COMPARISON OF DIFFERENT RAINFALL INPUTS IN A CONTINUOUS RAINFALL-RUNOFF MODEL – A CASE STUDY FOR ARGENTINA

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“Comparison of different rainfall inputs in a continuous rainfall-runoff model – a case study for Argentina”

Hydrological models are mainly used for planning and design of flood protection measures or for flood forecasting. These models are applied to simulate the rainfall-runoff processes and they rely on the precipitation data with a proper resolution in space and time. As different sources of rain data are available, the aim of this work is to study and compare between the types of data that are typically available in Argentina, and draw conclusions regarding their use for hydrological modeling.

The work consists of applying different rain data as input for a rainfall-runoff hydrological model. The north-catchment of the Neuquén river in Argentina will be used to investigate the available information. Daily station data registered in 20 stations in the case study region will be compared to the daily TRMM dataset of satellite – derived precipitation. A geostatistical analysis will be performed in order to spatially interpolate the point observation to raster cells. The three sets of rainfall input, i.e. the station data, the interpolation and the precipitation derived from the TRMM datasets, will be used as inputs in a continuous rainfall-runoff simulation and the results will be compared to the observed flows. The modelling will be carried out for 10 years on a daily time step basis. The rainfall data will be compared in terms of the simulation results, different evaluation criteria must be specified which are relevant for an efficient management of the water resources. A comparison between the results in different catchment scales will be performed.

Especially the following tasks have to be carried out:
- Literature research and state of art
- Analyse the study region and data and define the problem
- Geostatistical analysis and spatial interpolation of the station data
- Setting up of a semi-distributed hydrological model in HEC-HMS
- Upscaling of the rainfall data for the different subbasins, according to the spatial configuration of the hydrological model
- Calibration and validation of the model performance
- Developing and evaluation of methods for comparison between the different inputs

The candidate is provided with daily precipitation and discharge data in different locations of the study region. The available programs for this thesis are ArcGIS, HEC-HMS, Statistic Software System R and GSLIB (or other Geostatistical Software). A computer working place will be provided if necessary. The completed work should give a well sorted overview over the topic using diagrams and tables. One electronic and three hardcopy versions of the work have to be submitted. The student has to present his work in a talk of 15 minutes duration.

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DECLARATION

I declare that this research paper for the degree of Master of Science in Water Resources and Environmental Management, Faculty of Civil Engineering and Geodetic Science, Leibniz Universität Hannover hereby submitted has not been submitted by me or anyone else for a degree at this or any other university. That it is my own work and that materials consulted have been properly acknowledged.

Hannover, August 2013
ABSTRACT

Precipitation data is the main input parameter in order to simulate rainfall-runoff processes, since it is strongly dependent on the accuracy of the spatial and temporal representation of the precipitation. In regions where rainfall stations are scarce, additional data sources may be considered necessary. In this manner, remote sensing from satellite platforms has provided a satisfactory alternative due to its global coverage. Although a wide range of satellite-based estimations of precipitation is available, not all the satellite products are suitable for all regions. Most of the studies performed with the purpose of evaluating their accuracy are focused in particular areas of the world. In this fashion, particular models have to be conducted in order to evaluate their performances, specially in regions with complex geography as high mountains.

Additionally, to perform an appropriate spatial representation of the rainfall and consequently to improve the available data, interpolation techniques are used, e.g. simple techniques as Nearest Neighbour or Inverse Distance methods, and some more complex as geostatistical (Kriging) methods. This last one offers the advantage of adding relevant additional information in the interpolation, providing a chance to compensate a low network density. Moreover, in data scarce regions in which interpolation schemes are applied, it becomes difficult to have an accurate performance assessment; in this manner, other comparison tool is required as rainfall-runoff models.

In this manner, the aim of this study is to perform a comparison between different types of available rainfall data by means of a hydrological model. The work is focused in Neuquén catchment, a mountainous region of Argentina where several rainfall stations and flow gauges are available. In this fashion, a satellite-based estimated precipitation already validated in mountainous areas and southern latitudes, CMORPH, is used as well as the available rainfall stations as input. Moreover, to improve the rainfall stations measurements, CMORPH data and topography are used during the interpolation as additional variables. Consequently, five precipitation input cases are generated and compared. To accomplish the main objective, at first several interpolation techniques are tested and assessed by means of cross-validation for each precipitation input. Subsequently, a hydrological model HEC-HMS is set up for every case and thus its outcomes are compared using indices of reliability.

Regarding the cases that consider the rainfall stations data, assess from the interpolation technique showed that the best performance is obtained with the case without external drift. Conversely, the hydrological model showed the most accurate precision when topography was used as additional information. Input cases with the satellite-based estimations as external drift improved considerably the results in comparison to the case in which rainfall stations are considered alone. However, results showed that the case with CMORPH data as only input, the estimation of the observed discharge was not able to be reproduced precisely. Finally it could be concluded that, in those cases in which the rainfall stations networks are not dense enough and do not represent the spatial variability of the area correctly additional information is extremely useful to simulate more accurately the observed discharge in the area.

Keywords: Rainfall-runoff model, Rainfall, CMORPH, interpolation schemes, Kriging methods, HEC-HMS, Neuquén catchment
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1 Introduction

1.1 Problem setting and objective of the work

Hydrological models are a useful main tool used for planning and answering questions related to water resources. These models simulate rainfall-runoff processes mostly using precipitation information as the main input parameter. Precipitation data has a strong spatial and temporal variability requiring an appropriate and accurate representation for large scale areas. Thus, it is a prerequisite for hydrological planning to have spatially and temporarily precipitation inputs. Consequently, the quality of a hydrological modelling outcome is highly dependent on the feature of the available data.

In many regions of the world, rainfall stations are scarce. In this manner, additional data sources of precipitation are required. In developing countries, ground based precipitation station may even be none-existing due to the costs of establishing and maintenance of such system. Thus, during the last years, remote sensing from satellite platforms has provided a satisfactory alternative source, being a complementary option due to its global coverage.

A wide range of satellite-based estimations of precipitation are available in high spatial and temporal resolution, which makes them useful for distributed hydrological models. However, not all the satellite products are suitable for all the regions. Therefore, hydrologists are still sceptic in applying these products directly in hydrological applications knowing that lots of uncertainties are still involved in such techniques (Bitew and Gebremichael, 2011).

Several studies have been focused in comparing different satellite sources and their accuracy with the intention of predicting floods in hydrological modelling (Thiemig et al., 2012; Bitew and Gebremichael, 2011; Cohen Liechti et al., 2012). Nevertheless, most of the studies are focused in particular areas of the world without a viable extrapolation to other regions. Hence, particular models have to be performed in order to compare the truthfulness of the satellite-based precipitation source on a particular area.

Additionally, the geography of a region is also affecting the accuracy of satellite-based precipitation estimations. For example, high mountains experience strong weather and climate variability because of their topography. Therefore, they are considered as a quite challenging environment for remote-sensing-based precipitation estimations. Moreover, they are characterized for their lack of climate data (Scheel et al., 2011). Hence, a common question that can be asked is how to narrow this gap in these particular regions.

Moreover, in those areas where the available rainfall stations network is not enough an improvement of the data must be performed to represent the spatial variability. Thus, interpolation techniques are used to perform an appropriate spatial representation of the data.

Several interpolation techniques are available and commonly used (Isaaks and Srivastava, 1989). In case of short time scales, spatial patterns become more heterogenous and marked, therefore appropriate interpolation schemes are required (Wagner et al., 2012). Some of the interpolation techniques are simpler, as Nearest Neighbour or Inverse Distance methods, and others may be even more complex as geostatistical (Kriging) methods.
The first step in geostatistical methods is the determination of the semivariogram. In mountainous areas it becomes crucial when there is a sparse network of rainfall stations so the spatial persistence can be hardly represented (Verworn and Haberlandt, 2011).

Furthermore, geostatistical techniques offer the advantage of adding relevant additional information in the interpolation (Goovaerts, 1997). Previous studies have shown that bivariate or multivariate geostatistical methods outperform univariate methods (Haberlandt, 2006). Moreover, they may compensate a low network density (Wagner et al., 2012). The additional variable which is included during the interpolation should be able to explain the interpolated variable. Therefore, satellite estimated precipitations can be used also as a tool to improve the rainfall stations data, providing an extra use for the satellite-based rainfall estimations. Moreover, when the study catchment is characterized with high variability in the topography, elevation can be as well used as an external drift during the interpolation.

In data scarce regions where interpolation schemes are applied, it is difficult to have an accurate performance assessment. Cross-validation is the most often used method to evaluate it, being the accuracy of the interpolation methods related to the amount of rainfall stations in the study area. Thus, when the number of rainfall stations is not representative for the study region, these criterion is hardly accomplished (Wagner et al., 2012). Accordingly, areal precipitation can be compared and evaluated by means of hydrological models.

In this manner, the present study is focused in the Neuquén catchment, a region of Argentina where several rainfall stations are available in daily bases. The study area is a medium-large watershed of around 32,500 km² located in a region that experiences a strong variation of topography from high mountains in the north-west to flat areas in the south-east.

As there is no available validation of any satellite-based precipitation estimations in this region, the product to be used is selected according to its application in different similar areas. The Climate Prediction Centre (NOAA-CPC) morphing method, CMORPH has been validated in southern areas in Australia (Joyce et al., 2004). Moreover, this product showed usefulness to monitor and forecast large-scale organized weather systems in South America (Pereira Filho et al., 2010) and additionally, accurate results in the Ethiopian mountainous areas have been obtained with it (Bitew and Gebremichael, 2011). Therefore, is chosen to be tested during this work.

Consequently, to study the performance of the different precipitation inputs, interpolation techniques are applied to the five different cases to be studied. Four of them have rainfall stations as the main input and the fifth case has satellite estimations. From the cases with rainfall stations as main inputs, only one considers this data alone, while the other three cases are combined with external drifts as topography, satellite estimations or the combination of both.

Accordingly, a rainfall-runoff model is performed to compare the different precipitation inputs. This research focuses in long-term continuous modelling with Hydrological-Modelling-System Version 3.3 (HEC-HMS) of the US Army of Engineers (Feldman, 2000). Consequently, HEC-HMS is chosen to compare the different rainfall inputs in daily bases.

Hydrological models, as HEC-HMS, are based on physical processes that occur in a particular catchment. Usually, for large scale models is not possible to describe the hydrological cycle in physical detail (Chow et al., 1988). Furthermore, usually there is not
enough data to represent the hydrological processes in a basin. Hence, calibration techniques are required with the purpose of estimating uncertain parameters (Beven, 2001).

Available rainfall stations measurements, satellite-based estimations of precipitations and flow observations, are presented for 12 years in daily bases within the study area. For modelling purposes two time windows of 6 years are studied, the first for calibration (1998-2003) and the second period for validation (2006-2011).

In this context, the main objective of this work is to compare the different types of available precipitation data by means of a hydrological model. Therefore, every model must be calibrated independently and objectively for each rainfall input. Consequently, the selected tool with the intention of performing the calibration is the dynamically dimensioned search (DDS) algorithm developed by Tolson and Shoemaker (2007).

1.2 Structure of the work

Subsequently to the “Introduction” the “Literature Review” section is presented which is divided in three subsections. The first subsection gives an overview of the main hydrological processes with references to some of the publications and books related to them. Moreover, in this subsection, the two main sources of precipitation data, rainfall stations and satellite-based estimations, are described. Regarding the satellite rainfall estimations, a description of available sources and previous publications with their application are stated. The second subsection, involves the interpolation techniques and a brief description of some of the publications related with their application. Finally, the “Literature Review” section closes with a description of the main characterizations of a hydrological model and a review of some possible relevant rainfall-runoff models available in the market.

The next section is the “Methodology” which is divided into a set of subsections with a description of the methods, equations and assumptions performed in the different steps of the calculations. These steps are set up in chronological order of application, starting from the applied interpolation methods and followed by the hydrological model. Regarding the interpolation schemes, the different applied techniques are described, while for the hydrological model different methods of each process are explained. In both subsections, performance assessments used to evaluate the methodologies are stated.

In the section “Study Area and Data”, a brief description of the study catchment is presented. Moreover, the available hydrological information used for the work with a measure of its accuracy is introduced. In addition, some complementary information is included.

The section “Results” includes the outcomes obtained in the different steps of the calculations, which is described in the section “Methodology”. The “Interpolation” subsection includes the results regarding the base variogram, cross-validation and interpolation results for different tests for precipitation and temperature. In the case of precipitation, the results for the five cases are shown. The “Rainfall-runoff model” subsection first describes the main characteristics of the model followed by the presentation of the main inputs. The parameters adopted for the Basins and Rivers are also introduced. Regarding the implemented calibration technique, first the parameters left out for it are established and afterwards the obtained optimum parameters for all the cases are showed. Finally, the hydrographs and flow mass curves obtained for the validation and calibration periods are presented and discussed.
A summary with conclusions and final discussions is given in the chapter “Conclusions and discussion”. Ideas regarding further studies can be found in the “Future Works” section. The subsequent section is “Acknowledgments”.

In the “References” section, all details regarding the mentioned references in the work can be assessed.

Lastly, four appendices are included. The first appendix presents the gaps of the recorded data for rainfall stations and flow gauges. The second appendix introduces the files, which were used to read the satellite-base rainfall estimations. The third appendix shows the optimum parameters obtained by means of the calibration technique while finally the fourth appendix resumes the input file for running the hydrological model.
2 Literature review

As stated in the previous section the main aim of this work is the comparison of different rainfall inputs by means of a hydrological model. To accomplish this objective, the hydrological processes involved in a catchment must be understood. Therefore, in the beginning of this section the main hydrological processes and the interaction between them as well as a brief description of some methodologies for their estimation is presented.

In order to generate different inputs, different interpolation techniques are commonly used and consequently are presented in this section. There are an important number of works and publications in which these techniques were applied and compared. In the following paragraphs, the contents and conclusions of some of these publications are briefly described.

Finally, in the end of this section different classifications of hydrological models are introduced. Moreover, available hydrological models are presented and compared regarding the different performed applications.

2.1 Hydrological processes

As stated in Maidment (1993) “Hydrology is concerned with the circulation of water and its constituents through the hydrologic cycle. It deals with precipitation, evapotranspiration, infiltration, groundwater flow, runoff, streamflow, and the transport of substances dissolved or suspended in flowing water. Hydrology is primarily concerned on water on or near the land surface”.

Therefore, at a particular point on a channel the streamflow is generated by a contribution area. Their boundaries are mainly delimitated by topography and it can be distinguished between surface and subsurface catchments. Thus, catchments are usually the units of study of the hydrological processes in which a relation of them can be performed by means of the Water Balance equation (1).

\[ P = ET + R + \Delta S \]

where P is the precipitation, ET the evapotranspiration, \( \Delta S \) is the storage change and R is the runoff. Additionally, R includes the surface runoff, the interflow, the groundwater runoff, the inflow and outflow from the system, transfers and withdrawals of water.

The hydrology phenomena are extremely complex. For practical purpose, usually few processes of the entire hydrologic cycle are considered. In addition, a small portion of the surface of the earth is taken into account; therefore the global system is reduced to the concept of control volume. Moreover, a hydrologic system is defined by Chow et al (1988) as “a structure or volume in space, surrounded by a boundary, that accepts water and other input, operates on them internally, and produces them as outputs”.

According to Chow et al (1988), hydrologic processes convert the distribution in space and time of water during the hydrological cycle. Physical properties as the shape and size of a stream influence the motion of water in the hydrologic system. Moreover, there are several physical laws that govern the operation of the system. Consequently, the control volume is used to develop continuity, momentum and energy balance for various hydrologic processes.
2.1.1 Precipitation

Chow et al (1988) defines precipitation as liquid or solid water dropped from the atmosphere. It includes all the processes and ways of water falling to the land as rain, snow, hail, sleet, etc. The phenomena of hydrology are mainly driven by precipitation. Precipitation is characterized for its variability in space and time and its uncertainty. This variability depends on the general pattern of atmospheric circulation and also according to local factors. These characteristics are usually pronounced in mountainous areas, where orographic effects influence the precipitations. (Wilson and Guan, 2004). Moreover, seasonal variability can occur as well.

In catchments with high-mountainous ranges snow cover and melting become an issue. Usually snow affects the discharge mechanism of a stream, mainly originating delays. To estimate the snow-melt rate two different models can be used: energy-balanced models and temperature-index methods (Dingman, 1994). The second one is the simplest model, based on the temperature distribution which is related to the topography (temperature as the only input to represent all the available energy). Furthermore, this method is recommended for hydrological models running in daily basis, considering that with lower time steps radiation becomes more important. On the other hand, the energy-balanced model requires extensive observations and data because involves more physical processes.

Precipitation data can be obtained by different sources. Rainfall stations networks have always been rarely sparse in developing countries. Moreover, missing values and the reliability of the data is dubious. Hence, hydrological models become more important in those regions to evaluate the accuracy of the data. Nevertheless, the exactness of those models relies on the precise representation of the catchment precipitation inputs.

In this manner, new approaches are needed in order to provide these inputs or to complement the available data (Hughes, 2006). Therefore, during the last years, remote sensing from satellite platforms has provided a satisfactory alternative source, being a complementary option due to its global coverage.

2.1.1.1 Rainfall stations

Measurements of the precipitation commonly vary in the accuracy and precision along the different locations. Moreover, precipitation gauges measurements are punctual, representing a single site, and therefore the amount is usually underestimated (Maidment, 1993). However, the main problem is the low density of measurements in certain areas. Nevertheless, by means of well-established spatial interpolation techniques spatial estimates can be performed and consequently improve the rainfall stations data.

2.1.1.2 Satellite rainfall estimations

There are several global satellite rainfall products, which are becoming increasingly available at high spatial (<0.25°) and temporal (<3h) resolutions. This type of data is suitable for fully and semi distributed hydrological models. However, these products are still uncommonly used in operational hydrological applications. The rainfalls estimated by satellites are usually subjected to a variety of error sources, therefore validations are required (Bitew and Gebremichael, 2011).
Satellite rainfall estimations combine information from microwave (MW), longwave (LV) and infrared (IR) sensors from satellites. MW information is considered more accurate but infrequent, while IR is more frequent but indirect (Bitew and Gebremichael, 2011).

As stated in Scheel et al (2011) the most well-known satellite estimations are:

- TRMM Multi-satellite Precipitation Analysis - TMPA (Huffman et al., 2007) which is the only one which carries precipitation radars;
- CPC Morphing Technique - CMORPH (Joyce et al., 2004);
- The National Environmental Satellite, Data and Information Service – NESDIS – Hydro-estimator (Scofield and Kuligowski, 2003);
- The Naval Research Laboratory – NRL – Blended Technique (Turk and Miller, 2005);
- Estimation of precipitation using Remotely Sensed Information Using Artificial Neuronal Networks - PERSIANN (Sorooshian et al., 2000).

In mountainous areas there is usually lack of rainfall stations and there are challenges due to environmental conditions for remote sensing estimations. This is mainly due to variation in the topography and climate. However, not so many studies have been performed in this type of geography to validate the rainfall estimations of the satellite data. A study in the central Andes region in South America, showed that TMPA did not have a good correlation between the stations and the satellite estimation for daily basis, nevertheless results were acceptable for monthly basis. Also in the same study area, it was stated that precautions should be taken when applying it in hydrological models (Scheel et al., 2011). In another study in the Ethiopian Highlands (Bitew and Gebremichael, 2011) a hydrological model approach was performed in order to compare satellite rainfall products. In this study it was observed that TMPA and CMORPH were capable to estimate rainfalls very close to each other with the highest performance in comparison the other satellites estimations studied.

Another issue regarding satellite estimations is the latitude because not all algorithms have been validated for all the latitudes. Regarding southern latitudes, CMORPH has been reported to outperform other satellite rainfall estimations over the Australian tropics (Joyce et al., 2004). Furthermore, it was proved the effectiveness of the CMORPH analyses to monitor and forecast large-scale organized weather systems in South America (Pereira Filho et al., 2010). In other study in South-America (La Plata basin), it was concluded that models using TMPA as rainfall input showed good results in daily simulations (Su et al., 2008).

### 2.1.2 Evapotranspiration

As described by Maidment (1993) "evaporation is defined as the rate of liquid water transformation to vapour from: open water, bare soil, or vegetation with soil beneath". When there are soils with vegetation, transpiration is defined as “the part of the total evaporation which enters the atmosphere from the soil through the plant”. The sum of both is called evapotranspiration.

Chow et al (1988) explained that there are two main factors that affect the evaporation in an open water surface: the amount of energy, which provides the latent heat of vaporization, and the way the vapour is transported from the evaporative surface. These factors depend mainly on the solar radiation, the wind velocity over the surface and the gradient of humidity in the air above it. In addition, a third factor that influences the evapotranspiration is the moisture at the surface.
It can be distinguished between potential and real evapotranspiration. On the one hand, the potential occurs when there is a well vegetated surface without limiting in the moisture supply. On the other hand, the real evapotranspiration occurs when the soil dries out, this means only the actual water is available and might be equal or below the potential (Chow et al., 1988).

There are several ways to measure evapotranspiration. These can be distinguished between the loss from the surface or what the atmosphere gains from water. In the first case, it is measured in the liquid phase with the usage of lysimeters or evaporation pans. Since they are closed system, it can be deduced the amount that was lost in a certain time. The second type of measurement is in the vapour phase, and as it is an open system the rate of flow of vapour is measured. Therefore, balloons can be used to estimate the evaporation rate. However, this last technique is not usually used in the hydrologic practices because of its complexity (Maidment, 1993).

Empirical equations with can be distinguished for the calculation of potential and real evapotranspiration. Depending on the type of method, there are some calculations that are based on the energy balance equation (based on temperature and solar radiation), aerodynamics (based in the wind velocity and the saturation deficit) and also the combination of both. When including the soil properties and the soil moisture in the equation, it implies the calculation of the real evapotranspiration. To account the evapotranspiration in a cropping area, the calculated evapotranspiration from the grass or a reference crop is affected by a coefficient that depends on the studied crop (Chow et al., 1988). Also is important to know that in semi-arid areas evaporation from bare soils has a higher importance in comparison to the transpiration of plants.

Usually it is relatively difficult to obtain sufficient data in order to calculate all parameters involved in the calculation of evapotranspiration. For that reason, measurements of the evaporation in an open water surface are practical and can be used to estimate the real evapotranspiration by affecting it by certain coefficient.

Moreover, remote sensing can be used to estimate the evapotranspiration. There are many methods that can be used; most of them estimate the energy balance equation calculating the real evapotranspiration as a residual from this equation.

### 2.1.3 Subsurface water

Regarding subsurface water, three main processes are involved: infiltration of water from the surface; unsaturated flow through the soil and saturated flow through the soil (Chow et al., 1988). The water in the subsurface area is responsible for the flow generation processes. Furthermore, it determines the soil moistures and the real evapotranspiration, limiting the available water to the plants. Unsaturated flow is considered when within the porous media there is still air available while in the saturated flow the voids are filled with water.

One of the main forces that influence the water movement in the soil and the infiltration is governed by the Darcy’s Law (2), where the flow is proportional to the head loss and inversely proportional to the length of the flow path.

\[ Q = A \cdot K \cdot \frac{\Delta H}{\Delta L} \]  

(2)
where Q is the volumetric discharge through the cross section A; ΔL is the flow path length; ΔC is the difference in the heads and K is the hydraulic conductivity.

2.1.3.1 Infiltration

Water movement is mainly influenced by the type of soil and its physical properties as particle size as well as morphological and chemical properties. Within its properties the water retention related to the matrix potential, the porosity and the hydraulic conductivity play an important role. The infiltration rate is affected by the same factors than the water movement and it is also influenced by the vegetation in the surface.

Usually soils are divided vertically in different horizons, but they also vary in the horizontal plane. Consequently, soils experience great variability within space and time, what it makes complex the calculation of the infiltration (Chow et al., 1988).

Richard’s equation (3) governs the time dependent rate of infiltration into the soil. To complete the equation the initial conditions of the soil, including the moisture, must be known. These conditions usually vary in the vertical profile of the soil. This complex equation requires data as the Darcy’s velocity, the saturated hydraulic conductivity \((K(\Theta))\), suction head as function of the soil moisture \((\Psi(\Theta))\), soil moisture \((\Theta)\), the specific moisture capacity and the sources and sinks of the system. For finite-differences or finite-element, numerical models are usually applied in order to solve the Richards’ equation. However, the main problem of the equation is to obtain the data of the hydraulic conductivity and suction head (Maidment, 1993).

\[
\frac{\partial}{\partial x}\left(K_x(\Theta) \frac{\partial \Psi}{\partial x}\right) + \frac{\partial}{\partial y}\left(K_y(\Theta) \frac{\partial \Psi}{\partial y}\right) + \frac{\partial}{\partial z}\left(K_z(\Theta) \frac{\partial \Psi}{\partial z}\right) = \frac{\partial \Psi}{\partial t} \cdot C - S ,
\]

where C is the specific moisture capacity and S are the sources and sinks.

To deal with this, operational models with simplified concepts are used. There are three kinds of models that are used: empirical, approximate and physical approaches. Richards’ equation can be included in the last group. Many models include the excess rainfalls which include all the losses together: infiltration, depression storage and interception. The simplest model is the Index model, where a constant fraction or constant loss rate is generated. This model requires only one or two parameters. The estimation of the index model parameters is performed using the flow records (Maidment, 1993).

Another loss method is the SCS-method or curve number, in which an estimation of the runoff coefficient is performed without a direct analysis of the possible events, using only the physical characteristics of the basin. In this method the maximum loss is related to a curve number which is dependent on the type of soil, land use and antecedent soil conditions, the only parameter that is required in the model (Maidment, 1993).

Regarding the empirical models, Horton’s method is an approach that considers the soil moisture accumulation during the event. The estimation is performed considering an exponential decay of the infiltration. This method has the restriction that it depends on a specific soil and moisture condition.

In the Approximate based-theory models the major difficulty is the estimation of the parameters and variables because of the lack of accurate measurements. From this group a well-known model is the Green-Ampt. This model is based on Darcy’s Law (2). The main
parameters to be estimated in this model are the hydraulic conductivity, the porosity, and the wetting front soil suction head (Chow et al., 1988).

### 2.1.3.2 Groundwater

The unsaturated zone is located between the water table and the soil surface. However, some capillary rise may saturate the area in a short distance. Darcy’s velocity is used to account the velocity and flow in a vertical direction of the soil with special consideration that the suction force must be taken into account in the unsaturated zones. This is due to the electrostatic forces generated in the void spaces filled partially with water. Therefore, there is an adhesion between the particle and the water, leaving air in the voids. Consequently, the head is the sum of the suction and gravity heads (Chow et al., 1988).

The downward movement of water in the soil profile is ruled by percolation. Moreover, the portion of subsurface water, which entirely fills the voids, is called groundwater. Its flow is caused only by gravitational and friction forces in contrast to the water in the unsaturated zone.

### 2.1.4 Runoff

The streamflow is generated combining the baseflow from groundwater, an interflow from the subsurface and a saturated overland flow from the surface (Maidment, 1993). In order to represent the runoff, a discharge hydrograph, which is the flow rate as a function of time in a certain point of the stream, can be used. In addition hydrographs can be annual or can represent a flood event. The peaks in a hydrograph are caused by the quick flows, which is the combination of the interflow and the overland flow, while the slow varying flow in a rainless period is the baseflow (Chow et al., 1988). This last one can usually be separated from the other flows in the hydrograph. Several techniques have been implemented to perform these baseflow-separation techniques which usually involve subjectivity caused by the lack of scientific basis involved in the processes (Chen et al., 2006).

In this manner, summing up the discharges over time, result in the flow mass curve which is a useful tool to calculate the storage volume. In addition, flood volume can also be an interesting variable to investigate, when the aim of the work is to study the water availability.

In order to estimate the direct runoff of the hydrograph, two main processes must be studied; first the runoff generation and afterwards the runoff concentration.

In regard to the runoff generation, it can be estimated by defining the amount of rain that contributes to the flow. This can be performed separating the losses and applying the models presented in section 2.1.3. The unsaturated zone is known as the responsible of some processes like groundwater recharge and direct flood runoff.

Not all the water from the precipitation is infiltrated into the subsurface. Initial losses should be accounted as canopy, which represents the amount of precipitation that does not reach the soil, being intercepted by trees, shrubs or the grass. Once the canopy is fulfilled, surface interception storage occurs, which is the amount of water that it is held in shallow surfaces depressions. In this case, the water comes from the non-captured precipitation by canopy and the excess of the infiltration rate. In urban areas special considerations should the taken into account mainly because of the amount of impervious areas. After these initial losses, the water can be stored in the top layer of the soil. The water stored in the soil might suffer
losses because of evapotranspiration (in the tension zone) as well as percolation. However, all this water must be first infiltrated from the surface into the subsurface (Feldman, 2000).

Finally, the runoff concentration can be defined as the transformation of the generated runoff into a discharge in a river. The Unit Hydrograph (UH) proposed by Sherman (1932) is one of the most well-known hydrological methods to calculate the runoff concentration. UH of a catchment is the direct runoff hydrograph resulting from specific rainfall duration with constant intensity and uniformly distributed over the area. For each catchment a particular UH, system operator, should be estimated (Sherman, 1932). There are several derivations of UH performed by different authors: Sydney, SCS or Clark (Feldman, 2000). These types of synthetic UHs may vary depending on the applied methodology. In regard to Sydney’s UH, its coefficients are related to the watershed characteristics, while on the other hand Clark’s instantaneous UH is based on the linear reservoir model. Furthermore, the SCS’s UH is a triangular hydrograph where the peak flow and the time to reach it are the main characteristics (Maidment, 1993).

Despite from the hydrological methods, conceptual models of UHs based on models of watershed storage can be used to model runoff concentration. In these types of models two main processes are considered: translation and retention. These two processes can be combined together or act separately in order to generate the runoff concentration. In translation models the input is changed in time, without changing the form, in order to obtain the output. Linear translation occurs when the translation is constant in time. On the other hand, in the retention models the output is obtained without a lag and just by changing the shape. The simple case of these models is the Linear Reservoir, where the output (O) is proportional to the reservoir storage (S) (Chow et al., 1988):

\[ S = K \cdot O, \]  

(4)

where K is the storage proportionality constant.

Continuity is applied in these cases, where the variation of the storage (S) of water in time (t) in a hydrological system can be related to the inflow (I) and Outflow (O), as is shown in the following formula (Chow et al., 1988):

\[ \frac{dS}{dt} = I - O \]  

(5)

Linear reservoir in series, better known as the Nash-Cascade, can be used to represent a watershed. Therefore, all the reservoirs are considered with the same storage proportionality constant (Nash, 1957).

2.1.5 Streamflow

During the overland flow, water travels through the surface as a thin layer, reaching a channel where the depth of the water is increased. Those channels can be classified as perennial: never dries; intermittent: dries a certain time of the year; or ephemeral: water flows only after a rainfall. A set of several channels, which are intersected in certain points and travel towards the same outlet, form a stream.

In a river, the transformation of flood waves regarding travel time and shape is called flood routing. These methods calculate the discharge (in some cases the stage can also be calculated) and are based on the Saint Venant equations. These equations include the
continuity (6) and momentum (7) equations (a substitute of the momentum equation can be found in some hydrological routing methods) (Maidment, 1993).

\[
\frac{\partial (AV)}{\partial x} + \frac{\partial A}{\partial t} - q = 0 ,
\]

\[
\frac{\partial V}{\partial t} + V \frac{\partial V}{\partial x} + g \left( \frac{\partial h}{\partial x} + S_f \right) = 0 ,
\]

where \( t \) is the time, \( x \) the distance in the flow path, \( A \) the cross-section of the river, \( V \) the velocity, \( q \) the lateral inflow or outflow distributed along \( x \), \( g \) the gravity acceleration, \( h \) the water stage and \( S_f \) is the friction slope.

Some simplified solutions as the kinematic wave method can be performed. This equation is based on the assumption that there is no difference between the bottom slope and the water slope. Another simply method is the Lag model, where the flow is not attenuated. In this particular model the inflow hydrograph is the same as the out hydrograph, translated by a specific duration (Feldman, 2000). Other methods, as the Muskingam-Kunge apply a distributed flow routing. In this method the flood routing can be described as a superposition of a prism storage representing a steady discharge and a wedge storage representing the unsteady discharge (Maidment, 1993).

### 2.2 Interpolation techniques

Spatial interpolation can be used to estimate data in regions without observations as well as improving it in case of scarce rainfall stations networks. There are several methods that can be used for interpolation. The main idea is the estimation of the target points by means of weighting averages using values measured at known points, where there is available data:

\[
Z^*(u_0) = \lambda_1. Z(u_1) + \lambda_2. Z(u_2) + \ldots + \lambda_n. Z(u_n)
\]

where \( Z^*(u_0) \) is the estimation of the unknown point, \( Z(u_i) \) is the value of target variable at some sampled location and \( \lambda_i \) are the weights for the \( n \) possible neighbours to be considered.

The weights are standardized therefore the sum of them is one. In consequence it can be defined as, the regionalization of the variables in locations where there is not available data.

There several methods that can be applied in order to estimate the weights for the interpolation of a target variable, e.g. for areal precipitation:

1. Arithmetic mean,
2. Thiessen-Polygon method (nearest neighbour),
3. Inverse-Distance method,
4. Isohyetal method,
5. Geostatistical (Kriging) methods.

The first four methods can be considered as conventional or mechanical methods, which are widely used; since the calculations are relatively simple being commonly applied in data scarce regions (Wagner et al., 2012).

The main difference between the conventional methods and Kriging is that this last method uses the variogram to consider the spatial variability of the target variable. Moreover, conventional methods usually depend on the network without considering the target variable, thus ignoring the attribute of specific persistence. In this context, geostatistical methods
generally are applied in areas where there is enough data availability or a small time resolution although (Wagner et al., 2012). In addition, Kriging interpolation methods also allow the inclusion of covariates or multivaribles which can also improve the results.

Furthermore, spatial distributed variables can be used as external drift in geostatistical methods. Usually the topography is used as an additional variable. Moreover, other variables as satellite derived data, the distance to an orographic barrier, the location (Wagner et al., 2012) or the sum of an event (Haberlandt, 2006) can be used as additional variables.

In this manner, several studies have focused in comparing the different interpolation techniques. Haberlandt (2006) observed that multivariate methods outperformed the univariate ones. In the same study it was concluded that the radar information as an external variable was more important than the elevation for that specific region. In Verwon and Haberlandt (2011) and Wagner et al (2012) the same results were achieved. Additionally, in Verwon and Haberlandt (2011) it was shown that the elevation as an external drift did not improve the results in comparison to univariate Kriging method. Moreover, Wagner et al (2012) concluded as well that the interpolation with satellite-based rainfall estimations as an external variable had a better performance in comparison to the other cases. Furthermore, in the same study it was observed that Inverse-Distance methods had an acceptable performance.

2.3 Hydrological models

Hydrological models are the main tool where all the hydrological processes are combined and simulations are performed to obtain a certain output.

In regard to the inputs of a hydrological system, precipitation becomes the most important variable. Precipitations, as stated in section 2.1.1, has the particularity of high variability in space and time and usually are inherently random. Therefore, hydrological models are focused in relating inputs and outputs, and are approximations of the actual system.

With the intention of obtaining the discharge, hydrological (rainfall-runoff) models are applied. These models have three main phases to account for: Runoff generation, runoff concentration and flood routing as described in section 2.1.4.

Hydrological models can be classified in physical and abstract models. The first group includes scale and analogue models and the second group represent the system in a mathematical form. Regarding the interest of this study, the focus is in the last group.

Depending on the aim of the investigation, models can be deterministic, which do not consider randomness (used for forecasting), or stochastic, where the model outputs are at least partially random (used for prediction). Although all the hydrological processes are random, when the variability in the output is small in comparison with the one of the known factors, deterministic models can be used (Chow et al., 1988).

Variability in space is also an issue to determine in a model. When talking about deterministic models, these can be generated in a lumped, semi-distributed or distributed way. Lumped models, aggregate the processes of the system into a simple point. On the other hand, distributed models consider the variables as a function of the space dimensions in several points. However, Semi-distributed models emerged in order to avoid the limitation of the lumped models and to overcome the computational demand that the distributed ones
generate (Nemee, 1993). Regarding the stochastic models, they can be defined as space dependent or correlated, depending on how much the random variables influence each other at different points (Chow et al., 1988).

In addition, time variability must be taken into account in hydrologic models. In deterministic models, it can be considered that the flow does not change in time (steady flow) or it varies during time (unsteady flow). In the case of the stochastic ones, they can be time independent or correlated, and the outputs always vary in time (Chow et al., 1988).

In hydrological modelling usually deterministic models are used. According to the degree of causality this ones can be classified in (i) fundamental laws models, physically based; (ii) conceptual models with simplify approaches; and (iii) Black-box models, where there is an unknown inner structure. Usually models based on fundamental laws are defined as distributed models, while black-box models are lumped. Hence, conceptual models can be either distributed or lumped models (Nemee, 1993).

Finally models can be classified according to their temporal structure. In Continuous models the simulation is not interrupted along a large period of time, while event based models are focused on a certain event that occurs in a short period of time.

In Figure 2.1 a diagram shows the precipitation and run-off processes that occur in a basin to be included in a continuous model (Cunderlink and Simonovic, 2004). As it can be seen, all the main hydrological processes described in section 2.1 are included.

Figure 2.1: Precipitation run-off processes that occur in a basin included in a continuous model (Cunderlink and Simonovic, 2004)

There are several commercial hydrological models available in the market. One of the most recognized full distributed models is SHE-modelling, developed by the British Institute of Hydrology and the Danish Hydraulic institute and SOGREAH (France) (Abbott et al., 1986). Another well-known distributed model is the Water Flow and Balance Simulation Model WaSiM-ETH, (Schulla, 1997) which successfully can reproduce the different hydrological processes in different scales.
In the category of conceptual models, the Hydrologiska Byråns Vattenbalansavdelning (HBV model) includes conceptual numerical descriptions of hydrological processes at a catchment scale. This model can also be used as a semi-distributed model by dividing the catchment into subbasins (Bergström, 1976). This is a user-friendly model applied in several studies where its capability to reproduce runoff in an accurate way was achieved (Seibert, 2000).

Regarding semi-distributed models, one well-known-free-software is the Hydrologic Engineering Centre, Hydrological-Modelling-System Version 3.3 (HEC-HMS) of the US Army of Engineers. HEC-HMS (Feldman, 2000). Moreover, Soil and Water Assessment Tool SWAT (Arnold and Fohrer, 2005) is another semi-distributed model capable to model runoff in different soil, land uses and management conditions. Studies performed with this both models showed a good performance in streamflow simulations (Haberlandt et al., 2009).

Another relevant issue to deal within hydrological models is the model calibration. Physical parameters, e.g. the catchment area or the flow slope, and the process parameters, e.g. the average depth of the soil storage, must be set in a model. However, some physical parameters are difficult to measure therefore calibration should be performed (Pechlivanidi et al., 2011).

Calibration process can be either manual or automatic. In the first case parameters are adjusted by hand and the results depend mainly on the modeller. The adjustment of the parameters is performed until the modeller decides that the results match with the observed data or until some criteria is reached. The second type of calibration is more objective and reduces the need of expertise of the modeller (Pechlivanidi et al., 2011). Therefore, an objective function is frequently set up in order to reach a certain criterion and it is a measure of the difference between the simulated and observed data. Thus, this objective function can be reached by converging into a desired value or by fixing a maximum amount of iterations.

Finally, a model verification and validation should be performed to evaluate the performance of it. Usually this is done splitting the data into two independent periods, using one period for the calibration and another for the validation (Pechlivanidi et al., 2011).
3 Methodology

In this chapter the methodology adopted for the calculation steps is presented. First the methodology performed to obtain the different inputs is described. This includes the interpolation methods that are used and also the criteria to evaluate their performances.

In the previous subsection 2.2, the main equation of interpolation is presented. Therefore, in the following Interpolation subsection, a distinction between the different types of interpolation models used in this study are resumed, which are mechanical and statistical methods. Moreover, in the subsection of statistical interpolation the main equations used for Kriging are presented. Afterwards, the particularities that the Kriging methods considered in the main equation are stated. Subsequently, in the end of this interpolation subsection, a criterion to evaluate and compare the different interpolation methods is described. Furthermore, an objective function is proposed to have a measure of the accuracy of the different interpolation methods used.

Hydrological modelling is the chosen tool to compare the different inputs of precipitation. The rainfall-runoff models are used to simulate precipitations and runoff process that occurs in a watershed. As observed flow data is available for the study period, a comparison between the simulated and the observed on can be performed to measure the accuracy of the model. In addition, in the Hydrological Model subsection the chosen model along with the methods to perform the rainfall-runoff model is shown with a brief description and justification of the applied methodology. A distinction within the models used to develop the runoff generation, runoff concentration and routing methods described in section 2.1 is presented. In addition, a description of the meteorological model adopted is presented in this subsection. Therefore, as the main objective of this work is to perform a comparison of different precipitation inputs, an objective calibration strategy is chosen and consequently described in this section. Finally, the hydrological modelling subsection finishes with a criterion to evaluate the model performance of the calibration and validation windows separately.

3.1 Interpolation schemes

The estimation of the weights \((8)\) in the interpolation can be performed by Mechanical/Empirical or Statistical models (Hengl, 2007). From the first group, Thiessen polygons and Inverse distance are used in this study while, from the second one Kriging methods are applied.

These interpolation schemes are carried out on a 20 km grid. The resolution of the grid is adopted considering the distance between the stations and also taking into account the satellite grid (see Figure 4.6) which is described in section 4.2.2.

3.1.1 Mechanical interpolation models

Mechanical models are older than the statistical ones and modest to implement. They are also called empirical models because the parameters of the model are chosen without any statistical analysis. Commonly this type of models sub-performs the statistical ones. Nevertheless, there are some special cases where they can perform as good as the statistical models, and moreover, they may even out-perform them (Hengl, 2007). Moreover, they require easy calculations and consequently less computer time in comparison to other type of interpolation methods, therefore are implemented in this study.
3.1.1 Thiessen polygons

Thiessen polygons approach assigns the value of the nearest neighbour to each point in the grid. By means of polygons, individual areas of influence around each of a set of points are defined. This is a simple method, where the contributions of the nearest stations are balanced within each catchment (Isaaks and Srivastava, 1989).

It is known a priori that this method does not perform properly in the presence of complicated topographies. Mainly this occurs because as a univariate method it does not account for the effect of the altitude and the different precipitation patterns observed in high altitudes. However, for the study purposes is implemented as a comparison tool considering that it is a well-known and a frequently used method.

3.1.1.2 Inverse Distance Methods

Inverse distance weighting (IDW) is a well-known mechanical spatial prediction model. The main goal of this method is to give more weight to the closest stations and less to the ones that are more far away. Therefore, as stated in Isaak and Srivastava (1989), the weight for each station is obtained inversely proportional to the distance to the point where the estimation is being made.

\[ \lambda_i = \frac{1}{\sum_j \frac{1}{d_{0j}^p}}, \]

where \(d_{0i}\) is the distance between the sample point \(x_i\) to the estimated point \(x_0\), \(d_{0j}\) are the distances to the \(n\) stations and \(p\) is the “power” value.

Finally, the impact of the known points can be controlled by modifying this “power” value. As higher is the “power”, more emphasis is placed in the nearest points. A power of 2 is usually used, therefore is adopted for the present study.

3.1.2 Statistical interpolation model, Kriging Methods

Geostatistical methods apply probabilistic methods in order to regionalized variables. By means of statistical techniques, the main aim of geostatistics is to relate spatial data, mainly sampled field data. Spatial interpolation is one of the main uses; this means the prediction of values of a sampled variable over the study area accounting the idea that closer variables should be likely close in values (Isaaks and Srivastava, 1989).

To perform spatial interpolation, the weights (\(\lambda\)) in the interpolation equation (8) are optimized based on the measured data (Wagner et al., 2012). The different weights can be calculated solving the following Kriging system of equations (Haberlandt, 2006):
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

\[ \sum_{j=1}^{n} \lambda_j \gamma(u_i - u_j) + \mu_0 + \sum_{k=1}^{m} \mu_k Y_k(u_i) = \gamma(u_i - u) \quad i = 1, \ldots, n \quad (10) \]

\[ \sum_{j=1}^{n} \lambda_j = 1 \]

\[ \sum_{j=1}^{n} \lambda_j Y_k(u_i) = Y_k(u) \quad k = 1, \ldots, m \]

where \( n \) is the number of neighbours to be considered, \( m \) is the number of additional variables \( Y_k \) that might be added and \( \mu_k \) are \( m + 1 \) the Lagrange factors. \( \gamma(h) \) represents the value of the semivariogram function for a specified distance, \( u_i \) and \( u_j \) are different points and \( u \) is the estimated location.

As it can be seen in the Kriging system of equations (10), it only depends on the distance between the vectors and not in the location of them. The number of equations of the system is \( n + m + 1 \). Moreover, the additional variables \( Y_k \) must be known in all the at all the points \( u \) (Goovaerts, 1997).

### 3.1.2.1 The semivariogram

The first step for the interpolation in the Kriging methods is the analysis of the spatial persistence of the precipitations by means of the analysis of semivariograms. This may be critical in mountainous areas, where it is critical to analyse the semivariograms based on distant rain stations networks (Verworn and Haberlandt, 2011).

The semivariogram (or variogram) is the central tool of the geostatistics. Hence, when performing interpolation in time series, a reliable variogram for each time step should be obtained. This may be a particular problem considering that the spatial structure of rainfall depends on many factors that may be static in space and time as the topography or dynamic as the weather conditions.

In this particular study, continuous time series are used as inputs for the modelling. For that reason, the experimental variogram for each data set is obtained as an average of the variogram of each time step of the time series. Therefore, the experimental variogram is obtained with the following equation For each time step (Verworn & Haberlandt, 2011):

\[ \gamma(h) = \frac{1}{2 \cdot N(h)} \sum_{i=1}^{N(h)} (Z(u_i) - Z(u_i + h))^2 \quad , \quad (11) \]

where \( N(h) \) is the set of pairs of observed \( i \) and \( h \) is the distance vector of the data pairs. \( Z(u_i+h) \) is the value of the neighbour at distance \( u_i+h \). Afterwards, this experimental variograms, are plotted showing the change of the half of the squared differences between the sampled values, with the distance between the points.

The experimental variogram finally is the averaging for all the time steps with the standardization by the variance:
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\[
\gamma_{ev}(h) = \frac{1}{n} \sum_{i=1}^{n} \frac{\gamma(h, i)}{\text{var}(i)},
\]

(12)

where for \( n \) time steps, the variance \( \text{var}(i) \) and semivariogram \( \gamma(h, i) \) for the distance \( h \) is calculated. In the present work several inputs are compared, so this procedure is done for all the different precipitation data sets independently.

After calculating the experimental variogram, this one can be fitted using some of the commonly-used variogram models, such as linear, spherical, exponential, circular, Gaussian, Bessel, power and similar (Isaaks and Srivastava, 1989). In this case only the spherical (13) and the exponential (14) models are applied (Maidment, 1993).

\[
\gamma(h) = C_o + \begin{cases} 
  c \cdot \left( \frac{3}{2} \frac{h}{a} - \frac{1}{2} \frac{h^3}{a^3} \right) & \text{for } h \leq a \\
  c \cdot 1 - \exp \left( -\frac{h}{3a} \right) & \text{otherwise}
\end{cases}
\]

(13)

\[
\gamma(h) = C_o + c \cdot \left[ 1 - \exp \left( -\frac{h}{3a} \right) \right],
\]

(14)

where \( a \) is the range, \( c \) is the sill and \( C_o \) is the nugget.

For each theoretical variogram a partial sill, nugget and range have to be adopted as it is shown in Figure 3.1. The experimental variograms can be fitted whether manually or automatically. In this particular case, for each data set, a manual fitting is performed in order to detect possible errors and to avoid a blind fitting considering that it requires substantial judgment (Wagner et al., 2012).

![Theoretical semivariogram](image)

**Figure 3.1: Theoretical semivariogram. Principal variables: Sill, nugget and range.**

### 3.1.2.2 Ordinary Kriging

When a variable has similar statistical properties (similar histogram, similar variogram) within the whole study area, it is called stationary (Hengl, 2007). Two orders of stationary can be considered: the first-order stationarity (or the stationarity of the mean value) and the second-order stationarity (or the covariance stationarity). Therefore, the requirements for Ordinary Kriging (OK) are mean and covariance stationarity and a normal distribution of values.

The main steps for OK interpolation are:

1. Estimation of the theoretical variogram variables (see (13) and (14)) based on the experimental variogram (see (11) and (12)).
2. For each unknown target point of the grid, a minimum and maximum number of neighbors are chosen for each data set. In the case of the rainfall stations, the neighbors are set around 4 and 8 respectively, taking into account that the total of rainfall stations is considered as a small sample. Regarding the satellite estimations, the amount of estimated points in the study area is large enough to be considered as a large sample; therefore, the neighbors to be included in the interpolation are around 12 as minimum and 24 as maximum. A slight variation of the amount of neighbors adopted is performed in order to be tested the performance in step 3.

3. A validation of the interpolation scheme by means of Cross-Validation is done (see section 3.1.3). Consequently, the shape of the variogram with its corresponding minimum and maximum neighbors to be adopted during the interpolation is selected.

4. The interpolation is performed and consequently the different weights \( \lambda_i \) are obtained by solving the Kriging system equations (see (10)). In this case the number of additional variables \( Y_k \) is cero and thus only one Lagrange parameter is required. Likewise, the number of equations of the Kriging system is reduced to \( n + 1 \).

5. The estimation of the target variable for each unknown point is performed (see (8)) using the weights obtained in the previous step.

### 3.1.2.3 Kriging with External Drift

Kriging methods consider the spatial variability and the possibility to use additional information, which may vary or not in time. As stated by Verwon and Haberlandt (2011), this additional information is assumed to be linearly related to the expected value of the target variable. For these particular cases External Drift Kriging (EDK) method is used which is a non-stationary method that allows trends in space. In contrast to OK, EDK does not consider the intrinsic hypothesis that assumes a constant value of the expected value of the target variable (Haberlandt, 2006).

When interpolating with EDK the same procedure adopted in OK is used. Only step 4 experiences a difference in which the number of additional variables \( Y_k \) is different from cero and can be larger than one. Consequently, the \( m + 1 \) Lagrange factors are required related to the number of additional variables (see (10)). The semivariograms to be estimated in step 1 are inferred from the original target variable and not from the drift residuals. It has been observed by Haberlandt (2006), that there are slight differences in applying this technique than considering also the residual's semivariogram of the EDK variables. Furthermore, this previous technique implies an iterative process which is extremely demanding, thus for this study the experimental variograms will be estimated based only on the observed target variables.

### 3.1.3 Performance assessment

Cross-validation is used to evaluate and compare the performances of the interpolation methods. This method is chosen considering that the sample of rainfall stations is small, thus other methods cannot be applied. In the cross-validation method or so called “leave-one-out-method” an estimation of the rainfall for each observed data is performed not considering the known value in the particular location that is being studied (Verworn and Haberlandt, 2011). Therefore, for each sample point an estimated value \( (Z^*(u)) \) is obtained which is compared with the observed one \( (Z(u)) \).
The performance criteria to compare, evaluate and validate the interpolation methods are the bias (15), the root mean square error (RMSE) normalized with the observed average (16) and the Relative Variance (RVar) coefficient (17). This last index measures a relationship of the variance of the observed data compared to the variance of the interpolated values. It is aimed to have a RVar index of 1 in order to preserve the observed variance as much as possible in order to avoid the smoothing effect of the target variable (Verworn & Haberlandt, 2011).

\[
BIAS = \frac{1}{n} \sum_{i=1}^{n} [Z'(u_i) - Z(u_i)] \quad (15)
\]

\[
RMSE = \frac{1}{Z} \sqrt{\frac{1}{n} \sum_{i=1}^{n} [Z'(u_i) - Z(u_i)]^2} \quad (16)
\]

\[
RVar = \frac{Var[Z'(u)]}{Var[Z(u)]} \quad (17)
\]

Additionally, the correlation between the original and the estimated data with the interpolation is also considered in the evaluation.

According to Verwon and Haberlandt (2011) the main index to evaluate the performance of the different precipitation cases is the RMSE. Therefore, the subsequent indices to consider are the RVar and coefficient of correlation, and at last the BIAS which is the most unstable coefficient. Hence, the following objective function (OF) is proposed to compare the different cases:

\[
OF = 0.5 \cdot RMSE + 0.2 \cdot (1 - RVar) + 0.2 \cdot (1 - Corr) + 0.1 \cdot BIAS \quad , (18)
\]

For this established objective function the optimal result will be the closer to 0.

### 3.1.4 Study cases for the interpolation

In this work five study cases of interpolated precipitation are analysed and compared by means of a hydrological model. These cases have as main data either the rainfall stations data or the satellite estimated rainfall.

For the EDK interpolation schemes, the additional variables used are the topography and the estimated satellite precipitation data. The first drift variable is used mainly because it is well-known the linear relationship between the elevation and the precipitation. The second variable is chosen in order to analyse the possibility of improving the accuracy and resolution rainfall stations records and in order to have an additional possible usage of this data.

### 3.2 Hydrological Modelling

The hydrological model used to compare the different inputs in terms of modelled streamflow versus the observed discharge is developed by the Hydrologic Engineering Centre, the well-known Hydrological-Modelling-System Version 3.3 (HEC-HMS) of the US Army of Engineers. As described in Feldman (2000), HEC-HMS is a mathematical model that it is able to
represent the reaction of a hydrological system by means of a set of equations due to changes in hydrometeorological features.

There are several available and reliable hydrological models in the market. However, HEC-HMS is chosen mainly because is a free and recognized software. This model does not require a large number of parameters and is considered easy to be handled. Moreover, it does not require large computer time for each run (Haberlandt et al., 2009).

The mathematical model performed for the study is a continuous, semi-distributed, empirical and deterministic model (see section 2.3).

The horizontal structures that represent the semi-distributed model are subbasins. In Figure 3.2 the vertical structure used of the HEC-HMS model is represented (Bennet and Peters, 2000).

Figure 3.2: HEC-HMS vertical structures (Bennet and Peters, 2000).

HEC-GeoHMS (Flemig and Doan, 2013) a software extension for the ArcGIS platform (ESRI, 2011), is used, along with available terrain and land-use geospatial data, to develop the basin geometry in the study catchment. HEC-GeoHMS is also used to delineate the stream with the aid of known flow paths in the basin.

The main processes that are involved in a hydrological model are: runoff generation, runoff concentration of the surface runoff, base-flow transformation and flow routing methods as described in section 2.1. Furthermore, a meteorological model is set up where the climate variables are included and are used as input for the model. Therefore, all these main processes and meteorological models are described in the following subsections.

3.2.1 Runoff generation

The Soil Moisture Accounting (SMA) loss model is used to calculate the loss rate within the runoff generation module in the sub-basins with HEC-HMS. The interaction between infiltration, surface runoff and subsurface processes takes place within a subbasin element. To perform this, the soil layers are divided depending on the moisture content and the
relevant hydrological processes. Therefore, infiltration and evaporation processes are modelled in the upper layer of the soil which is unsaturated, whereas percolation in the lower layers occurs under mostly saturated conditions.

SMA method uses 5 layers: canopy interception, surface depression storage, soil, upper groundwater and lower groundwater. These 5 layers are used to represent the dynamics of water movement above in and below the soil (Scharffenberg and Fleming, 2008). As stated in Scharffenberg and Flemig (2008), the method is suitable for long term or continuous simulations.

As described in Feldman (2000), the SMA model simulates the movement of water in the soil surface, soil profile and in the groundwater layers. This simulation also includes the storage of water on vegetation. By means of the inputs of the meteorological model, which include the precipitation and potential evapotranspiration, the model computes in the entire catchment the surface runoff, the flow in the groundwater, the losses due to the evapotranspiration and the percolation. In Figure 3.2 the conceptual schematic of the SMA algorithm is shown.

The SMA model continuously accounts for soil moisture, considering evapotranspiration, percolation into the deeper layers, and lateral flow conserving the mass. Lateral flow, from both bottom layers, contributes to base flow through the Linear Reservoir method (Vuyovich and Daly, 2012).

The SMA model has 19 parameters that must be defined for each subbasin. Therefore it is necessary to have knowledge about the land use and soil components.

The initial parameters to define in the SMA model are the capacity of each layer as well as the initial storage (as a percentage of that capacity). In addition infiltration rates for the soil and groundwater layers have to be estimated (based on soil types) and consequently the tension zone capacity for the soil profile layer and storage coefficients for the groundwater layer.

To define the canopy and surface storage, values are set up depending on the land use in the catchment area. The maximum infiltration rate is defined according to the different soil types as is shown in Table 3.1 (Akan, 1993).

Infiltration in this model is accounted as the water that enters the soil profile from the ground surface. Hence, the infiltration in each time step is the amount of precipitation that passes the canopy added to the water that is already in the surface storage. Moreover, the potential infiltration can be computed as (Feldman, 2000):

\[ P_{inf} = MaxInf - \frac{VolSoil_0}{MaxVol} \cdot MaxInf \]  

where \( MaxInf \) is the maximum initial infiltration rate of the soil, \( VolSoil_0 \) is the volume of water storage in the soil at the beginning of the time step and \( MaxVol \) is the maximum volume of the soil storage.
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Table 3.1: Maximum initial infiltration rates according to the soil type and the surface coverage (Akan, 1993).

<table>
<thead>
<tr>
<th>Soil type and coverage</th>
<th>Maximum (Initial) Infiltration mm/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry sandy soils with little or no vegetation</td>
<td>127</td>
</tr>
<tr>
<td>Dry loam soils with little or no vegetation</td>
<td>76.2</td>
</tr>
<tr>
<td>Dry clay soils with little or no vegetation</td>
<td>25.4</td>
</tr>
<tr>
<td>Dry sandy soils with dense vegetation</td>
<td>254</td>
</tr>
<tr>
<td>Dry loam soils with dense vegetation</td>
<td>152</td>
</tr>
<tr>
<td>Dry clay soils with dense vegetation</td>
<td>51</td>
</tr>
<tr>
<td>Moist sandy soils with little or no vegetation</td>
<td>43</td>
</tr>
<tr>
<td>Moist loam soils with little or no vegetation</td>
<td>25</td>
</tr>
<tr>
<td>Moist clay soils with little or no vegetation</td>
<td>7.6</td>
</tr>
<tr>
<td>Moist sandy soils with dense vegetation</td>
<td>84</td>
</tr>
<tr>
<td>Moist loam soils with dense vegetation</td>
<td>5.1</td>
</tr>
<tr>
<td>Moist clay soils with dense or no vegetation</td>
<td>18</td>
</tr>
</tbody>
</table>

Regarding the soil percolation the values are set up according to the recommendations of the FAO (FAO, 1998). In the model the rate of percolation is between the soil storage and the upper groundwater layer and between the layers of groundwater.

Table 3.2: Maximum percolation estimated for the different types of soils (FAO, 1998)

<table>
<thead>
<tr>
<th>Soil type</th>
<th>Mean percolation cm/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sandy</td>
<td>5</td>
</tr>
<tr>
<td>Loam-sandy</td>
<td>2.5</td>
</tr>
<tr>
<td>Loam</td>
<td>1.3</td>
</tr>
<tr>
<td>Loam-clay</td>
<td>0.8</td>
</tr>
<tr>
<td>Clay-Silt</td>
<td>0.25</td>
</tr>
<tr>
<td>Clay</td>
<td>0.05</td>
</tr>
</tbody>
</table>

As there is not so much available data regarding the groundwater, the parameters related to it are subjected to the calibration technique. These parameters, for both groundwater layers are: groundwater storage, groundwater percolation and groundwater coefficient.

The percolated rate between the groundwater layers is calculated as (Feldman, 2000):

$$ P_{per} = \text{Maxper} - \left( \frac{\text{VolGW1}_0}{\text{MaxGW1}} \right) \cdot \left( 1 - \frac{\text{VolGW2}_0}{\text{MaxGW2}} \right), $$

(20)

where Maxper is the maximum percolation rate, VolGW1_0 is the volume of water storage in the upper groundwater layer at the beginning of the time step and MaxGW1 is the maximum volume of the upper groundwater layer. Finally, VolGW2_0 is the volume of water storage in the lower groundwater layer at the beginning of the time step and MaxGW2 is the maximum volume of the lower groundwater layer.

Potential evapotranspiration in the SMA model considers the loss of water from canopy interception and surface storage. The next available layer is always used to fulfill in the situations where there is unsatisfied potential evapotranspiration.
3.2.2 Runoff Concentration

In the present hydrological model, surface runoff is the amount of water that exceeds the infiltration. Consequently, this volume of water is the direct runoff and is described in this subsection. Additionally, the baseflow model originated by groundwater is presented.

3.2.2.1 Direct Runoff

Clark’s Unit hydrograph method is used to model the runoff concentration, which involves the excess precipitation that does not infiltrate the soil and travels in the surface. This method is considered as a synthetic unit hydrograph, which is different to a regular unit hydrograph since it assumes that effective precipitation is applied to a drainage basin in an infinitesimally short period of time.

As it is stated in section 2.1.4, Clark’s Unit Hydrograph method is based on the Linear Reservoir method where the linear storage (4) and continuity (5) equations are applied. Combining these two equations and solving them with simple finite differences method, the output in a certain time step \( O_t \) is estimated as (Feldman, 2000):

\[
O_t = C_A \cdot I_t + C_B \cdot O_{t-1}
\]  

(21)

Where \( C_A \) and \( C_B \) are the routing coefficients, \( I_t \) the average inflow at the time step and \( O_{t-1} \) the outflow from storage at the previous time step. The routing coefficients are obtained from (Feldman, 2000):

\[
C_A = \frac{\Delta t}{K + 0.5 \Delta t}
\]  

(22)

\[
C_B = 1 - C_A
\]  

(23)

where \( K \) is the storage coefficient from equation (4) and \( \Delta t \) is the time step.

The translation hydrograph resulting from the precipitations builds a time versus area curve. Afterwards, this performed translation hydrograph is routed through a linear reservoir to account for storage attenuation effects through the subbasin (Scharffenberg and Fleming, 2008). In consequence, to transform precipitation into outflow two parameters are required: time of concentration (\( T_c \)) and storage coefficient (\( K \)). To estimate the time of concentration (\( T_c \)) the Kirpich formula is used (Chow et al., 1988):

\[
T_c = 0.0663 \left( \frac{L}{I} \right)^{0.77}
\]  

(24)

where \( L \) is the distance from head to outlet in km, \( I \) the average slope for maximum elongation of the basin and \( T_c \) is the time of concentration in hours.

The storage of rainfall in the watershed, before it can be drained, is measured by the storage coefficient (\( K \)). As this coefficient is also measured in time units, it is assumed that as bigger the \( K \) compared to \( T_c \), the higher the storage within the catchment. Not much data about this coefficient is available, therefore it is subjected to the calibration method.

3.2.2.2 Baseflow

The Linear Reservoir Method (LRM) is chosen to model the interflow and baseflow within HEC-HMS. As described in Scharffenberg and Flemig (2008), within the subbasin, this
method conserves the mass and moreover is also connected to the released lateral flow of the SMA method. Therefore, in order to simulate continuous subsurface flow, LRM uses the lateral flow released from the SMA method (Vuyovich and Daly, 2012). Consequently, the outflow from the linear reservoir from both groundwater layers is combined to compute the total baseflow of each subbasin (Feldman, 2000).

To compute the method, for each of the groundwater layers it is necessary to determine two different parameters: storage coefficient and maximum storage. Hence, the Linear Reservoir formulas used in section 3.2.2.1 are applied to calculate the baseflow.

### 3.2.3 Routing method

Hydrologic routing is useful for understanding the entire movement of water from rainfall to runoff. Essentially, the continuity equation is applied to indicate storage between upstream and downstream conditions (Chow et al., 1988).

There are several methods that can be used for the routing as described in section 2.1.5. For this model, the Lag method is chosen to route the flow downstream through each stream. This method requires the setting of a lag time for each stream to represent the translation of the flood waves. In contrary to the linear reservoir, the shape of the outflow in comparison to the inflow it is not changed because there is no attenuation.

Consequently, with the Lag method, the downstream outflow hydrograph at a certain time step \(O_t\) is computed as following (Feldman, 2000):

\[
O_t = \begin{cases} 
I_t & t < \text{lag} \\
I_{t - \text{lag}} & t \geq \text{lag} 
\end{cases},
\]

(25)

Where \(I_t\) is the inflow hydrograph at the same time step and lag is the time which the inflow hydrograph is delayed. The estimation of the lag is performed as a relationship between the length (L) and the mean velocity (\(v_m\)) of each stream:

\[
lag = \frac{L}{v_m},
\]

(26)

As the observed mean velocity is not always available for every stream, an estimation of it is performed (Rodriguez-Iturbe et al., 1982) using the following equation:

\[
v_m = a_m \frac{1}{m_s} Q_m \left( \frac{m_s - 1}{m_s} \right),
\]

(27)

\[
a_m = \frac{S_m \frac{1}{2}}{b_m \frac{1}{2} n_m},
\]

(28)

where \(a_m\) and \(m_s = 5/3\) are the kinematic wave parameters, with \(S_m\) the average slope, \(b_m\) the average width, and \(n_m\) the average Manning’s coefficient of the stream. Finally, \(Q_m\) is the mean flow of the reach.

### 3.2.4 Meteorological model

A meteorological model is included in the hydrological model which varies temporally and spatially and sets the boundary conditions of the subbasins. This model receives as input
data the time series of daily precipitation, the mean monthly evaporation and the mean daily temperature for all the sub-basins.

The precipitation gauged method is chosen to simulate the rainfall in each subbasin of the catchment. The precipitation data first is interpolated following the steps set in section 3.1 obtaining a time series for every point of the grid. For each subbasin an areal precipitation is assigned obtained from the previous interpolated values. Each interpolation point has a square area of influence which is crossed with the subbasins area. From this cross, a percentage of influence of each interpolation point in each subbasin is obtained. Consequently the areal precipitation of each subbasin is calculated using the weights of influence of each point, obtaining finally a time series for each subbasin. The following formula presents the calculation for an individual time step:

\[
P_{\text{PCP}}_{i,j} = \alpha_1 \cdot p_{1,j} + \cdots + \alpha_n \cdot p_{n,j}
\]

where PCP is the precipitation average estimated for the ith subbasin in a specific time step j, \(n\) is the number of interpolated points that have influence in the subbasin, \(p\) are the values of precipitation obtained for the particular time step and \(\alpha\) are the percentages of influence of the points in the subbasins.

This methodology is applied for the different precipitation inputs generated with the interpolation methods, obtaining a set of time series for each case of precipitations. As the time series are already aggregated for each subbasin the gage coefficient to be included in the HEC-HMS is 1 in all the cases.

To calculate the evapotranspiration a Monthly Average method is used in which a monthly average of evapotranspiration rate is set to each subbasin, considered accurate enough for continuous simulations. Therefore, every time step within the month during the simulation is going to have the same evapotranspiration rate. To calculate the potential evapotranspiration the monthly rate is multiplied by a coefficient that corrects the measured evaporation, into a real one.

The calculation of the snow-melt is performed with the Temperature-Index method explained in Scharffenberg and Fleming, 2008. The temperature is the main input to calculate the snow component, which is separated into solid and liquid phase.

The time series of the mean temperature are given, as for the precipitation, for certain stations. In order to generate time series within the whole catchment an interpolation is also performed using an external drift Kriging method as it is described in section 3.1.2.3. The only external drift used is the elevation knowing the linear relationship between the temperature and altitude. However, in contrast to the precipitation cases only one interpolation is performed and included in the models for the different precipitation cases. Consequently, time series in all the grid points are obtained and thus the corresponding ones for each subbasin.

The temperature index method computes a fixed amount of snowmelt for each degree above freezing (Scharffenberg and Fleming, 2008). To accomplish this, each subbasin must have a specified lapse-rate and mean temperature time series. This temperatures time series are related to an elevation where the measurements were taken. Therefore, the lapse-rate is set up according to the theory considering that there are no meteorological stations with strongly different heights close enough to compute a local rate. Finally, the equation used is:
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\[ T = T_0 - 6.5 \frac{h(m)}{1000}, \]  

where the temperature \( T_0 \) decreases 6.5 °C every 1000 m in a higher altitude.

To represent the gradient of height within a subbasin, different elevation bands are set up in each of them. The amount of elevation bands are decided depending on the variability of the topography along the subbasin. For those cases with slight variation in the topography only one elevation band is established. For each elevation band a mean elevation is adopted in which the lapse-rate is applied.

### 3.2.5 Calibration and validation

An accurate estimation of the model parameters for a specific basin is one of the difficult and important problems in conceptual rainfall-runoff modelling. Manual or automatic calibration techniques are used for estimating model parameters. As it is described in section 2.3, manual techniques adjust the parameters subjectively based on specific characteristics of the flow predictions. Conversely, automatic techniques estimate parameters based on the changes in the value of a quantifiable error criterion function.

As the objective of the work is to compare the accuracy of different input data an automatic calibration method is followed in this work. This procedure is chosen considering the need of an objective calibration without taking side of any of the precipitations inputs cases.

To perform the calibration only a certain period of the available data is used, leaving the remaining period for the validation.

For the purpose of finding the best parameter set of the rainfall-runoff model, the dynamically dimensioned search (DDS) algorithm is used. The DDS stochastic global search optimization algorithm is applied to calibrate the parameters automatically (Wallner et al., 2012). This algorithm was developed to find good global solutions, rather than globally optimal solutions, by converging to a region of global optimum in the best case or a region of the local optimum in the worst case. The transformation from global to local approach is achieved by dynamically and probabilistically reducing the number of parameters to be changed in each step. Therefore, as the number of iterations is increased the number of dimensions is decreased. Moreover, the search of the solver is more global in the beginning and more locally at the end of the process (Tolson and Shoemaker, 2007).

Tolson and Shoemaker (2007) were motivated to incorporate this feature due to their experience in manual calibration. They obtained an improvement in the calibration results where they found that it became necessary to only modify a few and not all parameters simultaneously.

The global solution adopted in the DDS depends on the simulated discharge and the observed one. Thus, the observed time series is included in the inputs of the model obtaining a simulated discharge for each iteration. An objective function (31) based on the root mean square error is set up to be minimized and consequently find an optimum result.
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\[
OF = \left( \sqrt{\frac{N}{Q_{obs}}} \sum_{i=1}^{N} (Q_{sim_i} - Q_{obs_i})^2 \right)^{0.30}, \tag{31}
\]

where \( N \) is the number of steps, \( Q_{sim} \) is the simulated flow and \( Q_{obs} \) is the observed flow for each time step \( i \) and \( Q_{obs} \) is the mean value of the observed time series.

The precipitation inputs are prepared for each subbasin and for each model. However, more parameters to be calibrated imply more computational time, therefore some subbasins are grouped setting up for them the same parameters. The subbasin-group within an individual model will be subjected to the available data and the similarity between the subbasins. A minimum of two subbasin-groups for each model is established. With this technique, the dimension of the search space it is reduced only for the number of unknown parameters and not to the number of subbasins. However, the climate variables are still set for each subbasin, being still represented, but only losing the spatial variability of the calibrated parameters (Wallner et al., 2012).

For each subbasin-group the same set of decision variables are calibrated. The other parameters in the model are fixed up according to the available data of each subbasin. This means that each subbasin-group will have the same calibrated while the rest of the parameters might be different. The set of parameters to be calibrated (decision variables) are chosen according to their variability and uncertainty. Nevertheless, a maximum number of decision variables are fixed considering the available computational time.

For each decision variable a maximum and minimum range for each unknown parameter is established. This range is adopted according to the available data of the subbasins and the variability that the parameter may have. Furthermore, results obtained in previous works and available theory of HEC-HMS model is used as a reference.

As the main goal is to have an objective calibration in order to be able to perform a neutral comparison of the model results, the same initial parameters for the DDS are established in each run and each subbasin group.

In order to reduce the number of unknown variables is the calibration runs the catchment is divided into subcatchments. Therefore, the subcatchments that are independent are run separately adopting the optimized parameters of them in a global model. All this procedure is performed for each of the different rainfall inputs.

As the DDS was designed to converge to the region of the global optimum that is set, this may require infinite iterations, reason why a maximum number of iterations are fixed up for this study. The number set for the iterations is proportional to the amount of unknown parameters to estimate in each individual run. This proportional number is adopted considering the computer time required for each run based on the available time for the present study and the total cases that should be run.

The validation is performed for the last period of the available data adopting the optimized parameters obtained in the calibration as valid ones. For each precipitation case a run with calibrated parameters is performed analysing the results for each independent subcatchment and the global one.
3.2.6 Indices of reliability

The measurement of the performance is estimated comparing the observed flows in the outlets against the simulated ones. The performance is evaluated separately for the calibration and the validation and for each independent subcatchment and the global one.

As the optimum calibrated parameters are found with an algorithm based on the Root Mean Square error formula (31), the calibration and validation performance evaluated for each of the simulations is done using Nash-Sutcliffe efficiency criterion (NSC), which is calculated as follows:

\[
\text{NSC} = 1 - \frac{\sum (Q_{\text{obs}_i} - Q_{\text{sim}_i})^2}{\sum (Q_{\text{obs}_i} - \bar{Q}_{\text{obs}})^2},
\]

where the summation to be performed is for the total number of observed flows used for validation.

The NSC efficiency can range from -\infty to 1, and the efficiency of 1 is considered the perfect match between the observed and estimated values. An efficiency of 0 implies that the estimations are as accurate as the mean value of the observed data and negative efficiencies means that the observed mean is a better estimation than the model. So the closer the NSC efficiency value is to 1, the more accurate the model is. Thus, the simulation that gets closer to this value will be considered the one with the best performance during the validation.

Additionally as a measure of comparison, the performance of the hydrological model is assessed with the root-mean-square error standardized with the observed average (RMSE):

\[
\text{RMSE} = \frac{1}{Q_{\text{obs}}} \sqrt{\frac{\sum (Q_{\text{sim}_i} - Q_{\text{obs}_i})^2}{N}},
\]

where N is the number of steps, Q_{\text{sim}} is the simulated flow and Q_{\text{obs}} is the observed flow for each time step i and \(\bar{Q}_{\text{obs}}\) is the mean value of the observed time series.

The set of parameters that delivers a RMSE closer to zero simulation that gets closer to this value will be considered as the one with the best performance during the calibration.
4 Study area and Data

4.1 Description of the study catchment

The catchment of river Neuquén is located in the eastern side of the Andes Mountains, in the middle-west of the Republic of Argentina between the latitudes 36° 10’ S and 39° 10’ S and longitudes 68° W and 71° W. The surface drainage of the whole basin is around 50,000 km². However, the study area covered by the most downstream gauging station (Paso de los Indios) is of 32,000 km² (see Figure 4.1). Hence, from now onwards the study area will be considered as the Neuquén catchment.

As the west and north boundary of the catchment is a chain of mountains and the outlet is located in a flat area in the south-east, the local topography experiences great variability. Therefore, its elevation ranges from approximately 500 m.a.s.l. in the station Paso de los Indios up to 3,770 m.a.s.l. on the top ridges in the Andes Mountains (Figure 4.1).

Neuquén river along with the Limay river are sources of the Negro river which drains towards the east and into the Atlantic Ocean. The major flows to the basin mainly come from the mountains through the Trocomán river which is within the Andacollo subcatchment, and the mighty Agrio river. It has a torrential regime with extreme high flows that in the past were causing unexpected floods in the Negro River. Neuquén river has practically no lakes, and since 1914 the excess flow of the river was diverted to the Pellegrini Lake, an enclosed basin. Nowadays the floods are controlled by means of the Cerro Colorado complex and other complementary constructions which are located downstream the study area.
The high flows of the river are originated by precipitations between the months of May and August, period were around the 75% of the precipitations of the year occur, and also by the melting of snow between November and December (see Figure 4.2 and Figure 4.3). Therefore, the system is characterized by having two peaks per year, in which the winter peak represents in mean values 34% of the total amount (AIC, 2006). The mean flow of the river is 312 m$^3$/s (measured at the gauge station Paso de los Indios) (SSRRHH de la República Argentina, 2011).

![Figure 4.2: Mean, maximum and minimum monthly flows at the flow gauge Paso de los Indios in the Neuquén catchment (SSRRHH de la República Argentina, 2011).](image)

The higher precipitations, of around 3,000 mm per year, are registered at the mountains in the northern limit with Chile. In the east part of the basin the mean yearly precipitation is around 200 mm. This sharp difference is caused by the loss of the humidity of the cold air masses that come from the Pacific Ocean in the ridges of the wall of mountains along the basin.

The catchment has a dry and cold climate with strong winds during all the year and permanent snow in the ridges of the mountains. It is characterized by seasonal rainfall and snow during the winter and it has a cold winter and template summer weather. During the winter, from May to August, most of the precipitation falls and is partly stored as snow in the highest mountains of the catchment.

In Figure 4.3 the mean monthly precipitation and temperatures are shown for 2 different locations. As it can be seen in Figure 4.1 the meteorological station 1022 (Varvarco) is located in a stream at the mountains in the north-west of the catchment while station 1018 (Paso de los Indios) is in the outlet of the catchment, south-east of the study area. From Figure 4.3 it can be observed the difference in amount of precipitation and the high variation of the temperature within the catchment (SSRRHH de la República Argentina, 2011).
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Figure 4.3: Mean monthly precipitation (P) and temperature (T) for the stations 1022 (Varvarco) located in a river in the mountains of the catchment (north-west) and 1018 (Paso de los Indios) located in the outlet of the Neuquén catchment (south-east) (SSRRHH de la República Argentina, 2011).

The economic activities of the basin include mining, forestation, tourism, agriculture and cattle. The land use is dominated by natural vegetation as it can be seen in Figure 4.4 (FAO, 2010). The basin is characterized by the lack of vegetation coverage, only dispersed bushes and pasture with little development can be found. Consequently, there is a reduced retention capacity of the precipitations in the basin. Moreover, the lack of natural lakes increases this phenomenon (AIC, 2006). Besides, from Figure 4.4 it can be observed the lack of urban areas within the catchment.

Figure 4.4: Land uses in the study area of the Neuquén catchment (FAO, 2010)

Instituto Nacional de Tecnología Agropecuaria from Argentina (AGyP – INTA – Proyecto PNUD ARG/85/019-Instituto de Suelos y EEA, del INTA., 2008) provided the soil components of the study area. The main groups of soils in the study area are rocks in the mountainous areas and inceptisols and entisols with mainly clay and silt soils. The classification of the soils is made according to the soil taxonomy (Soil Survey Staff, 1999).
4.2 Rainfall data input

The aim of the work is to compare different rainfall inputs by means of hydrological model; therefore the two main sources of rainfall to be compared are introduced in this section: Rainfall stations and satellites estimations. The rainfall stations data is obtained by means of measurements in punctual gauges while the areal satellite estimations are obtained by means of an algorithm using as base the passive microwave obtained with radars.

As the available data from the satellite-based estimations is from 1998 onwards and the available measurements from the rainfall stations and flow gauges is generally until 2011 the study period is defined between 1998 and 2011.

4.2.1 Rainfall stations database

Daily measurements of precipitation at 22 stations within or close to the catchment (Figure 4.1) were provided by the Water Resources Deputy Department which depends on the Department of Public Works of Argentina (SSRRHH de la República Argentina, s.d.).

From the 22 rainfall stations only 2 had long incomplete terms for the study period as it is shown in Table 4.1. As additional information in Appendix I the entire period of data is presented in order to show the completeness and gaps of the records.

To test the consistency of the data the double mass curve method is applied (Searcy et al., 1960). Considering that the topography varies within the catchment and there are large distances between the stations, to perform the test the stations are grouped. Therefore, five different groups are defined considering the location of the stations. The cumulative rainfall of each station that is used in the study, are plotted and compared against the cumulative precipitation of the reference values (see Figure 4.9). Finally, as there is not a reliable station in every group, the mean cumulated precipitation of each group is used as reference value.

There is no clear evidence of inconsistence in the data. The only expected group which presented significant break in the slope is Group 2. Station 1012 showed a sharp break in the slope compared to the other stations and this may be due to the large distance in the location between them. However, as the comparison is made against the cumulative precipitations in a year, gaps in the data may produce breaks in the curve (see Appendix I).
### Table 4.1: Precipitation stations used for the study. Latitude, longitude and elevation of the stations and the degree of completeness and gaps of the data in the study-period.

<table>
<thead>
<tr>
<th>ID</th>
<th>Station Name</th>
<th>Latitude (°)</th>
<th>Longitude (°)</th>
<th>Elevation (m.a.s.l)</th>
<th>Comp. and gaps of the station data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1001</td>
<td>Andacollo</td>
<td>37.18</td>
<td>70.68</td>
<td>1024.2</td>
<td>FC</td>
</tr>
<tr>
<td>1002</td>
<td>Auquinco</td>
<td>37.31</td>
<td>69.97</td>
<td>1472.4</td>
<td>&lt;3M</td>
</tr>
<tr>
<td>1004</td>
<td>Cajon Curileuvu</td>
<td>36.96</td>
<td>70.39</td>
<td>1405.9</td>
<td>&lt;1Y</td>
</tr>
<tr>
<td>1005</td>
<td>Chochoy Mallin</td>
<td>37.36</td>
<td>70.79</td>
<td>1191.6</td>
<td>&lt;1Y</td>
</tr>
<tr>
<td>1006</td>
<td>Chorriaca</td>
<td>37.94</td>
<td>70.10</td>
<td>1030.1</td>
<td>FC</td>
</tr>
<tr>
<td>1007</td>
<td>Chos Malal</td>
<td>37.38</td>
<td>70.27</td>
<td>886.4</td>
<td>FC</td>
</tr>
<tr>
<td>1008</td>
<td>El Alamito</td>
<td>37.26</td>
<td>70.41</td>
<td>979.9</td>
<td>&lt;1Y</td>
</tr>
<tr>
<td>1009</td>
<td>El Cholar</td>
<td>37.44</td>
<td>70.65</td>
<td>1172.1</td>
<td>&lt;1Y</td>
</tr>
<tr>
<td>1010</td>
<td>El Huecu</td>
<td>37.65</td>
<td>70.58</td>
<td>1343.9</td>
<td>&lt;3M</td>
</tr>
<tr>
<td>1011</td>
<td>Estancia Chacayco</td>
<td>37.39</td>
<td>70.87</td>
<td>1205.7</td>
<td>2007 till 2011</td>
</tr>
<tr>
<td>1012</td>
<td>Las Lajas</td>
<td>38.53</td>
<td>70.37</td>
<td>711.7</td>
<td>2007 till 2011</td>
</tr>
<tr>
<td>1013</td>
<td>Las Ovejas</td>
<td>36.99</td>
<td>70.75</td>
<td>1390.3</td>
<td>&lt;3M</td>
</tr>
<tr>
<td>1014</td>
<td>Loncopue</td>
<td>38.08</td>
<td>70.62</td>
<td>994.3</td>
<td>FC</td>
</tr>
<tr>
<td>1017</td>
<td>Los Miches</td>
<td>37.22</td>
<td>70.78</td>
<td>1080.7</td>
<td>FC</td>
</tr>
<tr>
<td>1018</td>
<td>Paso de Indios</td>
<td>38.53</td>
<td>69.41</td>
<td>517.0</td>
<td>FC</td>
</tr>
<tr>
<td>1019</td>
<td>Pichi Neuquen</td>
<td>36.63</td>
<td>70.80</td>
<td>1327.8</td>
<td>FC</td>
</tr>
<tr>
<td>1021</td>
<td>Tricao Malal</td>
<td>37.04</td>
<td>70.32</td>
<td>1352.3</td>
<td>FC</td>
</tr>
<tr>
<td>1022</td>
<td>Varvarco</td>
<td>36.86</td>
<td>70.68</td>
<td>1213.1</td>
<td>&lt;3M</td>
</tr>
<tr>
<td>1023</td>
<td>Vilu Mallin</td>
<td>37.45</td>
<td>70.76</td>
<td>1113.6</td>
<td>FC</td>
</tr>
<tr>
<td>1101</td>
<td>Buta Ranquil</td>
<td>37.10</td>
<td>69.73</td>
<td>851.5</td>
<td>FC</td>
</tr>
<tr>
<td>1102</td>
<td>Bardas Blancas</td>
<td>35.87</td>
<td>69.78</td>
<td>1429.0</td>
<td>FC</td>
</tr>
<tr>
<td>1103</td>
<td>Arroyo La Vaina</td>
<td>35.92</td>
<td>69.98</td>
<td>1592.0</td>
<td>&lt;3M</td>
</tr>
</tbody>
</table>

- **FC**: The data is fully complete in the study period
- **<3M**: Less than 3 months is missing in the data
- **<1Y**: Between 3 months and a year is missing in the data (not continuously)
- **More than a year is missing in the data (written are the missing years)**

For the interpolation, the rainfall stations with missing values are ignored for the periods with gaps. Hence, as a result of the interpolation these gaps can be completed using the information of the rest of the stations.
4.2.2 Satellite rainfall estimates, CMORPH

Several remote sensing methods have been developed for estimating the precipitation. Satellite-based estimations of rainfall can provide the data for the areas where there are no rainfall stations or can help to improve the data in those areas where there is a low density of stations (Thiemig et al., 2012).

Many studies have been performed in order to evaluate, validate and compare the different types of satellite-based rainfall estimates. Results differ depending on the locations and topography. There are not so many works analysing the performance of this products in mountainous regions. Therefore, some previous studies showed a better performance in algorithms based in microwave-based compared to the ones based on infrared. Though, in the Ethiopian highlands, it was observed that CMORPH rainfall estimates had a higher performance among all the other satellites considered for the study (Bitew and Gebremichael, 2011). Additionally, this same satellite algorithm, as is stated in section 2.1.1.2, was validated in southern latitudes. Therefore, CMORPH is chosen as the satellite rainfall estimation to evaluate in this study.

The Climate Prediction Center (NOAA-CPC) morphing method, CMORPH (Joyce et al., 2004), is a process that yields spatially and temporally independently the microwave-derived precipitation analyses from the infrared temperature field. In this algorithm, the Infrared is only used to interpolate between the two passive microwave derived rainfall fields (TRMM Microwave Imager and the Special Sensor Microwave/Imager). Therefore, the satellite precipitation rainfall estimates are only based on the passive microwave (Thiemig et al., 2012). These satellite rainfall estimates were validated with high quality resolution data over Australia and the United States, along with radar data (Joyce et al., 2004). The satellite resolution is 0.25° x 0.25° (8 km at the Equator) and is available globally from 60°N to 60°S (CMORPH, n.d.).

By the moment there are two different data sources of CMORPH: Version 1.0 and Version 0.x. As stated in CMORPH (n.d.), the first one uses a fixed algorithm with inputs of the same
version while Version 0.x, performed since 2002, has an evolving algorithm in which inputs of changing versions over the entire data period are used. Version 0.x, at the moment of the present study, was not released for the whole study period, therefore this version is used for the last study period (2006-2011). Version 1.0 is used for the remaining years, (1998-2005). However, as explained in CMORPH (n.d.) the differences between both versions are minor and are described in the following bullets::

- “The Version 1.0 covers the entire TRMM/GPM era from Jan.1998 to the present, while the Version 0.x started from Dec.2002”;
- “The Version 1.0 is generated using a fixed algorithm and inputs of fixed versions to ensure best possible homogeneity, while the Version 0.x has been produced using an evolving algorithm and inputs of changing versions and therefore presents substantial inhomogeneities especially over the earlier years of its operations (2003-2006)”;
- “The Version 1.0 includes the raw, satellite only precipitation estimates as well as bias corrected and gauge-satellite blended precipitation products; while the Version 0.x only has the satellite-only products”.

CMORPH rainfall data is provided in a 3hs and daily basis in a grid of 0.25° x 0.25°, which for the study area provides an average resolution of around 22 km x 27.8 km. CMORPH data is provided in binary format. Thus, with the aid of Grid Analysis and Display System (GrADS) software (GrADS, 2009), raw daily data of CMORPH is converted into text files in order to be processed and presented as time series.

The processing of the data involves the generation of a “CTL” file for each day and afterwards a “script” file, also per day. Both files must be run consequently in the program GrADS taking into account that this “script” file uses as input the “CTL” file. In Appendix II the “CTL” and the “script” files used for one day are presented as an example.

The grid adopted for the interpolation is chosen based on the spatial resolution provided by the satellite data.. As the satellite grid in these latitudes and longitudes has an average resolution of 22 km x 27.8 km, the chosen interpolation grid is 20 km x 20 km. Moreover, the rainfall stations are located in an inhomogeneous way, having a scarce density in the south-east area. In Figure 4.6 the satellite and the interpolation grids are presented together to the rainfall stations.
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Figure 4.6: Grid adopted for the interpolation (20km x 20km) compared to the grid of the satellite (0.25° x 0.25°; around 22km x 27.8 km for the present study) and the location of the 22 available rainfall stations.

4.2.3 Comparison between Rainfall stations and CMORPH data

The estimation of the rainfall by satellites gives areal precipitation in a resolution of 0.25° x 0.25° whereas the rainfall stations provide the precipitation in a point. Consequently, in order to compare both data, the area of influence of the stations in a certain area of a satellite point is estimated. In some cases, the amount of rainfall stations influencing the area of the satellites is more than one. Therefore, the percentage of influence of each station in each satellite point is considered. In other cases, mainly in the southern part of the study area, where the density of rainfall stations is low, only one rainfall station may affect the area of influence of the satellite estimations.

Several satellite points, in different random locations of the study area, are chosen and used for the comparison between both inputs. The daily, monthly and yearly correlation between the two different data is made for the whole study period (1998-2011) as it can be seen in Table 4.2. Furthermore, to have another criterion of comparison, the total cumulative rain is compared in Table 4.2. In Figure 4.6 the location of the stations and satellite grid points can be observed.
Table 4.2: Comparison between the areal precipitation estimated with CMORPH and the calculated with the rainfall stations (RS): Correlation between both data (daily, monthly and yearly) and differences in the cumulative rain for the whole study period (1998-2011).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>r027</td>
<td>1019</td>
<td>0.10</td>
<td>0.08</td>
<td>0.31</td>
<td>11241</td>
<td>6861</td>
<td>63.85%</td>
</tr>
<tr>
<td>r030</td>
<td>1005-1011-1017-1023</td>
<td>0.19</td>
<td>0.10</td>
<td>0.26</td>
<td>7414</td>
<td>5238</td>
<td>41.54%</td>
</tr>
<tr>
<td>r044</td>
<td>1022-1004-1013</td>
<td>0.11</td>
<td>0.02</td>
<td>0.53</td>
<td>9559</td>
<td>5656</td>
<td>69.01%</td>
</tr>
<tr>
<td>r047</td>
<td>1010</td>
<td>0.18</td>
<td>0.40</td>
<td>0.24</td>
<td>6955</td>
<td>2995</td>
<td>132.19%</td>
</tr>
<tr>
<td>r049</td>
<td>1014</td>
<td>0.25</td>
<td>0.37</td>
<td>0.33</td>
<td>4172</td>
<td>2898</td>
<td>43.98%</td>
</tr>
<tr>
<td>r080</td>
<td>1006</td>
<td>0.17</td>
<td>0.26</td>
<td>0.11</td>
<td>4273</td>
<td>2094</td>
<td>104.09%</td>
</tr>
<tr>
<td>r122</td>
<td>1018</td>
<td>0.21</td>
<td>0.36</td>
<td>0.32</td>
<td>2350</td>
<td>1805</td>
<td>30.22%</td>
</tr>
</tbody>
</table>

Regarding to the cumulative data from the last table it can be concluded that there is a clear trend to underestimate the rainfall by the satellites in comparison to the measurements in the stations.

When analysing the correlation between both data no clear relationship between them is observed. However, better correlations can be perceived in cases were the centroid of the satellite estimation is close to the rainfall station being analyse, r049 and r047. Moreover, when the satellite is affected by several stations the daily correlation is improved, as in r030 and r044. Nevertheless, there are some cases where there are almost no daily or monthly correlation as in r027 and r044.

In Figure 4.7, the comparison between the precipitations measured in station 1014, which results in the best correlation, and the estimated areal precipitation in r049 with the satellite is presented. It can be seen how the precipitation estimated with CMORPH cannot reach the high values, what results in the reduction in the cumulative precipitation.

Moving correlation, expecting temporal shifts, is also applied without finding satisfactory results. The monthly and yearly accumulation is also compared resulting no temporal pattern between both cases. Therefore, is difficult to find a trend between both data series.
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Figure 4.7: Comparison between the rainfalls measured in station 1014 (considered as areal precipitation as it is the only station affecting the satellite area) and the estimated in r049 with CMORPH during 2001.

Figure 4.8 shows the accumulated precipitation for rainfall station 1014 and satellite point r049 during 2001. From this example it can be observed how the total underestimation of CMORPH during a year is around 50% having a strong impact from the winter precipitations. Consequently, this gap between both data is sharply affected because of the impossibility of CMORPH to reproduce the high peaks and snow during the winter period.

Figure 4.8: Comparison between the accumulated rainfalls measured in station 1014 (considered as areal precipitation as it is the only station affecting the satellite) and the cumulative estimated in r049 with CMORPH during 2001.

4.3 Flow Data

Daily flow measurements at 7 hydrometric gauges within to the catchment (Figure 4.1) were provided by the Water Resources Deputy Department which depends on the Department of Public of Argentina (SSRRHH de la República Argentina, n.d.). From the 7 stations only one has the complete measurements for the study period as it is shown in Table 4.3. However, three gauges are used for the modelling avoiding the missing period. These three stations are chosen mainly because of the completeness of the data and the location. For the modelling it is important to have as reference downstream outlet (Station Paso de los Indios)
and also some isolated catchments that can be modelled independently (Andacollo and Bajada del Agrio).

As additional information in Appendix I the entire period of data is presented in order to show the completeness of the recorded data and showing where the gaps can be found.

Table 4.3: Flow Gauges used for the study. Latitude, longitude and elevation of the stations and the grade of completeness and gaps of the data in the study-period (1998-2011).

<table>
<thead>
<tr>
<th>ID</th>
<th>Station Name</th>
<th>Latitude (°)</th>
<th>Longitude (°)</th>
<th>Elevation (m.a.s.l)</th>
<th>Comp. and gaps of the station data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1001</td>
<td>Andacollo</td>
<td>37.1833</td>
<td>70.6800</td>
<td>1024.2</td>
<td>04.2004 till 12.2005</td>
</tr>
<tr>
<td>1003</td>
<td>Bajada del Agrio</td>
<td>38.3655</td>
<td>70.0329</td>
<td>668.3</td>
<td>04.2004 till 12.2005</td>
</tr>
<tr>
<td>1015</td>
<td>Los Carrizos</td>
<td>37.1216</td>
<td>70.7699</td>
<td>1154.1</td>
<td>04.2004 till 12.2005</td>
</tr>
<tr>
<td>1016</td>
<td>Los Maitenes</td>
<td>37.3191</td>
<td>70.2786</td>
<td>978.0</td>
<td>04.2004 till 12.2005</td>
</tr>
<tr>
<td>1018</td>
<td>Paso de los Indios</td>
<td>38.5319</td>
<td>69.4136</td>
<td>517.0</td>
<td>FC</td>
</tr>
<tr>
<td>1020</td>
<td>Rahueco</td>
<td>37.3557</td>
<td>70.4533</td>
<td>917.1</td>
<td>04.2008 till 12.2011</td>
</tr>
<tr>
<td>1022</td>
<td>Varvarco</td>
<td>36.8572</td>
<td>70.6795</td>
<td>1213.1</td>
<td>04.2004 till 12.2005</td>
</tr>
</tbody>
</table>

*FC* The data is fully completed in the study period

More than a year is missing in the data (written are the missing years)

The available flow data is on daily basis. The measurements were performed following the standards provided by ISO (ISO 748, 2007) which specifies methods for determining the velocity and cross-sectional area of water flowing in open channels without ice cover, and for computing the discharge. Moreover, ISO-748 covers methods of employing current-meters or floats to measure the velocities and it deals only with single measurements of the discharge.

To test the consistency of the data the double mass curve method is applied (Searcy et al., 1960). Due to the lack of data between 2004 and 2005 as it is shown in Table 4.3, the test is divided into two different periods, between 1998 and 2003 and between 2007 and 2011. The cumulated recorded data on yearly basis is obtained and consequently the cumulated mean of them (the missing values are ignored). As a reference value for the test, the mean of the cumulated flow is used. The cumulative flow of the stations that is used in the study, are plotted and compared against the cumulative flow of the reference values (see Figure 4.9). The graphs show a clear evidence of consistence in the data.

![Figure 4.9: Double mass curve method applied to the flow gauges according to (Searcy et al., 1960). Cumulative flow of a station is plotted against the mean cumulative flow of the group being studied.](image)

For some of the flow gauges additional information is available, e.g. the mean flow ($Q_m$), the section, the width ($b$) and the mean flow velocity ($V_m$) (SSRRHH de la República Argentina, 2011):
Table 4.4: Flow Gauges with measurements of the mean flow (Q), section, width (b) and mean flow velocity (Vm) (SSRRHH de la República Argentina, 2011)

<table>
<thead>
<tr>
<th>Gauge</th>
<th>Qm</th>
<th>Section</th>
<th>b</th>
<th>Vm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Andacollo</td>
<td>103.41</td>
<td>83.91</td>
<td>89.75</td>
<td>1.01</td>
</tr>
<tr>
<td>Rahueco</td>
<td>207.73</td>
<td>153.02</td>
<td>101.83</td>
<td>1.09</td>
</tr>
<tr>
<td>Bajada del Agrio</td>
<td>81.38</td>
<td>73.88</td>
<td>75.45</td>
<td>0.94</td>
</tr>
<tr>
<td>Los Maitenes</td>
<td>16.73</td>
<td>20.94</td>
<td>44.33</td>
<td>0.56</td>
</tr>
<tr>
<td>Paso de los Indios</td>
<td>312.00</td>
<td>317.73</td>
<td>220.50</td>
<td>0.80</td>
</tr>
</tbody>
</table>

4.4 Complementary data

Daily mean temperatures at 18 meteorological stations within the catchment (Figure 4.10) were provided by the Water Resources Deputy Department which depends on the Department of Public of Argentina (SSRRHH de la República Argentina, n.d.). Not all the stations have the complete time series, having in most of the stations available data until 2009. An interpolation procedure is applied in order to obtain the time series of the temperatures in the same grid as for the precipitation for the whole study period (see section 3.2.4).

![Figure 4.10: Neuquén catchment with its topography (m.a.s.l.) and the available temperature and evaporation stations.](image-url)

Bardas Blancas

Las Chacras

Cajon de Los Chacars

Roca de Chacaico

Los Laguneros

Villa Colorada del C.L.

Los Hareres

Andacollo

Bajo de los Indios

Estancia La Chacana

Pítulo

Mateju-Los Alarifes

Chos Malal

Buta Mallín

Campana Matilda

Bajada del Agrio

Paso de los Indios

Tabanos

100 50 0 100 Km

Temperature Stations

Evaporation Stations

Topography

High: 377.165

Low: 177.213
Regarding the evaporation only two stations with daily data are available (SSRRHH de la República Argentina, 2011). From these data, the mean monthly values are obtained (Figure 4.10).

Table 4.5: Mean monthly values obtained for the evaporation hydrometeorological stations Chos Malal (CHM) and Paso de los Indios (PDI) (SSRRHH de la República Argentina, 2011)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CHM</td>
<td>6.34</td>
<td>5.64</td>
<td>4.13</td>
<td>2.78</td>
<td>2.18</td>
<td>1.90</td>
<td>1.52</td>
<td>2.69</td>
<td>3.24</td>
<td>4.52</td>
<td>5.26</td>
<td>6.74</td>
</tr>
<tr>
<td>PDI</td>
<td>11.11</td>
<td>9.35</td>
<td>6.86</td>
<td>3.98</td>
<td>2.15</td>
<td>1.84</td>
<td>1.84</td>
<td>2.94</td>
<td>4.26</td>
<td>6.68</td>
<td>8.71</td>
<td>10.65</td>
</tr>
</tbody>
</table>
5 Results

In the following sections the results obtained during the calculation process are presented. Two main group of calculation can be distinguished: the applied to perform the interpolation schemes and the hydrological model.

Concerning interpolation techniques of the precipitations, a comparison between mechanical methods, which include Thiessen Polygon and Inverse distance methods, and statistical methods, which comprise Ordinary point Kriging (OK) and External Drift Kriging (EDK) are resumed.

With the aim of accomplishing the main objective of the present work, five different cases of precipitation are considered in which the interpolation schemes are applied:

- C1: Considers only data measured with the Rainfall Stations.
- C2: Considers only data estimated with the satellite, CMORPH algorithm.
- C3: Considers data measured with the rainfall stations combined with the satellite estimations.
- C4: Considers data measured with the rainfall stations combined with the topography.
- C5: Considers data measured with the rainfall stations combined with the satellite estimations and the topography.

Thus, mechanical methods are only be applied in cases C1 and C2, while statistical schemes are used along the five cases. Therefore, OK is utilized in cases C1 and C2 whereas EDK is implemented in cases C3, C4 and C5.

Concerning Kriging methods, the first step to follow is the estimation of the experimental variogram with the consequently obtaining of the theoretical variogram variables. Thus, to obtain the most accurate profile, two different shapes are tested together with different amount of neighbours to be considered during the performance assessment.

Cross-validation is the selected tool used to compare the performances of all the tested interpolation methods. For each precipitation case, an evaluation is performed where mechanical and statistical models are compared together. Finally, by means of the Objective Function (OF) shown in (18) the different tests are compared.

Consequently, the parameters of the test with best performance are used for the interpolation of the precipitations. Therefore, five different sets of precipitation time series are estimated to be used as input in the hydrological model.

Interpolation of the mean daily temperature time series is also developed as this input is also a requirement for the hydrological model. Hence, EDK is applied with the topography as external drift.

As stated in section 3.2, a hydrological model with HEC-HMS is developed and run for the five precipitation cases (Feldman, 2000). To set up the model several parameters must be established and consequently are presented in this subsection. For the calibration of each of the five models, the dynamically dimensioned search (DDS) algorithm is used (Tolson and Shoemaker, 2007). Thus, parameters adopted for the calibration together with the optimum results obtained are shown in this subsection.
Different time windows are established for the calibration and validation simulations. In both instances, a continuous hydrograph and the consequent flow mass curve are obtained and compared to the observed flows. Therefore, results obtained are evaluated with Nash-Sutcliffe efficiency criterion (NSC).

Finally in the end of this section, a comparison of the accomplishment of the five different cases is performed and evaluated in order to obtain the most accurate input that simulates the observed flow in the studied catchment.

## 5.1 Interpolation

The adopted interpolation grid is presented in Figure 4.6. This grid is adopted for the five precipitation cases and the temperature data and its spatial resolution is 20 km x 20 km.

### 5.1.1 Precipitation

In this subsection results obtained for the mechanical and statistical schemes are presented in the Cross Validation subsection. Previously, for the Kriging methods, the experimental and theoretical variogram main variables are calculated.

#### 5.1.1.1 Kriging methods: Variogram

The generation of the experimental variogram is the first instance to complete in a Kriging scheme. To accomplish it, the data of the whole time series is used.

As there are two main sources of precipitation data: rainfall stations and satellite estimations, two different experimental variograms are calculated: For both cases, in order to get an accurate result, several numbers of lags and lags separations are tested as it is shown in Figure 5.1.

Regarding the rainfall stations, as it can be seen in Figure 4.1, the density of stations in some areas is not representative. In Figure 5.1 this can be confirmed with the dispersion of the obtained points in the experimental variogram, which makes it not easy to fit.

![Figure 5.1: Experimental variograms calculated for the rainfall stations and satellite-based estimations, CMORPH data. Several trials (Vi) are performed changing the number of lags and the lags separation. Theoretical variogram variables deduced from the satellite estimations are applied for the rainfall stations data.](image)

As the resolution of the interpolation grid is established in accordance to the satellite grid, the experimental variogram obtained with the satellites estimations is easy to fit (Figure 5.1). Consequently, the theoretical variogram main variables can be adopted easily.
As the experimental variogram of the rainfall stations cannot provide a direct theoretical variogram, the adopted with the satellite estimation is used as well for this case. Consequently, the theoretical variogram main variables adopted for the rainfall stations and the satellite estimations has the following characteristics:

- Nugget effect: 0.2
- Range: 150,000
- Partial sill: 0.8
- Sill: 1

5.1.1.2 Cross Validation

As stated in section 3.1 several interpolation techniques are applied for this study. Concerning the mechanical methods Nearest Neighbour (NN) and Inverse Distance (InvD) are used. Regarding the statistical methods Ordinary Kriging (OK) and External Drift Kriging (EDK) are calculated.

As can be seen in Table 5.1 several tests are performed to compare the performances of the interpolation techniques. Mechanical methods and OK are only applied for the first two precipitation cases where no additional information is considered, C1 and C2. Therefore, for cases C3, C4 and C5, EDK is the only possible interpolation technique to be used. In all tests, only daily time steps with average precipitation greater than 2mm/day are considered for the cross-validation.

To evaluate the variogram profile, spherical and exponential shapes are tested for the statistical methods. Moreover, to assess the interpolation the amount of neighbours to consider is varied. Therefore, as the total number of available rainfall stations is 22 (considered a small sample) for cases C1, C3, C4 and C5, the minimum amount of neighbours to be tested are between 3 and 4, while the maximum are between 8 and 12. In contrary, for case C2 where the satellite estimations are evaluated alone, the minimum number of neighbours tested is between 10 and 12, whereas the maximum number adopted is 24, considering that there are 129 satellite points along the area.

In Table 5.1 the characteristics adopted for all the cross-validations tests to be performed for each precipitation case are presented. These include the type of interpolation technique (NN, InvD, OK or EDK), the shape of the variogram to be considered if necessary (spherical or exponential) and the minimum and maximum amount of neighbours to be included.

<table>
<thead>
<tr>
<th>XV Tests</th>
<th>Interpolation Technique</th>
<th>Shape</th>
<th>Min number of Neighbors C1/C3/C4/C5</th>
<th>Max number of Neighbors C1/C3/C4/C5</th>
<th>C2</th>
<th>C2</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>NN</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>R2</td>
<td>InvD</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>R3</td>
<td>OK</td>
<td>OK</td>
<td>EDK</td>
<td>sph</td>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td>R4</td>
<td>OK</td>
<td>OK</td>
<td>EDK</td>
<td>exp</td>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td>R5</td>
<td>OK</td>
<td>OK</td>
<td>EDK</td>
<td>sph</td>
<td>3</td>
<td>10</td>
</tr>
<tr>
<td>R6</td>
<td>OK</td>
<td>-</td>
<td>EDK</td>
<td>sph</td>
<td>3</td>
<td>-</td>
</tr>
<tr>
<td>R7</td>
<td>OK</td>
<td>-</td>
<td>EDK</td>
<td>sph</td>
<td>4</td>
<td>-</td>
</tr>
</tbody>
</table>
For each of the study cases the performance assessment indices stated in section 3.1.3 are calculated. Moreover, the objective function (18) is obtained and used for the evaluation. Case C2 has as only input the satellite estimations data which its resolution is similar to the adopted for the interpolation. Therefore, results obtained for case C2 are shown separately from the other cases as they are not comparable.

In Figure 5.2 results obtained for case C2 for each performance index are presented. It can be seen that test R1, in which the NN method is applied, obtained the worst performance. However, InvD showed the best performance in C2 due to the large amount of satellite estimation points in the area, being the performance of the Kriging methods slightly worst.

A comparison of the obtained indices for precipitation cases C1, C3, C4 and C5, in which the main data is provided by the rainfall stations, are presented in Figure 5.3. From this figure in which the different tests are compared along the precipitation cases, it can be observed that case C1 presented the best performance for the RMSE, correlation, BIAS, while C3 has better achievement for the RVar coefficient. Therefore, according to the obtained results with the OF it can be concluded that C1 is the case with the best performance followed by cases C4 and C5.

Moreover, from Figure 5.3 it can be seen that when rainfall input is used as main data, statistical methods outperform mechanical schemes.
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Figure 5.3: Cross-validation tests (XV Tests) for cases C1/C3/C4/C5 (trim limit value 2mm/day): Root Mean Square error (RMSE), variance relationship (RVar), Correlation, BIAS and Objective Function.

Furthermore, the best result obtained for each precipitation case, based on the calculated objective function is shown in Table 5.2 with its corresponding test. For cases C3, C4 and C5 there is a slight difference between the obtained best indices of each test. Moreover, in C1 the statistical methods showed a higher performance in comparison to the mechanicals methods.

Table 5.2: Cross validation optimum results (trim limit value 2mm/day) for each precipitation case: Cross validation test (XV test), Bias, Root mean square error (RMSE), Correlation (Corr), variance relationship (RVar) and objective function (OF).

<table>
<thead>
<tr>
<th>Input Case</th>
<th>XV Test</th>
<th>Bias</th>
<th>RMSE</th>
<th>Corr</th>
<th>RVar</th>
<th>OF</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>R7</td>
<td>0.253</td>
<td>1.431</td>
<td>0.127</td>
<td>0.527</td>
<td>1.010</td>
</tr>
<tr>
<td>C3</td>
<td>R7</td>
<td>0.317</td>
<td>1.449</td>
<td>0.124</td>
<td>0.550</td>
<td>1.021</td>
</tr>
<tr>
<td>C4</td>
<td>R7</td>
<td>0.317</td>
<td>1.445</td>
<td>0.122</td>
<td>0.541</td>
<td>1.022</td>
</tr>
<tr>
<td>C5</td>
<td>R6</td>
<td>0.319</td>
<td>1.449</td>
<td>0.125</td>
<td>0.547</td>
<td>1.022</td>
</tr>
<tr>
<td></td>
<td>C2</td>
<td>R2</td>
<td>-0.013</td>
<td>0.929</td>
<td>0.627</td>
<td>1.064</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.854</td>
</tr>
</tbody>
</table>
Finally, as it can be seen in Table 5.2 for most of the cases where rainfall stations are the main input parameter, test R7 presented the best result. Consequently, parameters adopted from this test are used in the interpolation of cases C1, C3, C4 and C5 (see Table 5.1). In contrary, for case C2, the best result is obtained with test R2, thus the interpolation of this particular case is performed with the Inverse distance method scheme.

5.1.1.3 Interpolation results

After performing the interpolation, for each precipitation case different rainfall time series are obtained for every point of the interpolation grid. Consequently, these values are used in the hydrological model as precipitation inputs.

To observe the variation of the precipitation within the catchment, the yearly average precipitation obtained by means of the corresponding interpolation technique for the whole study period (1998-2011) is calculated. A map with the calculated values is shown in Figure 5.4.

From Figure 5.4 it can be appreciated that case C2 presents the sharpest gradient of precipitations. On the contrary, the lowest difference of temperature along the catchment is obtained with only the rainfall stations, case C1.

The incorporation of external drift variables, C3, C4 and C5, helps to reproduce the strong precipitations in the high mountains at the north-west area of the catchment. Accordingly, the inclusion of the satellite estimations, case C3, increased more the precipitations in that area in comparison to the topography, case C4. However, the incorporation of both additional data together, case C5, helps to reach the maximum values in the ridges of the mountains.

Finally, it can be concluded that case C2 provides in average, the minimum total amount of precipitation while in contrary, case C5, obtained the maximum. Therefore, cases C1, C3 and C4 reached values in between.
Figure 5.4: Average of the yearly precipitation (mm/year) for each precipitation input case calculated with the corresponding interpolation method calculated between 1998 and 2011.
5.1.2 Temperature

Mean temperature time series measured in the hydrometeorological stations (see Figure 4.10) are used in order to develop the experimental variogram. In order to get an accurate result, several numbers of lags and lags separations are tested to obtain an experimental variogram.

From Figure 4.10 it can be observed that the density of stations in some areas is not representative of the study catchment. Furthermore, there are no stations in the high points along the region. In Figure 5.5 the calculated experimental variogram and the obtained theoretical variogram variables are shown. From this figure it can be confirmed the lack of spatial persistence of the stations considering the dispersion of the obtained points.

![Variogram Plot]

Figure 5.5: Experimental and theoretical variograms obtained for the temperature stations data. Several trials where performed (V1) changing the number of lags and the lags separation.

Finally, the theoretical variogram variables adopted for the temperature stations interpolation have the following characteristics:

- Nugget effect: 0.6
- Range: 130,000
- Partial sill: 0.5
- Sill: 1.1

To assess the performance, cross validation is done testing two different theoretical variograms profiles: spherical shape and exponential shape. For both tests the parameters found with the experimental variogram are adopted. In Figure 5.6 the results obtained in the cross validation for both tests is presented.

For both tests presented in Figure 5.6 the same indices of reliability calculated during the precipitation interpolation are evaluated. Moreover, the same objective function is appraised. From the results it can be appreciated that there is no variability between the performed tests, showing a slight difference in favour of the spherical shape (test R1), reason why this last one is adopted for the interpolation.
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

5.2 Rainfall-runoff model

In this subsection the main characteristics of the performed rainfall-runoff model are presented. This covers the disaggregation of the catchment into subcatchments to minimize the uncertainty of the model and also the division into several subbasins where the model parameters and inputs are included.

Regarding the model inputs, the main input to establish in each subbasin are the time series of the precipitations. Therefore, five different precipitation cases were generated by means of interpolation techniques in section 5.1.1, as well as the temperature time series. Subsequently, they are aggregated into the adopted subbasins areas and are included in each precipitation model. Moreover, average monthly evaporation is comprised as complementary input for the model.

To define the model, parameters of the basins and rivers are needed. These parameters are obtained from the available data of the site and described in this subsection. Moreover, parameters set up for the calibration algorithm are presented together with its obtained optimum result.

Consequently, continuous hydrographs and flow mass curves obtained for the validation and calibration period are showed together with the obtained indices of reliability calculated for each case. Finally, results are compared concluding which case presented the most accurate performance.

5.2.1 Model characteristics

In order to reduce the uncertainty in the model a disaggregation of the whole catchment is performed. In this particularly study two independent subcatchments are run separately, Andacollo and Agrio. Finally, a global catchment Neuquén that includes these two independents subcatchments is run. In Figure 5.8, the disaggregation of the catchment can be observed. The outlet of the catchment Neuquén is established in station Paso de los Indios, while for the other subcatchments is located in the stations with their corresponding name (see Figure 4.1).
The whole catchment is divided in 35 subbasins. To each subbasin, the generated time series of the precipitation and temperature are assigned as well as a mean monthly evaporation. The size of each subbasin is related to the interpolation grid resolution and the topography of the catchment. Consequently, the statistics calculated for the areas of all the subbasins are:

- Maximum area: 2382.7 km²
- Minimum area: 121.81 km²
- Average area: 930.63 km²
- Standard deviation of the areas: 505.27 km²

Figure 5.7: Subcatchments and outlets used in the hydrological model: Andacollo, Agrio and Neuquén (whole study area). 34 subbasins and 8 subbasin-groups are set up for the calibration.

In order to characterize the model, for all the subbasins a set of parameters for the calculation methods is assigned. Some of the parameters are left out to be established during the calibration phase. Therefore, to reduce the numbers of parameters to be calibrated the subbasins are grouped and as a result, they receive the same values for the calibrated parameters.

For each subcatchment, which represents an independent model, a minimum of two subbasin-groups are assigned as it can be seen in Figure 5.7. Finally, a total of 8 subbasin-groups are established: two for Andacollo subcatchment, two for Agrio subcatchment and four for Neuquén subcatchment.

Each of the subbasins is characterized differently. Andacollo subcatchment is the smallest of the three modelled subcatchments with 4,780 km². The topography along this subcatchment varies strongly from 3,700 m.a.s.l. to 1,050 m.a.s.l. Conversely, Agrio subcatchment is bigger than Andacollo subcatchment with almost 7,700 km². The variation of the topography in
Agrio subcatchment is not as sharp as for Andacollo subcatchment, although it has a strong variability on the elevations from 2,400 m.a.s.l. to 655 m.a.s.l. Finally, Neuquén catchment involves the previous subcatchments plus around 19,900 km², reaching the total extent of the study area of 32,300 km². The outlet of the catchment Neuquén is located in the station Paso de los Indios where the altitude is around 535 m.a.s.l.

The main stream of the catchment is divided into 19 segments. Only one segment is included in Andacollo subcatchment while in Agrio subcatchment 5 segments are considered. The slope of the river in Andacollo subcatchment is of 0.4% and only includes the river formed in the convergence of the mountains. The average slope of the rivers in Agrio subcatchment is 0.47%. In the end, the remaining streams of the Neuquén catchment have an average slope of 0.35%, reaching 0.1% in the outlet.

To perform the computing, the model is run at an hourly time step although the precipitation and flow data have a daily time step. The adopted time step of the simulation is established considering that the time of concentration in the basins and the lag time in the rivers in several cases are less than 24 hs.

As the whole study period is of 14 years, 1998-2011, having available data in all the flow gauges for 12 years the calibration is performed for the first 6 years of the available data. As for 2004 and 2005 there is no available information in some flow gauges, the remaining period 2006-2011 is used for the validation.

### 5.2.2 Model inputs

The model inputs are included in each of the subbasins. Precipitation time series are the main input and, as additional information, the time series of the temperature and the mean monthly evaporation are included.

Afterwards, for each of the adopted methods the parameters require to be assigned in each subbasin and river. Regarding the subbasins, parameters for the runoff generation are established in the Soil Moisture Accounting loss model. Subsequently, the runoff concentration methods are established. Therefore, the direct runoff is simulated using as input the parameters of the Clark’s Unit Hydrograph while for the baseflow, the inputs are the parameters of the Linear Reservoir method.

Finally, to model the dynamic of the stream, the Lag model is used as routing method. Thus, the main input parameter is the Lag time to be established in every stream.

### 5.2.2.1 Daily Precipitation

As stated in section 2.1.1, the main inputs of a hydrological model are the precipitations. As described in section 5.1.1, precipitations in the complete study area are estimated by means of interpolation in a grid with a resolution of 20 km x 20 km (see Figure 4.6). Consequently, for each subbasin, an influence area of the grid points is calculated which is obtained as described in subsection 3.2.4. Finally, the areal precipitation is included in each subbasin as an input for the hydrological model.

In the end, each subbasin has five different precipitation inputs as presented in section 5.1.1. In Figure 5.8, the yearly precipitations calculated for the subcatchments Andacollo and Agrio and for Neuquén catchment are shown obtained by the aggregation of the corresponding...
subbasins. Therefore, a comparison of the five precipitation cases estimated by the interpolation is performed as shown in Figure 5.4.

![Graphs showing mean yearly precipitation for Andacollo, Agrio, and Neuquen for different precipitation cases (C1, C2, C3, C4, C5).](image)

Figure 5.8: Mean yearly precipitation (pcp) calculated from the interpolation (for the 5 precipitation cases) obtained for the subcatchments Andacollo and Agrio and for Neuquén catchment.

As expected according to the precipitation maps (see Figure 5.4), the inputs calculated showed that the strongest precipitation comes from the mountainous area, where subcatchment Andacollo is located. Therefore, this region has the strongest precipitations in comparison to Agrio subcatchment and the mean values of the whole catchment, Neuquén.

Comparing the different precipitation cases, C2 presented higher precipitations the first year; being almost equal to the others in the second one (only in Andacollo the precipitations are overestimated during the second year). Conversely, its values are hardly reduced in the following years in comparison to the other cases, experiencing an increase in the last two years. As stated in section 4.2.2, CMORPH algorithm is slightly different between 1998-2005 and 2006-2011 (see section 4.2.2). However, there is no trend in the changing of the values between those different periods.

Regarding the other precipitation inputs, C5 presented in all the subcatchments the highest precipitations, usually followed by C4 which induces the strong impact of the topography and subsequently the satellite estimations.
5.2.2.2 Mean daily temperature

Complementary inputs are needed for the simulations, specially the temperature as indicated in 3.2.4 for the Temperature Index method.

After calculating the time series of the temperatures by mean of the interpolation (see 5.1.2) the values of the interpolation grid are aggregated for each subbasin and included in the model. To accomplish this, the same procedure as for the precipitations is done.

In Figure 5.9 the mean monthly temperatures calculated for the whole study period (1998-2011) are presented. The lower average temperatures are computed in Andacollo subcatchment, where the high mountains can be found. Therefore, the average monthly temperatures of Agrio subcatchment are similar to the calculated in the entire catchment Neuquén.

![Figure 5.9: Mean temperature per month calculated from the time series of the whole study period (1998-2011) obtained by means of the interpolation for Andacollo and Agrio subcatchments and Neuquén catchment.](image)

5.2.2.3 Mean monthly evaporation

The hydrological model HEC-HMS (Feldman, 2000) requires as input for the meteorological model the evaporation values in each subbasin or parameters to estimate it. As described in section 3.2.4, the monthly average evaporation methodology is used in this case. Thus, the values measured in the stations presented in section 4.4 are compiled obtaining the mean monthly evaporation for the study period for both stations which are presented in Figure 5.10.

A nearest neighbour technique is adopted to assign the mean monthly evaporation in each subbasin. Moreover, the average of both stations is used in the basins in between of both meteorological stations.
Figure 5.10: Mean yearly evaporation measured in two stations (Chos Malal and Paso de los Indios) and the average between them.

5.2.2.4 Parameters of the Basins

To perform the runoff generation Soil Moisture Accounting (SMA) loss model is used as stated in section 3.2.1. This method needs 19 parameters to be completed. Therefore, 9 are left for the calibration technique while the other 10 are established for each of the subbasins.

Within the 10 parameters to be established in the SMA method, 5 of them are related to initial conditions as a percentage. Thus, one for each of the layers that the model accounts for (canopy interception, surface depression storage, soil, upper groundwater and lower groundwater) are set up.

Consequently, the other 5 parameters are accounted according the land use and the type of soil. Canopy storage, surface storage and the percentage of impervious areas are related to the land use while soil storage, tension storage and soil percolation are related to the soil components. Finally, the parameters related to the groundwater layers in the SMA method are left out for the calibration.

In order to pass directly the water from the surface to the groundwater, avoiding soil calculations, the soil storage and the tension storage (amount of water that does not drain by gravity) are set to cero in this model.

Regarding the runoff concentration to account for the direct runoff Clark Unit Hydrograph (CUH) method is utilized while for the baseflow calculations Linear Reservoir (LR) model is developed.

To calculate the time of concentration of the CUH method, Kirpich formula is used (24). The minimum calculated time of concentration is 1.74 hs, the maximum 19.84 hs, while the average is 6.01 hs. The other parameter needed to be calculated in this method is the storage coefficient in hours, which is excluded for the calibration technique.

Regarding the LR method two parameters are needed for each groundwater layer: initial baseflow and groundwater coefficient both in hours. For the first one the baseflow calculated from the observed flow is used. To obtain this value, the flow duration curve of all the observed flows is performed and therefore the flow with an exceedance of 95% is used as the baseflow. Finally, the last parameter, groundwater coefficient, is left out for the calibration.
Finally, the complete list of the parameters adopted for each subbasin can be found in Appendix IV, where the basins HEC-HMS file for Neuquén catchment is presented.

5.2.2.5 Parameters of the Rivers

Lag method is the used routing method as stated in section 3.2.3. This method requires only one parameter, the lag coefficient. Therefore, equation (26) is used with the observed mean velocity of the streams when available; otherwise the estimated value with equation (27) is applied. As the stream is divided in 19 segments and in only 5 segments the observed mean velocity is available, for the remaining cases the estimation is performed.

To obtain the mean velocity, the length of the stream is required. Accordingly, with the aid of HEC-GeoHMS (Flemig and Doan, 2013) an ArcGIS (ESRI, 2011) tools using the topography of the study area, the calculation is performed.

Finally in Table 5.3 mean, maximum and minimum values of the lengths, mean velocities and lag times deduced from the calculation of the 19 streams, are shown.

Table 5.3: Stream's maximum, minimum and average values of the length, mean velocity (Vm) and the Lag time.

<table>
<thead>
<tr>
<th></th>
<th>Length (m)</th>
<th>Vm (m/s)</th>
<th>Lag (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max.</td>
<td>58833.41</td>
<td>1.17</td>
<td>19.17</td>
</tr>
<tr>
<td>Min.</td>
<td>4249.94</td>
<td>0.56</td>
<td>1.07</td>
</tr>
<tr>
<td>Mean</td>
<td>29386.35</td>
<td>0.94</td>
<td>8.81</td>
</tr>
</tbody>
</table>

As it can be seen in Table 5.3, the mean lag time is 8.81 hs, reason why the model is run in a hourly time step instead of a daily time step.

Finally, the complete list of the parameters adopted for each subbasin can be found in Appendix IV, where the basins HEC-HMS file for Neuquén catchment is presented.

5.2.3 Model Calibration

5.2.3.1 DDS Algorithm results

As stated in section 3.2.5 an automatic calibration technique, dynamically dimensioned search (DDS) algorithm is used to estimate the unknown parameters. The parameters left out for the calibration in each subbasin-group are 9. For each parameter the same boundary condition is set up for all the subcatchments as well as the same initial value to be adopted in the iterations. Therefore, 6 of the parameters correspond to the Soil Moisture Accounting method (SMA), 1 corresponds to the Clark Unit Hydrograph (CUH) and 2 correspond to the Linear Reservoir (LR) method as it can be seen in Table 5.4.

Consequently, the boundaries of the parameters are set up according to the possible variation that they may have according to the available data and theory (Scharffenberg and Fleming, 2008).
Table 5.4: Summary of the calibrated parameters and its upper and lower boundary.

<table>
<thead>
<tr>
<th>Method</th>
<th>Parameter</th>
<th>ID</th>
<th>Units</th>
<th>Lower boundary</th>
<th>Upper boundary</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMA</td>
<td>Groundwater 1 Maximum Storage</td>
<td>G1S</td>
<td>mm</td>
<td>200</td>
<td>700</td>
</tr>
<tr>
<td>SMA</td>
<td>Groundwater 1 Storage Coefficient</td>
<td>G1SC</td>
<td>h</td>
<td>5</td>
<td>200</td>
</tr>
<tr>
<td>SMA</td>
<td>GW 1 Max. Percol.</td>
<td>G1P</td>
<td>mm/h</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>SMA</td>
<td>Groundwater 2 Maximum Storage</td>
<td>G2S</td>
<td>mm</td>
<td>100</td>
<td>1200</td>
</tr>
<tr>
<td>SMA</td>
<td>Groundwater 2 Storage Coefficient</td>
<td>G2SC</td>
<td>h</td>
<td>200</td>
<td>4000</td>
</tr>
<tr>
<td>SMA</td>
<td>GW 2 Max. Percol.</td>
<td>G2P</td>
<td>mm/h</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>CUH</td>
<td>Storage Coefficient</td>
<td>CSC</td>
<td>h</td>
<td>1</td>
<td>200</td>
</tr>
<tr>
<td>LR</td>
<td>Groundwater 1 Storage Coefficient</td>
<td>LRG1</td>
<td>h</td>
<td>5</td>
<td>200</td>
</tr>
<tr>
<td>LR</td>
<td>Groundwater 2 Storage Coefficient</td>
<td>LRG2</td>
<td>h</td>
<td>200</td>
<td>6000</td>
</tr>
</tbody>
</table>

From the results in Figure 5.11 it can be seen that most of the parameters vary along the boundaries. A reduction in the number of parameters to be estimated and of the boundaries limits implies a decrease of the uncertainty of the calibration algorithm. Accordingly, some parameters do not show the same deviation along the limits for all the subcatchments. For example, G2SC and G2P do not reach the upper limit in the subcatchments. Moreover, those parameters experienced a slight variability. Another example is parameter CSC, where in all the subcatchments the upper limit is not reached. The complete list of the optimum parameters calculated during the calibration can be found in Appendix III.

Finally, the upper limit for G2SC in Andacollo and Agrio subcatchments could have been 1500 h instead of 4000 mm/h. Furthermore, G2P for those same subcatchments might not have been subjected to the calibration, considering that its values for all the input cases ranged around 0.05 mm/h. That same parameter, for the whole catchment Neuquén, could have had an upper boundary of 5.5 mm/h instead of 10 mm/h. In addition, the upper boundary of parameter CSC could have been set up around 160 h instead of 200.

The number of iteration set up in each subcatchment model depends on the amount of parameters to be calibrated which is related to the amount of subbasin-groups of each model. Andacollo and Agrio subcatchment have 2 subbasin-groups each while Neuquén has 4 subbasin-groups. Considering that each subbasin-group has 9 parameters to be calibrated the dimension of Andacollo and Agrio subcatchments model is 18, while for Neuquén catchment is 36.
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Figure 5.11: Best parameters obtained for each calibrated variable. Values are given related to the maximum and minimum limits adopted. For Andacollo and Agrio subcatchment 10 parameters are obtained (2 subbasin-groups for each of the 5 precipitation cases) while for Neuquén catchment 20 parameters are obtained (4 subbasin-groups for each of the 5 precipitation cases).

Moreover, a sensitivity of the iterations is performed to evaluate the variation of the algorithm with the number of iterations. According to Tolson and Shoemaker (2007) 30 iterations per degree of uncertainty is acceptable. However, as many number of iterations more computer time consuming. Thus, the sensitivity is performed against half of the recommended value.

In Figure 5.12 an example of the sensitivity performed in Andacollo subcatchment is presented. As it can be seen, the difference between the reached optimization values is similar in both cases. Consequently, for this study a minimum of 15 iterations per dimension of the model is established.
Figure 5.12: Global optimization performed with the DDS calibration for Andacollo subcatchment: sensitivity varying the number of iterations.

An Objective Function (31) is calculated, for each iteration which is based on the observed discharge and the simulated discharge. In Figure 5.13, the evolution of the calculated objective function for each subcatchment and for all the precipitation cases is shown.

To perform the calibration algorithm in Neuquén catchment model, the optimized parameters found in subcatchments Andacollo and Agrio are included. Thus, the obtained objective function calculated for whole study area is executed adopting for Andacollo and Agrio subcatchments the optimum parameters obtained.

Consequently in Figure 5.13, it can clearly be observed that for all the models the precipitation case that considers only the satellite estimations, C2, has the worst performance in comparison to the other four cases. Moreover, cases C1, C3, C4 and C5 showed a quite similar performance during the optimization procedure with the calibration algorithm. Nevertheless, case C4 outperformed the other cases in Andacollo and Neuquén models, while C5 has the best performance for subcatchment Agrio model.
5.2.3.2 Model results

After obtaining the optimum parameters with the DDS algorithm, the hydrograph for the calibration of the different models can be performed. Therefore, to perform Neuquén catchment model, the optimized parameters found in subcatchments Andacollo and Agrio are included. Consequently, the hydrograph of whole study area is executed combining all the optimum parameters obtained.

In Figure 5.14 the hydrographs obtained for the different models during the calibration time window are shown (1998-2003). Moreover, a comparison of the different rainfall inputs is presented.
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Figure 5.14: Daily hydrographs calculated during the calibration period (1998-2003) for the 5 precipitation cases: subcatchments Andacollo and Agrio and for Neuquén catchment.

As it can be seen, the summer peak produced because of the snow melting can hardly be simulated in the different models. Hence, in Andacollo subcatchment, where the highest mountains can be found and also the subcatchment with the lowest extension, this effect can strongly be appreciated. Moreover, the winter high peaks are reproduced without being able to reach the maximum observed values. Nevertheless, the main pattern of the hydrograph can be replicated quite accurately by almost all the precipitation cases. Thus, case C2, is the only case that can barely reproduce the shape of the hydrograph.
A flow mass curve can be constructed from the simulated and observed daily discharges. The aim of this graph is to observe the variation of the volumes of water along the study period. In Figure 5.15, the flow mass curve graphs for the three models during the calibration period and for the five precipitation cases are presented.

From the flow mass curve of Andacollo subcatchment, it can be seen that none of the cases can reach the observed volume of water during the calibration period. Nevertheless, case C2 reproduced the flow mass curve from 1998 till 2001 in an accurate way, from that year onwards the volume of water decreased in comparison to the observed volume, being finally the case with less performance. Conversely, case C5 is the case that could better simulate the volume of water as it is the case with more precipitation input as can be seen from Figure 5.8.
Regarding Agrio subcatchment, C2 is the only precipitation case that is not able to reproduce the flow mass curve. Nevertheless, all the other precipitation inputs slightly overestimated the volume during the first years, reaching finally almost the same observed volume.

Finally, in Neuquén catchment the volume of water is overestimated mainly during the whole period with all the precipitation inputs. However, precipitation case C1, which only considers the data from the rainfall stations, has the best performance in relation to the observed volume.

As the optimization used to obtain the optimum parameter set during the calibration is set to minimize the Root Mean Square Error (RMSE) (see section 3.2.5), the efficiency of the calibration is evaluated with the Nash-Sutcliffe (NSC) criterion.

In Table 5.5 a summary of the calculated NSC for each precipitation case is presented. Moreover, a relation of the simulated final volume in comparison to the observed volume during the calibration period is calculated.

Table 5.5: Results obtained for Nash-Sutcliffe efficiency criterion (NSC) and difference in volume (in comparison to the observed volume which is 100%) for the calibration simulations (5 precipitation cases). Results are presented for the subcatchments Andacollo and Agrio and for Neuquén catchment.

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibration: NSC</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Andacollo</td>
<td>0.496</td>
<td>0.126</td>
<td>0.462</td>
<td><strong>0.517</strong></td>
<td>0.454</td>
</tr>
<tr>
<td>Agrio</td>
<td>0.440</td>
<td>-0.285</td>
<td>0.477</td>
<td>0.490</td>
<td><strong>0.507</strong></td>
</tr>
<tr>
<td>Neuquén</td>
<td>0.560</td>
<td>-0.044</td>
<td>0.550</td>
<td><strong>0.582</strong></td>
<td>0.570</td>
</tr>
<tr>
<td><strong>Calibration: Volume diff.</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Andacollo</td>
<td>84.67%</td>
<td>67.56%</td>
<td>86.98%</td>
<td>83.10%</td>
<td><strong>90.47%</strong></td>
</tr>
<tr>
<td>Agrio</td>
<td>89.00%</td>
<td>75.81%</td>
<td>96.99%</td>
<td>100.40%</td>
<td><strong>100.00%</strong></td>
</tr>
<tr>
<td>Neuquén</td>
<td><strong>101.73%</strong></td>
<td>90.96%</td>
<td>109.89%</td>
<td>109.45%</td>
<td>110.05%</td>
</tr>
</tbody>
</table>

From the previous table it can be evaluated the performance of the calibration. Therefore, case C4 (precipitation case of the rainfall stations combined with the topography) outperformed during the calibration in Andacollo subcatchment and Neuquén catchment. Regarding Agrio subcatchment, case C5 (precipitation case of the rainfall stations combined with the topography and the satellite estimations) has the best achievement in comparison to the other precipitation cases.

Finally, case C2, showed the worst performance in comparison to the other precipitation cases, presenting negative values of NSC in Agrio subcatchment and Neuquén catchment.

**5.2.4 Model Validation**

As the observed flow data between 2004 and 2005 is not completed for all the gauges, the period between 2006 and 2011 is used for the validation. This period is characterized because of having fewer peaks in comparison to the calibration time window.

Therefore, the same optimum parameters obtained with the DDS algorithm used in the calibration period are adopted for the validation. Consequently, the hydrograph for the validation for the different models can be obtained from the simulations.

In Figure 5.16 the hydrographs of the different subcatchments for the different rainfall inputs obtained during the validation are shown.
Figure 5.16: Daily hydrographs calculated during the validation period (2006-2011) for the 5 precipitation cases: subcatchments Andacollo and Agrio and for Neuquén catchment.

As it can be seen from Figure 5.16, the summer peak produced because of the snow melting can hardly be simulated in all the models as it occurred during the calibration simulations. In the model performed for the whole catchment Neuquén, this effect is strongly reduced and can barely be appreciated. The first high peak observed during the winter precipitations is reproduced without being able to reach the maximum value in the three models. However, in Andacollo and Neuquén models the following peaks are reproduced accurately. Moreover,
the main pattern of the hydrograph can be reproduced quite precisely by all the precipitation cases.

In Figure 5.17, the flow mass curve graphs in daily basis of the three models during the validation period and for the five precipitation cases are presented.

For the calibration period the performance is assessed using the with the Nash-Sutcliffe (NSC) criterion, therefore for the validation the same index is used to evaluate the efficiency.

In Table 5.6 a summary of the calculated NSC for each precipitation case during the validation time window is presented. Moreover, a relation of the simulated final volume in comparison to the observed volume during the validation period is calculated.
### Table 5.6: Results obtained for Nash-Sutcliffe efficiency criterion (NSC) and difference in volume (in comparison to the observed volume) for the validation simulations (5 precipitation cases). Results are presented for the subcatchments Andacollo and Agrio and for Neuquén catchment.

<table>
<thead>
<tr>
<th>Validation: NSC</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Andacollo</td>
<td>0.324</td>
<td>0.241</td>
<td>0.397</td>
<td>0.421</td>
<td>0.430</td>
</tr>
<tr>
<td>Agrio</td>
<td><strong>0.387</strong></td>
<td>0.127</td>
<td>0.225</td>
<td>0.326</td>
<td>0.108</td>
</tr>
<tr>
<td>Neuquén</td>
<td>0.534</td>
<td>0.140</td>
<td><strong>0.555</strong></td>
<td>0.544</td>
<td>0.549</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Validation: Volume diff.</th>
<th>Andacollo</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Andacollo</td>
<td>83.44%</td>
<td>93.59%</td>
<td>82.79%</td>
<td>77.08%</td>
<td>88.08%</td>
<td></td>
</tr>
<tr>
<td>Agrio</td>
<td>91.63%</td>
<td>82.13%</td>
<td>111.69%</td>
<td>102.01%</td>
<td><strong>115.86%</strong></td>
<td></td>
</tr>
<tr>
<td>Neuquén</td>
<td><strong>98.69%</strong></td>
<td>96.50%</td>
<td>109.66%</td>
<td>103.81%</td>
<td>112.43%</td>
<td></td>
</tr>
</tbody>
</table>

From the previous table it can be evaluated the performance of the validation simulations. Case C5 (precipitation case of the rainfall stations combined with the topography and the satellite estimations) outperformed during the validation in Andacollo subcatchment model followed by case C4, which considers only the topography. Regarding Agrio subcatchment, case C1 (precipitation case that considers only the rainfall stations) has the best achievement in comparison to the other precipitation cases, followed once more by C4.

Finally, for Neuquén catchment model, the best performance is obtained using the rainfall stations as inputs combined with the satellite estimations, case C3, followed in this case by case C5.

Additionally, it can be observed that case C2 showed the worst performance in comparison to the other precipitation cases, presenting the lowest NSC values in the three models.

#### 5.2.5 Comparison and best results

In this subsection a comparison of the results obtained during the calibration and validation periods, for the three models and the five precipitation cases, is performed. For the comparison Root Mean Square Error (RMSE) and Nash-Sutcliffe (NSC) criterion are calculated in each case to evaluate the performance of the rainfall-runoff model.

In Figure 5.18 the calculated values of RMSE and NSC calculated for the subcatchments Andacollo and Agrio and catchment Neuquén are presented. In each case, a comparison between the results obtained for the different precipitation cases is performed.

It can be seen from Figure 5.18 that the worst performance is achieved in all the studied cases by C2 which is due to the difficultness of this case to represent the observed hydrographs (see Figure 5.14 and Figure 5.16).
Moreover, regarding Andacollo subcatchment, it can be noticed that the calculated indices of reliability in C1, C3, C4 and C5 have a slight difference between them. Thus, for the validation this difference is increased.

Concerning Agrio subcatchment, results obtained with the RMSE for the calibration and validation simulations showed an equal performance for cases C1, C3, C4 and C5. However, results obtained with NSC presented a similar trend for the calibration period, but not for the validation time window where a clearly higher performance from C1, flowed by C4.

With reference to Neuquén catchment model, both studied indices presented the same trend with the worst performance on case C2. Moreover, the performance obtained during the validation is comparable to the obtained during the calibration period.

Finally, the overall performance of the study catchment Neuquén, for the precipitation cases where the rainfall stations are taken into consideration is acceptable for both the calibration and validation periods. From Table 5.5 it can be observed that a value of 0.7 for the NSC can be reached with C4 during the calibration simulation while from Figure 5.18 a RMSE of 0.86 can be obtained for the validation period.

In Table 5.7 the best precipitation estimates obtained in each model for both, calibration and validation periods, are presented.
Table 5.7: Best precipitation estimates obtained for the Root Means Square Error (RMSE), Nash-Sutcliffe efficiency criterion (NSC) and difference in volume (in comparison to the observed volume) with the calibration and validation simulations.

<table>
<thead>
<tr>
<th>Subcatchment</th>
<th>Calibration</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>NSC</td>
</tr>
<tr>
<td>Andacollo</td>
<td>C4</td>
<td>C4</td>
</tr>
<tr>
<td>Agrio</td>
<td>C5</td>
<td>C5</td>
</tr>
<tr>
<td>Neuquén</td>
<td>C4</td>
<td>C4</td>
</tr>
</tbody>
</table>

For the calibration time window there is clear evidence that precipitation case C4 has the best performance in comparison to the other cases. On the contrary, for the validation time window there is not a clear leader case. Furthermore, case C4 obtained the second best performance in Andacollo and Agrio subcatchments models while case C5 obtained the second best achievement in Neuquén catchment model. In both cases the second positions have slight difference from the best cases. Consequently, the best validation cases are obtained with cases C4 and C5.
6 Conclusions and discussion

A rainfall-runoff model is performed to compare different rainfall inputs, which are based on observations in rainfall stations and satellite estimations obtained from the Climate Prediction Center (NOAA-CPC) morphing method, CMORPH (Joyce et al., 2004) algorithm. Moreover, to improve the data obtained from the rainfall stations, additional data as topography, satellite estimations or the combination of both are used in the geostatistical interpolation techniques as external drifts. Consequently, five different precipitation inputs are generated and compared.

In order to obtain different inputs for the rainfall-runoff model, several interpolation schemes were tested. After all, the test with the best performance assessment was used to estimate the time series of precipitations in the interpolation grid.

The hydrological model, used to compare the different rainfall inputs, was Hydrological-Modelling-System Version 3.3 (HEC-HMS) of the US Army of Engineers (Feldman, 2000). In addition, an automatic calibration technique was used in order to have an objective calibration for each of the different inputs. To accomplish this aim, the dynamically dimensioned search (DDS) algorithm developed by Tolson and Shoemaker (2007) was applied. According to the available data, the calibration and validation time windows were selected. Finally, the performance of the hydrological model was assessed by means of indices of reliability.

The conclusions are divided considering the relevant items of the present study. Firstly, some remarks are done about the raw data of the satellite-bases rainfall estimations, CMORPH. Subsequently, certain conclusions regarding interpolation of precipitation and the hydrological model are presented. Finally, some overall conclusions of the entire study, regarding the interaction between the two main stages, interpolation and hydrological model, likewise the accuracy of the raw input data, are done.

6.1 Satellite-based rainfall estimations raw data

As it is mentioned in section 4.2.3, in most cases there was no correlation in daily basis between satellite estimations and rainfall stations for a common area of influence. The maximum value achieved for correlation in daily time step was 0.25 while the maximum yearly correlation was of 0.53. In addition, CMORPH, in almost all cases, underestimate in more than 50% the cumulative precipitations in comparison to the rainfall stations during the whole study period (1998-2011). Moreover, in Figure 4.8 it can be observed that during winter period the underestimation by CMOPRH is higher than in summer season. This is possibly due to the lack of snow precipitation detection during the winter period. However, it can be clearly observed that the high precipitation peaks, measured with the rainfall stations, are not able to be detected by satellite-based estimations.

Finally, no possible explanation was found (e.g. shift in time) with the intention of relating rainfall estimation by CMORPH and the stations measurements.

6.2 Interpolation techniques for the precipitation inputs

The experimental variogram of the rainfall stations did not provide an easy theoretical variogram fitting. Moreover, it showed that the distribution of rainfall stations is not adequate for the study area. Hence, it is not able to reproduce the spatial persistence presenting them
as “unreliable” data. In this manner, the main variables for the theoretical variogram deduced from the experimental variogram of the satellite were used for the rainfall stations tests.

For the interpolation of the rainfall stations, statistical interpolation techniques showed a better achievement than mechanical methods according to the cross validation assessment presented in section 5.1.1.2. Nevertheless, for satellite estimations, Inverse distance interpolation technique outperformed the tested methods. This was possibly due to the large amount of satellite estimation points in comparison to the available rainfall stations in the area.

Concerning all cases with rainfall stations as main interpolation input; there are minor differences between them regarding the performance indices through all the cross validation tests. However, case C1 showed a slight improvement in all performed tests for almost all calculated indices, including the adopted objective function.

Results from the cross validation assessment for the different tests showed that a slight increase in the maximum number of neighbours improved the performance of the test. Moreover, a spherical shape of the theoretical variogram outperformed the exponential shape.

Additionally, the interpretation of the interpolation results in terms of average yearly precipitation (Figure 5.4) showed that case C2 presented the sharpest gradient of precipitations. On the contrary, the lowest difference in values along the catchment was obtained only with rainfall stations, case C1.

Finally, the incorporation of external drift variables, cases C3, C4, and C5, helped to reproduce the strongest precipitations in the high mountains in the north-west area of the catchment. Thus, the inclusion of the satellite estimations, case C3, increased more the precipitations in that area in comparison to the topography, case C4. However, the incorporation of both additional data together, case C5, helped to reach the maximum values in the ridges of the mountains.

6.3 Rainfall-runoff model

The calculated inputs presented that the strongest precipitation comes from the mountainous area, therefore subcatchment Andacollo has the highest precipitations in comparison to both, Agrio subcatchment and the mean values of the whole catchment Neuquén (see Figure 5.8). Comparing the different precipitation cases, case C2 presented the utmost values for the first year, being almost equal to the others in the second year. Conversely, its values are hardly reduced in the following years in comparison to the other cases, experiencing an increase in the last two years. It is known that the CMORPH algorithm is slightly different between 1998-2005 and 2006-2011 (see section 4.2.2). However, there is no trend in the change of the values between those different periods.

Regarding the other precipitation inputs (see Figure 5.8); case C5 presented in all subcatchments the highest amount, usually followed by C4, which induces a strong impact due to the topography followed by the satellite estimations.

Andacollo was the smallest studied subcatchment with also the highest gradient in the topography. Results obtained during the calibration showed that the summer peak is hardly reproduced during the simulations. Furthermore, winter peaks are represented, but cannot
reach the maximum values. Although, case C5 is the case with the highest precipitation inputs, the best performance in the calibration is obtained with C4. Thus, regarding the flow mass, case C5 showed more similarities to the observed volume.

In contrast, Agrio subcatchment has larger surface than Andacollo, with more flat areas. The performance during calibration in comparison to Andacollo was lower, showing the best results for case C5 when comparing the hydrographs and the accumulated volume to the observed ones. The second best case for this subcatchment was C4, which experiences slight differences in the results in comparison to C5.

In regard to the whole catchment Neuquén, during the calibration period, the performance through the continuous hydrographs with case C4 was found to be higher in comparison to the other cases. However, case C1 showed that it was able to reproduce almost the same daily volume of water in comparison to the observed flow mass curve, even though the shape was not exactly the same in the beginning of the calibration period. Conversely, interpolated cases with additional information, C3, C4 and C5, overestimated the total observed volume.

The validation period in comparison to the calibration time window had fewer amounts of peaks and consequently less volume of water per day. Therefore, the shape of the flow mass curve is easy to be reproduced in all subcatchments. However, in Andacollo subcatchment the same pattern as in the calibration period occurred and none of the cases could reach the volume for that time window. As larger the catchment is, easier the flow mass curve is reproduced, as occurred as well in the hydrograph. Moreover, the whole performance of the validation showed minor differences in regarding to the performance assessment in comparison to the calibration simulation.

6.4 General discussion

Results in the cross validation of the interpolation did not have the same pattern than the results obtained with the hydrological model. According to the interpolation assessment, rainfall stations alone, case C1, had the best performance in comparison to the other cases. However, results achieved with the hydrological model showed completely the opposite trend, being the cases with additional information, C3, C4 and C5, the ones with an overall better performance. Moreover, for the calibration, case C4 presented a better global achievement followed by case C5. Regarding the validation, although case C4 never reached the optimum assessment indices in any of the subcatchments models, it also had the overall best performance, followed in this case by case C3.

These results can be due to the lack of accurate data. Regarding the rainfall stations, their density might not be enough for the study area. The lack of an adequate rainfall stations network can be deduced from the none-easy-fitting variogram, showed in Figure 5.1.

Although, the distribution of rainfall stations is adequate, with more stations in the mountainous area than in the flat areas, the location is not the optimum considering that there are no hydrometeorological stations in the ridges of the mountains. This final statement was concluded with the results from the hydrological model. The inclusion of the topography as an additional variable in the precipitation improved the performance of the input in the hydrological model. Finally, case C4 is considered the case with the global best results during the calibration and validation. Moreover, temperature time series were also included
after being interpolated with the topography as external drift. No comparison with other interpolation cases was performed; however, considering the locations and distribution of the temperature stations (see Figure 5.5), the inclusion of the topography as additional information helped to improve the model.

The accuracy of the validation an interpolation technique is conditioned to the location and distribution of rainfall stations within the study area. Therefore, in rainfall stations network without an appropriate spatial distribution, results obtained from the interpolation should be subjected to other types of evaluation, not just cross-validation. Consequently, rainfall-runoff models showed that are good tools to perform these comparisons.

On the contrary to the rainfall stations network, there are enough satellite estimation points in the area; however, CMORPH data seems not to be accurate enough for this particular region. Results performed with the hydrological model showed that the simulated flow with only satellite data had the lowest performance assessment. In addition, during the calibration, negative values of the Nash-Sutcliffe were obtained.

Previous studies indicate that not all the satellite-based rainfall estimations are suitable for all regions (Thiemig et al., 2012; Bitew and Gebremichael, 2011; Cohen Liechti et al., 2012). Additionally, satellite-based rainfall estimations algorithms have their limitation, since they are still under development and validation, causing particularly dissimilarities with the ground-based observations (Thiemig et al., 2012).

Furthermore, satellites have the trend to smooth localized phenomena which can substantially affect a comparison to rainfall stations. Therefore, for this particular satellite-based rainfall estimation, CMORPH, and region the results were not satisfactory when considering the satellite estimations alone. However, as additional variable it helped to improve considerably the performance of the hydrological model, making it comparable to the achievement obtained in cases in which included the topography as additional information.
7 Future works

Results obtained with the hydrological model showed that the usages of satellite-based rainfall estimations as input are not able to simulate an adequate discharge in the study area. However, not all the satellite-based rainfall estimations are suitable for all regions. Therefore, other satellite-based rainfall estimations can be tested to see if they are more appropriate for this region.

Results obtained from this study indicated that the incorporation of topography, in a scarce rainfall stations network in a region with variable topography, can improve the results of a hydrological model. Likewise, satellite-based estimations as external drifts provided a comparable performance as well. Hence, the inclusion of another variable or satellite-based rainfall estimation may improve even more the results.

The rainfall-runoff model developed can also be improved. Therefore, sensitivity analysis of the parameters can be performed. According to the optimum parameters found during the calibration, most of them ranged between the minimum and maximum boundaries. Nevertheless, some of them did not reach the upper boundary or are around the same value. Future studies should take this into account when setting boundaries. Sensitivities can be performed in order to reduce the amount of uncertain parameters and consequently computer timing.

The selected software was HEC-HMS (Feldman, 2000), in which some parameters were set up according to the recommendations. Therefore, sensitivities can be performed with the intention of improving the model, considering that one of the main weaknesses of it was the impossibility to represent the summer peaks produced by the snow melting. Nevertheless, other suitable software may be used.

8 Acknowledgments

Thanks to all the people who helped on this work, particularly to my supervisor Ana C. Callau Poduje. Additionally, many thanks to Markus Wallner for helping in the development of the hydrological model and the calibration technique; and to Christian Berndt for the aid given regarding the interpolation schemes.

The access to the ground-based data used for this work was granted by the Subsecretaría de Recursos Hídricos de la República Argentina. The satellite-based rainfall estimations were provided by the National Oceanic and Atmospheric Administration (NOAA) Department of Commerce of the United States of America. Particular thanks to Robert Joyce and Robert Kuligowski from NOAA for assistance in clarifying technical data regarding CMORPH.

Finally, thanks to the World Meteorological Organization (WMO) for supporting the Master Programme.
References


Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Haberlandt, U., Buchwald, I., Vander Heijden, S. & Verworn, A., 2009. Requirements for hydrological models to be used as part of decision support systems in integrated water resources management. IAHS, 327(2009), pp. 29-35.


Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina


APPENDIX I – FLOW AND RAINFALL STATIONS COMPLETENESS AND GAPS OF THE DATA

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Flow Gauges available data.
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

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## Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

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Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina
APPENDIX II – “CTL” AND “SCRIPT” FILES USED IN THE GRADS SOFTWARE TO READ THE CMORPH DATA

“CTL” FILE:
DSET ^c:\CMORPH-PCP\CMORPH_V1.0\data\CMORPH_V1.0_RAW_0.25deg-DLY_00Z_19980101
OPTIONS little_endian
TITLE
UNDEF -999.0
XDEF 1440 LINEAR  0.125  0.25
YDEF  480 LINEAR -59.875  0.25
ZDEF  01 LEVELS 1
TDEF 99999 LINEAR  01jan1998 1dy
VARS 1
  cmorph 1  99 yyyyy CMORPH Version 1.0 daily precipitation (mm)
ENDVARS

“SCRIPT” FILE:
***** Read time information from .ctl file
file19980101='c:\CMORPH-PCP\CMORPH_V1.0\Data\CTL\CMORPH_19980101.ctl'
* Opens GrADS control file for reading
* Reads first line in control file and extracts the first record to see if the file exists
rec=read(file19980101)
rc1=sublin(rec,1)
* If the file exists, extract the second record which contains the data
if (rc1=0)
  rc2=sublin(rec,2)
  'open 'file19980101
* The time string is 8 characters long and starts with the 39th character in the first line
  time=substr(rc2,71,8)
* Create the output file name which includes the time string
  outfile19980101='c:\CMORPH-PCP\CMORPH_V1.0\Data\OUT\time'.txt'
***** Write selected data range to ASCII file
* Specifies ASCII print output
  'set gxout print'
* Range of x values to print
  'set x 1151 1170'
* Range of y values to print
  'set y 81 101'
* Output will be 5-digit real numbers with 1 decimal place, 20 entries per row, 1 space in between
  'set prnopts %5.1f 20 1'
* Write the field values to the output file and close the file
  'd cmorph'
  rc=write(outfile19980101,result)
  rc=close(outfile19980101)
  reinit
else
  say file' not found!'
endif
APPENDIX III – SUBBASINS-GROUPS AND BEST PARAMETERS FOUND DURING THE CALIBRATION USING THE DDS ALGORITHM

Table III-a: List of subbasins and subbasins-groups (for location see Figure 5.7)

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Table III-b: Optimized parameters found during the calibration of the five precipitation cases for Andacollo subcatchment. The parameters can be identified by the “Parameter ID” (see Table 5.4) followed by the subbasin-group number (see Table III-a)

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Table III-c: Optimized parameters found during the calibration of the five precipitation cases for Agrio subcatchment. The parameters can be identified by the “Parameter ID” (see Table 5.4) followed by the subbasin-group number (see Table III-a)

<table>
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Table III-c: Optimized parameters found during the calibration of the five precipitation cases for Agrio subcatchment. The parameters can be identified by the “Parameter ID” (see Table 5.4) followed by the subbasin-group number (see Table III-a)

<table>
<thead>
<tr>
<th></th>
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APPENDIX IV – HEC-HMS FILE FOR NEUQUÉN CATCHMENT

Basin: NQN
Description: All the catchment
Last Modified Date: 20 June 2013
Last Modified Time: 07:03:54
Version: 3.3
Unit System: Metric
Missing Flow To Zero: No
Enable Flow Ratio: No
Allow Blending: No
Compute Local Flow At Junctions: No

Sediment Grade Scale: NONE
Enable Sediment Routing: No
Enable Quality Routing: No

Subbasin: C_1_01
Canvas X: 1627502.1013442255
Canvas Y: 5952695.978729579
Area: 1336.7733
Downstream: J_1_01

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.59
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 87.22
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 49.22
GW 1 Max. Storage: ?GW1_S_C_21?
GW 1 Storage Coef.: ?GW1SC_C_21?
GW 1 Max. Percol.: ?GW1_P_C_21?
GW 2 Max. Storage: ?GW2_S_C_21?
GW 2 Storage Coef.: ?GW2SC_C_21?
GW 2 Max. Percol.: ?GW2_P_C_21?

Transform: Clark
Time of Concentration: 2.2
Storage Coefficient: ?CH_SC_C_21?

Basflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear Reservoir
Sma Groundwater Layer: 1

Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_21?
Initial Flow: 8.06
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_21?
Initial Flow: 8.06
Water Quality: ZERO
End Water Quality:
Erosion: None

Subbasin: C_1_02
Canvas X: 1602839.730357886
Canvas Y: 5956673.78050157
Area: 858.7577
Downstream: J_1_02

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.62
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 115.62
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 67.50
GW 1 Max. Storage: ?GW1_S_C_21?
GW 1 Storage Coef.: ?GW1SC_C_21?
GW 1 Max. Percol.: ?GW1_P_C_21?
GW 2 Max. Storage: ?GW2_S_C_21?
GW 2 Storage Coef.: ?GW2SC_C_21?
GW 2 Max. Percol.: ?GW2_P_C_21?

Transform: Clark
Time of Concentration: 7.3
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Storage Coefficient: ?CH_SC_C_21?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_21?
Initial Flow: 8.06
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_21?
Initial Flow: 8.06
Water Quality: ZERO
End Water Quality:
Erosion: None
End:
Subbasin: C_1_03
Canvas X: 1601248.60964909
Canvas Y: 5926442.487034444
Area: 495.1517
Downstream: J_1_03
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.45
End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 72.06
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 135.81
GW 1 Max. Storage: ?GW1_S_C_22?
GW 1 Storage Coef.: ?GW1SC_C_22?
GW 1 Max. Percol.: ?GW1_P_C_22?
GW 2 Max. Storage: ?GW2_S_C_22?
GW 2 Storage Coef.: ?GW2SC_C_22?
GW 2 Max. Percol.: ?GW2_P_C_22?
Transform: Clark
Time of Concentration: 6.1
Storage Coefficient: ?CH_SC_C_22?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_22?
Initial Flow: 16.378
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_22?
Initial Flow: 16.378
Water Quality: ZERO
End Water Quality:
Erosion: None
End:
Subbasin: C_2_01
Canvas X: 1622938.855172106
Canvas Y: 5909195.875065886
Area: 788.4991
Downstream: J_2_01
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.50
End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 72.06
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 35.14
GW 1 Max. Storage: ?GW1_S_C_22?
GW 1 Storage Coef.: ?GW1SC_C_22?
GW 1 Max. Percol.: ?GW1_P_C_22?
GW 2 Max. Storage: ?GW2_S_C_22?
GW 2 Storage Coef.: ?GW2SC_C_22?
GW 2 Max. Percol.: ?GW2_P_C_22?
Transform: Clark
Time of Concentration: 6.1
Storage Coefficient: ?CH_SC_C_22?
Comparison of different rainfall inputs in a continuous rainfall-runoff model – A case study for Argentina

Canopy Maximum Storage: 3.11
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 110.61
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 62.79
GW 1 Max. Storage: ?GW1_S_C_22?
GW 1 Storage Coef.: ?GW1SC_C_22?
GW 1 Max. Percol.: ?GW1_P_C_22?
GW 2 Max. Storage: ?GW2_S_C_22?
GW 2 Storage Coef.: ?GW2SC_C_22?
GW 2 Max. Percol.: ?GW2_P_C_22?
Transform: Clark
Time of Concentration: 8.2
Storage Coefficient: ?CH_SC_C_22?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_41?
Initial Flow: 0.712
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_41?
Initial Flow: 0.712
Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_4_01
Canvas X: 1645538.451810970
Canvas Y: 5906167.063145214
Area: 1646.8196
Downstream: J_4_01

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 0
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 109.11645
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 62.541
GW 1 Max. Storage: ?GW1_S_C_41?
GW 1 Storage Coef.: ?GW1SC_C_41?
GW 1 Max. Percol.: ?GW1_P_C_41?
GW 2 Max. Storage: ?GW2_S_C_41?
GW 2 Storage Coef.: ?GW2SC_C_41?
GW 2 Max. Percol.: ?GW2_P_C_41?
Transform: Clark
Time of Concentration: 7.1
Storage Coefficient: ?CH_SC_C_41?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_41?
Initial Flow: 0.712
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_41?
Initial Flow: 0.712
Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_4_02
Canvas X: 1663478.337802646
Canvas Y: 5885897.321829944
Area: 564.9532
Downstream: J_4_01

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 0
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10.00
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 114.0262121
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 67.9566289
GW 1 Max. Storage: ?GW1_S_C_41?
GW 1 Storage Coef.: ?GW1SC_C_41?
GW 1 Max. Percol.: ?GW1_P_C_41?
GW 2 Max. Storage: ?GW2_S_C_41?
GW 2 Storage Coef.: ?GW2SC_C_41?
GW 2 Max. Percol.: ?GW2_P_C_41?
Transform: Clark
Time of Concentration: 3.7
Storage Coefficient: ?CH_SC_C_41?
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Canopy Maximum Storage: 1.9122
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 1
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 117.748335
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 68.8704581
GW 1 Max. Storage: ?GW1_S_C_51?
GW 1 Storage Coef.: ?GW1SC_C_51?
GW 1 Max. Percol.: ?GW1_P_C_51?
GW 2 Max. Storage: ?GW2_S_C_51?
GW 2 Storage Coef.: ?GW2SC_C_51?
GW 2 Max. Percol.: ?GW2_P_C_51?
Transform: Clark
Time of Concentration: 5.0
Storage Coefficient: ?CH_SC_C_51?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_51?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_51?
Initial Flow: 5
Water Quality: ZERO
End Water Quality:
Erosion: None

End:

Subbasin: C_5_04
Canvas X: 1601292.1155839234
Canvas Y: 5852873.460784624
Area: 426.7630
Downstream: J_5_01

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.5573
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 2
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 133.3412309

Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 74.900
GW 1 Max. Storage: ?GW1_S_C_51?
GW 1 Storage Coef.: ?GW1SC_C_51?
GW 1 Max. Percol.: ?GW1_P_C_51?
GW 2 Max. Storage: ?GW2_S_C_51?
GW 2 Storage Coef.: ?GW2SC_C_51?
GW 2 Max. Percol.: ?GW2_P_C_51?
Transform: Clark
Time of Concentration: 3.4
Storage Coefficient: ?CH_SC_C_51?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_51?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_51?
Initial Flow: 5
Water Quality: ZERO
End Water Quality:
Erosion: None

End:
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Canopy Maximum Storage: 1.97
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 3
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 104.79
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 60.89
GW 1 Max. Storage: ?GW1_S_C_61?
GW 1 Storage Coef.: ?GW1SC_C_61?
GW 1 Max. Percol.: ?GW1_P_C_61?
GW 2 Max. Storage: ?GW2_S_C_61?
GW 2 Storage Coef.: ?GW2SC_C_61?
GW 2 Max. Percol.: ?GW2_P_C_61?
Transform: Clark
Time of Concentration: 6.7
Storage Coefficient: ?CH_SC_C_61?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_61?
Initial Flow: 8
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_61?
Initial Flow: 8
Water Quality: ZERO
End Water Quality:
Erosion: None
End:

Subbasin: C_6_04
Canvas X: 1612346.4045731323
Canvas Y: 5766579.333830115
Area: 1408.8026
Downstream: J_6_04
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.76
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 3
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 104.72
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 62.17
GW 1 Max. Storage: ?GW1_S_C_62?
GW 1 Storage Coef.: ?GW1SC_C_62?
GW 1 Max. Percol.: ?GW1_P_C_62?
GW 2 Max. Storage: ?GW2_S_C_62?
GW 2 Storage Coef.: ?GW2SC_C_62?
GW 2 Max. Percol.: ?GW2_P_C_62?
Transform: Clark
Time of Concentration: 6.1
Storage Coefficient: ?CH_SC_C_62?
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Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_62?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_62?
Initial Flow: 5
Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_6_06
Canvas X: 1616716.7048711914
Canvas Y: 5719138.299685608
Area: 762.8443
Downstream: J_6_06
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.48
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 4
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 105.07
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 61.50
GW 1 Max. Storage: ?GW1_S_C_62?
GW 1 Storage Coef.: ?GW1SC_C_62?
GW 1 Max. Percol.: ?GW1_P_C_62?
GW 2 Max. Storage: ?GW2_S_C_62?
GW 2 Storage Coef.: ?GW2SC_C_62?
GW 2 Max. Percol.: ?GW2_P_C_62?
Transform: Clark
Time of Concentration: 5.5
Storage Coefficient: ?CH_SC_C_62?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_62?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_62?
Initial Flow: 5
Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_6_07
Canvas X: 1630855.9117178537
Canvas Y: 5716567.534804396
Area: 396.4283
Downstream: J_6_06
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 2.13
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 4
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 121.04
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 71.99
GW 1 Max. Storage: ?GW1_S_C_62?
GW 1 Storage Coef.: ?GW1SC_C_62?
GW 1 Max. Percol.: ?GW1_P_C_62?
GW 2 Max. Storage: ?GW2_S_C_62?
GW 2 Storage Coef.: ?GW2SC_C_62?
GW 2 Max. Percol.: ?GW2_P_C_62?
Transform: Clark
Time of Concentration: 4.1
Storage Coefficient: ?CH_SC_C_62?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_62?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_62?
Initial Flow: 5
Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_6_08
Canvas X: 1616686.017054598
Canvas Y: 5734188.008708427
Area: 1216.3864
Downstream: J_6_08
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.65
End Canopy:
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Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 4
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 67.66
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 46.358
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?

Transform: Clark
Time of Concentration: 1.7
Storage Coefficient: ?CH_SC_C_71?

End Water Quality:
Erosion: None

Subbasin: C_7_01
Canvas X: 1650136.6483269387
Canvas Y: 5870493.622307079
Area: 121.8109
Downstream: J_7_01

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 0.90732
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 4
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 81.3461246
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 46.358
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?

Transform: Clark
Time of Concentration: 1.7
Storage Coefficient: ?CH_SC_C_71?

Baseflow: SMA Groundwater

End: Subbasin: C_7_02
Canvas X: 1648307.6137598893
Canvas Y: 5846232.273680366
Area: 802.5070
Downstream: J_7_02

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 2.1097
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 66.357
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 38.470
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?

Transform: Clark
Time of Concentration: 4.3
Storage Coefficient: ?CH_SC_C_71?

End: Subbasin: C_7_01
Canvas X: 1650136.6483269387
Canvas Y: 5870493.622307079
Area: 121.8109
Downstream: J_7_01

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 0.90732
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 4
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 67.66
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 46.358
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?

Transform: Clark
Time of Concentration: 1.7
Storage Coefficient: ?CH_SC_C_71?

Baseflow: SMA Groundwater

End: Subbasin: C_7_02
Canvas X: 1648307.6137598893
Canvas Y: 5846232.273680366
Area: 802.5070
Downstream: J_7_02

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 2.1097
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0.0
Initial Soil Storage Percent: 10
Initial GW1 Storage Percent: 0
Initial GW2 Storage Percent: 0
Soil Maximum Infiltration: 66.357
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 38.470
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?
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End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 56.647864
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 32.950
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?
Transform: Clark
Time of Concentration: 6.3
Storage Coefficient: ?CH_SC_C_71?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_71?
Initial Flow: 3
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_71?
Initial Flow: 3
Water Quality: ZERO
End Water Quality:
Erosion: None
End:
Subbasin: C_7_06
Canvas X: 1660888.8325072983
Canvas Y: 5818226.958084846
Area: 1452.4930
Downstream: J_7_05
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.9480
End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 79.020
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 45.146
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?
Transform: Clark
Time of Concentration: 7.9
Storage Coefficient: ?CH_SC_C_71?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_71?
Initial Flow: 3
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_71?
Initial Flow: 3
Water Quality: ZERO
End Water Quality:
Erosion: None
End:
Subbasin: C_7_07
Canvas X: 1702837.3283917708
Canvas Y: 5784565.226874953
Area: 1609.6520
Downstream: J_7_07
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.9480
End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 65.520
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 38.578
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?
Transform: Clark
Time of Concentration: 9.3
Storage Coefficient: ?CH_SC_C_71?
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Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_71?
Initial Flow: 30.35
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_71?
Initial Flow: 30.35
Water Quality: ZERO
End Water Quality:
Erosion: None
End:

Subbasin: C_7_08
Canvas X: 1659490.9193131418
Canvas Y: 5784042.1842622785
Area: 1166.1480
Downstream: J_7_08
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.4991
End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 73.461
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 43.3400582
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?
Transform: Clark
Time of Concentration: 3.9
Storage Coefficient: ?CH_SC_C_71?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_71?
Initial Flow: 3
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_71?
Initial Flow: 3
Water Quality: ZERO
End Water Quality:
Erosion: None
End:

Subbasin: C_7_09
Canvas X: 1656820.6370180883
Canvas Y: 5761382.022833978
Area: 367.1924
Downstream: J_7_09
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.5212
End Canopy:
Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:
LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 60.5141214
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 35.760
GW 1 Max. Storage: ?GW1_S_C_71?
GW 1 Storage Coef.: ?GW1SC_C_71?
GW 1 Max. Percol.: ?GW1_P_C_71?
GW 2 Max. Storage: ?GW2_S_C_71?
GW 2 Storage Coef.: ?GW2SC_C_71?
GW 2 Max. Percol.: ?GW2_P_C_71?
Transform: Clark
Time of Concentration: 3.9
Storage Coefficient: ?CH_SC_C_71?
Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_71?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_71?
Initial Flow: 5
Water Quality: ZERO
End Water Quality:
Erosion: None
End:

Subbasin: C_7_11
Canvas X: 1655064.1941983127
Canvas Y: 5704145.194384875
Area: 2311.2023
Downstream: J_7_11
Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.6605
End Canopy:
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Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 4.45
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 89.538
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 52.833
GW 1 Max. Storage: ?GW1_S_C_72?
GW 1 Storage Coef.: ?GW1SC_C_72?
GW 1 Max. Percol.: ?GW1_P_C_72?
GW 2 Max. Storage: ?GW2_S_C_72?
GW 2 Storage Coef.: ?GW2SC_C_72?
GW 2 Max. Percol.: ?GW2_P_C_72?

Transform: Clark
Time of Concentration: 11.8
Storage Coefficient: ?CH_SC_C_72?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir

Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_72?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_72?
Initial Flow: 5

Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_7_12
Canvas X: 1679294.689563693
Canvas Y: 5681545.597746011
Area: 2382.7005
Downstream: J_7_11

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.4600
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 1.53
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 130.8949325
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 77.953
GW 1 Max. Storage: ?GW1_S_C_72?
GW 1 Storage Coef.: ?GW1SC_C_72?
GW 1 Max. Percol.: ?GW1_P_C_72?
GW 2 Max. Storage: ?GW2_S_C_72?
GW 2 Storage Coef.: ?GW2SC_C_72?
GW 2 Max. Percol.: ?GW2_P_C_72?

Transform: Clark
Time of Concentration: 19.8
Storage Coefficient: ?CH_SC_C_72?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir

Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW1_C_C_72?
Initial Flow: 5
Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
GW Storage Coef.: ?GW2_C_C_72?
Initial Flow: 5

Water Quality: ZERO
End Water Quality:

Erosion: None
End:

Subbasin: C_7_13
Canvas X: 1695639.1867243792
Canvas Y: 5737331.195668297
Area: 561.5041
Downstream: J_7_13

Canopy: SMA
Initial Canopy Storage Percent: 0
Canopy Maximum Storage: 1.3437
End Canopy:

Surface: SMA
Initial Surface Storage Percent: 0
Surface Maximum Storage: 5
End Surface:

LossRate: Soil Moisture Account
Percent Impervious Area: 0
Initial Soil Storage Percent: 10
Initial Gw1 Storage Percent: 0
Initial Gw2 Storage Percent: 0
Soil Maximum Infiltration: 123.6581076
Soil Maximum Storage: 0
Soil Tension Storage: 0
Soil Maximum Percolation: 74.136
GW 1 Max. Storage: ?GW1_S_C_72?
GW 1 Storage Coef.: ?GW1SC_C_72?
GW 1 Max. Percol.: ?GW1_P_C_72?
GW 2 Max. Storage: ?GW2_S_C_72?
GW 2 Storage Coef.: ?GW2SC_C_72?
GW 2 Max. Percol.: ?GW2_P_C_72?

Transform: Clark
Time of Concentration: 6.6
Storage Coefficient: ?CH_SC_C_72?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear
Reservoir
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Soil Maximum Percolation: 51.747
GW 1 Max. Storage: ?GW1_S_C_72?
GW 1 Storage Coef.: ?GW1SC_C_72?
GW 1 Max. Percol.: ?GW1_P_C_72?
GW 2 Max. Storage: ?GW2_S_C_72?
GW 2 Storage Coef.: ?GW2SC_C_72?
GW 2 Max. Percol.: ?GW2_P_C_72?

Transform: Clark
Time of Concentration: 3.9
Storage Coefficient: ?CH_SC_C_72?

Baseflow: SMA Groundwater
Sma Groundwater Transform: SMA Linear

Reservoir
Sma Groundwater Layer: 1
Number Groundwater Reservoirs: 1
Initial Flow: 34.9

Sma Groundwater Layer: 2
Number Groundwater Reservoirs: 1
Initial Flow: 34.9

Water Quality: ZERO
End Water Quality:
Erosion: None
End:

Junction: J_7_10b
Canvas X: 1715176.9998215851
Canvas Y: 5741444.419478236
Downstream: Ri_7_14
End:

Junction: J_7_11
Canvas X: 1694096.7277956523
Canvas Y: 5726791.059655331
Downstream: Ri_7_14
End:

Junction: J_7_14
Canvas X: 1732401.1245257012
Canvas Y: 5730904.283465269
Observed Hydrograph Gage: Ri714
End:

Reach: Ri_7_14
Canvas X: 1732401.1245257012
Canvas Y: 5730904.283465269
From Canvas X: 1715176.9998215851
From Canvas Y: 5741444.419478236
Downstream: J_7_14
Route: Lag
Lag: 499.81
Channel Loss: None
Route Sediment: No
End:

Reach: Ri_7_13
Canvas X: 1715176.9998215851
Canvas Y: 5741444.419478236
From Canvas X: 1694096.7277956523
From Canvas Y: 5726791.059655331
Downstream: J_7_13
Route: Lag
Lag: 511.82
Channel Loss: None
Route Sediment: No
End:

Junction: J_7_13
Canvas X: 1715176.9998215851
Canvas Y: 5741444.419478236
Downstream: Ri_7_14
End:

Junction: J_6_01
Canvas X: 1616202.5518949493
Canvas Y: 5815213.110195082
Downstream: Ri_6_02
End:

Junction: J_6_02
Canvas X: 1622629.4640979774
Canvas Y: 5791258.676689744
Downstream: Ri_6_03
End:

Junction: J_6_03
Canvas X: 1622629.4640979774
Canvas Y: 5784060.535022353
Downstream: Ri_6_04
End:

Junction: J_6_04
Canvas X: 1634712.0593096707
Canvas Y: 5741187.342990114
Downstream: Ri_6_05
End:

Junction: J_6_05
Canvas X: 1634712.0593096707
Canvas Y: 5741187.342990114
Downstream: Ri_6_06
End:

Junction: J_6_06
Canvas X: 1634712.0593096707
Canvas Y: 5741187.342990114
Downstream: Ri_6_07
End:

Junction: J_6_07
Canvas X: 1634712.0593096707
Canvas Y: 5741187.342990114
Downstream: Ri_6_08
End:

Junction: J_6_08
Canvas X: 1673530.6087459617
Canvas Y: 5754555.320372413
Observed Hydrograph Gage: Ri608
Downstream: Ri_7_10a
End:

Reach: Ri_6_02
Canvas X: 1622629.4640979774
Canvas Y: 5791258.676689744
From Canvas X: 1616202.5518949493
From Canvas Y: 5815213.110195082
Downstream: J_6_02
Route: Lag
Lag: 680.56
Channel Loss: None
Route Sediment: No
End:

Reach: Ri_6_03
Canvas X: 1622629.4640979774
Canvas Y: 5784060.535022353
End:
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Reach: Ri_6_06
Canvas X: 1641000.5858963428
Canvas Y: 5741187.342990114
Downstream: J_6_06
Route: Lag
Lag: 64.27
Channel Loss: None
Route Sediment: No
End:

Reach: Ri_6_08
Canvas X: 1673530.6087459617
Canvas Y: 5754555.320372413
Downstream: J_6_06
Route: Lag
Lag: 189.87
Channel Loss: None
Route Sediment: No
End:

Reach: Ri_6_04
Canvas X: 1634712.0590396707
Canvas Y: 5784060.535022353
Downstream: J_6_04
Route: Lag
Lag: 828.44
Channel Loss: None
Route Sediment: No
End:

Junction: J_6_06
Canvas X: 1622629.4640979774
Canvas Y: 5791258.676689744
Downstream: J_6_08
End:

Basin Schematic Properties:
Last View N: 5855075.850769702
Last View S: 5835109.887859003
Last View W: 1663295.911146624
Last View E: 1688586.1308335103
Maximum View N: 5956673.78050157
Maximum View S: 5681545.597746011
Maximum View W: 1582166.3870092065
Maximum View E: 1719135.2155971553