158.4	180.0	192.8	214.4	219.8	219.8	223.5	231.9	519.59
					M	2.2	4.5	6.7	9.0	11.3	13.5	15.8	18.1	20.3	22.6	
		S	42	6	A	99.7	115.4	126.2	134.5	141.6	148.0	153.9	159.4	164.5	170.0	
					M	2.3	4.6	6.9	9.2	11.5	13.8	16.1	18.4	20.7	23.0	
	August	O	48	7	A	71.2	88.2	106.8	118.6	131.6	131.6	131.6	149.4	166.4	185.4	648.38
					M	2.0	4.1	6.2	8.2	10.3	12.3	14.4	16.5	18.6	20.6	
		S	45	7	A	86.0	101.7	112.0	120.6	127.5	133.7	139.8	145.3	150.5	155.4	
					M	2.1	4.3	6.4	8.5	10.6	12.8	14.9	17.0	19.1	21.3	
	September	O	22	8	A	84.6	99.8	112.4	140.2	140.2	154.4	169.4	169.4	169.4	175.6	476.69
					M	3.9	7.9	11.8	15.7	19.7	23.6	27.5	31.4	35.4	39.3	
		S	26	8	A	96.1	115.2	130.1	142.4	153.9	163.7	173.1	182.5	190.5	198.9	
					M	4.0	8.0	12.1	16.1	20.1	24.1	28.2	32.2	36.2	40.2	
	October	O	17	7	A	94.0	110.6	141.6	149.4	170.6	178.4	179.8	179.8	184.2	198.2	489.83
					M	4.2	8.4	12.5	16.7	20.8	25.0	29.1	33.2	37.3	41.5	
		S	21	8	A	96.7	115.5	129.5	141.5	152.0	162.0	171.3	180.3	188.7	197.5	
					M	4.3	8.5	12.8	17.0	21.3	25.6	29.8	34.1	38.4	42.6	
	November	O	17	8	A	69.6	102.0	106.4	122.8	122.8	140.4	140.4	147.0	155.4	165.6	399.05
					M	3.8	7.7	11.5	15.3	19.2	23.0	26.9	30.7	34.5	38.3	
		S	21	7	A	89.8	107.1	120.5	130.8	140.3	148.8	157.6	166.0	173.5	180.9	
					M	3.9	7.9	11.8	15.7	19.7	23.6	27.5	31.4	35.4	39.3	
	December	O	14	13	A	85.6	113.4	171.4	189.4	193.4	193.4	193.4	243.4	247.4	247.4	458.36
					M	6.0	12.0	17.9	23.9	29.9	35.9	42.0	48.0	54.0	60.1	
		S	16	11	A	105.6	128.8	146.8	162.7	176.4	189.4	201.3	213.4	224.9	236.2	
					M	6.1	12.2	18.3	24.4	30.5	36.6	42.7	48.9	55.0	61.1	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
União da Vitória (UV)	January	O	19	19	A	124.2	159.7	163.5	164.1	167.5	209.5	222.3	222.9	234.9	236.4	532.89
					M	5.0	10.1	15.2	20.2	25.3	30.3	35.4	40.4	45.4	50.4	
		S	15	12	A	93.0	111.7	126.7	139.2	151.5	162.3	172.7	182.6	191.9	201.5	
					M	5.1	10.3	15.4	20.6	25.7	30.8	36.0	41.1	46.3	51.4	
	February	O	14	15	A	81.2	112.8	154.4	162.0	162.0	162.0	165.4	175.0	212.0	219.6	327.63
					M	5.8	11.7	17.6	23.4	29.3	35.2	41.1	46.9	52.8	58.7	
		S	13	14	A	96.8	117.0	134.0	149.0	162.1	174.1	186.4	197.6	208.6	219.1	
					M	6.0	11.9	17.9	23.9	29.9	35.8	41.8	47.8	53.7	59.7	
	March	O	15	11	A	99.8	127.3	127.3	149.2	154.4	154.4	154.4	158.7	168.9	177.6	329.73
					M	4.2	8.5	12.7	17.0	21.2	25.5	29.8	34.1	38.3	42.6	
		S	16	10	A	90.7	107.7	120.9	132.2	142.1	152.0	160.9	169.5	177.4	185.1	
					M	4.3	8.7	13.0	17.3	21.6	26.0	30.3	34.6	39.0	43.3	
	April	O	37	9	A	68.1	125.4	132.8	147.4	153.5	197.4	199.6	199.6	203.8	215.0	325.17
					M	3.8	7.6	11.4	15.2	18.9	22.6	26.3	30.0	33.7	37.4	
		S	22	8	A	100.6	119.9	134.8	146.0	155.7	165.8	174.8	183.3	190.8	198.5	
					M	3.9	7.8	11.7	15.5	19.4	23.3	27.2	31.1	35.0	38.9	
	May	O	27	7	A	154.6	214.2	261.1	261.1	261.1	261.3	311.3	340.3	340.3	340.3	468.05
					M	4.7	9.4	14.2	18.9	23.6	28.4	33.1	37.9	42.7	47.4	
		S	25	8	A	131.8	156.2	174.7	189.4	203.2	215.1	226.6	236.9	247.9	258.2	
					M	4.9	9.7	14.6	19.4	24.3	29.2	34.0	38.9	43.8	48.6	
	June	O	23	8	A	87.9	144.0	184.2	188.4	197.4	197.4	197.4	205.8	205.8	205.8	831.2
					M	4.6	9.3	13.9	18.6	23.3	27.9	32.6	37.3	42.0	46.7	
		S	24	9	A	132.1	156.1	172.8	187.1	200.0	211.7	223.0	235.4	245.2	254.3	
					M	4.8	9.5	14.3	19.0	23.8	28.6	33.3	38.1	42.9	47.6	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
União da Vitória (UV)	July	O	27	9	A	121.4	192.0	269.8	326.8	345.4	378.1	396.7	414.9	421.3	435.3	518.03
					M	4.3	8.7	13.0	17.4	21.8	26.1	30.5	34.9	39.3	43.6	
		S	26	9	A	119.2	142.3	160.2	174.3	186.3	197.1	207.1	217.4	226.9	235.8	
					M	4.4	8.9	13.3	17.7	22.2	26.6	31.0	35.5	39.9	44.3	
	August	O	24	10	A	110.0	149.1	191.5	231.9	236.1	236.1	241.5	245.7	246.1	246.6	520.25
					M	3.7	7.5	11.3	15.0	18.8	22.6	26.3	30.1	33.9	37.7	
		S	30	9	A	114.7	136.0	152.0	166.0	177.8	188.8	197.6	206.6	214.7	223.3	
					M	3.8	7.7	11.5	15.3	19.2	23.0	26.8	30.7	34.5	38.3	
	September	O	17	15	A	112.0	146.3	152.5	170.6	207.5	222.8	244.4	260.3	268.3	298.4	466.36
					M	5.3	10.7	16.0	21.4	26.7	32.0	37.4	42.7	48.1	53.4	
		S	21	10	A	117.0	141.8	160.6	175.7	189.5	202.1	214.7	225.9	237.2	248.0	
					M	5.4	10.9	16.3	21.7	27.2	32.6	38.0	43.4	48.9	54.3	
	October	O	18	11	A	87.4	122.1	122.1	127.0	155.2	180.4	195.4	205.3	239.7	239.7	513.91
					M	5.7	11.5	17.2	23.0	28.8	34.5	40.3	46.0	51.7	57.5	
		S	17	9	A	116.8	140.0	158.0	173.2	186.2	199.1	212.2	224.4	235.4	246.4	
					M	5.8	11.6	17.5	23.3	29.1	34.9	40.7	46.5	52.4	58.2	
	November	O	18	8	A	84.4	115.2	144.4	155.8	166.7	178.1	186.6	187.1	187.2	195.1	488.67
					M	4.7	9.4	14.1	18.8	23.5	28.2	32.9	37.5	42.2	46.8	
		S	19	9	A	99.4	119.0	133.8	147.0	159.2	170.3	180.3	189.9	199.6	208.8	
					M	4.8	9.6	14.4	19.2	23.9	28.7	33.5	38.3	43.1	47.9	
	December	O	14	13	A	156.2	156.7	198.3	202.1	202.6	203.1	203.3	207.3	245.1	263.9	524.19
					M	5.5	10.9	16.4	21.9	27.3	32.8	38.3	43.8	49.3	54.8	
		S	16	11	A	107.3	128.6	145.4	159.2	171.9	183.7	195.2	206.2	217.1	227.2	
					M	5.6	11.2	16.7	22.3	27.9	33.5	39.0	44.6	50.2	55.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Taiamã (Ta)	January	O	14	13	A	137.0	159.0	175.0	177.0	179.0	201.0	201.0	214.0	236.0	244.0	478.83
					M	7.3	14.7	22.0	29.4	36.8	44.1	51.5	58.9	66.4	73.8	
		S	15	9	A	121.9	149.0	169.3	187.7	203.9	219.1	233.8	247.6	260.5	273.7	
					M	7.4	14.9	22.3	29.8	37.2	44.6	52.1	59.5	66.9	74.4	
	February	O	11	10	A	130.0	140.0	148.0	223.0	223.0	223.0	242.0	242.0	278.0	363.0	450.91
					M	7.1	14.2	21.2	28.3	35.5	42.6	49.7	56.9	64.0	71.1	
		S	13	8	A	123.6	146.7	164.8	180.9	196.7	211.0	224.3	236.6	249.2	262.0	
					M	7.2	14.4	21.6	28.8	36.0	43.2	50.4	57.6	64.8	72.0	
	March	O	21	7	A	96.0	100.1	144.2	153.1	153.1	153.1	153.1	164.0	192.2	195.4	462.22
					M	5.4	10.8	16.3	21.7	27.2	32.6	38.1	43.5	49.0	54.5	
		S	16	7	A	100.9	121.1	137.7	151.1	163.0	174.5	185.7	196.3	206.7	216.7	
					M	5.5	11.0	16.5	22.1	27.6	33.1	38.6	44.1	49.6	55.2	
	April	O	24	5	A	87.0	89.0	93.0	106.0	108.0	117.0	130.0	130.0	136.0	136.0	480.08
					M	2.7	5.5	8.2	11.0	13.7	16.5	19.2	22.0	24.7	27.5	
		S	29	5	A	82.7	96.2	105.4	113.6	120.8	127.6	133.9	140.3	145.9	151.3	
					M	2.8	5.6	8.4	11.2	14.0	16.8	19.6	22.4	25.2	28.0	
	May	O	44	4	A	72.1	78.7	84.6	87.3	87.3	87.3	87.3	100.0	110.0	110.0	470.16
					M	1.7	3.4	5.1	6.8	8.5	10.2	11.9	13.5	15.2	16.9	
		S	52	4	A	81.4	94.7	103.0	108.7	114.1	119.0	123.3	127.0	130.8	134.9	
					M	1.8	3.5	5.3	7.0	8.8	10.5	12.3	14.0	15.8	17.5	
	June	O	98	3	A	66.0	66.0	66.0	81.0	81.0	82.0	95.0	95.0	97.0	97.0	424.55
					M	0.6	1.1	1.7	2.2	2.8	3.3	3.9	4.5	5.0	5.6	
		S	103	3	A	66.3	72.9	75.7	77.4	79.2	80.3	81.6	82.5	83.9	85.5	
					M	0.6	1.2	1.7	2.3	2.9	3.5	4.1	4.7	5.2	5.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Taiamã (Ta)	July	O	222	2	A	59.0	59.0	59.0	59.0	61.0	61.0	61.0	61.0	61.0	61.0	428.11
					M	0.3	0.7	1.0	1.4	1.7	2.0	2.4	2.7	3.1	3.4	
		S	158	2	A	57.3	60.3	61.5	62.4	63.3	64.0	64.8	65.7	66.5	67.2	
					M	0.4	0.7	1.1	1.5	1.8	2.2	2.5	2.9	3.3	3.6	
	August	O	113	2	A	80.0	80.0	80.0	80.0	80.0	94.0	94.0	94.0	94.0	94.0	451.81
					M	0.5	1.0	1.5	2.0	2.5	3.1	3.5	4.0	4.5	5.0	
		S	122	2	A	79.3	83.4	85.0	86.3	87.3	88.6	89.6	90.7	92.1	93.6	
					M	0.5	1.1	1.6	2.1	2.6	3.2	3.7	4.2	4.7	5.3	
	September	O	47	4	A	60.0	60.0	60.0	60.0	60.0	70.0	74.0	74.0	74.0	74.0	394.28
					M	1.5	3.0	4.5	6.0	7.5	9.0	10.5	11.9	13.4	14.9	
		S	42	4	A	68.9	77.3	82.1	86.4	91.1	95.3	99.2	102.6	106.0	108.8	
					M	1.6	3.1	4.7	6.2	7.8	9.4	10.9	12.5	14.1	15.6	
	October	O	36	5	A	100.0	100.0	100.0	103.0	105.0	105.0	105.0	122.0	122.0	127.0	480.97
					M	2.9	5.8	8.7	11.6	14.5	17.3	20.2	23.1	25.9	28.8	
		S	28	5	A	88.7	102.1	111.2	120.3	127.5	133.8	140.5	147.1	153.0	158.8	
					M	3.0	6.0	9.0	12.0	15.0	17.9	20.9	23.9	26.9	29.9	
	November	O	24	7	A	124.0	204.4	211.8	216.1	221.1	225.4	230.2	230.2	237.7	237.7	435.03
					M	5.5	11.0	16.4	21.9	27.3	32.8	38.2	43.7	49.2	54.6	
		S	17	6	A	130.7	148.3	163.2	176.8	189.1	200.7	211.9	222.2	232.1	241.5	
					M	5.5	11.1	16.6	22.1	27.7	33.2	38.7	44.3	49.8	55.3	
	December	O	24	12	A	157.0	201.0	226.0	246.0	271.0	291.0	315.0	355.0	375.0	400.0	451.91
					M	7.1	14.2	21.3	28.5	35.5	42.7	49.8	56.9	64.0	71.2	
		S	15	8	A	128.6	154.2	175.0	192.6	207.9	222.8	236.9	251.3	264.5	276.3	
					M	7.2	14.4	21.6	28.8	36.1	43.3	50.5	57.7	64.9	72.1	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Caracol (Co)	January	O	25	5	A	72.0	89.8	98.0	121.5	164.7	168.1	168.1	202.1	223.6	223.6	187.91
					M	4.5	9.0	13.5	18.1	22.6	27.2	31.8	36.3	40.9	45.5	
		S	23	6	A	107.3	126.5	141.7	153.8	165.2	175.8	185.7	194.6	204.0	212.8	
					M	4.6	9.2	13.7	18.3	22.9	27.5	32.1	36.7	41.3	45.8	
	February	O	18	9	A	128.0	218.8	235.2	235.2	235.2	243.2	245.8	245.8	251.0	253.8	238.08
					M	5.0	9.9	14.9	19.8	24.8	29.8	34.8	39.8	44.8	49.8	
		S	19	7	A	105.3	125.3	140.2	153.3	165.0	175.7	185.7	195.6	204.8	214.8	
					M	5.0	10.1	15.1	20.1	25.2	30.2	35.3	40.3	45.3	50.4	
	March	O	21	6	A	160.0	162.0	171.3	171.3	178.7	181.0	202.0	234.0	234.0	343.2	323.63
					M	4.5	8.9	13.4	17.8	22.3	26.8	31.3	35.8	40.3	44.8	
		S	26	6	A	158.9	176.9	190.1	201.7	212.2	221.8	231.1	240.0	249.0	256.6	
					M	4.5	9.0	13.5	18.1	22.6	27.1	31.6	36.1	40.6	45.1	
	April	O	43	4	A	112.0	154.6	180.2	180.2	180.2	200.8	200.8	200.8	200.8	200.8	355.75
					M	3.9	7.8	11.7	15.6	19.5	23.4	27.4	31.3	35.3	39.3	
		S	34	5	A	132.5	155.4	170.9	182.0	192.4	201.8	211.5	220.5	229.0	237.1	
					M	4.0	7.9	11.9	15.8	19.8	23.7	27.7	31.6	35.6	39.5	
	May	O	39	5	A	120.0	137.6	201.6	219.2	219.2	219.2	219.2	219.2	219.2	219.2	351.06
					M	3.2	6.4	9.5	12.7	15.9	19.1	22.3	25.5	28.7	32.0	
		S	35	6	A	136.3	155.8	168.8	177.9	186.9	195.6	203.0	210.5	216.9	223.4	
					M	3.3	6.6	9.9	13.1	16.4	19.7	23.0	26.3	29.5	32.8	
	June	O	31	4	A	86.0	86.0	86.0	96.0	100.0	100.0	100.0	105.3	105.3	108.8	296.05
					M	2.3	4.6	6.9	9.3	11.6	13.9	16.2	18.6	20.9	23.3	
		S	34	6	A	85.7	99.8	109.3	116.7	123.2	129.0	134.1	139.4	144.3	149.1	
					M	2.4	4.8	7.2	9.5	11.9	14.3	16.7	19.1	21.5	23.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Caracol (Co)	July	O	73	5	A	78.8	79.8	98.6	107.4	114.2	114.2	114.2	114.2	114.3	114.3	275.3
					M	1.2	2.5	3.7	4.9	6.2	7.4	8.7	9.9	11.1	12.4	
		S	55	4	A	81.0	89.8	94.7	98.8	102.3	105.4	108.5	111.4	114.1	116.8	
					M	1.3	2.6	3.8	5.1	6.4	7.7	8.9	10.2	11.5	12.8	
	August	O	50	3	A	101.0	101.0	141.0	198.0	198.0	198.0	198.0	254.2	263.2	263.2	308.91
					M	1.6	3.1	4.7	6.3	7.8	9.4	11.0	12.6	14.2	15.8	
		S	52	4	A	88.4	99.1	105.6	110.7	114.7	118.7	122.4	126.0	129.5	132.9	
					M	1.6	3.2	4.8	6.4	8.0	9.6	11.2	12.8	14.4	16.0	
	September	O	46	6	A	61.8	85.5	89.7	89.7	102.5	116.0	120.2	120.2	120.2	120.2	302.56
					M	2.5	5.0	7.5	10.0	12.6	15.1	17.6	20.1	22.6	25.1	
		S	31	5	A	72.6	86.6	96.7	104.4	111.1	117.4	122.9	128.8	134.0	139.4	
					M	2.6	5.2	7.8	10.3	12.9	15.5	18.1	20.7	23.2	25.8	
	October	O	20	5	A	93.0	170.0	170.0	170.0	170.0	170.0	170.0	179.1	179.1	180.9	298.94
					M	4.2	8.3	12.5	16.7	20.8	25.0	29.2	33.3	37.5	41.7	
		S	25	5	A	120.4	138.4	151.1	162.0	172.3	181.7	190.9	199.7	208.0	216.2	
					M	4.2	8.5	12.7	16.9	21.1	25.4	29.6	33.8	38.0	42.3	
	November	O	17	8	A	118.6	137.6	161.0	167.4	168.3	168.3	192.8	194.8	194.8	206.3	282.75
					M	5.5	10.9	16.4	21.8	27.2	32.5	37.8	43.2	48.5	53.9	
		S	22	5	A	129.7	152.7	169.5	183.0	195.4	207.2	218.3	229.2	240.6	250.1	
					M	5.5	11.1	16.6	22.1	27.7	33.2	38.8	44.3	49.9	55.4	
	December	O	16	5	A	92.0	142.2	178.2	178.2	190.6	190.6	190.6	190.6	190.6	190.6	298.14
					M	6.2	12.4	18.6	24.9	31.1	37.4	43.7	50.0	56.3	62.6	
		S	23	6	A	144.8	173.6	193.2	211.0	225.8	239.9	252.7	264.9	277.0	288.5	
					M	6.3	12.5	18.8	25.0	31.3	37.5	43.8	50.1	56.3	62.6	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Passo Ma-rombas (PM)	January	O	22	11	A	106.6	106.6	124.4	124.4	132.8	148.6	153.7	183.8	188.6	188.6	440.92
					M	5.0	10.1	15.1	20.2	25.2	30.3	35.3	40.3	45.3	50.3	
		S	19	10	A	89.2	110.3	126.1	140.1	152.6	164.4	175.4	186.0	196.0	205.5	
					M	5.2	10.3	15.5	20.7	25.9	31.0	36.2	41.4	46.6	51.7	
	February	O	22	10	A	88.7	93.3	108.9	128.4	149.8	154.3	169.0	171.9	197.4	220.1	413.44
					M	5.6	11.3	16.9	22.5	28.2	33.9	39.6	45.2	50.9	56.5	
		S	17	12	A	95.2	115.7	132.2	146.1	159.0	171.0	182.7	194.4	204.9	216.0	
					M	5.7	11.5	17.2	23.0	28.7	34.5	40.2	46.0	51.7	57.4	
	March	O	21	5	A	74.2	74.2	79.3	82.9	109.2	120.5	120.9	122.1	130.5	160.0	461.48
					M	3.5	7.0	10.5	14.0	17.5	21.0	24.6	28.1	31.6	35.2	
		S	23	8	A	86.4	102.7	114.9	125.0	134.2	142.3	150.1	157.7	165.3	172.3	
					M	3.6	7.2	10.7	14.3	17.9	21.5	25.1	28.7	32.2	35.8	
	April	O	52	6	A	94.8	126.0	133.1	133.1	149.8	173.1	185.6	185.6	186.4	193.9	275.31
					M	3.6	7.1	10.7	14.2	17.7	21.3	24.8	28.3	31.8	35.4	
		S	30	8	A	98.7	118.1	132.6	144.6	154.3	163.4	172.3	180.3	188.1	196.3	
					M	3.6	7.2	10.8	14.5	18.1	21.7	25.3	28.9	32.5	36.1	
	May	O	27	6	A	104.2	172.4	205.7	212.0	214.2	214.2	261.9	268.2	270.4	272.6	495.23
					M	3.8	7.6	11.3	15.1	18.9	22.7	26.5	30.3	34.2	37.9	
		S	31	7	A	114.3	135.4	150.2	162.8	173.9	184.2	193.1	201.6	209.7	217.9	
					M	3.8	7.7	11.5	15.4	19.2	23.0	26.9	30.7	34.5	38.4	
	June	O	19	6	A	80.2	100.4	124.6	124.6	142.7	162.5	162.5	162.5	180.9	182.0	468.78
					M	4.0	7.9	11.9	15.9	19.9	23.9	27.9	31.9	35.9	39.9	
		S	25	8	A	104.9	124.0	138.0	149.5	160.1	169.6	178.2	187.0	195.7	203.7	
					M	4.1	8.1	12.2	16.3	20.3	24.4	28.5	32.5	36.6	40.7	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Passo Ma-rombas (PM)	July	O	27	7	A	128.6	165.4	232.8	275.6	314.0	382.2	428.3	428.3	444.2	444.2	457.59
					M	4.2	8.4	12.6	16.8	21.0	25.2	29.4	33.7	37.9	42.1	
		S	29	9	A	142.4	162.4	177.2	188.9	198.9	209.0	218.5	228.4	237.0	244.8	
					M	4.3	8.5	12.8	17.0	21.3	25.5	29.8	34.0	38.3	42.5	
	August	O	24	9	A	117.3	224.0	264.2	276.8	277.9	313.7	326.3	327.4	329.5	329.5	481.94
					M	4.0	8.0	12.0	16.0	20.0	24.0	28.0	32.0	36.0	40.0	
		S	30	8	A	106.1	128.7	144.9	158.2	169.7	180.5	190.2	199.7	208.4	217.6	
					M	4.0	8.1	12.1	16.2	20.2	24.3	28.3	32.4	36.4	40.4	
	September	O	18	10	A	99.8	106.1	119.6	152.9	184.6	185.9	189.4	198.5	230.2	233.7	509.44
					M	4.6	9.2	13.8	18.4	23.0	27.6	32.2	36.8	41.4	46.0	
		S	24	9	A	102.3	123.9	138.8	152.6	165.1	176.1	186.8	196.6	206.0	215.3	
					M	4.7	9.4	14.0	18.7	23.4	28.1	32.8	37.4	42.1	46.8	
	October	O	12	8	A	91.6	112.8	175.8	175.8	175.8	232.6	247.8	247.8	253.0	265.4	645.53
					M	5.3	10.6	15.9	21.2	26.5	31.8	37.1	42.4	47.7	53.0	
		S	20	8	A	112.1	134.8	151.1	166.0	178.8	190.8	202.4	213.6	223.9	234.4	
					M	5.4	10.8	16.1	21.5	26.9	32.3	37.6	43.0	48.4	53.8	
	November	O	20	10	A	80.2	113.8	126.6	141.5	143.6	143.6	149.8	162.6	177.5	185.7	643.17
					M	4.4	8.9	13.3	17.7	22.2	26.6	31.1	35.5	39.9	44.3	
		S	20	8	A	90.5	109.2	122.8	135.2	145.9	155.7	164.3	173.8	182.5	190.9	
					M	4.5	9.1	13.6	18.2	22.7	27.2	31.8	36.3	40.9	45.4	
	December	O	17	9	A	93.5	123.1	137.9	147.3	154.3	169.1	169.1	174.1	181.0	212.8	765.63
					M	4.9	9.8	14.8	19.7	24.6	29.6	34.5	39.5	44.4	49.4	
		S	20	8	A	97.3	118.9	135.4	149.5	161.3	172.4	183.5	193.2	202.9	212.6	
					M	5.0	10.1	15.1	20.1	25.1	30.2	35.2	40.2	45.3	50.3	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days) 1	2	3	4	5	6	7	8	9	10	Time (s)
Linha Cescon (LC)	January	O	38	10	A	119.0	138.0	162.0	184.3	189.5	208.6	208.6	212.2	212.7	226.0	206.41
					M	5.4	10.8	16.2	21.7	27.1	32.5	37.9	43.3	48.8	54.2	
		S	27	8	A	126.6	153.1	173.9	190.8	205.2	218.2	231.3	242.7	253.5	264.0	
					M	5.5	11.0	16.5	22.0	27.5	32.9	38.4	43.9	49.4	54.9	
	February	O	33	7	A	103.8	122.1	156.1	167.1	171.4	182.4	195.5	224.4	237.0	237.0	183.45
					M	5.7	11.5	17.2	22.9	28.7	34.4	40.1	45.9	51.6	57.2	
		S	22	7	A	123.7	148.9	168.9	185.5	200.4	213.0	224.9	236.3	248.1	258.4	
					M	5.8	11.6	17.4	23.2	29.0	34.7	40.5	46.3	52.1	57.9	
	March	O	55	6	A	87.2	142.0	158.0	158.0	158.0	170.0	188.5	188.5	197.4	221.4	201.39
					M	3.6	7.2	10.8	14.4	18.0	21.6	25.2	28.8	32.5	36.1	
		S	33	5	A	114.3	133.0	146.7	158.0	168.0	176.4	184.6	193.3	201.1	208.6	
					M	3.6	7.3	10.9	14.6	18.2	21.9	25.5	29.1	32.8	36.4	
	April	O	52	7	A	113.0	134.1	174.1	185.1	205.1	223.1	236.3	236.3	258.4	258.4	195.09
					M	4.5	8.9	13.4	17.9	22.4	26.8	31.3	35.8	40.3	44.9	
		S	34	6	A	136.2	163.6	182.6	198.4	211.3	222.7	234.0	244.3	254.0	263.4	
					M	4.5	9.0	13.5	18.0	22.6	27.1	31.6	36.1	40.6	45.1	
	May	O	28	5	A	176.0	311.8	369.9	382.3	382.3	382.3	382.3	382.3	382.3	382.3	201.36
					M	5.0	10.1	15.2	20.2	25.2	30.3	35.3	40.4	45.5	50.5	
		S	32	6	A	185.3	211.6	229.7	245.3	259.3	272.4	284.3	295.3	307.2	318.9	
					M	5.1	10.3	15.4	20.5	25.6	30.8	35.9	41.0	46.1	51.3	
	June	O	18	7	A	120.0	134.8	184.0	210.2	234.6	280.3	315.9	365.3	389.7	392.6	195.42
					M	5.2	10.4	15.7	20.9	26.2	31.4	36.7	42.0	47.3	52.6	
		S	29	7	A	134.5	163.2	182.6	200.1	214.4	228.2	239.7	251.2	262.5	274.1	
					M	5.3	10.6	15.9	21.2	26.5	31.8	37.1	42.4	47.7	53.0	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Linha Cescon (LC)	July	O	23	10	A	103.2	147.2	208.4	221.0	241.4	277.4	318.0	318.0	333.1	348.4	202.25
					M	5.0	10.0	15.0	20.1	25.1	30.1	35.2	40.3	45.3	50.4	
		S	29	7	A	133.2	159.8	178.3	194.3	209.0	222.5	234.2	245.6	256.4	266.2	
					M	5.1	10.1	15.2	20.2	25.3	30.4	35.4	40.5	45.6	50.6	
	August	O	37	7	A	144.0	230.1	260.1	277.3	277.3	292.1	309.3	309.3	309.3	309.3	202.19
					M	4.6	9.2	13.8	18.4	23.0	27.7	32.3	36.9	41.5	46.1	
		S	32	7	A	128.8	155.1	174.2	189.2	203.1	215.5	226.7	237.9	248.4	258.2	
					M	4.7	9.4	14.1	18.7	23.4	28.1	32.8	37.5	42.2	46.9	
	September	O	26	9	A	132.8	138.1	138.1	149.4	156.9	177.4	202.2	207.2	218.4	255.7	208.69
					M	5.2	10.5	15.8	21.0	26.3	31.6	36.9	42.2	47.5	52.8	
		S	28	7	A	133.1	160.9	181.1	198.2	213.4	228.5	240.4	252.6	264.7	276.3	
					M	5.3	10.7	16.0	21.3	26.7	32.0	37.3	42.7	48.0	53.3	
	October	O	24	8	A	134.0	186.0	206.6	237.2	257.8	261.6	294.7	315.3	335.8	335.8	208.48
					M	6.1	12.2	18.4	24.5	30.7	36.8	43.0	49.1	55.3	61.4	
		S	25	7	A	150.5	178.6	200.6	218.5	235.0	250.2	262.9	275.3	287.9	300.0	
					M	6.2	12.4	18.6	24.8	31.0	37.2	43.4	49.6	55.8	62.0	
	November	O	39	5	A	156.2	156.2	159.6	159.6	159.6	159.6	170.6	202.8	202.8	202.8	201.39
					M	4.6	9.1	13.7	18.2	22.8	27.3	31.8	36.3	40.7	45.1	
		S	30	5	A	134.8	156.7	172.9	187.6	200.1	210.9	222.2	234.0	244.3	252.7	
					M	4.6	9.3	13.9	18.6	23.2	27.9	32.6	37.2	41.9	46.5	
	December	O	38	5	A	129.2	129.2	129.2	149.8	149.8	149.8	153.5	194.9	194.9	201.3	208.24
					M	5.0	9.9	14.8	19.8	24.7	29.7	34.7	39.7	44.6	49.6	
		S	29	5	A	143.1	167.6	183.7	199.3	211.8	222.8	233.7	245.3	255.8	265.3	
					M	5.0	10.0	15.0	20.0	25.0	30.0	35.0	40.0	45.0	50.0	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Cacequi (Cq)	January	O	27	9	A	116.0	210.0	255.0	255.0	255.0	286.4	286.4	286.4	286.4	286.4	208.53
					M	4.5	9.0	13.5	18.0	22.5	27.0	31.5	36.0	40.4	44.9	
		S	29	6	A	136.5	159.3	175.5	188.4	200.9	212.8	223.3	233.4	243.8	252.5	
					M	4.6	9.2	13.7	18.3	22.9	27.5	32.0	36.6	41.2	45.8	
	February	O	21	8	A	114.3	156.2	239.0	255.2	255.2	255.2	255.2	255.2	255.2	255.2	194.88
					M	5.0	10.0	15.0	20.0	25.0	30.0	35.0	39.9	44.9	49.8	
		S	25	6	A	132.9	156.9	173.3	187.4	200.8	212.8	223.7	235.1	245.4	254.5	
					M	5.1	10.1	15.2	20.3	25.4	30.5	35.5	40.6	45.7	50.8	
	March	O	29	9	A	98.6	120.0	120.0	127.0	151.0	151.0	160.0	198.0	222.0	222.0	208.89
					M	4.3	8.7	13.0	17.3	21.7	26.1	30.4	34.8	39.2	43.6	
		S	30	6	A	124.7	148.5	164.7	177.9	189.8	201.3	212.0	221.4	231.0	240.4	
					M	4.4	8.8	13.2	17.6	22.0	26.4	30.8	35.2	39.6	44.0	
	April	O	30	7	A	203.7	261.5	312.4	312.4	312.4	317.7	324.5	350.0	358.5	359.7	195.99
					M	5.4	10.7	16.1	21.4	26.7	32.1	37.5	42.8	48.2	53.6	
		S	27	6	A	183.4	206.1	224.1	237.8	251.0	263.8	275.7	287.2	298.4	309.1	
					M	5.4	10.9	16.3	21.8	27.2	32.7	38.1	43.6	49.0	54.5	
	May	O	30	5	A	106.2	131.2	176.2	184.6	189.2	233.2	233.2	234.5	247.3	262.0	207.95
					M	4.5	9.1	13.7	18.2	22.8	27.3	31.9	36.5	41.1	45.7	
		S	35	6	A	148.2	175.8	195.8	211.7	225.1	236.6	248.2	259.2	269.9	279.8	
					M	4.6	9.2	13.8	18.4	23.0	27.6	32.2	36.8	41.4	46.0	
	June	O	21	5	A	137.6	179.2	191.6	191.6	195.5	197.3	197.3	208.8	217.7	231.5	201.86
					M	4.4	8.8	13.1	17.5	21.9	26.4	30.8	35.2	39.6	44.1	
		S	28	6	A	143.1	162.9	177.2	188.7	200.3	211.3	221.0	230.7	239.9	248.7	
					M	4.5	8.9	13.4	17.8	22.3	26.7	31.2	35.6	40.1	44.5	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

continue

conclusion

Stations	Months	Series	Maximum Dry Period (days)	Maximum Wet Period (days)	Type	Total amount (mm) per class (days)										Time (s)
						1	2	3	4	5	6	7	8	9	10	
Cacequi (Cq)	July	O	25	8	A	107.8	108.4	122.6	145.8	150.1	153.3	170.4	179.9	179.9	202.1	208.41
					M	4.6	9.1	13.7	18.3	22.8	27.4	32.0	36.6	41.2	45.8	
		S	27	6	A	120.4	142.2	158.3	172.4	184.6	196.6	206.7	217.1	226.5	235.5	
					M	4.7	9.3	14.0	18.6	23.3	27.9	32.6	37.2	41.9	46.6	
	August	O	34	7	A	136.0	152.0	152.0	152.0	152.2	167.4	167.4	167.4	167.4	181.4	208.56
					M	3.2	6.4	9.5	12.7	15.9	19.1	22.3	25.5	28.6	31.8	
		S	33	6	A	109.5	128.0	140.4	151.1	159.9	168.4	176.0	183.3	190.4	197.5	
					M	3.2	6.5	9.7	12.9	16.2	19.4	22.7	25.9	29.1	32.4	
	September	O	21	5	A	135.0	165.5	178.8	183.6	190.1	207.1	207.1	207.1	265.8	265.8	202.13
					M	4.9	9.8	14.7	19.6	24.5	29.5	34.4	39.3	44.3	49.3	
		S	27	6	A	141.0	165.3	183.6	197.9	210.6	222.6	234.0	244.9	256.5	266.6	
					M	5.0	9.9	14.9	19.9	24.9	29.8	34.8	39.8	44.8	49.7	
	October	O	33	7	A	138.8	140.0	147.8	160.7	177.9	212.1	228.3	228.3	245.8	258.1	208.08
					M	4.8	9.6	14.4	19.3	24.1	29.0	33.7	38.5	43.2	48.0	
		S	28	6	A	137.2	161.3	178.3	192.3	204.5	216.4	226.8	237.1	247.4	256.6	
					M	4.9	9.8	14.7	19.6	24.5	29.4	34.3	39.2	44.1	49.0	
	November	O	30	5	A	115.8	158.2	160.0	161.4	178.4	182.8	182.8	199.4	229.8	272.2	202.39
					M	4.4	8.8	13.3	17.7	22.1	26.5	30.8	35.1	39.4	43.8	
		S	27	5	A	128.3	147.3	162.8	174.3	186.6	197.6	207.2	217.1	225.4	233.8	
					M	4.5	9.0	13.5	18.0	22.5	27.0	31.5	36.0	40.5	45.0	
	December	O	25	3	A	135.6	135.6	154.0	154.0	208.7	208.7	208.7	208.7	237.9	237.9	208.75
					M	3.5	7.0	10.5	14.1	17.6	21.1	24.6	28.1	31.7	35.2	
		S	33	5	A	116.3	134.6	148.1	158.1	167.6	176.6	184.5	193.1	200.6	208.0	
					M	3.6	7.2	10.7	14.3	17.9	21.5	25.0	28.6	32.2	35.8	

O – Observed; S – Synthetic; A – Absolute Terms; M – Mean Terms.

ANNEX H - COMPLETE ALGORITHMS OF THE COMPUTATIONAL PROGRAM DEVELOPED

In this Annex, the complete algorithms of the four modules developed are exhibit. Information about inputs, outputs and what each module calculates can be found in the main text (section 3).

1) Module 1 – "*Ordem_Markov.m*"

```
%ANALYSIS OF THE ORDERS OF THE MARKOV CHAINS (limited to the second order) %Version 1.0
- 11/11/2009
%Author: Daniel Henrique Marco Detzel
%Theory for the calculus contained in this algorithm can be found in Wilks (2006. p.
248-252);

%BEGINNING OF THE PROCEDURE
clear all
clc
tic
rmin=input('Enter with the minimum value for a day to be considered wet (mm):');
%Opening of the archive containing data from the respective rainfall stations;
fid=fopen('serie.m','r');
O=fscanf(fid, '%g');
%Initial declaration of variables;
x=O(:); n=length(O); s=1; t=1; u=1; v=1; a=1; b=1; c=1; d=1; e=1; f=1; g=1; h=1; y=1;
z=1;
A=1; B=1; C=1; D=1; E=1; F=1; G=1; H=1; S=1; T=1; U=1; V=1; Y=1; Z=1;
%Beginning of the calculations of zero order (Bernoulli trials) and first order
probabilities;
for i=(1:n)
    if x(i)>rmin
        S(s)=1;
        s=s+1;
    elseif x(i)<rmin
        T(t)=1;
        t=t+1;
    end
end
for i=(2:n)
    if x(i-1)<rmin & x(i)<rmin
        U(u)=1;
        u=u+1;
    elseif x(i-1)>rmin & x(i)>rmin
        V(v)=1;
        v=v+1;
    elseif x(i-1)>rmin & x(i)<rmin
        Y(y)=1;
        y=y+1;
    elseif x(i-1)<rmin & x(i)>rmin
        Z(z)=1;
        z=z+1;
    end
end
```

```
%Count of the number of days with different configurations;
N1=length(S); N0=length(T); N00=length(U);
N11=length(V); N01=length(Y); N10=length(Z);
%Probabilities determination;
p0=N0/n; p1=N1/n; p00=N00/N0;
p10=1-p00; p11=N11/N1; p01=1-p11;
disp ('-----------------------------------------------------------------------------');
disp ('TRANSITION PROBABILITIES');
fprintf ('Prob. of dry day, given dry day (p00): %1.4f\n', p00);
fprintf ('Prob. of wet day, given dry day (p10): %1.4f\n', p10);
fprintf ('Prob. of dry day, given wet day (p01): %1.4f\n', p01);
fprintf ('Prob. of wet day, given wet day (p11): %1.4f\n', p11);
%End of the calculations of zero order (Bernoulli trials) and first order
probabilities;
%Beginning of the calculation of second order probabilities;
for i=(3:n)
    if x(i-2)<rmin & x(i-1)<rmin & x(i)<rmin
        A(a)=1;
        a=a+1;
    elseif x(i-2)>rmin & x(i-1)<rmin & x(i)<rmin
        B(b)=1;
        b=b+1;
    elseif x(i-2)<rmin & x(i-1)>rmin & x(i)<rmin
        C(c)=1;
        c=c+1;
    elseif x(i-2)>rmin & x(i-1)>rmin & x(i)<rmin
        D(d)=1;
        d=d+1;
    elseif x(i-2)<rmin & x(i-1)<rmin & x(i)>rmin
        E(e)=1;
        e=e+1;
    elseif x(i-2)>rmin & x(i-1)<rmin & x(i)>rmin
        F(f)=1;
        f=f+1;
    elseif x(i-2)<rmin & x(i-1)>rmin & x(i)>rmin
        G(g)=1;
        g=g+1;
    elseif x(i-2)>rmin & x(i-1)>rmin & x(i)>rmin
        H(h)=1;
        h=h+1;
    end
end
%Count of the number of days with different configurations;
N000=length(A); N001=length(B); N010=length(C); N011=length(D);
N100=length(E); N101=length(F); N110=length(G); N111=length(H);
%Probabilities determinaton;
p000=N000/(N000+N001); p001=N001/(N000+N001); p010=N010/(N010+N011);
p011=N011/(N010+N011); p100=N100/(N100+N101); p101=N101/(N100+N101);
p110=N110/(N110+N111); p111=N111/(N110+N111);
%End of the calculation of second order probabilities;
%Beginning of the determination of likelihood functions (Lm);
%Zero order:
L0=(N0*log(p0))+(N1*log(p1));
%First order:
L1=(N00*log(p00))+(N01*log(p01))+(N10*log(p10))+(N11*log(p11));
%Second order:
L2=(N000*log(p000))+(N001*log(p001))+(N010*log(p010))+(N011*log(p011))+...
        (N100*log(p100))+(N101*log(p101))+(N110*log(p110))+(N111*log(p111));
```

```
%End of the determination of likelihood functions (Lm);
%Beginning of the calculation of AIC (Akaike. 1974) and BIC (Schwarz. 1978) criteria
%Zero order:
AIC0=-2*L0+2*(2^0*(2-1));
BIC0=-2*L0+((2^0)*log(n));
fclose(fid);
%First order:
AIC1=-2*L1+2*(2^1*(2-1));
BIC1=-2*L1+((2^1)*log(n));
%Second order:
AIC2=-2*L2+2*(2^2*(2-1));
BIC2=-2*L2+((2^2)*log(n));
%End of the calculation of AIC (Akaike. 1974) and BIC (Schwarz. 1978) criteria
disp ('---------------------------------------------------------------------------');
disp ('TESTS FOR OPTIMUM ORDER OF MARKOV CHAIN (AIC AND BIC)');
%VERDICT;
%Akaike Criterion:
if AIC0<AIC1 & AIC0<AIC2
    disp ('According to AIC criterion, optimum order to the Markov chain is ZERO');
elseif AIC1<AIC0 & AIC1<AIC2
    disp ('According to AIC criterion, optimum order to the Markov chain is ONE');
elseif AIC2<AIC0 & AIC2<AIC1
    disp ('According to AIC criterion, optimum order to the Markov chain is TWO);
end
%Bayesiano Criterion:
if BIC0<BIC1 & BIC0<BIC2
    disp ('According to BIC criterion, optimum order to the Markov chain is ZERO');
elseif BIC1<BIC0 & BIC1<BIC2
    disp ('According to BIC criterion, optimum order to the Markov chain is ONE');
elseif BIC2<BIC0 & BIC2<BIC1
    disp ('According to BIC criterion, optimum order to the Markov chain is TWO');
end
disp ('---------------------------------------------------------------------------');
T=toc;
fprintf ('Total processing time was (seconds): %1.2f\n', T);
%END OF PROCEDURE.
```

2) Module 2 – "*Gerar.m*"

```
%GENERATION OF SYNTHETIC SERIES OF PRECIPITATION
%Version 1.0 - 11/11/2009
%Author: Daniel Henrique Marco Detzel
%Theory used to determinate the elements present in this algorithm is referred in the
commentaries of each procedure;

%BEGINNING OF THE PROCEDURE
clear all
clc
tic;
%Opening of the archive containing data from the respective rainfall stations;
fid=fopen('serie.m','r');
C=fscanf(fid, '%g');
p10=input ('Enter with the prob. of wet day, given dry day (p10): ');
p11=input ('Enter with the prob. of wet day, given wet day (p11): ');
rmin=input('Enter with the minimum value for a day to be considered wet (mm):');
mult=input ('Enter with the number of series to be generated: ');
x=C(:); n=length(C); cont=0; k=1; t=1; z=0; erro=1; ni=0; Lf_anterior=0; rt=0; pc=0;
M=0;
%Beginning of the procedure of estimation of parameters, through the Moments
%                Method, according Rider (1961);
disp ('-----------------------------------------------------------------------------');
disp ('INITIAL ESTIMATIVE OF PARAMETERS - MOMENTS METHOD:');
for i=(1:n)
    if x(i)>rmin
        z(t)=x(i);
        t=t+1;
    end
    m1=mean(z);
    m2=var(z);
    m3=skewness(z.0);
end
M=[(6*((2*(m1^2))-m2)) (2*(m3-(3*m1*m2))) ((3*(m2^2))-(2*m1*m3))];
B_raiz=roots(M);
%Application of adaptations in the method to maintain the configuration of
%        parameters according with physical interpretation (B1>0. B2>0 e 0<a<1);
B=real(B_raiz);
if B(1,1)<0
    B(1,1)=(-1)*B(1,1);
elseif B(2,1)<0
    B(2,1)=(-1)*B(2,1);
end
if B(1,1)>B(2,1)
    B1_est_inicial=B(1,1);
    B2_est_inicial=B(2,1);
elseif B(1,1)<B(2,1)
    B1_est_inicial=B(2,1);
    B2_est_inicial=B(1,1);
elseif B(1,1)==B(2,1)
    B1_est_inicial=B(1,1)+10;
    B2_est_inicial=B(2,1);
end
a_est_inicial=abs(((m1-B2_est_inicial)/(B1_est_inicial-B2_est_inicial)));
if a_est_inicial>1
    a_est_inicial=1/a_est_inicial;
else
```

```
    a_est_inicial=a_est_inicial;
end
fprintf ('Initial estimate of alpha is: %1.4f\n', a_est_inicial);
fprintf ('Initial estimate of beta 1 is: %1.4f\n', B1_est_inicial);
fprintf ('Initial estimate of beta 2 is: %1.4f\n', B2_est_inicial);
%End of the procedure of estimation of parameters, through the Moments Method
%Beginning of the procedure of definite estimation of parameters, through
%      EM Algorithm, according to Wilks (2006, p. 117);
disp ('---------------------------------------------------------------------------');
disp ('DEFINITE ESTIMATION OF PARAMETERS - MAX. LIKELIHOOD METHOD: ');
%Counting of numbers of rainy days of the respective rainfall station;
while k<=n
   if x(k)>rmin
       cont=cont+1;
   end
   k=k+1;
end
%EM Algorithm development (Wilks. 2006, p. 117);
a=a_est_inicial;
B1=B1_est_inicial;
B2=B2_est_inicial;
int=1;
while erro>=0.0001 & ni<5000
    for i=(1:n)
        if x(i)<rmin
            Pfi(i)=0;
            lnL(i)=0;
        else
            F=((a/B1)*exp(-(x(i)/B1)))+(((1-a)/B2)*exp(-(x(i)/B2)));
            f1=(a/B1)*exp(-(x(i)/B1));
            f2=((1-a)/B2)*exp(-(x(i)/B2));
            Pfi(i)=f1/(f1+f2);
            lnL(i)=log(F);
        end
    end
    a=(1/cont)*(sum(Pfi));
    B1=(1/(cont*a))*(Pfi*x);
    B2=(1/(cont*(1-a)))*((1-Pfi)*x);
    Lf_atual=sum(lnL);
    erro=abs(Lf_atual-Lf_anterior);
    Lf_anterior=Lf_atual;
    ni=ni+1;
    int=int+1;
end
if B1>B2
    ad=a;
    B1d=B1;
    B2d=B2;
else
    ad=1-a;
    B1d=B2;
    B2d=B1;
end
fclose(fid);
fprintf ('Definite estimate of alpha is: %1.4f\n', ad);
fprintf ('Definite estimate of beta 1 is: %1.4f\n', B1d);
fprintf ('Definite estimate of beta 2 is:%1.4f\n', B2d);
fprintf ('The number of iterations: %1.0f\n', int);
```

```
disp ('--------------------------------------------------------------------------------');
%End of the procedure of definite estimation of parameters;
%Generation of the series (Wilks, 1998);
%Occurrences determination;
Pr=[p10  p11];
%Renewing the seeds of random numbers;
rand('state', sum(100*clock));
rand('seed', sum(100*clock));
%Definition of Initial State;
for i=(1:mult)
        w1=rand(1);
        if  w1<= Pr(1,2)
            Einicial=1;
        else
            Einicial=0;
        end
    %Determination of the other occurrences
        if Einicial==0
           pc=Pr(1,1);
        elseif Einicial==1
           pc=Pr(1,2);
        end
        for j=(1:n)
            u=rand(1);
                if u<ad
                    B=B1d;
                else
                    B=B2d;
                end
    %Determination of amounts
            v=rand(1);
            rt=rmin-(B*(log(v)));
            w2 = randn(1);
                if w2<=pc
                    Xt=1;
                    Y=rt*Xt;
                    pc=Pr(1,2);
                else
                    Xt=0;
                    Y=0;
                    pc=Pr(1,1);
                end
             Yt(I,j)=Y;
         end
end
%Composition of output file;
dlmwrite('series_geradas.m',Yt,';')
T=toc;
fprintf ('Total processing time was (seconds): %1.2f\n', T);
disp ('--------------------------------------------------------------------------------');
%END OF PROCEDURE.
```

3) Módulo 3 – "*Validacao.m*"

```
%VALIDATION OF THE MODEL
%Version 1.0 - 11/11/2009
%Author: Daniel Henrique Marco Detzel
```

```
%BEGINNIG OF THE PROCEDURE
clear
clc
tic;
%Calculus of basic statistics of historical series;
fid=fopen('serie.m','r');
C=fscanf(fid, '%g');
%Initial declaration of variables;
alpham=input('Enter with the significance degree for the mean related tests, in
percentage: ');
alphad=input(' Enter with the significance degree for the Standard deviance related
tests, in percentage: ');
rmin=input('Enter with the minimum value for a day to be considered wet (mm): ');
disp ('-----------------------------------------------------------------------------');
disp ('ORIGINIAL SERIES STATISTICS:');
X=C(:); n=length(C); s=1; t=1; h=1; S=1; T=1;
%Beginning of calculus procedure;
%Basic statistics;
for i=(1:n)
    if X(i)>rmin
        U(s)=X(i);
        s=s+1;
    elseif X(i)<rmin
        V(t)=X(i);
        t=t+1;
    end
end
media=mean(U);
desvpad=std(U);
totalprec=sum(U);
maximo=max(U);
dchuva=length(U);
dseco=length(V);
fprintf ('The mean is: %1.2f mm\n', media);
fprintf ('The standard deviance is: %1.2f mm\n', desvpad);
fprintf ('Total amount is: %1.2f mm\n', totalprec);
fprintf ('Daily maximum amount is: %1.2f mm\n', maximo);
fprintf ('Total of wet days is: %1.0f dias\n', dchuva);
fprintf ('Total of dry days is: %1.0f dias\n', dseco);
%Determination of Confidence Intervals;
gl=dchuva-1;
alpha_auxm1=alpham/100;
alpha_auxm2=(1-alpha_auxm1)/2;
zm=norminv([alpha_auxm2 alpha_auxm1+alpha_auxm2],0,1);
ICMinf=(media+(zm(1)*(desvpad/sqrt(dchuva))));
ICMsup=(media+(zm(2)*(desvpad/sqrt(dchuva))));
fprintf ('Inferior limit for the mean’s Confidence Interval is: %1.2f mm\n', ICMinf);
fprintf ('Superior limit for the mean’s Confidence Interval is %1.2f mm\n', ICMsup);
alpha_auxd1=alphad/100;
alpha_auxd2=(1-alpha_auxd1)/2;
chi_sup=chi2inv(alpha_auxd1+alpha_auxd2,gl);
chi_inf=chi2inv(alpha_auxd2,gl);
ICDinf=sqrt(((desvpad^2)*(dchuva-1))/chi_sup);
ICDsup=sqrt(((desvpad^2)*(dchuva-1))/chi_inf);
fprintf ('Inferior limit for the standard deviance’s Confidence Interval is: %1.2f
mm\n', ICDinf);
```

```
fprintf (Superior limit for the standard deviance’s Confidence Interval is: %1.2f
mm\n', ICDsup);
fclose(fid);
%End of procedure for historical series;
disp ('---------------------------------------------------------------------------');
disp ('SYNTHETIC SERIES STATISTICS (mean of the generated series):');
%Calculus of basic statistics of synthetic series;
%Opening of the file containing the generated series (file automatically created with
the execution of Module 2 - "Gerar.m");
D=dlmread('series_geradas.m',';');
m=length(D); p=1; q=1; [p,q]=size(D);
for i=(1:p)
    u=1; v=1; UU=1; VV=1;
    for j=(1:q)
        if D(I,j)>rmin
            UU(u)=D(I,j);
            u=u+1;
        elseif D(I,j)<=rmin
            VV(v)=D(I,j);
            v=v+1;
        end
    end
    correl_calc=corrcoef(D(I,:),X);
    correl(i)=correl_calc(1,2);
    media_sint(i)=mean(UU);
    desvpad_sint(i)=std(UU);
    totalprec_sint(i)=sum(UU);
    maximo_sint(i)=max(UU);
    dchuva_sint(i)=length(UU);
    dseco_sint(i)=length(VV);
end
Media_media=mean(media_sint);
Media_desvpad=mean(desvpad_sint);
Media_totalprec=mean(totalprec_sint);
Media_maximo=mean(maximo_sint);
Media_dchuva=mean(dchuva_sint);
Media_dseco=mean(dseco_sint);
Media_correl=mean(correl);
fprintf ('The mean is: %1.2f mm\n', Media_media);
fprintf ('The standard deviance is: %1.2f mm\n', Media_desvpad);
fprintf ('Total amount is: %1.2f mm\n', Media_totalprec);
fprintf ('Daily maximum amount is: %1.2f mm\n', Media_maximo);
fprintf ('Total of wet days is: %1.0f dias\n', Media_dchuva);
fprintf ('Total of dry days is: %1.0f dias\n', Media_dseco);
fprintf ('Cross correlations coeficient is: %1.4f\n', Media_correl);
%Composition of output file;
Vetor_media_sint=media_sint';
fid = fopen('Vetor_media_sint.m', 'w');
fprintf (fid, '%8.4f\n', Vetor_media_sint);
fclose(fid);
Vetor_desvpad_sint=desvpad_sint';
fid = fopen('Vetor_desvpad_sint.m', 'w');
fprintf (fid, '%8.4f\n', Vetor_desvpad_sint);
fclose(fid);
%End of procedure for synthetic series;
%Statistical significance tests for means and standard deviances (t-test and chi-square
test);
disp ('---------------------------------------------------------------------------');
```

```
disp ('SIGNIFICANCE TESTS FOR MEANS:');
t_inf=tinv(alpha_auxm2,gl);
t_sup=-t_inf;
tcal=(media-Media_media)/(desvpad/sqrt(dchuva));
if tcal<t_sup & tcal>t_inf
    disp ('Accepted H0 hypothesis - Means are statistically equal.');
else
    disp('Rejected H0 hypothesis - Means are not statistically equal.');
end
disp ('-----------------------------------------------------------------------------');
disp ('SIGNIFICANCE TESTS FOR STANDARD DEVIATIONS:');
chi_cal=((dchuva-1)*desvpad)/Media_desvpad;
if chi_cal<chi_sup & chi_cal>chi_inf
    disp ('Accepted H0 hypothesis - Standard Deviations are statistically equal.');
else
    disp('Rejected H0 hypothesis - Standard Deviations are not statistically equal.');
end
disp ('-----------------------------------------------------------------------------');
T=toc;
fprintf ('Total processing time was (seconds): %1.2f\n', T);

%END OF PROCEDURE.
```

4) Module 4 – "*Valores_extremos.m*"

```
%EXTREME EVENTS ANALYSES
%Version 1.0 - 05/11/2009
%Author: Daniel Henrique Marco Detzel

%BEGINNING OF THE PROCEDURE
clear
clc
rmin=input('Enter with the minimum value for a day to be considered wet (mm): ');
tic
%Analysis of the historical series:
disp ('-----------------------------------------------------------------------------');
disp ('ANALISE DA SERIE HISTORICA ORIGINAL:');
%Opening of the file containing the historical series;
fid=fopen('serie.m','r');
C=fscanf(fid, '%g');

%DETERMINATION OF THE MAXIMUM NUMBER OF CONSECUTIVE DAYS IN THE SAME STATE:
%Initial declaration of variables;
X=C(:); n=length(C); Sc=zeros(1,n); sc=1; Mc=zeros(1,n); mc=1; aux=1;
for i=(2:n)
    if X(i-1)<rmin & X(i)<rmin
        aux=aux+1;
    else
        Sc(sc)=aux;
        sc=sc+1;
        aux=1;
    end
end
aux=1;
for i=(2:n)
    if X(i-1)>rmin & X(i)>rmin
        aux=aux+1;
```

```
    else
        Mc(mc)=aux;
        mc=mc+1;
        aux=1;
    end
end
Max_periodo_seco=max(Sc);
Max_periodo_molhado=max(Mc);
fprintf ('The larger period without rain (drought) is: %1.0f dias,\n',
Max_periodo_seco);
fprintf ('The larger rainy period is: %1.0f dias,\n', Max_periodo_molhado);

%COUNTING OF THE NUMBER OF CONSECUTIVE DRY DAYS IN A SAME STATE, PER CLASS:
S=zeros(1,n); aux=1;
for i=(2:n)
    if X(i-1)<rmin
        if X(i-1)<rmin & X(i)<rmin
            aux=aux+1;
        else
            S(aux)=S(aux)+1;
            aux=1;
        end
        if i==n & X(n)<rmin
            S(aux)=S(aux)+1;
        end
    end
end
%Vector "S" assumes the quantities of occurrences inside each class;
%DETERMINATION OF MAXIMUM AMOUNTS FOR 1 TO 10 DAYS OF DURATION:
%Initial declaration of vectors to be used;
T2=zeros(1,2); T3=zeros(1,3); T4=zeros(1,4); T5=zeros(1,5); T6=zeros(1,6);
T7=zeros(1,7); T8=zeros(1,8); T9=zeros(1,9); T10=zeros(1,10);
%One day:
Max_1=max(X);
Max_1M=mean(X);
%Two days:
t=1;
for i=(1:n-1)
    T2(t)=X(i)+X(i+1);
    t=t+1;
end
Max_2=max(T2);
Max_2M=mean(T2);
%Three days:
t=1;
for i=(1:n-2)
    T3(t)=X(i)+X(i+1)+X(i+2);
    t=t+1;
end
Max_3=max(T3);
Max_3M=mean(T3);
%Four days:
t=1;
for i=(1:n-3)
    T4(t)=X(i)+X(i+1)+X(i+2)+X(i+3);
    t=t+1;
end
Max_4=max(T4);
```

```
Max_4M=mean(T4);
%Five days:
t=1;
for i=(1:n-4)
     T5(t)=X(i)+X(i+1)+X(i+2)+X(i+3)+X(i+4);
     t=t+1;
end
Max_5=max(T5);
Max_5M=mean(T5);
%Six days:
t=1;
for i=(1:n-5)
     T6(t)=X(i)+X(i+1)+X(i+2)+X(i+3)+X(i+4)+X(i+5);
     t=t+1;
end
Max_6=max(T6);
Max_6M=mean(T6);
%Seven days:
t=1;
for i=(1:n-6)
     T7(t)=X(i)+X(i+1)+X(i+2)+X(i+3)+X(i+4)+X(i+5)+X(i+6);
     t=t+1;
end
Max_7=max(T7);
Max_7M=mean(T7);
%Eight days:
t=1;
for i=(1:n-7)
     T8(t)=X(i)+X(i+1)+X(i+2)+X(i+3)+X(i+4)+X(i+5)+X(i+6)+X(i+7);
     t=t+1;
end
Max_8=max(T8);
Max_8M=mean(T8);
%Nine days:
t=1;
for i=(1:n-8)
     T9(t)=X(i)+X(i+1)+X(i+2)+X(i+3)+X(i+4)+X(i+5)+X(i+6)+X(i+7)+X(i+8);
     t=t+1;
end
Max_9=max(T9);
Max_9M=mean(T9);
%Ten days:
t=1;
for i=(1:n-9)
     T10(t)=X(i)+X(i+1)+X(i+2)+X(i+3)+X(i+4)+X(i+5)+X(i+6)+X(i+7)+X(i+8)+X(i+9);
     t=t+1;
end
Max_10=max(T10);
Max_10M=mean(T10);
%End of procedure for the historical series;
disp ('----------------------------------------------------------------------------');
disp ('ANALYSIS OF SYNTHETC SERIES (means of the generated series):');
%Opening of the file containing the generated series (file automatically created with
the execution of Module 2 - "Gerar.m");
D=dlmread('series_geradas.m',';');
%DETERMINATION OF THE MAXIMUM NUMBER OF CONSECUTIVE DAYS IN THE SAME STATE:
%Initial declaration of variables;
m=length(D); [p,q]=size(D); Ss=zeros(p,q); Ms=zeros(p,q); aux=1; a=1; b=1; c=1; d=1;
```

```
Vs=zeros(1,p); Vm=zeros(1,p);
for i=(1:p)
    for j=(2:q)
        if D(i,j-1)<rmin & D(i,j)<rmin
            aux=aux+1;
        else
            Ss(a,b)=aux;
            b=b+1;
            aux=1;
        end
    end
    Ss(a,b)=aux;
    a=a+1;
    b=1;
    aux=1;
    Vs(i)=max(Ss(i,:));
    for j=(2:q)
        if D(i,j-1)>rmin & D(i,j)>rmin
            aux=aux+1;
        else
            Ms(c,d)=aux;
            d=d+1;
            aux=1;
        end
    end
    Ms(c,d)=aux;
    c=c+1;
    d=1;
    aux=1;
    Vm(i)=max(Ms(i,:));
end
Max_periodo_seco_medio=mean(Vs);
Max_periodo_molhado_medio=mean(Vm);
fprintf ('The larger period without rain (drought) is: %1.0f dias,\n'.
Max_periodo_seco_medio);
fprintf ('The larger rainy period is: %1.0f dias,\n'. Max_periodo_molhado_medio);
%COUNTING OF THE NUMBER OF CONSECUTIVE DRY DAYS IN A SAME STATE, PER CLASS:
R=zeros(p,q); Rmed=zeros(1,fix(Max_periodo_seco_medio)+1);
for i=(1:p)
    aux=1;
    for j=(2:q)
        if D(i,j-1)<rmin
            if D(i,j-1)<rmin & D(i,j)<rmin
                aux=aux+1;
            else
                R(i,aux)=R(i,aux)+1;
                aux=1;
            end
        end
        if j==q & D(i,q)<rmin
            R(i,aux)=R(i,aux)+1;
        end
    end
end
Rmed=mean(R);
%Vector "Rmed" assumes the quantities of occurrences inside each class;
%DETERMINATION OF MAXIMUM AMOUNTS FOR 1 TO 10 DAYS OF DURATION:
%Initial declaration of vectors to be used;
```

```
TS1=zeros(1,1); TS2=zeros(1,2); TS3=zeros(1,3); TS4=zeros(1,4); TS5=zeros(1,5);
TS6=zeros(1,6); TS7=zeros(1,7); TS8=zeros(1,8); TS9=zeros(1,9); TS10=zeros(1,10);
for i=(1:p)
    %One day:
    MaxS_1(i)=max(D(i,:));
    MaxS_1M=mean(MaxS_1);
    Med_1(i)=mean(D(i,:));
    MaxS_1MM=mean(Med_1);
    %Two days:
    t=1;
    for j=(1:q-1)
        TS2(i,t)=D(i,j)+D(i,j+1);
        t=t+1;
    end
    MaxS_2(i)=max(TS2(i.:));
    MaxS_2M=mean(MaxS_2);
    Med_2(i)=mean(TS2(i.:));
    MaxS_2MM=mean(Med_2);
    %Three days:
    t=1;
    for j=(1:q-2)
        TS3(i,t)=D(i,j)+D(i,j+1)+D(i,j+2);
        t=t+1;
    end
    MaxS_3(i)=max(TS3(i,:));
    MaxS_3M=mean(MaxS_3);
    Med_3(i)=mean(TS3(i,:));
    MaxS_3MM=mean(Med_3);
    %Four days:
    t=1;
    for j=(1:q-3)
        TS4(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(i,j+3);
        t=t+1;
    end
    MaxS_4(i)=max(TS4(i,:));
    MaxS_4M=mean(MaxS_4);
    Med_4(i)=mean(TS4(i,:));
    MaxS_4MM=mean(Med_4);
    %Five days:
    t=1;
    for j=(1:q-4)
        TS5(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(I,zj+3)+D(i,j+4);
        t=t+1;
    end
    MaxS_5(i)=max(TS5(i,:));
    MaxS_5M=mean(MaxS_5);
    Med_5(i)=mean(TS5(i,:));
    MaxS_5MM=mean(Med_5);
    %Six days:
    t=1;
    for j=(1:q-5)
        TS6(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(i,j+3)+D(i,j+4)+D(i,j+5);
        t=t+1;
    end
    MaxS_6(i)=max(TS6(i,:));
    MaxS_6M=mean(MaxS_6);
    Med_6(i)=mean(TS6(i,:));
    MaxS_6MM=mean(Med_6);
```

```
    %Seven days:
    t=1;
    for j=(1:q-6)
        TS7(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(i,j+3)+D(i,j+4)+D(i,j+5)+D(i,j+6);
        t=t+1;
    end
    MaxS_7(i)=max(TS7(i,:));
    MaxS_7M=mean(MaxS_7);
    Med_7(i)=mean(TS7(i,:));
    MaxS_7MM=mean(Med_7);
    %Eight days:
    t=1;
    for j=(1:q-7)
        TS8(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(i,j+3)+D(i,j+4)+D(i,j+5)+D(i,j+6)
+D(i,j+7);
        t=t+1;
    end
    MaxS_8(i)=max(TS8(i,:));
    MaxS_8M=mean(MaxS_8);
    Med_8(i)=mean(TS8(i,:));
    MaxS_8MM=mean(Med_8);
    %Nine days:
    t=1;
    for j=(1:q-8)
        TS9(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(i,j+3)+D(i,j+4)+D(i,j+5)+D(i,j+6)
+D(i,j+7)+D(i,j+8);
        t=t+1;
    end
    MaxS_9(i)=max(TS9(i,:));
    MaxS_9M=mean(MaxS_9);
    Med_9(i)=mean(TS9(i,:));
    MaxS_9MM=mean(Med_9);
    %Ten days:
    t=1;
    for j=(1:q-9)
        TS10(i,t)=D(i,j)+D(i,j+1)+D(i,j+2)+D(i,j+3)+D(i,j+4)+D(i,j+5)+D(i,j+6)
+D(i,j+7)+D(i,j+8)+D(i,j+9);
        t=t+1;
    end
    MaxS_10(i)=max(TS10(i,:));
    MaxS_10M=mean(MaxS_10);
    Med_10(i)=mean(TS10(i,:));
    MaxS_10MM=mean(Med_10);
end
%Creation of output table:
Res_ori=[Max_1, Max_2, Max_3, Max_4, Max_5, Max_6, Max_7, Max_8, Max_9, Max_10];
Res_sin=[MaxS_1M, MaxS_2M, MaxS_3M, MaxS_4M, MaxS_5M, MaxS_6M, MaxS_7M, MaxS_8M,
MaxS_9M, MaxS_10M];
Res_ori_M=[Max_1M, Max_2M, Max_3M, Max_4M, Max_5M, Max_6M, Max_7M, Max_8M, Max_9M,
Max_10M];
Res_sin_M=[MaxS_1MM, MaxS_2MM, MaxS_3MM, MaxS_4MM, MaxS_5MM, MaxS_6MM, MaxS_7MM,
MaxS_8MM, MaxS_9MM, MaxS_10MM];
disp (' ');
disp ('TABLE WITH THE TOTAL AMOUNTS PER PERIOD:');
disp
('+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
+++++++++++++++');
```

```
fprintf ('Period (days)     |   1\t      2\t      3\t      4\t      5\t      6\t
7\t      8\t      9\t      10\n');
fprintf ('Abs. Observed (mm)| %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t
%2.1f\t %2.1f\t %2.1f\n', Res_ori);
fprintf ('Abs. Generated (mm)   | %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t
%2.1f\t %2.1f\t %2.1f\t %2.1f\n', Res_sin);
fprintf ('Mean Observed (mm)|   %2.1f\t   %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t
%2.1f\t %2.1f\t %2.1f\t %2.1f\n', Res_ori_M);
fprintf ('Mean Generated (mm)   |   %2.1f\t   %2.1f\t %2.1f\t %2.1f\t %2.1f\t %2.1f\t
%2.1f\t %2.1f\t %2.1f\t %2.1f\n', Res_sin_M);
disp
('+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
+++++++++++++++');
disp (' ');
disp ('---------------------------------------------------------------------------');
T=toc;
fprintf ('Total processing time was (seconds): %1.2f\n', T);
```