Surface water assessment and water supply reliability: Pamplonita Basin, Colombia and Venezuela

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The findings, interpretations and conclusions expressed in this study do neither necessarily reflect the views of the UNESCO-IHE Institute for Water Education, nor of the individual members of the MSc committee, nor of their respective employers.
Dedicated to my family.
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Summary

The Pamplonita River Basin is a transboundary river basin between Colombia and Venezuela with an area of approximately 2100 km². Understanding the water balance in the Pamplonita River Basin is essential for further development of the region, mainly for agricultural activities. Most of the water is withdrawn from the surface hydrological system; however, surface resource availability has not been appropriately quantified, leading to water supply insecurity, especially in the middle and lower basin. The objective of this thesis was to determine the monthly surface water availability and demand in the basin but also its reliability in order to enhance agricultural activities in the basin.

The Budyko hydrological framework was implemented in order to determine the monthly surface water availability. Water demand for irrigation was estimated, and it was found to be highest in the middle basin, reaching approximately 17 Mm³ in the month of August. However, data scarcity in the basin means that the estimate of the surface water availability is uncertain.

The Budyko framework was extended to consider input and model parameter uncertainty, and through this the surface water reliability to satisfy the irrigation demand was estimated. For the middle basin the reliability was found to be less than 30% for most of the months when the water is extracted from an upstream source. Conversely, the reliability was high (>98%) in the lower basin irrigation areas when water was taken from a source located further downstream. The results show that the best area for irrigation development is the lower basin, which has higher supply reliability.

Including model parameter uncertainty provides a complete estimate of the water supply reliability, but the latter is influenced by the uncertainty in the model. Reducing the uncertainty in the model through improved data and perhaps improved model structure will improve the estimate of the water supply reliability and allow for better planning of water allocation.
# Table of Contents

Acknowledgements ................................................................................................................. i  
Summary ................................................................................................................................ iii  
List of tables ............................................................................................................................... vii  
List of figures .............................................................................................................................. vii  
List of symbols ........................................................................................................................... ix  
1. **INTRODUCTION** .................................................................................................................. 1  
2. **PROBLEM DEFINITION** ...................................................................................................... 2  
3. **HYPOTHESIS AND RESEARCH QUESTIONS** .................................................................. 3  
   3.1 Hypothesis ......................................................................................................................... 3  
   3.2 Research questions ............................................................................................................. 3  
4. **OBJECTIVES** ...................................................................................................................... 4  
   4.1 General objective ................................................................................................................. 4  
   4.2 Specific objectives ............................................................................................................... 4  
5. **LITERATURE REVIEW** ...................................................................................................... 5  
   5.1 Basic concepts of water balance ....................................................................................... 5  
   5.2 Water availability and demand ......................................................................................... 6  
   5.3 Water balance modelling ................................................................................................... 7  
   5.4 Uncertainty assessment ....................................................................................................... 11  
   5.5 Water supply reliability .................................................................................................... 13  
6. **CASE STUDY AREA** .......................................................................................................... 14  
   6.1 Location and hydrological conditions ............................................................................... 14  
   6.2 Agriculture production systems in the Pamplonita River Basin ....................................... 16  
   6.3 Social conditions ................................................................................................................. 16  
7. **DATA AND METHODS** ..................................................................................................... 17  
   7.1 Collection and analysis of data .......................................................................................... 17  
   7.1.1 Precipitation ................................................................................................................ 17  
   7.1.2 Potential Evapotranspiration ....................................................................................... 22  
   7.1.3 Water level stations ....................................................................................................... 25  
   7.2 Developing an understanding of the surface water availability ....................................... 26  
   7.2.1 Using the data .............................................................................................................. 26  
   7.2.2 Hydrological modelling ............................................................................................... 29  
   7.3 Developing an understanding of the water supply/demand reliability ................................ 42  
   7.3.1 Water supply reliability/demand analysis for different water offtakes in the Pamplonita River ................................................................. 42  
   7.4 Summary .......................................................................................................................... 45  
8. **RESULTS** ......................................................................................................................... 46  
   8.1 Surface water availability ................................................................................................ 46  
   8.2 Surface water demand ....................................................................................................... 48  
   8.3 Uncertainty of surface water availability ......................................................................... 50
List of tables

Table 5.1: Semi-distributed hydrological model input data ................................................................. 9
Table 6.1: Main agriculture production systems in the Pamplonita River Basin (Colombian side) ................................................................. 16
Table 7.1: Distribution of stations for CHAC-CEDEX data completion ........................................ 18
Table 7.2: Seventeen temperature stations ......................................................................................... 22
Table 7.3 Average soil depths and classification in the basin ............................................................. 28
Table 7.4 ETP and P distribution in subbasins .................................................................................... 35
Table 7.5. Crop coefficient Kc for rice and potato for different months according to the crop developing stage ........................................................................ 39
Table 8.1. Objective function F, BIAS, Pearson R and model calibration results ......................... 47
Table 8.2. BIAS and Pearson objective function results for validation ............................................ 48
Table 8.3. Weibull distribution results for monthly input precipitation distribution in the basin ......... 51
Table 8.4. Symbols for water balance ................................................................................................. 56

List of figures

Figure 5.1: Water balance in a river basin .......................................................................................... 5
Figure 6.1: Geographical location of Pamplonita River Basin .......................................................... 14
Figure 6.2: Digital Elevation Model, Pamplonita River Basin .......................................................... 15
Figure 7.1: Precipitation chronogram of time series (1973 to 2007). .................................................. 17
Figure 7.2: Annual precipitation values for the upper basin (group 1). .......................................... 20
Figure 7.3: Annual precipitation values for the middle basin (group 2). .......................................... 21
Figure 7.4: Annual precipitation values for the lower basin (group 3). ............................................. 21
Figure 7.5: ETP values for different calculation methods in Camilo Daza station (1601501). 23
Figure 7.6: Annual ETP (Hargreaves) vs elevation ......................................................................... 24
Figure 7.7: Annual ETP (Thornthwaite) vs elevation ....................................................................... 25
Figure 7.8: Measured discharge in the Pamplonita River ................................................................. 25
Figure 7.9: Thiessen raster map for average P values for June ......................................................... 26
Figure 7.10: Thiessen raster map for average ETP values for June .................................................. 27
Figure 7.11: Maximal soil moisture capacity (Smax) distribution in the basin .................................. 28
Figure 7.12: Calibration process of deterministic Budyko model .................................................... 33
Figure 7.13: Qt (i, j) values for the basin, upstream water level station Aguas Claras ..................... 34
Figure 7.14: Influence areas in the basin, based on temperature and precipitation correlation ......... 36
Figure 7.15: Obtaining the Qt distribution from uncertainty modelling (Budyko model) ............... 37
Figure 7.16: Irrigation demand areas in the basin ............................................................................. 38
Figure 7.17: Water concessions in Pamplonita River basin ............................................................... 41
Figure 7.18: Subbasin delimited from irrigation water offtake_1 from Pamplonita River ............. 43
Figure 7.19: Subbasin delimited from irrigation water offtake_2 from Pamplonita River ............. 43
Figure 7.20: Flow chart diagram, thesis methodology ................................................................. 45
Figure 8.1: Calibration results (including irrigation demand areas) ................................................ 46
Figure 8.2: Validation results (including irrigation demand areas)........................................47
Figure 8.3: Average surface irrigation withdrawals for high, middle and lower basin............49
Figure 8.4: Average surface irrigation withdrawals for high, middle and lower basin
(including Kc distribution). .........................................................................................49
Figure 8.5: Comparison of precipitation input distribution in the basin and Weibull
distribution (September). ................................................................................................51
Figure 8.6: Qt simulated values for a 90% and 50% confidence interval and Qt observed
values (input uncertainty). ..........................................................................................52
Figure 8.7: Different objective functions results for α_1 values.................................................53
Figure 8.8: Different objective functions results for α_2 values..................................................53
Figure 8.9: Different objective functions results for d values.....................................................54
Figure 8.10: Qt simulated values for a 90% and 50% confidence interval, and Qt observed
values (parameter uncertainty). ...................................................................................55
Figure 8.11: Qt simulated values for a 90% and 50% confidence interval, and Qt observed
values (combined uncertainty). ....................................................................................56
Figure 8.12: Surface water surplus in Cucuta’s city offtake_C. .................................................57
Figure 8.13: Minimal surface water surplus for maximal population scenario in Cucuta’s city
offtake_C. ....................................................................................................................58
Figure 8.14: Water resource reliability for Cucuta’s city water demand for existing population
(D_c) and water demand for double population. Precipitation and model
parameter uncertainties are included. .............................................................................59
Figure 8.15: Water offtakes in the Pamplonita River for irrigation demand areas in the middle
and lower basin area. .................................................................................................59
Figure 8.16: Water surplus/deficit in offtake 1 and offtake 2, considering withdrawals for
middle basin irrigation areas and lower basin irrigation areas, respectively..............61
Figure 8.17: Water surplus in offtake_2 considering withdrawals for middle basin irrigation
areas and lower basin irrigation areas. .........................................................................62
Figure 8.18: Water resource reliability for irrigation in the middle basin area (Isw_m) and
reliability for irrigation in the lower basin area (Isw_l) given different water
availability options (Qtn_1 and Qtn_2). Precipitation uncertainty included.............63
Figure 8.19: Water resource reliability for irrigation in the middle basin area (Isw_m) and
reliability for irrigation in the lower basin area (Isw_l) given different water
availability options (Qtn_1 and Qtn_2). Precipitation and model parameter
uncertainty included. .................................................................................................64
List of symbols

$ETP$ or $ET_0$: Potential Evapotranspiration or Reference Evapotranspiration

$ET_c$: Crop evapotranspiration

$ET$ or $ET_A$: Actual Evapotranspiration

$P$: Precipitation

$S$: Storage

$R$: Recharge

$Q_d$: Direct runoff

$Q_b$: Baseflow

$Q_t$: Total runoff

$Q_{tn}$: Net total runoff

$Q_{t\_obs}$: Observed runoff

$d$: Recession constant

$I_d$: Irrigation demand

$I_{sw}$: Surface water irrigation withdrawals

$l$: Distance between stations

Mm$^3$: Million cubic meters

$r$: Reliability

$p$: probability
1. Introduction

This thesis is part of an "UNESCO-IHE Partnership Research Fund" (UPaRF) project that supports the implementation of river basin plans (COLCUENCAS) under the new integrated water resource management policy in Colombia implemented in 2010. Regional water management agencies in Colombia have been given the task to generate basin management plans known as: "Plan de Ordenación y Manejo de Cuencas Hídricas" (POMCH). The regional agency "Corporación Autónoma Regional de Norte de Santander" (CORPONOR) is in charge to develop management plan for the Pamplonita River Basin in the northeast of Colombia.

As a result of human socioeconomic activities the demand for water has increased considerably and will continue to do so in the near future (de Nooy and Jaspers 2012). Water is used for different purposes: agriculture (i.e. irrigation), domestic water, industry, navigation, recreation, and nature conservation. Among these categories water for irrigation is the most relevant, because it is the largest item on the balance, demanding approximate 70% (Schultz 2011).

An important unit in water resources studies is the river basin. In a river basin the interaction between water resources and human socioeconomic activities can generate positive or negative impacts for the inhabitants. To begin with, water scarcity can produce low agriculture productivity or even food insecurity; while excess water can generate floods, causing possible crop and community damage. Thus, studies have to be developed in order to assess the water availability and the effects of its use in a river basin context. Based on an understanding of the availability resource, a proper water allocation can be established.

It is generally accepted that the hydrological regime of a river basin has to be understood in order to undertake decisions concerning water allocation (FAO 2011). Unfortunately, many developing countries have not yet installed a proper and reliable hydro-meteorological measurement network. The lack of information and implementation of these systems is mainly due to insufficient economical resources. All this has led to weak hydrological baseline information.

A transboundary, data scarce basin was chosen in Colombia and Venezuela to undertake a water assessment study. It is quite a challenge to obtain reliable results in a data scarce basin. Thus, creative methodologies have to be developed to overcome this issue and to be able to quantify water resources.

This study has an important significance for a sustainable development of river basins, since surface water availability and water supply/demand reliability were established. Further on, this information can be used by development or environmental agencies (government or private) or further research projects for decision support.
2. Problem definition

Understanding the water balance in the Pamplonita River Basin is essential for further development of the region, mostly for agriculture activities. According to CORPONOR (2010) agriculture activities utilize 50% of the total water demand in the Pamplonita River Basin, which has found to be the most water demanding sector. However, CORPONOR (2010) results are underestimated, since they only take into consideration the Colombian side of the basin. The Venezuelan part contributes a large area in the Pamplonita River Basin that cannot be neglected both for water demand and water availability.

In the Pamplonita River Basin, most of the water is withdrawn from the surface hydrological system. However, the surface resource availability has not been appropriately quantified, leading to water supply insecurity. Water supply is essential for urban consumption and irrigated agriculture land, principally for rice in the middle and lower basin. Currently agriculture activities are stagnant, not integrated and have a low productivity. Consequently, it is important to establish a reliable estimate of the surface water availability to enhance agriculture development.

The lack of scientific research concerning water availability and demand causes inability for decision makers (government institutions, regional development agencies, etc) to undertake adequate solutions. The challenge is to improve the understanding of the hydrology of the river basin in order to establish proper water allocation that can help to improve the current agricultural situation in the area.
3. Hypothesis and research questions

3.1 Hypothesis

- An analysis of the surface water supply/demand in a data scarce basin, including an estimation of the uncertainty, can improve water allocation decisions and lead to agricultural development.

3.2 Research questions

At what level is the current supply/demand balance in the basin?

- How to reliably estimate the resource in a data scarce basin?
- What is the actual demand, especially from irrigation activities?
- What is the uncertainty of the surface water availability?
4. Objectives

4.1 General objective

To determine the surface water availability and demands, including the reliability of the water resource in the Pamplonita River Basin, in order to enhance agricultural development.

4.2 Specific objectives

1. To determine the monthly surface water availability in the Pamplonita River Basin.

2. To determine the water demand for irrigation and other water users in the River Basin.

3. To develop a surface water balance and a reliability analysis for different water abstraction strategies in the River Basin.
5. Literature review

5.1 Basic concepts of water balance

The water balance can be applied to a river basin (control volume, figure 5.1). The size of a river basin is determined by the point selected in the river as the outlet of the system (De Laat and Savenije 2009). Assuming a control volume in a soil-water system within a river basin boundary, the equation of the river basin water balance can be written in function of time step \( t \) (Álvarez, Vélez et al. 2008), as follows:

\[
P(t) - ET(t) - Q(t) = \frac{dS(t)}{dt}
\]  

(1)

In which, \( P(t) \) is the precipitation, \( ET(t) \) is the evapotranspiration, \( Q(t) \) is the runoff and \( S(t) \) is the water storage in the river basin. The units are in mm.

If the equation is integrated for large time steps, \( (t \to \infty) \) the change in water storage can be assumed to be zero, therefore \( \overline{Q} = \overline{(P - ET)} \) can be considered, where the line above the variables is an average value. This is only valid for yearly time steps.
Human interference (agriculture, urban/sanitary, industrial and livestock) plays an important role within the hydrological cycle (Schultz and Uhlenbrook 2012), thus equation 1 has to be adjusted to the following equation 2 (De Laat and Savenije 2009):

\[ \bar{Q}_c = \left[ \left( P - ET \right) \right] - \bar{C} \]  

(2)

In which, \( \bar{C} \) is the net water consumption due to water use in the basin.

### 5.2 Water availability and demand

Usually, the water availability and demand (water balance) is analyzed in a watershed level or so called river basin (figure 5.1). The water availability in a river basin is variable in space and time, thus it is necessary to understand its interaction and transport either in the surface, subsurface or ground level to determine the potential use by humans and environment (De Laat and Savenije 2009). In order to have a better spatial understanding, a river basin can be divided in three parts considering the height above sea level: upper, medium and lower catchment area. On the other hand, the variation of hydrologic conditions in each part can be analyzed in daily, monthly, or yearly time steps.

To obtain the surface water availability researchers have measured the flows in the rivers and obtained the historical precipitation data with meteorological stations (Álvarez 2007; Ortiz, Betancour et al. 2010). Depending on how precipitation, topography, and sunlight are interpolated or used to calculate the evapotranspiration, different surface water availability values can be obtained (Álvarez 2007).

Moreover, hydrological models have been used to simulate river basin behaviour (Fernández, Suarez et al. 2007; Amaya, Restrepo-Tamayo et al. 2009). However, the simulated results have to be compared with field data, thus the importance on field data accuracy.

As a result of human socioeconomic activities the demand for water has increased considerably and will continue to do so in the near future (de Nooy and Jaspers, 2012). Water is used for different purposes: agriculture (i.e. irrigation), domestic water, industry, navigation, recreation, and nature conservation. Among these categories water for irrigation is the most relevant, because it is the largest item on the balance, demanding approximate 70% (Schultz 2011).

The quantity of water needed to produce crops differ by type of crop and region, depending on climate, mode of cultivation, crop variety and length of growing season, and crop yields (de Fraiture and Wichelns 2010). Therefore, case studies are required to analyse specific river basin's water balance behaviour in order to determine if crop water demands are satisfied.
5.3 Water balance modelling

Applying hydrological models is irreplaceable in studies involving for example flood and drought prediction, water resource assessment (García, Sainz et al. 2008), climate and land use change impacts. Furthermore, one of the main application is modelling of large river basins for agricultural water resource allocation and management (Boughton 2005).

Specifically, water balance modelling is the mathematical representation of the response of a river basin system to hydrologic events during the time period under consideration (Gautman 2009). By definition a model is a simplified representation of reality, thus model parameters inevitable accumulates more complex and heterogeneous real-world features in simpler mathematical form (Wagener and Kollat 2007).

Model parameters are not directly measurable units and are known as 'conceptual' or 'effective' values. Therefore, the observed and simulated performance of the hydrological system has to be compared for different parameter sets in order to find the parameter set that better represents the system behavior (Wagener and Kollat 2007).

To obtain a unique and reproducible parameter set, automatic optimization techniques are available. These techniques are mathematical search algorithms that aim to find the minimal difference between modeled and observed discharges by systematic evaluation of alternatives in the range of the model parameters values (Xu and Singh 1998).

The quantitative measure of the fit of simulated discharge to the observed discharge is called the objective function. After each parameter search iterations the objective function is calculated, where successful iterations are those which produce smaller objective function values. The optimal parameter set is obtained based on the most suitable objective function (Xu and Singh 1998).

There has been a tendency in hydrologic research (Schuol and Abbaspour 2006; Yang, Reichert et al. 2008; Castiglioni, Lombardi et al. 2010) to not apply one optimal parameter set, but to use a certain number of them in a way that a set of 'behavioral' models are retained. Further details about methods to estimate these 'behavioral' models are explained in chapter 5.4.

One of the critical aspects of hydrological modelling research is the quality of the model input information in order to understand hydrological process (Xu and Singh 1998). Usually, the quality of input information in data scarce basins is low, because missing data values have to be determined by interpolation, extrapolation, regression methods or general assumptions based on regionalization. Therefore, in data scarce basins, it is important to find a balance between the amount of missing input data and the complexity of research objectives.

Precipitation and evapotranspiration are two important model input data, below some characteristics are explained:
**Precipitation**

- Precipitation is a main input for water balance models. The accuracy of measurement and computation of precipitation from a network of stations determines to a considerable extent the reliability of water balance computations (Xu and Singh 1998). Furthermore, the spatial and temporal variability of rainfall is much higher than evaporation. The major problem in water balance modelling regarding river basin scale is the sampling errors of the spatial variability of rainfall (Boughton 2005).

- Obtaining the correlation between rainfall stations is important to determine hydrological influence areas in the basin. The data from two rainfall stations can show a good correlation if they are close together. Moreover, correlation is better when the period of observation is larger (De Laat and Savenije 2009).

- The average monthly precipitation values for a river basin can be obtained by applying spatial interpolation methods such as the Thiessen Polygon method. In order to apply this method different rain gauges, inside or outside the river basin can be used (Villón 2004).

- The rainfall is the most readily available hydrological data; however it is important to carry out a data screening (De Laat and Savenije 2009). For daily rainfall it is important to do a tabular comparison, maximum values check, time series plotting and comparison and spatial homogeneity test.

**Evapotranspiration**

- Evaporation is defined as the transfer from water to vapour; furthermore it is the loss of water from bare soil, open water surfaces and water intercepted by vegetation. However, the total loss from water balance computations includes the transpiration by living plants, thus the total loss is called evapotranspiration (De Laat 2011).

- The potential evapotranspiration or reference evapotranspiration (ETP) is a theoretical rate of evapotranspiration, considering that the study area, in this case the River Basin, has unlimited water supply. ETP can be calculated based on
meteorological data. Researchers have developed different methods for estimating potential evapotranspiration. Equations range from the complex energy balance equations which require detailed climatological data like Penman-Monteith equation, to simpler equations which require only air temperature values like Hargreaves and Thornthwaite (De Laat and Savenije 2009).

- The crop evapotranspiration is the reference evapotranspiration multiplied by a crop coefficient $K_c$. While ETP represents the climatic demand, the $K_c$ value varies mainly in function of the crop characteristics. (Allen, Pereira et al. 1998) generated a record of $K_c$ values for different crop types and specific developing stages. To apply this methodology the following assumptions are required for crop development: the crop is free from diseases, soil has good fertilization conditions and growing must follow in a large field with optimal soil moisture conditions with total production (Allen, Pereira et al. 1998).

- The crop evapotranspiration is different to the reference evapotranspiration when the characteristics of soil cover, vegetation properties, and aerodynamic resistance are different to the pasture (Allen, Pereira et al. 1998).

- According to (De Laat 2011) the crop water requirement is defined as "the depth of water to meet evapotranspiration of a disease-free crop growing in large fields without restricting conditions on soil profile, soil moisture and fertility, thus achieving full production potential".

**Classification and selection of models:**

From the historical development of the hydrological models, modelling approaches can be classified as black-box models, conceptual models and deterministic (hydraulic) models. Moreover, conceptual models can be classified as lumped, distributed and semi-distributed (Gosain, Mani et al. 2009).

Below, the required input data for a semi-distributed hydrological model is presented.

<table>
<thead>
<tr>
<th>Spatial Data</th>
<th>Attributed Data</th>
<th>Time Series</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td>Soil profile characteristics</td>
<td>Climate data (Precipitation, temperature, etc)</td>
</tr>
<tr>
<td>Soil map</td>
<td>Crop parameters</td>
<td>Measured flow data</td>
</tr>
<tr>
<td>Land use map</td>
<td>Urbanization level, etc</td>
<td></td>
</tr>
</tbody>
</table>

(Source: adapted from Masih (2011))
It is important to remember, when selecting a model, that model complexity is not synonymous with the accuracy of the results. The decision for a correct selection of a model is highly related to the availability of data, this means that a complex distributed model should not be used when the available data do not support it. It is important to avoid that the model is more complex than the data assurance (Gautman 2009).

Even though there is no unique method for model selection or development stage, model structures should be chosen based on system characteristic, available data and modelling objective (Wagener and Kollat 2007).

**Monthly water balance models:**

Monthly water balance models can be applied in water resources management, drought assessment and reservoir simulation. There is enough evidence of monthly water balance models efficient performance (Mouelhi, Michel et al. 2005).

According to (Mouelhi, Michel et al. 2005) the following reasons motivate modelers to use monthly time steps:

- Inherent parsimony.
- They lend themselves to regionalisation.
- They can be used on ungauged basins, relating model parameters with physical characteristics of the basin.

Furthermore, monthly rainfall and potential evapotranspiration as input are more reliable, considering the way that input information is applied and handling hydrologic processes. Using these monthly input data, results in a better estimation of monthly discharge and other hydrological variables (Xu and Singh 1998).

Another benefit of using monthly water balance models is the quickness of simulation runs compared to lower time steps. This gives you the opportunity to explore parameter sensitivity and uncertainty analysis (Wang, Pagano et al. 2011).

For monthly conceptual water balance models the hydrological processes in the river basin are typically reproduced by interconnected storages. These storages represent control volumes where water flows from input as rainfall to output as runoff at the river basin outlet (Xu and Singh 1998).

The Thornthwaite Matter monthly model simulates water balances including the root zone as storage. However when this model is applied for river basins, not all water flowing out of the root zone is immediately available for runoff. Thus, the simulation of monthly runoff is not favorable, expect in those cases where a certain amount of flow is assumed to be used in every month (Steenhuis and van der Molen 1986).
Top down approach

Parsimonious models have the simplest model structure, trying to explain the hydrological process with a small number of parameters. This is known as the 'Top down' approach for model development (Wang, Pagano et al. 2011).

A couple of models with small number of parameters has been applied, aimed to estimate runoff from ungauged river basins in Australia: SFB model, AWBM model and MOSAZ model (Boughton 2005). For example, AWBM model is a semi-distributed model with lumped input data and has replaced the SFB model. MOZAZ is a 6 parameter monthly water balance model for semi-arid river basins.

Budyko (1958) determined that precipitation and potential evapotranspiration are the most important factors for estimating water availability at annual and longer time-scales. Zhang et al. (2008) used Budyko's framework to introduce a monthly timescale model. The Budyko monthly water balance model is a parsimonious lumped conceptual model, where the river basin is divided into root zone storage and groundwater storage. The Budyko monthly water balance model requires four parameters (Zhang, Potter et al. 2008).

According to (Xu and Singh 1998) for humid regions three to five parameters may be adequate to reproduce most hydrological record information on a monthly time step.

5.4 Uncertainty assessment

In water resources analysis, design and management, uncertainties could occur from different sources like: natural uncertainties, model structure uncertainty, model parameter uncertainties, input data uncertainties and operational uncertainties. The model parameter uncertainties results from the inability to quantify accurately the model input parameters (Bogardi and Kundzewicz 2002).

The probability density function (PDF) of the quantity subject to uncertainty is the most complete and ideal description of uncertainty. A different method to express the uncertainty of a quantity is to express it in terms of a reliability domain such as the confidence interval. The latter, a useful alternative to quantify the level of uncertainty is to use the statistical moments of the random variable; either the variance or standard deviation (Bogardi and Kundzewicz 2002).

In hydrological modelling, the simulations are compared with the observed discharges at the outlet from a river basin. Observed discharges may be the same inconsistent as the simulated ones due to measurement errors. It is difficult to split the sources of error that contribute to model error, therefore it can be treated as a single lumped additive variable as follows (Beven 2006):
\[ Q(X,t) = M(\theta, X, t) + \varepsilon(X,t) \]  \hspace{1cm} (3)

Where \( Q(X,t) \) is discharge, at point \( X \) and time \( t \); \( M(\theta, X, t) \) is the prediction of that variable from the model with parameter set \( \theta \); and \( \varepsilon(X,t) \) is the model error at that point in space and time.

**Model parameter uncertainty:**

Many hydrological models have been successfully applied to understand water availability and demand (Xiong and Shenglian 1999; Maneta, Torres et al. 2009; de Fraiture and Wichelns 2010; Wang, Pagano et al. 2011). Maneta, Torres et al. (2009) includes the precipitation and reference ET as stochastical variables in order to generate uncertainty bounds for irrigation demand and runoff results. Other authors maintained a deterministic model approach. Overall they did not include model parameter uncertainty.

As it was introduced in chapter 5.3, there has been a tendency in hydrologic research (Schuol and Abbaspour 2006; Yang, Reichert et al. 2008; Castiglioni, Lombardi et al. 2010), to not apply one optimal parameter set, but to use a certain number of them in a way that a set of 'behavioral' models are retained. Equifinality proposes that there are numerous suitable representations that should be taken into account in evaluating the uncertainty associated with predictions. This means that suitable parameter sets are selected based on the performance level in connection with the intended application (Beven 2006).

(Beven and Binley 1992) developed the **Generalized Likelihood Uncertainty Estimation (GLUE)** that has been large applied in hydrologic research for determining model parameter uncertainty (Werner 2004; Wagener and Kollat 2007; Yang, Reichert et al. 2008).

**Generalized Likelihood Uncertainty Estimation (GLUE)**

The GLUE method uses different sets of parameters in the calibration of hydrological models. Monte Carlo (MC) type sampling approach is essential to perform a search of suitable parameter sets, mainly because of non-linear model characteristics. For MC sampling range priori distribution are established (Wagener and Kollat 2007). A likelihood, which is a normalized objective function, is assigned for every parameter set value. Normally higher values of likelihood function indicate superior association between the model simulations and observations (Beven and Binley 1992; Blasone, Vrugt et al. 2008). Likelihood measures can be determined for different objective functions through application of Bayes theorem:

\[
L(\theta_i | Y) = \frac{L_i(Y | \theta_i) \cdot L_{0}(\theta_i)}{\sum_{j=1}^{N} L_j(Y | \theta_j) \cdot L_{0}(\theta_j)}
\]  \hspace{1cm} (4)
Where, $L_i(\theta_i)$ is the prior likelihood measure for parameter set $\theta_i$, $L_i(Y|\theta_i)$ is the likelihood measure derived by comparing model output using parameter set $\theta_i$ to observations $Y$ using a selected objective function, $L_i(Y|\theta_i)$ is the posterior likelihood of parameter set $\theta_i$ given observations $Y$, and $N$ is the number of parameter sets.

All the simulations with a behavioral threshold $L(\theta) \geq 0$ are considered. The likelihood values have to be rescaled in order to get a distribution for the parameter sets. The total sample of simulations is divided into behavioral and non-behavioral parameter sets. This threshold can be defined as a fixed percentage of the total number of simulations or a certain permitted deviation of the highest likelihood value in the sample. To obtain the cumulative distribution function (CDF) of the output simulation the likelihood values corresponding to selected behavioral parameter sets are rescaled (Beven and Binley 1992; Blasone, Vrugt et al. 2008).

### 5.5 Water supply reliability

According to (Hashimoto, Stedlinger et al. 1982) reliability, $r$ is the frequency or probability, $p$, that a system is in a satisfactory state (equation 5):

$$r = p[X_s, S_s]$$

(5)

Where, $X_s$ is a systems output state, and $S_s$ is a set of all satisfactory states.

Furthermore, the reliability can be defined as "the probability that no failure occurs within a fixed period of time, often taken to be the planning period" (Hashimoto, Stedlinger et al. 1982). Supply reliability is a measure of the frequency of years that full allocation occurs, and it is determined in function of stochastic supply and demand influences (Jones, Musgrave et al. 1991).

Water supply reliability has been determined from simulation results. For example modelling results are obtained incorporating hydrologic conditions and water management scenarios (Wurbs 2005). Deterministic input data ($P, ETP$, etc) and optimized parameter sets are used to simulate surface water availability. Even though, this research (Wurbs 2005) and others (Ji, Kang et al. 2006) analyse reliability, they do not include model parameter uncertainty. According to (Schuol and Abbaspour 2006) it is indispensable to clearly establish the uncertainty of the model results, to be able to establish an appropriate uncertainty and risk analysis.

In the case of agriculture production areas in a river basin, unsuitable irrigation supply reliability can indicate a net social loss of millions of dollars per annum (Jones, Musgrave et al. 1991). Thus, it is important to follow an accurate methodology to quantify the supply reliability.
6. Case study area

6.1 Location and hydrological conditions

The Pamplonita River Basin is located in the Norte de Santander department in Colombia and the Tachira department in Venezuela. It is part of the Caribbean hydrographic region.

![Diagram of Pamplonita River Basin](image)

**Figure 6.1: Geographical location of Pamplonita River Basin.**

[Source: adapted from CIA (2013)]

The Pamplonita River Basin is exposed to external and internal meteorological aspects that affect the climatic conditions. This river basin is affected by the Inter Tropical Convergence Zone (ZCIT), El Niño y La Niña phenomena, and humid air from the Maracaibo Lake and the Orinoco River. Furthermore, microclimate conditions exist mainly in the upper basin (CORPONOR 2010).

The Pamplonita River has an approximate length of 136 km starting from the paramo region of Pamplona (3648 meters above sea level) until the flatland region of Puerto Santander (42 meters above sea level) where it discharges into Gran Zulia River. The total area of the river basin is 2100 km² (figure 6.2).
In the selected area, 32 precipitation stations and 17 temperature stations are installed with a varied range of available data. In general, a high percent of historical data is missing.

Furthermore, there is one water level station located in the upper part of the river basin (Don Juana) and another one located in the downstream area (Aguas Claras). Both stations have discharge data from 1973 to 2007; however Aguas Claras station has missing data in some years.
6.2 Agriculture production systems in the Pamplonita River Basin

The following information about agriculture production systems in the Pamplonita River Basin was retrieved from (CORPONOR 2010). The majority of the agriculture area in the lower-middle basin is rice (60%) and is considered to be under irrigation. In the middle-high basin most of the region is covered with coffee (90%). Lastly, the agriculture area in the high basin is uniform distributed with vegetables, potatoes and fruit trees. According to (CORPONOR 2010) small irrigation districts are officially under operation in the upper basin, however no official irrigation districts are registered for the lower-middle basin.

<table>
<thead>
<tr>
<th>Location</th>
<th>Production systems</th>
<th>Irrigated</th>
<th>Area (km²)</th>
<th>Yield (t/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-middle</td>
<td>Rice</td>
<td>yes</td>
<td>17</td>
<td>6.33</td>
</tr>
<tr>
<td>Middle-high</td>
<td>Coffee</td>
<td>no</td>
<td>113</td>
<td>0.19-0.69</td>
</tr>
<tr>
<td>High</td>
<td>Potatoes and others</td>
<td>yes</td>
<td>19</td>
<td>-</td>
</tr>
</tbody>
</table>

[Source: adapted from CORPONOR (2010)]

It is important to mention that the agriculture area in table 6.1 does not include the Venezuelan part of the basin, thus the agriculture area is underestimated for the basin. Furthermore, based on processed satellite images from CORPONOR database and Corine Land Cover map (scale 1:100,000) provided by Instituto Geográfico de Colombia (IGAC); rice irrigation area is higher than suggested in table 6.1. Further information can be obtained in chapter 7.1.2.2.

6.3 Social conditions

The Pamplonita River Basin has social conflicts with high poverty indexes, unemployment, migration, vulnerability and dependency. Furthermore, there is a bad management and use of natural resources. The basin presents erosion, inadequate land use, conflicts for the use of water, contamination of water sources (CORPONOR 2010).

The area suffers from a conflict related to armed forces, generating an increase in unemployment, insecurity, and poverty. There is a production crisis, mainly because of lack of market integration for the regional producers. In addition, there is weak community organization (CORPONOR 2010).
7. Data and methods

7.1 Collection and analysis of data

7.1.1 Precipitation

Fifteen years of data was established as minimum data needed to establish a climatological behavior for each month, since La Niña and El Niño influence the meteorological conditions in Colombia every two or three years according to (Bedoya, Contreras et al. 2010).

Initially, an analysis was made with data sets from 1973 to 2007 to determine what range of years is the most favorable for this situation (figure 7.1). Data from 1973 to 2007 was selected because this is the range of years with available runoff information from water level stations Aguas Claras and Don Juana.

Given the high amount of missing data, the best option was to reduce the number of year observations and maintain most of the stations, in order to have more spatial information. Finally, a hydrological yearly data range from 1984-85 to 1998-99 was selected for 26 stations.

Figure 7.1: Precipitation chronogram of time series (1973 to 2007).
7.1.1.1 Data completion

The problem of the monthly precipitation information is the missing data. The software CHAC-CEDEX was used to fill in the gaps with the partial regression method. It uses the following operative phases for filling in missing data:

1. Establishment of the regression equation: Gives the values of P values of one station as a function of the other pair of stations.
2. Process of filling in data according to the matrix of assigned prioritize that permits the election of the pair of stations (i,j) with which a third one is completed. This is done in function of the correlation and the number of common data between the three stations. The minimal correlation coefficient to fill in data is 0.8.

The threshold to use a station was no more than 12 continuous months without data. However, three exceptions were made. Stations 4501, 4050, and 1601010 were included because the three of them are in important positions inside the basin. A total of 26 stations from 1984-85 to 1998-99 were used for CHAC-CEDEX data completion method.

For these 26 stations three separate groups were arranged according to the geographical location of each station (table 7.1), taking into account the basic basin division:

- Group I: Upper basin.
- Group II: Middle basin.
- Group III: Lower basin.

Double mass curves were used to established stations with better or worse correlation to decide the distribution of stations in the groups (Appendix A). In addition, stations with good correlation and lack of data were assigned in two groups. This happened only with station 1601010, being part of group II and group III.

<table>
<thead>
<tr>
<th>Table 7.1: Distribution of stations for CHAC-CEDEX data completion.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Group I (upper basin)</strong></td>
</tr>
<tr>
<td>3701001</td>
</tr>
<tr>
<td>1601002</td>
</tr>
<tr>
<td>1601502</td>
</tr>
<tr>
<td>1601503</td>
</tr>
<tr>
<td>1602008</td>
</tr>
<tr>
<td>4050</td>
</tr>
<tr>
<td>4051</td>
</tr>
<tr>
<td>4082</td>
</tr>
<tr>
<td>9006</td>
</tr>
<tr>
<td>-</td>
</tr>
<tr>
<td>-</td>
</tr>
<tr>
<td>-</td>
</tr>
</tbody>
</table>
In those cases where the correlation coefficient was lower than 0.8 the Inverse Distance Weighting method (IDW) was used. This method is the simplest spatial interpolator based on the spatial correlation between stations. The following are the equations used for this method (Mito, Ismail et al. 2011):

\[ P(x') = \sum_{i=1}^{n} w_i \cdot P(x_i) \]  

(6)

Where, \( P(x') \) is the interpolated value, \( P(x_i) \) are the values at the data values set, \( w_i \) are the weights assigned to each sampled point.

\[ w_i = \frac{l_i^{-2}}{\sum_{j=1}^{n} l_j^{-2}} \]  

(7)

Where, \( l \) is the distance from the sampled station to the unsampled station, for which an interpolated value is searched.

The closest stations around the missing data station were selected to use the monthly precipitation data for data completion with Inverse Distance Weighting method (IDW). The double mass curve was checked to verify correlation between stations. In the double mass curve a slope of 45 degrees is a perfect correlation match between station and a slope of 0 degrees or 90 degrees means they are not correlated at all. Therefore, a minimum slope of 22.5 degrees and a maximum slope of 67.5 degrees were established as boundary conditions to accept a station for IDW data completion.

In some cases, the stations around the missing data station also lacked data, therefore other stations further away had do be used. In addition, stations initially not considered by the CHAC-CEDEX data completion method can be used. In this case, station 1601509 with data from 1989-90 to 1998-99, was used to complete monthly precipitation for station 9006. A minimum of two stations were established to be used for data completion with IDW method, however the goal was always to find more stations to complete data.

In summary two criteria for data completion were implemented:

- Lowest distance between stations.
- Correlation between stations.

Station 4082 and 4026 were excluded because of low correlation. Finally, 24 stations with 15 years of monthly precipitation data were completed.
7.1.1.2  La Niña and El Niño phenomena and precipitation variability

In Colombia and in the surrounding region La Niña phenomena causes higher precipitation and El Niño phenomena causes lower precipitation (Bedoya, Contreras et al. 2010).

According to the classification of different phases of El Niño/Southern Oscillation (ENSO) the hydrological year 1988-1989 was highly affected by La Niña phenomena (Bedoya, Contreras et al. 2010). Specifically, in the Pamplonita River Basin (figure 7.2, 7.3 and 7.4) it can be determined that the annual precipitation for this year (1988-1989) is higher than the average annual precipitation, and higher compared to other years.

On the other hand, the hydrological year 1991-1992 was highly affected by El Niño phenomena (Bedoya, Contreras et al. 2010). Specifically, in the Pamplonita River Basin (figure 7.2, 7.3 and 7.4) it can be determined that the annual precipitation for this year (1991-1992) is lower than the average annual precipitation, and lower compared to other years.

It can be concluded that for the range of hydrological years (1984-1985 to 1998-1999) one "dry year" and one "wet year" in the Pamplonita River Basin matches correspondently with highly affected El Niño and La Nina phenomena according to the classification of different phases of ENSO.

Furthermore, based on these results it can be concluded that there is significant precipitation variability in the river basin and it is important to take this variability into account. Thus, precipitation uncertainty should be included in the hydrological model.

Figure 7.2: Annual precipitation values for the upper basin (group 1).
Figure 7.3: Annual precipitation values for the middle basin (group 2).

Figure 7.4: Annual precipitation values for the lower basin (group 3).
7.1.2 Potential Evapotranspiration

7.1.2.1 Temperature stations

Seventeen temperature stations were selected to estimate potential evapotranspiration (ETP) (table 7.2). From these temperature stations minimum and maximum daily monthly data was determined. Furthermore, the global radiation was obtained for each station in correspondence with their latitude. Later on, the temperature data was used to calculate the associated daily potential evapotranspiration using the Hargreaves method. In the later, an average monthly ETP was determined.

<table>
<thead>
<tr>
<th>Nr.</th>
<th>Station</th>
<th>Location</th>
<th>Information range for monthly data**</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CAMILO DAZA (1601501)</td>
<td>lower basin</td>
<td>1944-2011</td>
</tr>
<tr>
<td>2</td>
<td>ISER PAMPLONA (1601502)</td>
<td>higher basin</td>
<td>1972-2010</td>
</tr>
<tr>
<td>3</td>
<td>LA ESPERANZA (1601503)</td>
<td>higher basin</td>
<td>1973-2011</td>
</tr>
<tr>
<td>4</td>
<td>ISABEL (1601504)</td>
<td>lower basin</td>
<td>1969-2002</td>
</tr>
<tr>
<td>5</td>
<td>SAN FAUSTINO (1601505)</td>
<td>lower basin</td>
<td>1968-1983</td>
</tr>
<tr>
<td>6</td>
<td>SAN ISIDRO (1601507)</td>
<td>middle basin</td>
<td>1956-1968</td>
</tr>
<tr>
<td>7</td>
<td>PARQUE NAC. TAMA (1601509)</td>
<td>higher basin</td>
<td>1989-2011</td>
</tr>
<tr>
<td>8</td>
<td>CARMEN DE TONCHALA (1602501)*</td>
<td>middle basin</td>
<td>1969-2011</td>
</tr>
<tr>
<td>9</td>
<td>SALAZAR (1602503)*</td>
<td>middle basin</td>
<td>1974-2010</td>
</tr>
<tr>
<td>10</td>
<td>CINERA-VILLA OLGA (1602504)*</td>
<td>lower basin</td>
<td>1968-2011</td>
</tr>
<tr>
<td>11</td>
<td>LA FRIA (3061)*</td>
<td>lower basin</td>
<td>1972-1984</td>
</tr>
<tr>
<td>12</td>
<td>SAN ANTONIO (4022)</td>
<td>middle basin</td>
<td>1951-1986</td>
</tr>
<tr>
<td>13</td>
<td>SAN CRISTOBAL (4038)*</td>
<td>middle basin</td>
<td>1975-1984</td>
</tr>
<tr>
<td>14</td>
<td>HACIENDA BETANIA (4050)</td>
<td>higher basin</td>
<td>1978-1985</td>
</tr>
<tr>
<td>15</td>
<td>LAS ADJUNTAS (4063)</td>
<td>middle basin</td>
<td>1966-1984</td>
</tr>
<tr>
<td>16</td>
<td>CAPACHO (4079)*</td>
<td>middle basin</td>
<td>1978-1984</td>
</tr>
<tr>
<td>17</td>
<td>COLON (8092)*</td>
<td>lower basin</td>
<td>1971-1986</td>
</tr>
</tbody>
</table>

*Station outside the basin
**Not in all cases complete

7.1.2.2 Estimating potential evapotranspiration

According to (Hargreaves 1994), due Hargreaves potential evapotranspiration equation's simplicity and the accuracy of estimates, it is recommended for general use. This method only needs input data of temperatures and radiation; therefore it is a good option for scarcely gauged basins. Below, the Hargreaves equation is presented:

\[
ETP = 0.0023 \cdot \overline{R_e} \cdot (\overline{T} + 17.8) \cdot (T_{\text{max}} - T_{\text{min}})
\] (8)
In which, $ETP$ is the monthly potential evapotranspiration in mm/day, $\overline{R_e}$ is the daily average extraterrestrial radiation in mm/day, $(T_{\text{max}} - T_{\text{min}})$ is the mean maximum minus the mean minimum air temperatures in degrees Celsius, and $\overline{T}$ is the average of $T_{\text{max}}$ and $T_{\text{min}}$ in degrees Celsius.

Furthermore, Thornthwaite method to obtain potential evapotranspiration has been used by CORPONOR (2010) in the Pamplonita River Basin and can be used for comparison with Hargreaves method results.

In order to verify the Hargreaves method, the ETP values were compared with the Penman-Monteith values from station Camilo Daza (1601501) (figure 7.5). According to (Jensen, Burman et al. 1990) Penman-Monteith (PM) method is the empirical method that best fits to lysimeter results. Only this station has Penman-Monteith $ETP$ calculated values because it is an airport station that has all the necessary climatic measurements for calculation. The Penman-Monteith $ETP$ values were provided by the National Hydrometerological Institute (IDEAM).

Moreover, the $ETP$ was calculated with Thornthwaite method with the average monthly temperature data from station Camilo Daza (1601501), in order to compare the results with Hargreaves method (figure 7.5).

For Camilo Daza station the Thornthwaite method for monthly $ETP$ has the highest correlation $R$ with the $ETP$ values from IDEAM:

- $R = 0.75$ between Hargreaves and Penman-Monteith.
- $R = 0.9$ between Thornthwaite and Penman-Monteith.

![Figure 7.5: $ETP$ values for different calculation methods in Camilo Daza station (1601501).](image_url)
Even though the Thornthwaite method shows a higher correlation with Penman-Monteith method, a lower statistical BIAS is obtained for Hargreaves method:

- $\text{BIAS} = -3 \text{ mm}$ between Hargreaves and Penman-Monteith.
- $\text{BIAS} = -28 \text{ mm}$ between Thornthwaite and Penman-Monteith.

Thus, there is not enough proof to reject the Hargreaves method. There should be more stations with more meteorological information in the basin to compare the $ETP$ values, in order to have a better understanding of the real magnitude of the $ETP$.

Monthly $ETP$ values were multiplied by a correction factor in order to get similar Penman-Monteith annual values. In the case of Hargreaves method a correction factor of 1.016 was used to multiply each monthly value.

Both methods were applied for all stations in the basin. Thornthwaite and Hargreaves method show a high correlation with elevation. Interesting though is the magnitude of $ETP$ for Thornthwaite is half the magnitude of Hargreaves for high elevations (figure 7.6 and figure 7.7). Further analysis is made in chapter 9.

![Figure 7.6: Annual ETP (Hargreaves) vrs elevation.](image)

$y = -0.2884x + 2228.7$

$R^2 = 0.8078$
7.1.3 Water level stations

The water level station's discharge information is essential to undertake a hydrological model, since simulated flow has to be compared with measured flow.

Figure 7.8 shows the measured discharge ($Q_m$) in two water level stations in the Pamplonita River for the hydrological years 1984-1985 to 1998-1999. The institution in charge of these measurements in Colombia is the National Hydrometerological Institute (IDEAM). The water level station *Don Juana* is located in the upper basin with a drainage area of 423km². The water level station *Aguas Claras* is located in the lower basin with a total drainage area of 2000 km².
7.2 Developing an understanding of the surface water availability

7.2.1 Using the data

7.2.1.1 Spatial influence of $P$ and $ETP$

In the thesis, climatology input data set was used for hydrological modelling. This means that average monthly values of $P$ and $ETP$ for the representative range of hydrological years (1984-1985 to 1998-1999) were applied. As explained in chapter 7.1 precipitation has a high variability and it is included further on in the uncertainty model.

Spatial location of stations inside or close to the Pamplonita River Basin was provided by IDEAM. Point shapefiles for every station were generated in a Geographical Information System (GIS) and $P$ and $ETP$ monthly values were assigned for each station. The Thiessen method was applied to obtain the influence areas for each station in the basin. $P$ and $ETP$ raster maps were generated for the basin for each month. In figure 7.9 and figure 7.10, the Thiessen influence areas, and June $P$ and $ETP$ values are shown (see Appendix B for $P$ and $ETP$ values for all months).

Figure 7.9: Thiessen raster map for average $P$ values for June.
7.2.1.2 Pixel resolution

In order to generate a $P$ or an $ETP$ raster with an accurate resolution considering the amount of stations, the following procedure was established:

- Determine the minimum, the maximum and the average distance $d$ between stations.
- Calculate the resolution of the raster file by multiplying the average of the distance $l$ by $1/10$. The result is approximately 2000 m. However, in this case the minimum distance between two stations is lower than the calculated resolution; therefore a final resolution of 500 m is estimated.

7.2.1.3 Maximal soil moisture storage capacity

A soil map in shapefile format (scale 1:100,000) was facilitated by (UFPS 2012) for the Colombian side of the basin. Information about soil texture and soil depth was used to calculate the maximal soil moisture storage capacity ($S_{max}$). The following equation was used to calculate $S_{max}$ (De Laat 2011).
\[ S_{\text{max}} = d_s \cdot (F.C. - P.W.P) \]  \hspace{1cm} (9)

Where, \( d_s \) is the soil depth, \( F.C. \) is the field capacity and \( P.W.P \) is the permanent wilting point. Taken into account a pressure of -100 kPa for \( F.C. \) and -10,000 kPa for \( P.W.P \), each value is selected from De Laat (2011) according to every soil texture in the Pamplonita Basin.

In table 7.3 the average soil depths and classification used for this basin is shown.

<table>
<thead>
<tr>
<th>Soil depth classification</th>
<th>( d_s ) (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very deep</td>
<td>120</td>
</tr>
<tr>
<td>Deep</td>
<td>90</td>
</tr>
<tr>
<td>Medium</td>
<td>60</td>
</tr>
<tr>
<td>Shallow</td>
<td>30</td>
</tr>
<tr>
<td>Very shallow</td>
<td>15</td>
</tr>
</tbody>
</table>

After calculating the \( S_{\text{max}} \) with equation 9, the following raster map is generated (figure 7.11).

![Maximal soil moisture capacity (\( S_{\text{max}} \)) distribution in the basin.](image)
No information about soil texture and soil depth was obtained from the Venezuelan part of the basin, thus an extrapolation of the $S_{\text{max}}$ values was undertaken. This was done using GIS editing tools, where horizontal strips were generated for the no information area using known $S_{\text{max}}$ values near the border Colombia/Venezuela. Visually, the $S_{\text{max}}$ extrapolation values for the upper basin area (southeast) match with the pattern of the Colombian side. For the middle basin area the urban district of Cucuta in the Colombian side has a $S_{\text{max}}$ equal to 0. This is why it seems that the pattern of $S_{\text{max}}$ in the Venezuelan side in the middle basin area does not match with the Colombian side. Even though, there are urban areas in the Venezuelan middle part of the basin there are assumed to be smaller than in the Colombian side. In conclusion, the extrapolated $S_{\text{max}}$ values for the middle basin area generate a large area with high $S_{\text{max}}$ values (between 200 mm and 300 mm). In a water balance perspective, it means that there is more water storage potential and the monthly discharge in the rivers can be lower, thus a safe condition for a surface water supply reliability analysis required in this thesis.

7.2.2 Hydrological modelling

7.2.2.1 Selection of the model

After generating the $P$, $ETP$ and $S_{\text{max}}$ information for the basin, an adequate monthly water balance model was selected. In this case, the Budyko framework was chosen since it has been tested for data scarce river basins (Zhang, Potter et al. 2008) and is recommended for humid regions (Zhang, Potter et al. 2008).

According to literature review monthly Budyko framework is a four parameter model: $S_{\text{max}}$, $\alpha_1$, $\alpha_2$, and $d$ (Zhang, Potter et al. 2008). However, in this case $S_{\text{max}}$ parameter is estimated using physical soil information of the basin, thus a three parameter model was applied.

The following equations, based on the Budyko framework are used to obtain the monthly direct runoff $Q_d(t)$ and the monthly baseflow $Q_b(t)$, given precipitation and potential evapotranspiration input data (Zhang, Potter et al. 2008). Finally, the sum of $Q_d(t)$ and $Q_b(t)$ results in the total runoff or the surface water availability, $Q(t)$.

\[
X_0 = (S_{\text{max}} - S(t-1)) + ET_p(t) \quad (10)
\]

$X_0$: Demand limit (mm/month)

$S_{\text{max}}$: Maximum soil moisture storage capacity (mm).
$S(t-1)$: Soil moisture storage from the previous month (mm/month)

$ET_p(t)$: Monthly potential evapotranspiration (mm/month)

$$X(t) = P(t) \cdot \left[ 1 + \frac{X_0(t)}{P(t)} - \left( 1 + \left( \frac{X_0(t)}{P(t)} \right)^{\frac{1}{\alpha_1}} \right)^{1-\alpha_1} \right]$$  \hspace{1cm} (11)

$X(t)$: Basin rainfall retention (mm/month)

$\alpha_1$: Basin rainfall retention efficiency (model parameter 1). Where: $0 < \alpha_1 < 1$ (if $\alpha_1$ is high then $X(t)$ is high and $Q_0(t)$ is low).

$$Q_d(t) = P(t) - X(t)$$  \hspace{1cm} (12)

$Q_d(t)$: Direct runoff (mm/month)

$P(t)$: Monthly precipitation (mm/month)

$X(t)$: Catchment rainfall retention (mm/month)

$$W(t) = X(t) + S(t-1)$$  \hspace{1cm} (13)

$W(t)$: Water availability (mm/month)

$S(t-1)$: Soil moisture storage from the previous month (mm/month)

$$Y(t) = W(t) \cdot \left[ 1 + \frac{ET_p(t) + S_{\text{max}}}{W(t)} - \left( 1 + \left( \frac{ET_p(t) + S_{\text{max}}}{W(t)} \right)^{\frac{1}{\alpha_2}} \right)^{1-\alpha_2} \right]$$  \hspace{1cm} (14)

$Y(t)$: Evapotranspiration opportunity (mm/month)

$\alpha_2$: Evapotranspiration efficiency (model parameter 2). Where: $0 < \alpha_2 < 1$ (if $\alpha_2$ is high then $Y(t)$ is high and $R(t)$ is low).

$$ET_A(t) = W(t) \cdot \left[ 1 + \frac{ET_p(t)}{W(t)} - \left( 1 + \left( \frac{ET_p(t)}{W(t)} \right)^{\frac{1}{\alpha_2}} \right)^{1-\alpha_2} \right]$$  \hspace{1cm} (15)

$ET_A(t)$: Actual Evapotranspiration (mm/month)

$$S(t) = Y(t) - ET_A(t)$$  \hspace{1cm} (16)

$S(t)$: Soil moisture storage (mm/month)

$$R_c(t) = W(t) - Y(t)$$  \hspace{1cm} (17)

$R_c(t)$: Recharge (mm/month)
\( Q_b(t) = d \cdot G(t - 1) \) \hspace{1cm} (18)

\( Q_b(t) \): Baseflow (mm/month)

\( d \): Recession constant (model parameter 3)

\( G(t - 1) \): Groundwater storage from previous month (mm/month)

\[ G(t) = (1 - d) \cdot G(t - 1) + R(t) \] \hspace{1cm} (19)

\( G(t) \): Groundwater storage (mm/month)

\[ Q_i(t) = Q_d(t) + Q_b(t) \] \hspace{1cm} (20)

\( Q_i(t) \): Total monthly runoff or surface water availability (mm/month)

7.2.2.2 Calibration of deterministic model

The Budyko model was implemented using the GIS script language PCRaster in Python. Additional scripts were developed to help calibrate the deterministic model.

Climatological average \( P \) and \( ETP \) values for each month were calculated and applied as input data for the model. For the calibration procedure stable initial conditions are necessary. To achieve this, the model was run for several iterations using the series of 12 monthly climatological values until the end state and the start state were equal. It was found that five iterations were needed.

The objective function \( F \) (equation 20) was selected to optimise the model parameters \( (\alpha_1, \alpha_2, d) \). Furthermore, statistical BIAS and Pearson correlation values were calculated given the optimized parameters.

Objective function \( F \) is recommended to ensure that the optimal solution is not biased from above or below the observed values, it is a symmetric measure of the match between the average simulation and average observation (i.e. a BIAS Score) (Wang, Pagano et al. 2011; Peña 2012). used this type of error to adjust modelled extreme rainfall events with respect to observed data. For optimal calibration conditions the objective function \( F \) is equal to 0 and the range of values is \( 0 < F < \infty \). In equation 21, the objective function \( F \) is presented with two terms, one of which contains the model simulated value divided by the sample value and the other contains the reciprocal term (Cowpertwait, Isham et al. 2007).
In order to compare the results of runoff obtained of the calibration model with the observed data, objective functions were used. The correlation coefficient $R$ is a good measure of linear association or phase error (equation 25). It answers the question how well did the variability in the simulated values correspond to the variability in the observed values (Werner 2012).

$$
F = \sum_{t}^{N} \left[ \left( \frac{Q_{t,\text{sim}}}{Q_{t,\text{obs}}} - 1 \right)^{2} + \left( \frac{Q_{t,\text{obs}}}{Q_{t,\text{sim}}} - 1 \right)^{2} \right]
$$

(21)

Where,

$$
R = \frac{N \cdot \sum Q_{t,\text{obs}} \cdot Q_{t,\text{sim}} - \left( \sum Q_{t,\text{obs}} \right) \cdot \left( \sum Q_{t,\text{sim}} \right)}{\sqrt{N \cdot \left( \sum Q_{t,\text{obs}}^{2} \right) - \left( \sum Q_{t,\text{obs}} \right)^{2}} \cdot \sqrt{N \cdot \left( \sum Q_{t,\text{sim}}^{2} \right) - \left( \sum Q_{t,\text{sim}} \right)^{2}}}
$$

(22)

Where, $Q_{t,\text{sim}}$ is the average of the $Qt$ pixel flows upstream of the water level station, and $Q_{t,\text{obs}}$ is the observed or measured flow in the water level station for time step $t$. $N$ is the total number of months for the calibration period.

However, the correlation coefficient R does not consider statistical BIAS, thus it is sensitive to outliers. Therefore, the statistical BIAS also should be calculated to have a better understanding of the calibration results. The statistical BIAS expresses an average error and can answer the question if the prediction is over or underpredicting the values (Werner 2012).

$$
BIAS = \frac{1}{N} \sum_{t}^{N} Q_{t,\text{sim}} - Q_{t,\text{obs}}
$$

(23)

Where, $Q_{t,\text{sim}}$ is the average of the $Qt$ pixel flows upstream of the water level station, and $Q_{t,\text{obs}}$ is the observed or measured flow in the water level station for time step $t$. $N$ is the total number of months for the calibration period.

To minimize the objective function $F$, the L-BFGS-B (Broyden–Fletcher–Goldfarb–Shanno) algorithm was used (Geem 2006). This algorithm was applied in Python 2.7.3 with SciPy library scipy.optimize.fmin_l_bfgs_b (figure 7.12).
The latter, the $Q_t$ pixel values upstream of the water level station *Aguas Claras* are calculated with equation 24, an extension of equation 20 in a discrete form.

$$Q_t(i, j) = Q_d(i, j) + Q_b(i, j)$$  \hspace{1cm} (24)

Where, $Q_d(i, j)$ is the direct runoff in each pixel and $Q_b(i, j)$ is the baseflow in each pixel.

The $Q_d$ value is calculated in function of the soil water storage $S$, parameter $\alpha_1$, $ETP$ and $P$. For irrigation areas in the basin the soil water storage $S$ is assumed to be at its maximal capacity for every month. As it is expected the $Q_t(i, j)$ values are higher in the irrigation areas than in the other region (figure 7.13).

The $Q_{t,sim}$ value in the objective function $F$ is the average of all the $Q_t(i, j)$ pixel values upstream of the water level station *Aguas Claras* based on the basin drainage network:

$$Q_{t,sim} = \overline{Q_t(i, j)}$$  \hspace{1cm} (25)

The following raster map (figure 7.13) shows the $Q_t(i, j)$ values for June generated for each pixel for the calibration procedure (see appendix C for raster maps with $Q_t(i, j)$ values for all months).
From the generated raster maps for each month with $Q_t(i, j)$ information (water balance per pixel), the equation 25 was applied for calculating the $Q_{t,sim}$ value from any analysis point where surface water availability had to be determined. The upstream catchment was delimited according to the existing drainage network.

**7.2.2.3 Model uncertainty**

**Estimating parameter uncertainty:**

The deterministic model was developed for optimizing the parameter values for an objective function. In this case, GLUE method was applied to obtain the parameter uncertainty. One thousand random parameter sets, with uniform distribution for each parameter were generated. For $\alpha_1$ and $\alpha_2$ the high limit was set to 0.9, since values between 0.9 and 1 result in undefined $Q_t$ values.

The result is a table of 1000 parameter sets each with 1000 objective function values. However, the actual amount of parameter sets to be used to obtain the final $Q_t$ probability
distribution should be lower, since not every parameter set gives reasonable \( Q_t \). The probability distribution of different amount of parameter sets was obtained by applying the likelihood function and rescaling procedure explained in chapter 5. In this case, 400 parameter sets were found to be reasonable or behavioural, because for this amount of parameter sets the uncertainty bounds adjust better to the observed discharge trend.

According to equation 4, the likelihood values \( L_i \) can be calculated for each objective function value \( F_i \) with the following equation:

\[
L_i = \frac{F_{\text{max}} - F_i}{F_{\text{max}} - F_{\text{min}}}
\]  

(26)

Where, \( F_{\text{max}} \) is the maximal objective function value from all parameter sets, \( F_{\text{min}} \) is the minimal objective function value from all parameter sets and \( F_i \) is the objective function value for which the likelihood \( L_i \) is calculated.

**Estimating input data uncertainty:**

The objective was to generate influence areas in the basin to use them as input data for the uncertainty model. According to the correlation of temperature and precipitation data shown in chapter 7.1, three influence areas were defined in the river basin: upper, middle and lower basin (figure 7.14). In each area the interannual monthly precipitation \( P \) data sets were averaged between each station's entries \( P_{i,j} \) to obtain \( \overline{P_{i,j,u}} \), \( \overline{P_{i,j,m}} \), \( \overline{P_{i,j,l}} \) (where \( i \) is the year, \( j \) is the month, \( u \) is the upper basin, \( m \) is the middle basin, and \( l \) is the lower basin influence area). On the other hand, for the \( ETP \) calculated data, one representative station for each influence area was selected, considering amount of data and double mass curve results. Furthermore, an average data set for the total basin using all stations in the basin \( \overline{P_{i,j}} \) and \( \overline{ETP_{i,j}} \) was generated (table 7.4) (See appendix D).

<table>
<thead>
<tr>
<th>Influence area</th>
<th>( ETP_{i,j} ) data set</th>
<th>( P ) data set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper basin</td>
<td>( ETP_{i,j_u} ) [1601503]</td>
<td>( \overline{P_{i,j_u}} )</td>
</tr>
<tr>
<td>Middle basin</td>
<td>( ETP_{i,j_m} ) [4022]</td>
<td>( \overline{P_{i,j_m}} )</td>
</tr>
<tr>
<td>Low basin</td>
<td>( ETP_{i,j_l} ) [1601504]</td>
<td>( \overline{P_{i,j_l}} )</td>
</tr>
<tr>
<td>Total basin</td>
<td>( \overline{ETP_{i,j}} )</td>
<td>( \overline{P_{i,j}} )</td>
</tr>
</tbody>
</table>
Figure 7.14: Influence areas in the basin, based on temperature and precipitation correlation.

A best fit distribution analysis was done for each month in $P_{i,j}$ data sets; however for $ETP$ no uncertainty was included, given the low variability between interannual values in comparison to the uncertainty in the precipitation. In order to select the most suitable distribution, the following aspects were considered:

1. $P$ can have a distribution in the domain of $[0, \infty]$. In this case, the Weibull distribution was used.
2. Statistical chi square values were calculated for each distribution in order to check the selected distribution is acceptable.

Having selected the suitable distribution for each interannual monthly data set, the Monte Carlo method (MC) was applied generating randomly 100 values of the selected distribution.

Rather than sampling the individual distributions of the influence areas it was simpler to sample the monthly precipitation in the total basin. Due to high correlation between monthly precipitations in each influence area with the monthly precipitation in the total basin, lineal regression was applied in order to obtain the distribution for each input field.

Consequently, precipitation distribution for each influence area was used as new input data for the Budyko model, in this case an uncertainty model.
Combining model parameter uncertainty and input data uncertainty:

Uncertainty in precipitation is caused by natural variability. Conversely, model parameter uncertainty is caused by intrinsic error of the model. Uncertainty propagation throughout the model was applied using the mentioned uncertainties (precipitation and parameter) independently and combined, to generate different surface water availability distributions. This was done to compare the influence of each uncertainty in the final model results and determine the surface water availability distribution including both types of uncertainties. The GIS script language PCRaster in Pyhton was applied to run the model (figure 7.15).

![Diagram of model uncertainty propagation](image)

Figure 7.15: Obtaining the $Q_t$ distribution from uncertainty modelling (Budyko model).

7.2.2.4 Selection of irrigation demand areas

The selection of the irrigation demand areas were defined as follows:

1. Irrigation districts that are currently under operation. Based on the information given by CORPONOR staff. All of these districts are located in the upper river basin.

2. Even though, there is no official irrigation district or irrigation concession in the lower-middle part of the basin, there are agriculture areas mainly with rice in the Pamplonita and Tachira river flood plains. According to residents in the area, there are many illegal water offtakes from these rivers for irrigation. Therefore, these irrigation areas have to be estimated and included in the total irrigation demand. The following procedure was undertaken to obtain these areas:
a. To obtain the agriculture area in the lower-middle basin, satellite image (Alav 2A203133440, year 2009) from Venezuela, and Corine Land Cover Classification for Colombia were combined in GIS. Only agriculture and not agricultural areas were visualized.

b. Agriculture defined pixels that were located over the line-shapefile of the main rivers (Pamplonita and Tachira) were classified as irrigation demand areas. These pixels were defined as 'pivot' pixels. Other agriculture pixels (near the Tachira and Pamplonita River) connected with the 'pivot' pixel by its vertex or parallel positioned, were classified as irrigation demand areas, too.

c. Only irrigation demand areas upstream the water level station *Aguas Claras* were selected.

3. Possible illegal irrigation withdrawals in the upper basin were not taken into account because they were assumed to be significantly lower than the lower-middle basin irrigation withdrawals.

Given the previous assumptions a total rice irrigation demand area of 98 km² was estimated in the lower and middle part of the basin. In addition, the official irrigation area in the upper basin is 7.5 km². In figure 7.16, the upper and lower-middle irrigation demand areas in the basin are shown.

![Figure 7.16: Irrigation demand areas in the basin.](image)
7.2.2.5 Estimating irrigation demand

According to (CORPONOR 2010), agriculture activities represent 50% of the total water demand in the Pamplonita River Basin. However, no pumping records or data concerning detailed demands are available from agencies in this river basin. Therefore in order to calculate the current irrigation demand, information on crop $ET$, cropping patterns, cropped area, and estimates of irrigation efficiencies has to be obtained.

The monthly potential crop evapotranspiration ($ET_c$) can be calculated using the following equation (Masih 2011):

$$ET_c = \sum_{j=1}^{n} A_j \cdot Kc_j \cdot ET_0$$

In which, $ET_c$ is the total potential crop evapotranspiration (m³/month), $A_j$ is the area under the $j$th crop (m²), $ET_0$ is the reference evapotranspiration expressed in (m/month), $Kc_j$ is the crop coefficient for the $j$th crop (Allen, Pereira et al. 1998) and $n$ is the number of crop types.

As it is known from (CORPONOR 2010) the current large and medium agriculture production areas include the following crops: rice and potato. Actually rice is the crop with the highest area in the basin. Therefore, it is important to consider that for rice in the month before sowing or transplanting, water is needed for puddling. The amount of water needed depends on the soil type and rooting depth, however an average puddling depth of 200 mm can be assumed (Brouwer, Prins et al. 1989).

Based on information gathered on sowing and harvesting activities in the basin (CORPONOR 2010) the crop coefficient $Kc$ for rice and potato (Allen, Pereira et al. 1998) can be assigned for each month (table 7.5).

<table>
<thead>
<tr>
<th>Month</th>
<th>$Kc$, rice</th>
<th>$Kc$, potato</th>
</tr>
</thead>
<tbody>
<tr>
<td>jun</td>
<td>1.05</td>
<td>1.00</td>
</tr>
<tr>
<td>jul</td>
<td>1.13</td>
<td>1.08</td>
</tr>
<tr>
<td>aug</td>
<td>1.20</td>
<td>1.15</td>
</tr>
<tr>
<td>sep</td>
<td>0.90</td>
<td>0.75</td>
</tr>
<tr>
<td>oct</td>
<td>1.05</td>
<td>1.00</td>
</tr>
<tr>
<td>nov</td>
<td>1.13</td>
<td>1.08</td>
</tr>
<tr>
<td>dec</td>
<td>1.20</td>
<td>1.15</td>
</tr>
<tr>
<td>jan</td>
<td>0.90</td>
<td>0.75</td>
</tr>
<tr>
<td>feb</td>
<td>1.05</td>
<td>1.00</td>
</tr>
<tr>
<td>mar</td>
<td>1.13</td>
<td>1.08</td>
</tr>
<tr>
<td>apr</td>
<td>1.20</td>
<td>1.15</td>
</tr>
<tr>
<td>may</td>
<td>0.90</td>
<td>0.75</td>
</tr>
</tbody>
</table>

[Source: $Kc$ values adopted from Allen et al. 1998]
After obtaining the crop evapotranspiration, the irrigation demand can be estimated using the following equation (Masih 2011):

$$I_d = ET_c \left( 1 - \frac{e_p \cdot P}{ET_0} \right)$$  \hspace{1cm} (28)

In which, $I_d$ is the irrigation demand (m$^3$/month), $P$ is the precipitation (mm/month), $e_p$ is the fraction of the precipitation effectively used as $ET$, and $ET_0$ is the reference $ET$ (mm/month).

For this thesis, equation 28 was simplified for the irrigation demand areas in the Pamplonita River Basin as it is shown below:

$$I_d = ET_c - ET_A$$  \hspace{1cm} (29)

Where, $ET_A$ is the actual evapotranspiration determined from the hydrological model in chapter 7.2.2.2. Soil moisture storage capacity was assumed to be at its maximum capacity for every month.

The total irrigation withdrawals from surface sources in the study basin have to be obtained. Hence the possible abstractions from streams can be estimated using the following equation (Masih 2011):

$$I_{sw} = f_{sw} \cdot \frac{I_d}{\eta}$$  \hspace{1cm} (30)

In which, $I_{sw}$ is the surface water withdrawals (m$^3$/month), $f_{sw}$ is the fraction of surface supplies in the total irrigation withdrawals, in this thesis always considered as 1 (-) and $\eta$ is the scheme irrigation efficiency (-).

According to (Brouwer, Prins et al. 1989), a good irrigation scheme efficiency coefficient is between 0.5 to 0.6. For reasonable schemes values of 0.4 can be considered, while a scheme irrigation efficiency coefficient of 0.2 to 0.3 is poor. In chapter 7.3 the use of scheme irrigation efficiencies is explained.

**Other demands:**

For the Colombian side of the basin, information about surface water demands that are not irrigation demands (including industry and urban surface water concessions) were obtained from CORPONOR database (figure 7.17).

In the Venezuelan part of the basin, were no information about water concessions was available; water demand was estimated by an area weighting comparison with the Colombian side of the basin.
Figure 7.17: Water concessions in Pamplonita River basin.
[Source: Concession locations adopted from CORPONOR database, 2012]
7.3 Developing an understanding of the water supply/demand reliability

The assumption is made that 80% of the total non irrigation surface water withdrawals are returned to their original source in less than a one month period. This means a return coefficient of 0.8. According to (MinDesarrollo 2000) the return coefficients in Colombia for domestic residual water evacuation are between 0.7 and 0.85.

In the lower and middle basin surface irrigation is implemented and due to informal water withdrawals low conveyance efficiency is assumed. Therefore an irrigation scheme efficiency of 40% is assumed for the lower and middle part of the basin. Conversely, for the high basin sprinkler type irrigation is applied and there are official irrigation districts. Therefore, an irrigation scheme efficiency of 60% for the higher part of the basin is assumed. The estimation of scheme irrigation efficiencies are based on percentages recommended by (Brouwer, Prins et al. 1989).

Following these assumption, a simple water supply reliability analysis can be done for any proposed water offtake in the basin.

7.3.1 Water supply reliability/demand analysis for different water offtakes in the Pamplonita River

In order to make a water supply/demand reliability analysis, the first step was to locate the offtake from the water source.

There are 539 water concessions in the basin (CORPONOR database 2012), however only the offtakes with the highest water demand for irrigation and other demands (city, industry, etc.) were selected for analysis. In the case of irrigation demand areas, hypothetical withdrawal points were assumed in the lower basin and in the middle basin (offtake_1 and offtake_2). For urban demand, Cucuta's city water offtake is at the Pamplonita River, in the middle basin area (offtake_C).

To obtain the monthly surface water availability the upper catchment area for each withdrawal point was delimited in GIS, according to the drainage system (figure 7.18 and figure 7.19).
Figure 7.18: Subbasin delimited from irrigation water *offtake_1* from Pamplonita River.

Figure 7.19: Subbasin delimited from irrigation water *offtake_2* from Pamplonita River.
Afterwards, the mean value $Q_i$ of the $Q(i,j)$ pixel values was obtained in the properties of the raster file based on the hydrological model results. In order to calculate the amount of surface water availability the $Q_i$ value in mm/month was converted in m³/month with the following equation:

$$Q_i(m^3/month) = \frac{Q_i(mm/month) \cdot A}{1000}$$

Where, $A$ is the area of the upper catchment in m², determined by multiplying the amount of pixels by the area of one pixel (500 m × 500 m).

Furthermore, water demands (including industry and urban surface water concessions) were subtracted from the surface water availability considering a return coefficient of 0.8. In the Venezuelan part of the basin, no information about water concessions was available; water demand was estimated by an area weighting comparison with the Colombian side of the basin.

The monthly net water availability ($Q_{mn}$) was obtained, following the resolution 865 of 2004, IDEAM-MAVDT (Colombia) were the ecological flow is defined as 25% of the lowest monthly available water. The monthly available net water was subtracted by the demand in each water offtake to obtain results of surplus or deficit in the water supply.

In order to establish reliability water supply percentages per month, the model uncertainty was included for surface water availability. From the initial model uncertainty run for the basin (upstream water level station Agua Claras), it was assumed that the relative deviation between the simulated mean $Q_i$ value and their uncertainty bounds are representative for the entire basin. Therefore for any withdrawal point in the basin, the uncertainty bounds can be determined by multiplying the relative deviation by the deterministic simulated $Q_i$ value.

Finally, the monthly $Q_{mn}$ values for all the uncertainty bounds were subtracted by the demand $D$ in a specific withdrawal point or offtake, and the reliability percentages for each month were determined were ($Q_{mn} - D > 0$).
### 7.4 Summary

In figure 7.20 a summary of the data and methods used in this thesis is represented as a flow chart diagram.

![Flow chart diagram, thesis methodology.](image-url)

**Figure 7.20: Flow chart diagram, thesis methodology.**
8. Results

8.1 Surface water availability

Model calibration and sensitivity:

In figure 8.1 the Budyko model calibration results for the Pamplonita River Basin are presented including irrigation demand areas.

![Figure 8.1: Calibration results (including irrigation demand areas)](image)

The calibration was established assuming two different situations. First the Budyko model was calibrated assuming no irrigation demand areas. This means that the soil water storage varies due to rainfall for each pixel in the basin. On the other hand, calibration included irrigation demand ($I_d$) areas, where maximal soil water storage was defined for each irrigation pixel in the model.

Even though 5% of the total basin area is irrigated, the calibration results show that there is not a high difference in parameter estimation with or without including irrigation demand ($I_d$) areas (table 8.1). This provides an idea of the sensitivity of the model. However, given the information gathered for the basin, irrigation demand is a reality that must be included in the calibration procedure, thus all results of water availability were calculated with the irrigation areas included.
Finally, the result is a raster map with surface water availability for every month as explained in chapter 7.2.2.2. Thus, for every desired subbasin the water availability can be determined. Nevertheless, the size of the subbasin cannot be too small since the resolution is 500 m.

**Model validation:**

In order to validate the model, the observed discharge values in Station Dona Juana were compared with the simulated discharge values.

![Figure 8.2: Validation results (including irrigation demand areas).](image)

Results confirm an acceptable Pearson R objective function (R=0.789). The simulated values follow the same trend as the observed values. However, the statistical BIAS (-18.5 mm) represents a high average error (table 8.2). Furthermore, it can be determined that for each month the simulated discharge values are underestimated (figure 8.2). In some cases, the simulated discharge can be half of the magnitude of the observed data. In chapter 9 the reasons for this difference are discussed.
Table 8.2. BIAS and Pearson objective function results for validation

<table>
<thead>
<tr>
<th>Validation</th>
<th>BIAS (mm)</th>
<th>Pearson R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Including $I_d$</td>
<td>-18.5</td>
<td>0.789</td>
</tr>
</tbody>
</table>

8.2 Surface water demand

Irrigation demand:

Even though in CORPONOR (2010) it is stated that 50% of the total demand in the basin is for irrigation, actual irrigation concessions collected from CORPONOR database assert that only 9% of the total water demand is for this purpose, while the rest is for urban/industry supply. Given the uncertainty of CORPONOR information it was decided to calculate the irrigation demand based on crop evapotranspiration ($ET_c$) and actual evapotranspiration ($ET$) values for the defined irrigation areas explained in chapter 7.2.2.5.

According to equation 29 and equation 30 monthly irrigation demand ($I_d$) and monthly average surface irrigation withdrawals ($I_{sw}$) were calculated for low, middle and high basin regions. The scheme efficiency in the low and middle basin was assumed to be reasonable, but not good, since there is no official irrigation district and water withdrawals are made by motor pumps and ditches. According to (Brouwer, Prins et al. 1989) classification 0.4 is a reasonable efficiency. On the other hand, the scheme efficiency in the high basin area was considered to be good (0.6), since official small irrigation districts operate with an earth canal conveyance system and a sprinkler application system.

As it can be seen in figure 8.3, the highest surface irrigation withdrawal is in August in the middle basin area. On the other hand, the high basin area does not present high demands over all the year. Furthermore, the total yearly $I_{sw}$ in the basin is approximately 122 million cubic meters. This preliminary result considers that the crop evapotranspiration ($ET_c$) is equal to the reference evapotranspiration ($ET_0$), assuming that $Kc$ is equal to 1 for all the months. These results were generated in order to create a baseline for further calculations including crop coefficient $Kc$ monthly distributions.
Based on information of crop coefficient ($K_c$) distribution given in table 7.5 and puddling practices for rice, a different kind of monthly withdrawals can be estimated for each basin region (figure 8.4).

For the most demanding region in the basin (middle basin), the yearly $I_{sw}$ increases in 31%, reaching approximately 125 million cubic meters. Furthermore, August remains to be the month with the highest demand for the middle basin reaching approximately 17 million cubic meters. Based on the results, it can be concluded that the crop coefficient $K_c$
distribution increases the water demand in the basin in 33%, reaching approximately 162 million cubic meters.

It is important to remember that there is no information about irrigation concessions or irrigation districts in the lower-middle basin, thus there is no way to compare the modelled irrigation demands and the real surface water withdrawals. However, assuming that all the irrigation areas are located correctly in the basin, the model should be a reliable estimation of monthly irrigation demands, since it has been calibrated with measured basin outflow discharges.

**Other demands:**

Water concessions information retrieved from CORPONOR database for the Pamplonita River Basin register approximately 340 surface water concessions for 'other demands' category (human, industry, etc). This consists of a total volume of 59 million cubic meters per year, where 70% is used for human population water supply.

In figure 7.17, the spatial distribution of the surface water withdrawal points are shown. In the high basin most of the concessions are located near small urban areas, like the city of Pamplona. For the middle basin region, not a lot of concessions are visible; however, approximately 50% of the total surface water withdrawals (0.9 m³/s) are taken from one extraction point in the Pamplonita River approximately 3 km upstream of the city of Cucuta. According to "Aguas Kpital Cucuta S.A. E.S.P", the average consumption in the city is 6 m³/month per person, and the total population of 700.000. This results in a total necessary water supply of 1.62 m³/s.

### 8.3 Uncertainty of surface water availability

#### 8.3.1 Precipitation uncertainty propagation

**Precipitation distribution:**

According to chapter 7.2.2.3 precipitation distribution for each influence area was used as new input data for the Budyko model, in this case an uncertainty model. The precipitation for the basin was confirmed as a Weibull distribution according to the following results.

The Chi-Square test was applied for the chosen Weibull distribution and the actual interannual monthly distribution. In all the cases the Weibull distribution was statistically not rejected, since Chi-Square < Chi-Square* (table 8.3).
Table 8.3. Weibull distribution results for monthly input precipitation distribution in the basin.

<table>
<thead>
<tr>
<th>Month</th>
<th>Parameters ((\lambda, \kappa))</th>
<th>Chi-Square</th>
<th>Chi-Square*</th>
</tr>
</thead>
<tbody>
<tr>
<td>jun</td>
<td>((4.29,1.02e+2))</td>
<td>0.571</td>
<td>12.59</td>
</tr>
<tr>
<td>jul</td>
<td>((4.68,1.06e+2))</td>
<td>1.456</td>
<td>12.59</td>
</tr>
<tr>
<td>aug</td>
<td>((1.94,1.21e+2))</td>
<td>0.968</td>
<td>12.59</td>
</tr>
<tr>
<td>sep</td>
<td>((3.09,1.62e+2))</td>
<td>0.489</td>
<td>12.59</td>
</tr>
<tr>
<td>oct</td>
<td>((2.89,1.42e+2))</td>
<td>0.718</td>
<td>12.59</td>
</tr>
<tr>
<td>nov</td>
<td>((3.24,1.91e+2))</td>
<td>0.953</td>
<td>12.59</td>
</tr>
<tr>
<td>dic</td>
<td>((2.03,1.40e+2))</td>
<td>0.643</td>
<td>12.59</td>
</tr>
<tr>
<td>jan</td>
<td>((1.64,71.51))</td>
<td>0.712</td>
<td>12.59</td>
</tr>
<tr>
<td>feb</td>
<td>((1.75,81.12))</td>
<td>0.736</td>
<td>12.59</td>
</tr>
<tr>
<td>mar</td>
<td>((1.66,1.12e+2))</td>
<td>1.068</td>
<td>12.59</td>
</tr>
<tr>
<td>apr</td>
<td>((2.71,1.40e+2))</td>
<td>0.648</td>
<td>12.59</td>
</tr>
<tr>
<td>may</td>
<td>((3.39,1.50e+2))</td>
<td>0.624</td>
<td>12.59</td>
</tr>
</tbody>
</table>

From the Weibull distribution results (table 8.3) the best fit occurred for September values with a Chi Square of 0.489. Below, a graphical comparison is shown between precipitation input distribution and Weibull distribution (figure 8.5).

![Figure 8.5: Comparison of precipitation input distribution in the basin and Weibull distribution (September).](image)

**Uncertainty propagation:**

Hundred precipitation samples per month were generated for each influence area in the basin. The uncertainty of the surface water availability \(Q_t\) for each month was determined from precipitation uncertainty propagation and an optimal set of parameters. In figure 8.6, the uncertainty of the surface water availability is represented for different confidence intervals: 90% and 50%, between an upper and lower bound. The observed discharge \(Q_t, \text{obs}\) is inside the confidence interval for a 90% confidence interval, thus the simulated bands represent adequately the uncertainty of the surface water availability.
For a confidence level of 90%, the highest discharge uncertainty occurs in the wet season in the months of October and November, where $Q_t$ values range between 12 mm/month and 72 mm/month for October and 12 mm/month and 62 mm/month in November. These results match with the high precipitation variability for these months ($\sigma=87$ mm/month and $\sigma=61$ mm/month), thus discharge uncertainty can be confirmed. On the other hand, the lowest uncertainty occurs in July, where $Q_t$ values range between 10 mm/month and 24 mm/month.

Figure 8.6: $Q_t$ simulated values for a 90% and 50% confidence interval and $Q_t$ observed values (input uncertainty).

### 8.3.2 Model parameters uncertainty propagation

**Model parameters distribution:**

A uniform distribution was assumed for parameters set $\alpha_1$, $\alpha_2$ and $d$. According to (Zhang, Potter et al. 2008) the parameter values ranges between 0 and 1, however it was found that for $\alpha_1$ and $\alpha_2$ the high limit had to be set to 0.9, since values between 0.9 and 1 result in undefined $Q_t$ values. GLUE methodology was applied in order to find the behavioural parameter sets.
For $\alpha_1$ and $\alpha_2$, some of the objective function $F$ value results reach 1700 for high parameter values between 0.7 and 0.9. However, most of $\alpha_1$ and $\alpha_2$ parameter value results have an objective function $F$ threshold of 200 (figure 8.7 and figure 8.8). According to the results it was determined that $\alpha_1$ values between 0.4 and 0.7 are most likely to have low objective function $F$ values. In the case of $\alpha_2$ the value range is identical (0.4 to 0.7) for low $F$. On the other hand, objective function $F$ value results are evenly distributed for all $d$ parameter range (figure 8.9). This means that parameter $d$ is unsensitive, therefore for constant $\alpha_1$ and $\alpha_2$ values; any parameter combination can result in high or low $F$ values.

![Figure 8.7](image1.png)  
**Figure 8.7:** Different objective functions results for $\alpha_1$ values.

![Figure 8.8](image2.png)  
**Figure 8.8:** Different objective functions results for $\alpha_2$ values.
Following the methodology in chapter 7.2.2.3, the likelihood values were resampled in accordance to an objective function $F$ value limit. In this case, 400 resample likelihood values were found to be the behavioural amount according to graphical inspection between $Q_t$ observed values and $Q_t$ higher and lower bounds for a 90% confidence level.

As can be seen in figure 8.10, the 5th percentile line is skewed to the $Q_t$ observed values. Normally higher values of $\alpha_1$ and $\alpha_2$ result in lower $Q_t$ simulated values. In this case, the parameters were limited to a maximum value of 0.9 due to the fact that values between 0.9 and 1 result in undefined $Q_t$ values. The model is not taken into account higher parameter values that in theory should be included. Therefore the simulated uncertainty bounds are overestimated explaining the reason of the skew.

Even though, the shape of the $Q_t$ observed curve is identical to the $Q_t$ simulated curves (figure 8.10), there are four $Q_t$ observed values that remain outside the 50% confidence interval. This means that the uncertainty is underrepresented. However, measurement uncertainty can affect the $Q_t$ observed values, predominantly in dry months like January and February. Furthermore, despite the fact, that the model structure is assumed to be adequate for the basin conditions, according to these results inadequate model structure can be possible.

Overall, the obtained parameter uncertainty should not be rejected, keeping in mind that other uncertainties (structural, measurement) are affecting the results.
8.3.3 Combined uncertainty propagation

Following the methodology in Chapter 7.2.2.3, the combined uncertainty of input precipitation (Weibull distribution) and behavioural model parameter sets was obtained. The overall uncertainty is higher than the precipitation uncertainty generated independently. Furthermore, the 50th percentile converges better to the observed average flows ($Q_{t, \text{obs}}$).

For a given 90% confidence interval the highest uncertainty remains in October and November (wet months). For a 90% confidence interval, flow ranges between 14 mm/month and 110 mm/month for October, and 10 mm/month to 85 mm/month for November. Furthermore, the lowest uncertainties were obtained for June, July, and January, February (dry months). In these cases, the difference between high and lower bounds for a 90% confidence level did not overpass 50 mm/month (figure 8.11). For a 50% confidence interval the uncertainty is lower for every month and it can be noticed that the observed flow in December is outside the uncertainty bounds. This could be due to an inadequate model structure; therefore, even though discharge uncertainty can be estimated with a simple model as Budyko, its structure can be adjusted.
8.4 Water balance

Table 8.4 describes important symbols used for the following analysis of water balance results.

<table>
<thead>
<tr>
<th>Symbols</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_{tn-1}$</td>
<td>Net surface water availability in $offtake_1$ (proposed offtake upstream)</td>
</tr>
<tr>
<td>$Q_{tn-2}$</td>
<td>Net surface water availability in $offtake_2$ (proposed offtake downstream)</td>
</tr>
<tr>
<td>$Q_{tn-c}$</td>
<td>Net surface water availability in $offtake_C$ (existing offtake near the city of Cucuta)</td>
</tr>
<tr>
<td>$I_{sw-m}$</td>
<td>Surface water withdrawals for satisfying irrigation demand in middle basin agricultural area</td>
</tr>
<tr>
<td>$I_{sw-l}$</td>
<td>Surface water withdrawals for satisfying irrigation demand in the lower basin agricultural area</td>
</tr>
<tr>
<td>$D_{c}$</td>
<td>Cucuta's city water demand</td>
</tr>
<tr>
<td>$D2_{c}$</td>
<td>Cucuta's city water demand for doubling existing population</td>
</tr>
</tbody>
</table>
8.4.1 Water supply for the city of Cucuta

Water supply/demand results were obtained for the city of Cucuta, taken into account the rate of water demand estimated by the company "Aguas Kpital Cucuta S.A. E.S.P.", estimating only water withdrawals from the Pamplonita River from offtake_C (figure 7.17). Thus, a total demand of 4,200,000 m³/month ($D_c$) was calculated.

Following the methodology in chapter 6.2.3.1 the net surface water availability in offtake_C ($Q_{tn_c}$) was determined. The net surface water availability is higher than Cucuta's city water demand for each month, thus water surplus conditions exists in offtake_C.

Results show (figure 8.12) a maximal surplus of approximately 40 Mm³ for October. The minimal surplus is in July and March with approximately 5 Mm³.

As explained in chapter 7.3.1 a return coefficient of 0.8 was assumed for non irrigation surface water withdrawals. In order to understand the sensitivity of this coefficient different scenarios were applied. Considering a scenario where water return coefficients of upstream water demands are changed from 0.8 to 1, the water surplus in offtake_C increases between 1% and 3% for each month. Furthermore, if the return coefficient is changed from 0.8 to 0.2, the water surplus in offtake_C decreases between 1% and 8% for each month. Thus, changing the return coefficient has a small effect on the surface water availability.

![Figure 8.12: Surface water surplus in Cucuta's city offtake_C.](image-url)
Maximal population for water availability:

A maximal population of approximately 1.5 million was calculated to be the population limit where water demand is satisfied by existing net surface water availability conditions from offtake_C. This means that the double present population could be supplied with surface water from the Pamplonita River, being July the critical month of supply (figure 8.13). However, further reliability analysis has to be done considering this increase of population.

Reliability of the water resource considering precipitation and parameter uncertainty:

The previous water supply/demand results identified water surplus in one existing offtake for Cucuta's city water supply. Furthermore, the water resource reliability was identified considering precipitation and parameter uncertainty. According to (Jones, Musgrave et al. 1991) supply reliability is a measure of the frequency of years that full allocation occurs. Supply reliability higher than 80% for each month was found in offtake_C to satisfy water demand for the existing population in Cucuta (figure 8.14).

Considering a scenario where the existing population is doubled (D2_c) the reliability for satisfying water demand decreases lower than 70% for most of the months (figure 8.14). Only September, October, November and December remain with reliability values higher than 80%. A brief discussion of water supply reliabilities is made in chapter 9.3.
8.4.2 Water supply for irrigation demand areas

Water supply/demand results were obtained for the irrigation areas in the middle basin and in the lower basin, taking into account the water demand calculated in Chapter 7.2.2.5 with monthly crop coefficient ($K_c$) values. Approximately 125 million cubic meters per year were calculated as surface water withdrawals necessary to satisfy the irrigation demand in the middle basin. Conversely, 32 million cubic meters per year were determined for the lower basin area.

Currently, no information about the location of surface water offtakes for irrigation areas in the middle and lower basin are known. Therefore, two options for water withdrawals were taken into analysis. Water withdrawal option_1 was based on the assumption that irrigation demand for each subbasin is taken from separately offtakes upstream each area (offtake_1 and offtake_2). Conversely, water withdrawal option_2 is based on the assumption that all the irrigation demand is taken from one offtake (offtake_2). In figure 8.15 the different options are spatially explained in the basin.
Figure 8.15: Water offtakes in the Pamplonita River for irrigation demand areas in the middle and lower basin area.

**Water withdrawal option 1:**

Following the water balance results in figure 8.16 ($Qm_2 - Isw_l$) the demand for the lower basin irrigation area is satisfied if the withdrawals are managed from `offtake_2`. Moreover, water surplus is approximately 15 million cubic meters for July, August, and March, April, as the monthly minimum. Furthermore, in October water surplus can reach 70 million cubic meters. On the other hand, the demand for the middle basin irrigation area is not satisfied for June, July, August, and March, April, in `offtake_1`. The highest deficits take place in July and August with approximately 5 million cubic meters per month.
**Figure 8.16**: Water surplus/deficit in offtake 1 and offtake 2, considering withdrawals for middle basin irrigation areas and lower basin irrigation areas, respectively.

**Water withdrawal option 2:**

As it can be seen in figure 7.19, offtake_2 includes surface runoff from the Tachira River subbasin, thus surface water availability $Q_{tn_2}$ is higher than $Q_{tn_1}$ in offtake 1 ($Q_{tn_1}$). In order to satisfy the demand for middle basin irrigation area as well as the demand for the lower basin irrigation area, both water withdrawals can be managed from offtake_2. However, water has to be pumped upstream, causing a potential economical increase. Further details are discussed in chapter 9.3.

Preliminary results show no water deficit considering these withdrawals (figure 8.17); however uncertainty conditions have to be included in order to understand the reliability of the resource.
Reliability of the water resource considering precipitation uncertainty:

The previous water supply/demand results identify water surplus or deficit in two different (offtake_1 and offtake_2) for specified irrigation demand areas. Furthermore, the water resource reliability was identified considering precipitation uncertainty. For example, a high reliability was proved in offtake_2 to irrigate the lower basin area (Isw_l), since probabilities for satisfying the demand are higher than 99% for each month. Conversely, low reliabilities (r<30%) were determined in water offtake_1 to satisfy the irrigation demand in the middle basin area (Isw_m) for July, August, and March, April (figure 8.18).

In order to improve the water supply reliability for irrigated land in the middle basin the water withdrawals can be managed from offtake_2 (including water supply for the lower basin area). In this case, the reliability increases over 60% for most of the months; only August remains close to 30% (figure 8.18). Even though, the reliability of the water resource can be improved by withdrawing water in downstream offtakes, investment for pressurized pipeline systems increases to transport the water to upstream irrigation schemes. Thus, further cost-benefit analysis of specific locations of water withdrawals is recommended.

Figure 8.17: Water surplus in offtake_2 considering withdrawals for middle basin irrigation areas and lower basin irrigation areas.
Figure 8.18: Water resource reliability for irrigation in the middle basin area ($I_{sw\_m}$) and reliability for irrigation in the lower basin area ($I_{sw\_l}$) given different water availability options ($Qtn\_1$ and $Qtn\_2$). Precipitation uncertainty included.

Reliability of the water resource considering precipitation and model parameter uncertainty:

The previous reliability results only included precipitation uncertainty. The following results consider in addition the model parameter uncertainty. Reliability values decrease between 5% and 10% in most of the months; though the trend remains the same (figure 8.19).
Figure 8.19: Water resource reliability for irrigation in the middle basin area (Isw_m) and reliability for irrigation in the lower basin area (Isw_l) given different water availability options (Qtn_1 and Qtn_2). Precipitation and model parameter uncertainty included.

Below, a summary of the months with high reliabilities (r>70%) for satisfying irrigation demand is presented:

Table 7.3: Months with high reliabilities (r>70%) for satisfying irrigation demands in accordance to options and offtakes.

<table>
<thead>
<tr>
<th>Option_1</th>
<th>Option_2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Offtake_1</strong> for middle basin agriculture area</td>
<td><strong>Offtake_2</strong> for lower basin agriculture area</td>
</tr>
<tr>
<td>September, October, November, December, January, May</td>
<td>All months</td>
</tr>
<tr>
<td>June, September, October, November, December, January, February, May</td>
<td></td>
</tr>
</tbody>
</table>
9. Discussion

The general objective of this thesis was to determine the surface water availability and demands, including the reliability of the water resource in the Pamplonita River Basin, in order to enhance agricultural development. In the next sub-chapters a detailed discussion of the obtained results is presented.

9.1 Surface water availability

Model calibration and sensitivity analysis:

One of the objectives of this thesis was to determine the monthly surface water availability in the Pamplonita River Basin. A monthly water balance model based on the Budyko framework has been tested to determine the surface water availability. Originally, the Budyko framework is a model that uses monthly rainfall and potential evapotranspiration as input data (Zhang, Potter et al. 2008). In this case, the maximal soil moisture capacity is derived using soil depth and soil texture information. Thus, the number of parameters to be estimated in the Budyko framework is reduced from four to three. According to (Xu and Singh 1998) three to five parameters are generally adequate to reproduce monthly streamflow in humid regions, such as the Pamplonita River Basin. Calibration results (table 8.1) show a high correlation between simulated and observed discharge (R=0.89). Furthermore, from the calculated BIAS value (-0.2 mm) it can be noticed that the simulated flow in average is underestimating the discharge. However, the value is relatively close to 0, meaning that the water balance model can be accurately calibrated for the basin.

Sensitivity analyses show that the optimized parameter set \( \alpha_1 \), \( \alpha_2 \) and \( d \) increase in average 4%, when 5% of the river basin has irrigated field conditions \( (S(t) = S_{max}) \). This result is reasonable since parameter \( \alpha_1 \) represents basin rainfall retention efficiency, where higher values represent less direct runoff. Furthermore, parameter \( \alpha_2 \) is related to evapotranspiration efficiency, where larger \( \alpha_2 \) stands for higher partitioning of available water into evapotranspiration (Zhang, Potter et al. 2008). This means that less water is available for recharge. According to equation 18 and 19, the baseflow depends on recharge and the recession constant \( d \). Therefore, to maintain a constant baseflow the recession constant \( d \) has to increase.

The optimized parameter set offers a deterministic result of surface water availability for the basin. However, precipitation and model parameter uncertainty play an important role to understand the variability of surface water availability. In chapter 8.3, uncertainty is taken into account for further analysis.
Model validation:

The observed discharge in the Don Juana station was used to validate simulated discharge. The trend of the simulated monthly values is satisfactory, although statistical BIAS is high and monthly values are underestimated. To explain this underestimation, the first hypothesis was that the precipitation from stations outside the subbasin had lower values than the ones inside the subbasin. However, this hypothesis was rejected because the two stations outside had higher precipitation values (1866 mm/year and 1541 mm/year) than the stations inside the subbasin (903 mm/year and 1221 mm/year).

The underestimation of the simulated monthly flow is probably due to the fact that \( ETP \) calculated values are overestimated. In chapter 7.1.2.2 the methods used to calculate \( ETP \) values in the basin were explained and it was found that for higher altitude (>2000 m.a.s.l.) the annual Hargreaves \( ETP \) values double annual Thornthwaite \( ETP \) calculated values.

9.2 Water demand

The second objective was to determine the water demand for irrigation and other water users in the River Basin.

The results show a high demand for irrigation that is not officially registered in CORPONOR, mainly in the lower and middle basin. The irrigation demand was calculated with equation 29 where the crop evapotranspiration is determined with equation 27 and actual evapotranspiration with equation 15.

The Hargreaves method was applied for determining the potential evapotranspiration. According to Hargreaves (1994), Hargreaves method is recommended for general use due to its accuracy of estimates. However, verification is desirable, due to variability in climatological conditions. A high correlation (R=0.75) and a low statistical BIAS (BIAS=-3 mm) was obtained compared with monthly Penman-Monteith values for station Camilo Daza (IDEAM) located in the middle river basin. Penman-Monteith method varies approximately in 4% compared to lysimeter measurements for monthly values in humid locations (Jensen et al., 1990), therefore it can be considered a reliable reference in this basin. Furthermore, given the high correlation in temperature between Camilo Daza station and stations in lower and middle basin, it can be argued that the trend between Hargreaves and Penman-Monteith is similar in the region. Due to scarcity in meteorological information, no further verification can be developed with Penman-Monteith for the upper basin. However it is a fact that for higher altitude (>2000 m.a.s.l.) the annual Hargreaves \( ETP \) values double annual Thornthwaite \( ETP \) calculated values. This information is important in order to understand that there exits relatively variation between different \( ETP \) calculation methods and that final model results will depend on input data accuracy. For example, an \( ETP \) overestimation in the upper basin can help to explain why the discharge is underestimated in the water level station Don Juana.
Information about $Kc$ values given certain crops and sowing schedules is essential to not underestimate irrigation demand. For the lower and middle basin it is most certain that the predominant crop is rice. Normally, rice has higher water demands compared to other crops, due to puddling practices and higher $Kc$ values. Thus, $Kc$ values for rice were selected for different development stages. According to CORPONOR (2010) three rice harvests can be achieved in a year, this means that land is continuously prepared for rice production every 4 months. It was assumed that the hydrological year starting in June corresponds with the first land preparation, thus crop coefficients $Kc$ in table 7.5 are obtained.

On the other hand, the actual evapotranspiration is calculated with optimized parameters $\alpha_1$, $\alpha_2$, and average monthly precipitation values from the model results. Furthermore, the Budyko framework has been adjusted to include irrigation demand areas, assuming that the soil moisture storage for every time step is equal to the maximal soil moisture storage. Some water balance models propose that the actual evapotranspiration is equal to the potential evapotranspiration when precipitation is higher (Thornthwaite and Mather 1955). In this case, the actual evapotranspiration is lower than potential evapotranspiration for every month; because evapotranspiration efficiency (parameter $\alpha_2$) is lower than 1. This means that irrigation demand will never be equal to zero, considering the optimal model parameters.

Finally, the irrigation efficiency coefficient was assumed to be 0.4 for the lower and middle basin irrigation schemes. The irrigation withdrawals change for each month, due to precipitation, potential evapotranspiration and crop coefficient conditions. The months with the lowest irrigation requirements are September and January (figure 8.4). These results are reasonable, given that in these months precipitation increases and $Kc$ values are low, due to rice field preparation.

The irrigation demand in the Pamplonita River Basin was found to be underestimated by CORPONOR (2010), since Venezuelan part of the basin was not included and low-middle basin irrigation demand areas not correctly quantified. It has to be pointed out that river basins have no political boundaries, thus the importance of this work in order to make a proper delimitation and analysis of the water demand.

The monthly demand for irrigation is essential for a proper supply/demand reliability analysis. Furthermore, quantified information of 'other demands' upstream irrigation demand areas is important in order to obtain a net water availability amount. In this case, CORPONOR information of water concessions for urban and industry was taken into account, furthermore in the Venezuelan part of the basin water demand was estimated by an area weighting comparison with the Colombian side of the basin. Most of these demands come from urban areas in the high and middle basin. The city of Cucuta has the highest demand with a required water supply of 1.62 m³/s. Even though, it is known that approximately half of Cucuta's water supply is withdrawn from the nearby Zulia River Basin, the applied hydrological model was simplified considering no additional water from other basins.

Finally, subtracting 'other demands' and taking into account the ecological flow; the net monthly surface water availability was obtained.
9.3 Water supply/demand reliability analysis

Cucuta’s city water supply:

Results for surface water availability in an existing offtake in the Pamplonita River (offtake_C) prove a high reliability of satisfying Cucuta’s city monthly water demand. The surface water availability depends on the upstream conditions of the upper Pamplonita River subbasin. Several water demands (industry and urban) in these subbasins can have an effect on surface water availability downstream. Furthermore, upstream irrigation demands are implicitly included in the model. The results show that probabilities for satisfying the water demand for the existing population in Cucuta are higher than 90%. However in some months like March the reliability can drop down to 80% (figure 8.14). It is difficult to conclude if these are high reliabilities or not. What can be derived from this result is that population and institutions responsible for water supply in Cucuta’s city have to be aware that there is a chance of water deficit. Furthermore, they can use this information to be prepared for water shortage or develop a new strategy to obtain water from other resources.

Considering a scenario where the existing population is doubled (D2_c) the reliability for satisfying water demand decreases lower than 70% for most of the months (figure 8.14). Only September, October, November and December remain with "acceptable" reliability values (r>80%). The increase in Cucuta’s city population will have a serious impact in their water supply reliability. It is important to develop strategies to obtain water from other resources.

Irrigation supply:

Results for surface water availability in offtake_2 (figure 8.19) in the Pamplonita River prove a high reliability of satisfying the monthly irrigation demand in the lower river basin. The surface water availability in offtake_2 depends on the upstream conditions of the Pamplonita River and the Tachira River subbasin. Several water demands (industry and urban) in these subbasins can have an effect on surface water availability downstream, thus there are included assuming a return coefficient. Furthermore, upstream irrigation demands are implicitly included in the model.

The upper subbasin from offtake_2 is considerable larger than the upper subbasin from offtake_1, since offtake_2 includes the Tachira River subbasin. This means that there is more existing area to capture precipitation and make it available for runoff in offtake_2. Furthermore, total precipitation changes for each month, thus surface water availability vary accordantly. Due to precipitation uncertainty a certain month will have different precipitation for each year. Using the uncertainty model, including precipitation and parameter uncertainty, water supply reliability can be established. The model includes irrigation activities in the middle and lower basin, for any withdrawal option, the only aspect that changes is the offtake location for satisfying irrigation demand in the middle basin.
Results for surface water availability in offtake_1 in the Pamplonita River prove a low reliability of satisfying the monthly irrigation demand in the middle river basin. Irrigation demand in the middle basin is higher than in the lower basin. In addition, upstream area from offtake_1 only receives runoff from the Pamplonita River Subbasin, not including Tachira River flow. Based on the reliability results, the irrigated land in the middle basin area has to withdraw water from the Pamplonita River Basin from offtake_2; this means a location where the Tachira River already has discharged its flow into the Pamplonita River. In a practical point of view this option is not feasible, because the distance from downstream to upstream irrigation areas is high (reaching 30 km). In addition, given this condition (option_2), the initial reliability for lower basin agriculture area will decrease, because more water is being demanded from one single offtake. Hence, four months will suffer from low reliabilities ($r<30\%$). However, it has to be pointed out, that these recommendations are based on a complete yearly water supply reliability point of view. If the farmer only wants to produce in certain months, the reliability can be much higher. For example for offtake_1, water supply is reliable ($r>70\%$) for five consecutive months, hence rice production is sustainable for these months without large pipeline system investment.

According to water supply reliability results agricultural development, specifically in rice, should be focalized in the lower basin for all months. Furthermore, it is recommended that land owners get organized into farmers associations, in order to manage the use of water from the offtakes. A similar concept is applied in the neighbor Zulia River Basin in the Zulia irrigation district, where benefits and disadvantages can be analyzed in order to make a better decision for future irrigation practices in the Pamplonita River Basin.

**Limitations:**

- The applied model does not consider routing. Therefore, it is not possible to analyze or understand the variation of water supply for smaller time steps than a month.

- Only one hydrological model was applied to understand the water supply reliability. No further analysis was made on model structure due to time restrain.

- The water supply reliability results are constraint to the assumed irrigation demand areas. There is an uncertainty related to actual irrigation demand areas in the lower and middle basin, due to the fact that CORPONOR database information do not match with satellite images, land use cover maps and field observations.

- It was assumed that all Cucuta's city water demand is supplied from the Pamplonita River. Even though it is known that part of the water is supplied from the Zulia River, ambiguity remains on how the water distribution is managed.
10. Conclusions

- The monthly surface water availability in a humid tropical river basin with an area of approximately 2100 km² was determined with the monthly Budyko framework, a parsimonious lumped conceptual hydrological model. This type of model was chosen because it does not need a lot of input information and it uses small amount of parameters, thus ideal for data scarce basins. Three parameters ($\alpha_1$, $\alpha_2$ and $d$) and two input data sets ($P$ and $ETP$) were needed. Additional $S_{max}$ values were calculated from available soil information ranging from 0 mm to 338 mm in the basin.

- The monthly simulated discharge was successfully calibrated with measured discharge from a water level station located near to the outlet of the river basin. An automatic optimization procedure for an objective function was applied. The possible range of the selected objective function values is 0 to $\infty$, with 0 being a perfect match between simulated and observed discharge. In this case, an optimal objective function value equal to 0.79 was determined. Furthermore, statistical BIAS (average error) and Pearson correlation $R$ values confirm a satisfactory match between simulated and observed discharge (BIAS = -0.2 mm and $R = 0.889$).

- Optimized parameter values of $\alpha_1 = 0.667$, $\alpha_2 = 0.587$ and $d = 0.334$ were determined assuming that the soil moisture storage is equal to maximal soil moisture storage capacity ($S_{max}$) for irrigation demand areas. Sensitivity analysis shows that the parameters do not change significantly (4%) when soil moisture storage conditions in the irrigation demand areas (5% of the total basin area) are not set to $S_{max}$.

- Validation of the hydrological model in the upper basin comparing simulated and observed flow in the water level station (Don Juana) shows a higher bias (BIAS = -18.5 mm), even though the trend of the simulated values is satisfactory ($R = 0.789$). Model validation results suggest that surface water availability values in the high basin are underestimated because of overestimation of potential evapotranspiration $ETP$ in that area.

- In the analyzed river basin there are official and unofficial irrigation demand areas. The official irrigation demand areas are organized in irrigation districts in the higher basin with a total area of 7.5 km². The unofficial irrigation demand areas are mainly for rice production, located in the lower and middle basin with a total estimated area
of 98 km². Monthly irrigation demand was calculated considering monthly evapotranspiration values and crop coefficient ($K_c$) for different crop developing stages. Considering a scheme irrigation efficiency of 40%, total surface water withdrawals of 125 Mm³/year were determined for the middle basin irrigation areas. In the middle basin August was determined to be the month with the highest surface water withdrawals for irrigation demand reaching approximately 17 Mm³. The yearly surface water withdrawals for irrigation in the lower basin were found to be 26% of the yearly surface water withdrawals for irrigation in the middle basin. In the higher basin they are less than 4% compared to the middle basin irrigation area.

- To determine the uncertainty in the estimate of the water surface availability, parameter uncertainty and precipitation input data uncertainty were considered. The Generalized Likelihood Uncertainty Estimation (GLUE) was applied to determine the model parameter uncertainty. One thousand parameter sets ($\alpha_1$, $\alpha_2$ and $d$) were randomly generated, assuming uniform distribution for each parameter. Four hundred parameter sets were finally selected as behavioral. It was determined that for the selected behavioral data sets the model parameter uncertainty is higher than the input precipitation uncertainty for different confidence intervals. Both uncertainties were combined and the highest runoff variability in the Pamplonita River Basin was found to be in October and the lowest in February for different confidence intervals. The combined uncertainty results are essential for determining water supply reliability in any surface water withdrawal point in the basin.

- The Budyko framework was extended to consider input and model uncertainty, and through this the surface water reliability to satisfy the irrigation demand was estimated in the basin. For the middle basin the reliability was found to be less than 30% for most of the months when the water is extracted from an upstream source ($offtake_1$). Conversely, the reliability was high ($r>98\%$) in the lower basin irrigation areas when water was taken from a source located further downstream ($offtake_2$). The results show that the best area for irrigation development is the lower basin, which has the higher supply reliability.

- It was found that including model parameter uncertainty in the simulated monthly water balance, decreases reliability between 5% and 10% (compared to only considering precipitation uncertainty). Therefore it is important to include model parameter uncertainty for reliability studies to obtain more dependable results.

- Water supply reliability was determined in the largest city in the Pamplonita River Basin: Cucuta. Considering a scenario where the existing population is doubled the reliability for satisfying water demand decreases below 70% for most of the months.
Therefore, doubling Cucuta's city population will have a serious impact in their water supply reliability.

11. Recommendations

For the agriculture sector in the Pamplonita River Basin:

- The irrigation demand areas in the lower and middle basin are important rice production areas in the basin. To improve them the surface water reliability has to be considered and understood.

- Based on the results, the agriculture sector in the lower basin has a high water supply reliability considering one offtake point upstream (offtake_2). Further research is recommended to determine if this agriculture land has the proper conditions for agriculture development.

- If the agriculture land conditions are acceptable, a management strategy for distributing the water in the irrigation fields should be developed. Farmers should meet with public or private agriculture developing organizations, in order to find the best management strategy. Furthermore, it is recommended that land owners get organized into farmers associations, in order to manage the use of water from the offtakes. A similar concept is applied in the neighbour Zulia River Basin in the existing Zulia Irrigation District.

For further hydrologic and irrigation research:

- This thesis is a first step to understand model uncertainty, including parameter uncertainty and input uncertainty. Further uncertainties can be included to analyze the sensitivity of the model (structural model uncertainties and measurement uncertainties). Other methods to estimate uncertainties can be applied and compared with the results of this thesis.

- Further research can be done applying different hydrological models to understand water supply reliability. In addition, model structure can be analyzed in order to recommend the most adequate model for the basin.

- Further research can be done regarding combined hydrological modelling and irrigation management plans in the lower and middle basin.
- Further research on quantifying the actual irrigation demand areas and using different potential evapotranspiration $ETP$ calculation methods is recommended in order to get a more complete understanding of irrigation demands. In addition, estimating the demand uncertainty is recommended.

- Further research can be established in irrigation demand areas to verify the scheme irrigation efficiency, specifically conveyance and field application efficiencies.

- Even though in this thesis an ecological flow according to the resolution 865 of 2004, IDEAM-MAVDT (Colombia) was used to determine the net surface water availability, it is recommended to establish the actual ecological flow for Pamplonita River conditions.

- According to CORPONOR, floods are common in the lower basin area. Thus, a model with routing can be applied for a better understanding of floods in the agriculture areas.

- Apply a flow measurement programme in the area, especially in the Tachira River and after the intersection of the Pamplonita and Tachira River. In general more investment in precipitation and temperature stations in the Pamplonita River Basin. In addition, re-establish level and flow measurements in the water level stations $Aguas Claras$ and $Don Juana$ and precipitation and temperature measurements in the basin.
References


Peña, G. A. (2012). Evaluating the impact of climate change on urban scale extreme rainfall events: Coupling of multiple global circulation models with a stochastic rainfall generator. MSc., UNESCO-IHE.


Appendixes

Appendix A: Double mass curves
Appendix B: Climatology input data $P$ and $ETP$
Appendix C: Water balance per pixel for every month
Appendix D: Monthly precipitation $P$ average between stations for each influence area

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</tbody>
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