CORFU

FP7 Collaborative research on flood resilience in urban areas

Work Package: WP2 Urban Flood Modelling

Document Name: Report and papers with guidelines on calibration of urban flood models

**Date:** **12 August 2014**

**Report Number:** **D2.2**

**Revision Number:** **2**

**Deliverable Number:** **D2.2**

**Due date for deliverable:** **31 March 2011**
**Actual submission date:** **15 August 2014**

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*CORFU is co-funded by the European Community*
*Seventh Framework Programme.*
*CORFU is a Collaborative Project in the FP7 Environment Programme*
*Start date April 2010, duration 4 Years.*

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Document Dissemination: **PU (Public dissemination)**

Co-ordinator: University of Exeter, United Kingdom
Project Contract No: 244047
Project website: www.corfu7.eu

ACKNOWLEDGEMENTS
The work described in this publication was supported by the European Community's Seventh Framework Programme through the grant to the budget of CORFU Collaborative Research on Flood Resilience in Urban Areas, Contract 244047.

## DOCUMENT INFORMATION:

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|---|---|
| **Title** | Report and papers with guidelines on calibration of urban flood models |
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| **Distribution** | PU (Public dissemination) |
| **Document Reference** | D2.2 |

## DOCUMENT HISTORY:

| Date | Revision | Prepared by | Organisation | Approved by | Notes |
|---|---|---|---|---|---|
| 23 Oct. 2011 | v.0 | NSD | DHI | OM | |
| 10 Mar. 2014 | v.1 | NSD | DHI | | Updates for Barcelona Case Study |
| 12 Aug. 2014 | v.2 | SDj | UOE | OM | Minor updates |

## SUMMARY

Computer modelling offers a sound scientific framework for well-structured analysis and management of urban drainage systems and flooding. Computer models are tools that are expected to simulate the behaviour of the modelled real system with a reasonable level of accuracy. Assurance of accurate representation of reality by a model is obtained through the model calibration. Model calibration is an essential step in modelling. This report present concepts and procedures for calibration and verification of urban flood models. The various stages in the calibration process are presented sequentially. For each stage, a discussion of general concepts is followed by descriptions of process elements. Finally, examples and experiences regarding application of the procedures in the CORFU Barcelona Case Study are presented.

Calibration involves not only the adjustment of model parameters but also other activities such as model structural and functional validation, data checking and preparation, sensitivity analysis and model verification, that support and fortify the calibration process as a whole. The objective in calibration is the minimization of differences between model simulated results and observed measurements. This is normally achieved through a manual iterative parameter adjustment process but automatic calibration routines are also available, and combination parameter adjustment methods also exist. The focus of a model calibration exercise is not the same for all types of models. But regardless of the model type, good modelling practice should involve thorough model verification before application.

A well-calibrated model can give the assurance that, at least for a range of tested conditions, the model behaves like the real system, and that the model is an accurate and reliable tool that may be used for further analysis. However, calibration could also reveal that the model cannot be calibrated and that the correctness of the model and its suitability as a tool for analysis and management of real-world systems could not be proven.

The conceptualisation and simplification of real-world systems and associated processes in modelling inevitably lead to errors and uncertainty. Various modelling components introduce errors such as the input parameters, the model concept, scheme and corresponding model output, and the observed response measurements. Ultimately, the quality of the model as quantified by how much it deviates from reality is an aggregate of the errors that have been brought into it during the modelling process. Thus, it is important to identify the different error sources in a model and also account for and quantify them as part of the modelling.

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# 1 Introduction

Urban flooding is an inevitable problem for many cities around the world. It occurs in cities in developing countries as well as in industrialized nations. Flooding can bring about serious disruption to everyday life and high costs to society when recovering from the structural and non-structural damages sustained from the event. Whether flooding usually occurs at a smaller or larger scale according to the varying drainage system standard levels and/or environmental driving factors in an area, the aim is to be able to quickly recover from it and also try to develop resilience to its expected recurrence.

Strategies for mitigation of as well as adaptation to urban flooding are continuously being developed and improved upon, and it is recognized that the development of these strategies must begin with understanding the causes and mechanisms of the problem. An understanding of the physical system and how it interacts with environmental factors to result into flooding is needed for effective planning and management of urban drainage and flooding, and computer models have been found highly suitable for this purpose.

Computer modelling offers a sound scientific framework for well-structured analysis and management of urban drainage systems and flooding. It allows coherent process understanding and expedient analysis of various scenarios—actual and anticipated. Once the different processes have been analysed and understood, alleviation schemes can then be evaluated in order to identify the optimal scheme for implementation.

Flood modelling techniques that have been developed range from 1D dynamic pipe network models able to simulate the interaction of rainfall and flooding, to coupled 1D-2D pipe-overland flow models (Mark, et al. 2004). The use of these tools in model-based projects follows a systematic procedure such as the one shown in Figure 1 from (Parkinson & Mark, 2005). It involves the following steps:

1. Planning and preparation (including an assessment of data requirements).
2. Acquire data, and formulate and build the model.
3. Model calibration and verification.
4. Evaluate the performance of the calibration and verification. If necessary repeat Steps 2 and 3 to improve model accuracy if it is not considered to be satisfactory.
5. Model application and assessment of results.

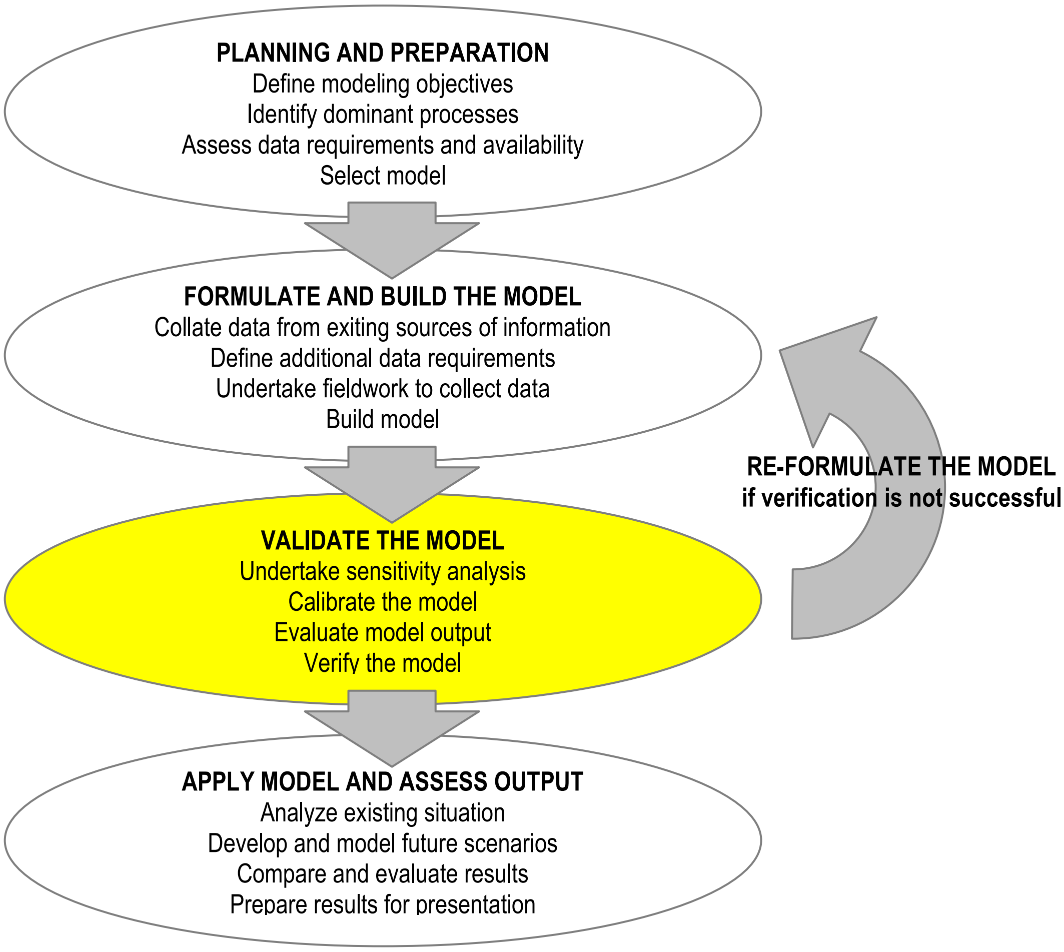



**Figure 1. A chart explaining the modelling procedure. The step for model validation is highlighted (Parkinson and Mark 2005).**

Model calibration and verification are essential steps in the procedure. In this document, steps and concepts regarding calibration and verification of urban flood models are presented. The objective is to provide hydroinformaticians and flood modellers a guideline for flood model calibration and verification.

The various steps in the calibration process are presented sequentially. For each stage, a discussion of general concepts is followed by descriptions of process elements. Finally, examples of the application of the procedure in CORFU Case Studies are presented. In particular, flood modelling and calibration experiences from the Barcelona Case Study by Clavegueram de Barcelona S. A. (CLABSA)are included as an illustration of the application of concepts described in the report.

# 2 The Calibration Process

A model is a simplified mathematical representation of a physical system. This representation may be deterministic (i.e. with a fixed relationship between physical disturbance and its effect) or stochastic (i.e. involving terms of probability into the model inputs and the interpretation of model results). Models for urban drainage and storm water management are predominantly deterministic. Deterministic models applied for urban drainage can be roughly classified as physically-based or conceptual depending on the mathematical sophistication of the treatment of the underlying physical processes of the system. Essentially, the models are classified according to the prominence of empirical parameters in the models' description of the processes. Models that rely heavily on empirical parameters are classified as conceptual and generally require verification against field measurements. Many hydrological models are classified as conceptual models, while hydrodynamic network models are physically-based deterministic models.

A computer model is a versatile and useful tool for obtaining good understanding of hydrologic and hydrodynamic processes in water systems for water management projects. Although computer models are now more able to make use of physically-based data (i.e. directly derived from observable characteristics) and simulate highly complex integrated systems and processes they are still simplified representations of a part of the real world and many models and model components are still represented by parameters representing an aggregation of several physical characteristics and behaviour. Thus, before the model can be used in applications like system design, analysis, risk assessment, and the like, steps must be taken to ensure that it can truly simulate the behaviour of real-world system at a reasonable level of accuracy.

Calibration is the procedure for ensuring an acceptable level of confidence in a model's ability to accurately represent the real system. It refers to the whole process of ensuring that a model behaves as similar to the real system as possible. The main undertaking in calibration is the adjustment of model parameters in order to minimize the difference between simulated results and observed measurements. However the process is not limited to this but is comprised of several steps:

1. Structural and functional validation
2. Data preparation and calibration data selection
3. Sensitivity analysis
4. Iterative adjustment of model parameters
5. Result verification

Figure 2 gives further explanation on the calibration and verification process (Parkinson & Mark, 2005) covering steps 4 and 5 in the list above. It describes various data elements and evaluation processes used in calibration and verification. Furthermore, it shows that if a model does not pass the verification procedure then a reassessment must be performed considering:

- If more data (i.e. observations) should be collected
- If the model structure is suitable for the purpose
- If another model would be more appropriate
- If it is not possible to achieve satisfactory results and that the modelling exercise should be stopped

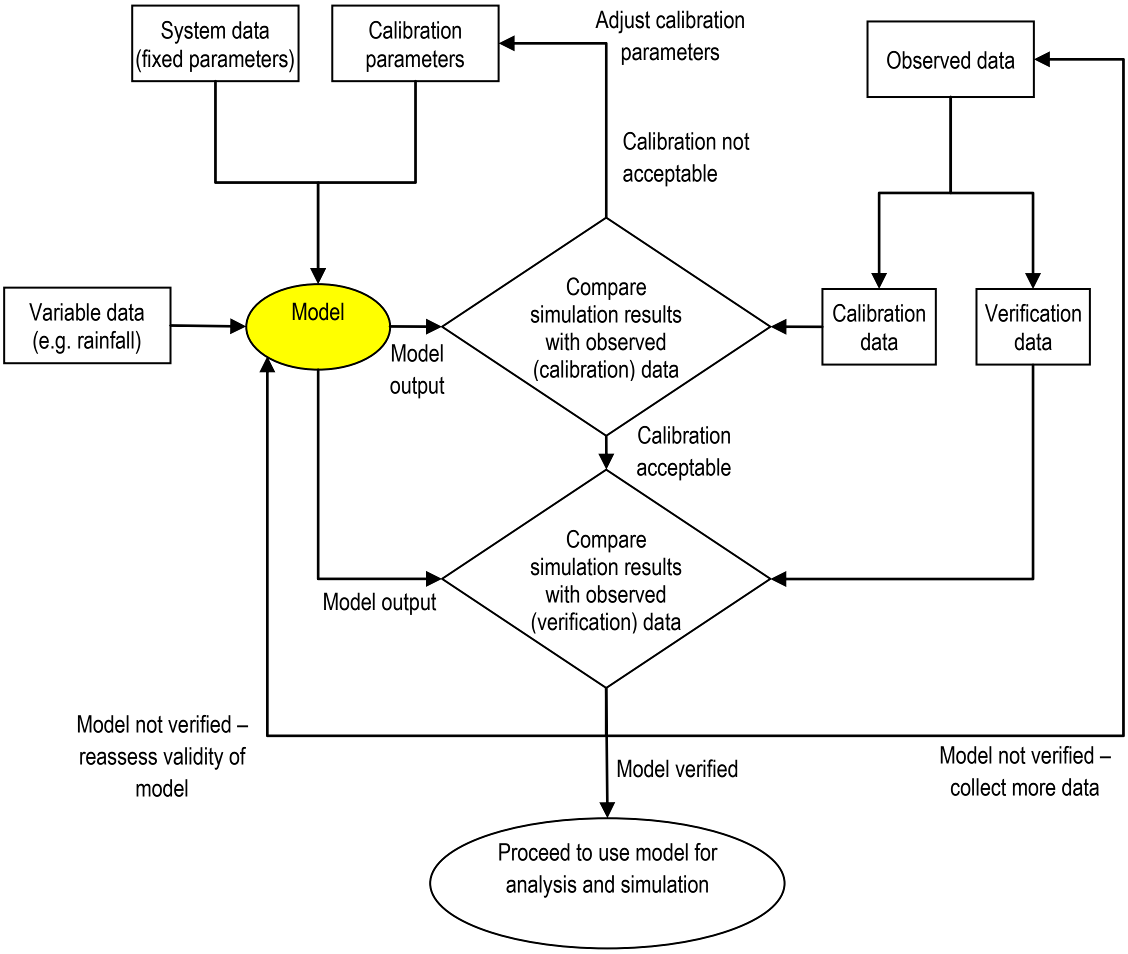



**Figure 2. The calibration and verification procedure (Parkinson and Mark 2005).**

## 2.1 Structural and Functional Validation

Structural and functional validation of the model is performed once it has been built from the available data. This mainly involves checking that the model is setup correctly such that elements are functioning logically and that the model runs without errors and is stable. The following activities are performed:

- Check the model configuration. Make sure that the components of the model represent the actual system as accurately as possible. For example, check for consistency in network connectivity, elevations compared to topographical data, dimensions, materials, etc.
- Ensure computational stability. The model should be computationally stable when subjected to loads of the same magnitudes as expected for the event being simulated as well as according to the eventual purpose of the model.
- Check volume balance. Volume errors must be kept within narrow limits. Causes for high volume errors must be identified and eliminated or minimized. The residual volume error should be taken into account in the calibration process.

The type of urban flood model that had been selected for the Barcelona Case Study is the coupled 1D/2D model type considering a 2D model for the overland flow and a 1D model for the sewer system. A major component of the overland model is the 2D unstructured mesh which they develop from DTM (Digital Terrain Model) data. The identified important flooding mechanism for the case study due to heavy rainfall events is characterized by low flow depths and high flow velocities due to the low roughness of urban surfaces. Thus, it was determined that an adequate and detailed representation of the ground surface topography is an essential aspect to take into account in order to achieve a realistic flood hazard assessment in the area.

The Case Study institution (CLABSA) had been carefully checking the integrity of the 2D mesh component of the model by obtaining the DTM data from a reliable source (i.e. the Catalan Institute of Cartography, or ICC), understanding how and when the data had been collected, and ensuring that grid resolutions (1 m) and precisions (15 cm) are of acceptable levels for their purpose. In addition, the DTM data was also validated by the Cartographic Department of CLABSA. Plotting of cross-section profiles with the DTM was part of the analysis to check that the data allows representation of several urban elements such as sidewalks, curbs and streets (Figure 3). The figure shows the DTM provided by ICC reasonably representing the section of Rambla Avenue in the case study area. It is also possible to observe the representation of the lateral sidewalks, the lanes for vehicular circulation and the central pedestrian area of the avenue.

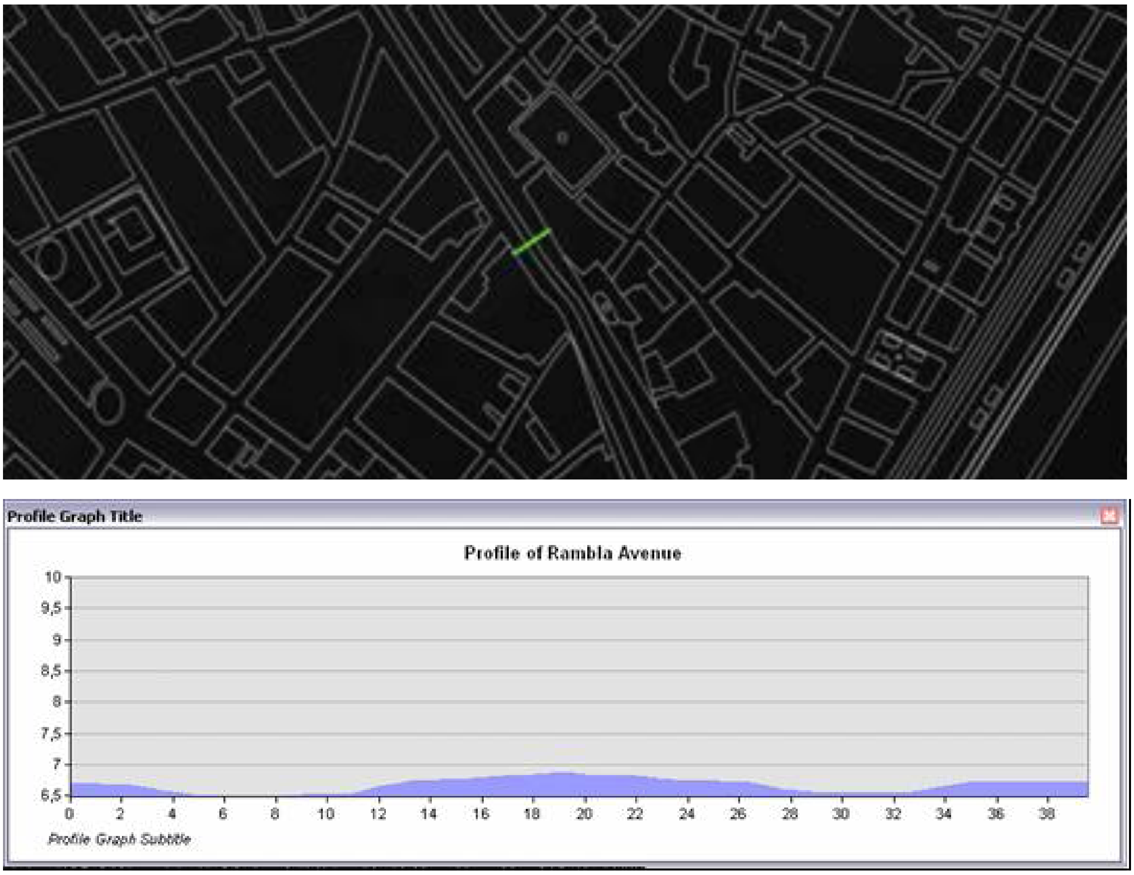



**Figure 3 Profile of a specific section of the Rambla Avenue in the Barcelona Case Study. In the figure it is possible to observe the representation of the sidewalks, lanes for vehicular circulation and central pedestrian areas (Barcelona Case Study).**

## 2.2 Data Preparation and Calibration Data Selection

It is important that data for input and calibration are available and reliable. Input data refers to records of model driver parameters such as rainfall, inflows, and the like. Calibration data are observations of system response parameters such as flow/discharge, water levels or flood extents, which could be from historical records or from measurement surveys conducted specifically for the modelling exercise.

A related issue is ensuring proper selection of measurement sites and correct procedures for data collection. Providing guidelines for gauge site selection is not the object of this report but is a concern for the gauging consultant responsible for conducting the measurement survey. Nevertheless, some considerations to consider in flow gauge site selection are:

- Hydraulic conditions must be suitable for the gauges to capture accurate data for the full range of flow conditions (low to high)
- Monitor locations to be at or in the proximity of known existing problems of network overflows
- Number of flow monitors enough to allow calibration of catchment runoff model and isolate catchments with high wet weather flows
- Avoid turbulent flow conditions at the gauging site
- The site is not affected by backwater from downstream
- The site is not influenced by indeterminate operation of structures like weirs, gates and pumps nearby
- Practical aspects such as safe and non-obstructive access to the gauging site

### 2.2.1 Data checking

The quality of the input and observation data is checked to ensure that subsequent comparison of model results and observations is valid. Moreover, the use of higher quality data in model calibration improves constraint over parameter adjustment within realistic ranges. Raw input data and observation records may be processed and verified by:

- Comparison against other similar records (e.g. rainfall measurements from various sources, flow measurements at nearby stations, etc.)
- Removal of “noise” from the raw records
- Removal of obvious “spikes” or outliers
- Interpolation and extrapolation of missing data

### 2.2.2 Calibration data selection

The type of data that is needed for calibration depends on the flood model being considered. For example, for 1D network flood models with lumped rainfall-runoff model components, calibration data could be flows at catchment outlets, flows and water levels at strategic, hydraulically stable and representative points in the network, as well as flows at network outlets.

Flow measurements are generally preferred for use in calibration. However, water levels can also be used especially for flood models. Flood extent maps developed from point observations or captured during flood events may also prove useful in model calibration especially when precise flow and level measurements are lacking. For flood models with sewage system elements, dry weather flow patterns are needed for calibration of that component of the model.

Generally, the data used in calibration are observations for particular events and not necessarily the complete time series of available measurements. For example it could be only data during high flow events that represent flooding in the model area. These events are identified and selected from the available records in consideration of the ultimate purpose of the model. A correctly calibrated model is expected to perform with reasonable accuracy for conditions that are relevant and likely to occur according to its intended purpose. Thus, calibration must be carried out using a data set representing a range of events or a period characterizing relevant expected operational conditions. For example, for flood models the selected set of calibration events must include the largest recorded flow/flood event. On the other hand, if the model will be used to study general flow conditions in an area, the model must be calibrated against a representative continuous "general" period including dry and high flow conditions.

To pick out individual events for calibration, the continuous rainfall records must be analysed to identify individual events and rank them by size. In this process a definition of what individual events are should be defined taking into account catchment characteristics and observed data of associated catchment responses such as flows and water levels.

Ideally, the number of events used for calibration should be larger than the number of parameters being changed to obtain unique parameter estimates. For urban surface runoff models, it is recommended that at least 3 events are used. The use of more events in the calibration would increase the overall reliability of the model. From the available data, some are used for parameter estimation while others must be kept for model verification.

The comparison of simulations against observations may be done in many ways and on different aspects, i.e. focusing on different qualities of the data in the comparison. Having different measures of comparison helps constrain and improve the parameter adjustment. In hydrological modelling, calibration is generally performed using continuous flow records and the objective is overall volume balance. The hydrographs should follow each other both in shape and in magnitude. For cases when overall volume balance is the target, base flow runoff must be correctly simulated so that slow seasonal changes are accurately described. The peak flows and the general shape of the simulated hydrographs must also be reasonably accurate. Indeed, the calibration may be performed as a compromise between the volume balance for the selected events and the peak flows. Including more events of different sizes in the calibration may improve the overall performance of the model with greater compromise between overall volume balance and peaks. For flood models, important criteria are peak flow and depth levels, timing of peaks, and also total volumes if the model will also be used for development of flood storage structures and general water management.

The 1D/2D model for the Barcelona Case Study evolved from an earlier 1D sewer model for the city that had been put through the calibration process. That modelling exercise for the 1D model had 3 sets of events used for calibration and verification. Two sets were used for calibration and one was used for verification:

- Event of 31/07/2002 (Calibration)
- Event of 17/09/2002 (Calibration)
- Event of 09/10/2002 (Verification)

All of the data were from 2002 and they consisted of rainfall data from 11 rain gauge stations and 35 water level and flow measurement (limnimeters) stations around the study area.

For the 1D/2D coupled flood model for the Barcelona Case study, it was validated and calibrated using data provided by the CLABSA Exploitation and Maintenance Department. The data were obtained from the CLABSA rain gauges network (made up of a total of 24 rain gauges). In the modelling, data from 11 selected rain gauges were used and their locations are shown in Figure 4

Due to the recent significant changes of the Barcelona sewer system (new infrastructure such as pipes and tanks were built in the past few years and regularly work now), 4 rainfall events from 2011 were selected for model calibration and verification. According to literature (DHI, 2002) and the guidelines defined in this deliverable, three storm events were selected for the calibration process, while one was selected for verification. The main characteristics of these events are shown in Table 1.

Flooding reports and 29 water level gauges located in manholes and conduits of the analysed domain were also used for the calibration/verification processes. Specifically, flow depth series calculated by the model were compared to flow depth series recorded by the water level gauges.

**Table 1 Events selected for calibration and verification of 1D/2D flood model (Barcelona Case Study).**

| Date event | Cumulative rainfall | Maximum rainfall intensity in 20 minutes | Maximum rainfall intensity in 5 minutes | Function of the event |
|---|---|---|---|---|
| | (mm) | (mm/h) | (mm/h) | |
| 15/03/2011 | 54.1 | 69.6 | 98.4 | Calibration |
| 07/06/2011 | 26.8 | 24.3 | 49.2 | Calibration |
| 19/07/2011 | 45.9 | 95.1 | 135.6 | Calibration |
| 30/07/2011 | 30.4 | 105.9 | 140.4 | Verification |

Other sources of information, such as emergency reports from policemen, firemen and the affected population during the heavy storm events, were also used in the calibration. They found that information about manhole covers being lifted by flow pressures, flow depth marks left by the flow in buildings, and backflow phenomena in buildings constituted very useful information for the calibration of the model as well as for the detection of critical points of the network where the presence of limnimeters were poor or where ultrasonic sensors did not work correctly because of surcharged pipe conditions.

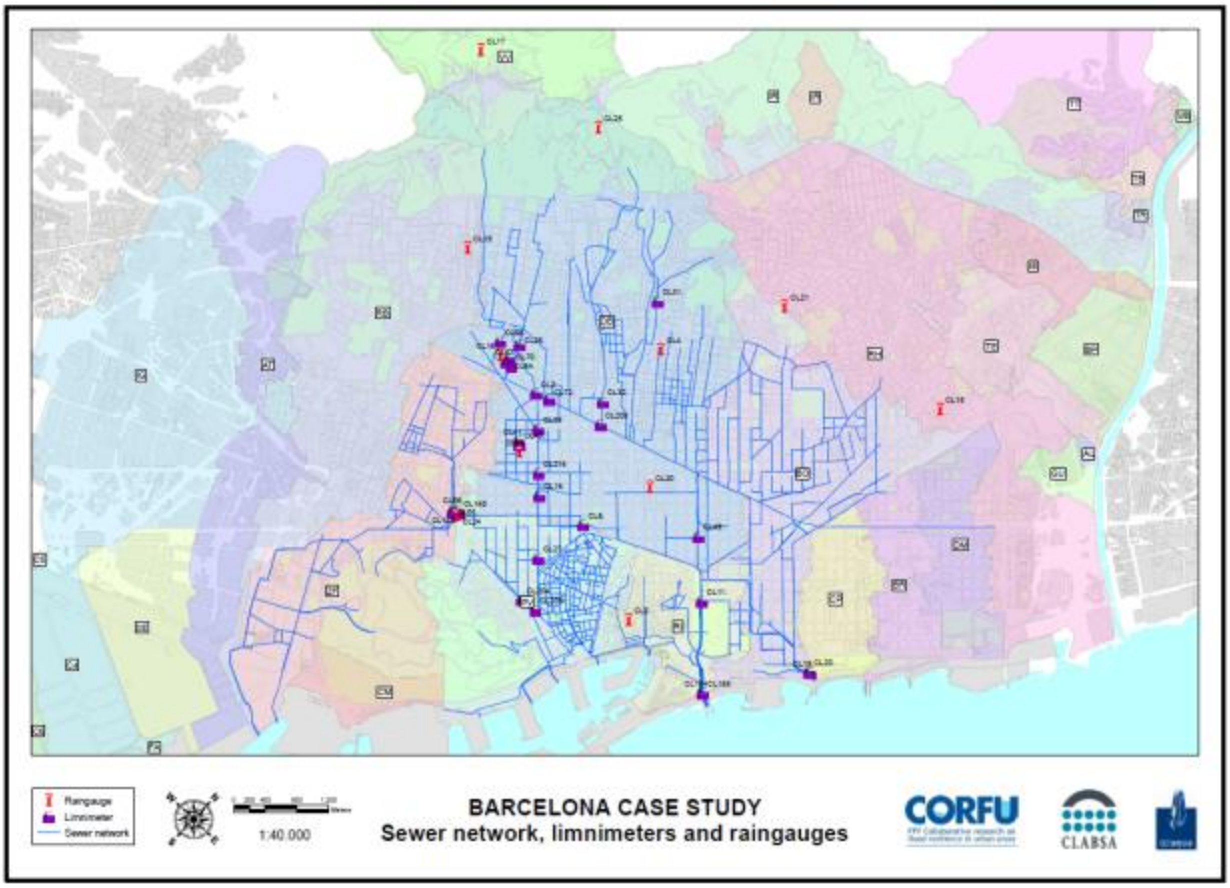



**Figure 4 Sewer pipes, rain and water level gauges in the 1D/2D model of the Barcelona case study.**

## 2.3 Sensitivity Analysis

Sensitivity analysis involves running simulations with the model while systematically varying the parameters and then making comparisons among the different results to observe the effect of the changes to the model. The analysis is performed in order to determine which of the parameters have the most significant influence on the model. The modeller can then focus on these parameters and more carefully estimate their values. Also, subsequent model parameter adjustment in the calibration process could be done more efficiently as the number of parameters to be adjusted is narrowed down. Performing sensitivity analysis can help in the identification of model parameters that will be adjusted in the calibration especially when the selected model is very complex and has a big number of parameters and components that must be assessed.

Sensitivity analysis may also be used to determine whether existing input data resolutions are sufficient for the selected model and its intended purpose. For example, the level of accuracy needed for describing surface roughness in a 2D flood model may be determined by running the model using surface roughness grids of different resolutions/grid sizes and levels of detail (e.g. number of categories) and comparing the results. These tests can also help determine if available data is enough for the type of model selected to give results of sufficient quality according to its intended use.

In the Barcelona Case Study they referred to a sensitivity analysis concerning the routing parameters in a 2D domain carried out by the Department of Civil & Structural Engineering of the Sheffield

University in deciding about the schematisation of their 1D/2D model. In the study, using a software system called Infoworks CS, tests regarding 2D model mesh resolutions and schematisations showed that simulated flood extents are relatively insensitive to mesh density, surface roughness and whether buildings are considered. Instead, the analysis showed that the modelling/representation of buildings in the 2D model has a significant effect on flood depths, and also surface roughness to a lesser extent. It was found that mesh density is important in refining flood paths and would have more significance where the floodplain is less well defined (Shepherd, et al., 2011).

## 2.4 Model Parameter Adjustment

The central step in the calibration process is the iterative adjustment of model parameters in order to match model results with observations. The complexity of the process depends on the number of calibration parameters being adjusted, and its transparency is determined by the character of the calibration parameters and the modelling concepts being applied.

### 2.4.1 Selection of calibration parameters

The parameters that are adjusted in calibration are generally the ones that cannot be directly assessed from field data. Determining which model parameters to adjust during calibration is influenced by the type of model selected. For example, a relatively simple lumped, conceptual rainfall-runoff model, which may be a component of an urban drainage flood model, may have only a few model parameters to begin with, such as concentration time, hydrological loss factor, etc., and all of them could be included in the calibration.

The initial 1D sewer model in the Barcelona Case Study was calibrated mainly on processes related to urban surface runoff. The following standard parameters in rainfall-runoff models were adjusted in the calibration:

- Hydrological initial losses. This parameter is related to the portion of rainfall that is not transformed to runoff. Specifically, wetting and storage losses were considered for impervious areas, while for pervious areas infiltration losses was taken into account using the Horton Equation.
- Surface roughness coefficients. This parameter plays an important role in the flow velocity of the surface runoff. Surface roughness coefficients were specified for each urban surface. Through the adjustment of these parameters it was found possible to correct hydrograph volumes.

For the 1D/2D flood model being developed in the Barcelona Case, the main processes identified for the modelling are rainfall-runoff transformation and flow propagation in the sewer network.

They have found that a large number of parameters can be considered in the process of calibration of the runoff model especially with their 1D/2D coupled model approach. They have identified that for the overland flow generated in the cells of the 2D domain, the calibration parameters could be:

1. Hydrological losses
2. Routing parameters (cells size, cells roughness coefficients, representation of the area excluded by 2D domain)

For the sewer flow component, the continuous friction loss and the head losses due to turbulence at singularities of the network are identified as common parameters for calibration. The calibration process adopted in the case study for the runoff produced in building areas (terraces, roof, etc.) are:

1. Adjustment of the model parameters globally affecting to all sub catchments. The parameters adjusted in this phase are the hydrological initial losses and the surface roughness coefficients.
2. Adjustments of specific parameters of the catchments. The parameters considered in this phase are the geometrical slopes and the impervious coefficients of the sub catchment. In this phase it is possible to calibrate each sub catchment on the base of the flow depth values recorded by limnimeters in the sewer system.
3. Detection of possible phenomena affecting the limnimeters measurements. The presence of jumps, changes in flow direction, flow confluences could not be adequately represented by the model. In these cases, the presence of these phenomena could be simulated by local head losses with the help of the real flow measurements recorded by limnimeters.

### 2.4.2 Setting of calibration objectives

Calibration may be understood as an optimization process involving one or several simultaneous objective functions. These objective functions represent in one form or another formalised measures of deviation between measurements and simulations. In manual calibration, these measures are used with visual observations in the evaluation of the goodness-of-fit of simulations to observations.

Some examples of statistical measures used in calibration are summarized in Table 2 below.

**Table 2 Statistical performance measures for goodness-of-fit evaluation.**

| Statistical Performance Measure | Equation |
|---|---|
| Probability of detection (hit rate) | $Fit = \frac{A_{obs} \cap A_{sim}}{A_{obs} \cup A_{sim}}$<br>Where<br>$A_{obs}$ = Observed flooded area<br>$A_{sim}$ = Simulated flooded area |
| Overall volume error | $F = \sum_{i=1}^{N} \left( Q_{obs,i} \Delta t - Q_{sim,i} \Delta t \right)$<br>Where<br>$Q_{obs,i}$ = Observed discharge at time i<br>$Q_{sim,i}$ = Simulated discharge at time i<br>$N$ = Number of time steps in the calibration period |

| | |
|---|---|
| Root mean squared error (RMSE) | $RMSE = \sqrt{\frac{\sum_{i=1}^{N}(OBS_i - SIM_i)^2}{N}}$ |
| Coefficient of variation (S) | $S = \frac{\sqrt{\frac{\sum_{i=1}^{N}(OBS_i - SIM_i)^2}{N}}}{\frac{1}{N}\sum_{i=1}^{N}OBS_i}$ |
| Coefficient of determination ($R^2$) | $R^2 = \frac{\left[\sum_{i=1}^{N}(OBS_i - \overline{OBS})(SIM_i - \overline{SIM})\right]^2}{\sum_{i=1}^{N}(OBS_i - \overline{OBS})^2 \sum_{i=1}^{N}(SIM_i - \overline{SIM})^2}$ |
| Peak error | $PE = \lvert \max\{OBS_i\} - \max\{SIM_i\} \rvert$ |
| Time-to-peak error | $TPE = \lvert t(\max\{OBS_i\}) - t(\max\{SIM_i\}) \rvert$ |

The probability detection has widely applied to evalulate the model accuracy by checking the correct positive predictions against the observations (Bates & De Roo, 2000). For cases that the prediction of simple occurrence is insufficient to determine the goodness of modelling results, the approach can be extended to a contingency test matrix to include more indicators (missed, false alarm and correct negative) for evaluations (Bennett, et al., 2013).

It may be possible to achieve high levels of volume balance agreement on a set of calibration events or a calibration period depending on the type of model. However, volume balance accuracy close to 100% does not guarantee a similar accuracy in the verification.

Root mean squared error (RMSE) is a statistical measure of deviation between measured and observed time series. The value of RMSE is dependent on the absolute values of the variable involved and it can be used for relative comparison in successive steps during the iteration.

Coefficient of variation (S) is a normalized form of RMSE. As such, S provides an objective measure of deviation of the measured and observed time series. The coefficient of variation in the range of 0.1 – 0.2 indicates a well- calibrated model. Another statistical measure of deviation is the coefficient of determination ($R^2$). However, there is no proof that some deviation measures are better than others.

### 2.4.3 Manual parameter adjustment

The traditional and most widely-used way of adjusting parameters in calibration is through a manual trial-and-error process. The modeller, after each parameter adjustment and simulation run, compares model results to observed data by visual inspection and evaluation of statistical measures in order to determine how to adjust the parameters for the next iteration. Because of the visual component a good graphical representation of the simulation results is needed for this method.

Manual parameter adjustment is highly recommended especially for more complex models. The main advantage of the method is that it allows more straightforward use of several performance indicators, both objective and subjective, simultaneously without having to explicitly formulate the selected quantitative measures into a function that will be optimized. Also, it is able to take advantage of an experienced modeller's judgement to obtain a very good model calibration.

The main disadvantage of the manual method is that it is labour intensive and can be time-consuming. The subjectivity involved in manual calibration is also a problem since because of this different modellers may obtain very different calibrated model parameter sets. Generally, extensive hands-on experience is required to obtain good results and the experiences gained in manual calibration are not easily transferred to others.

Manual parameter adjustment was performed for the (old) 1D network model in the Barcelona Case Study. Great effort was dedicated to the calibration of the hydraulic behaviour of the Diagonal pipe—a major component of the sewer system. The most important unknown parameter was the local head losses caused by a series of jumps and significant flow confluences coming from upstream sub catchments. It was found that depending on several estimations of local head losses in the Diagonal pipe, peak flows greatly varied (from 145 to 98 $m^3/s$). For this reason a specific physical model was built in the Technical University of Catalonia for the section and results confirmed that flow depths provided by the model were less than flow depths measured in the Diagonal pipe. With the results of the physical model and limnimeters data, specific head losses were included in the 1D sewer model for the Diagonal Avenue. Moreover % imperviousness and average slope values for sub catchments were also adjusted. In the following figures (Figure 5 and Figure 6) calibration results in terms of flow depth series for the 1D sewer model are shown.

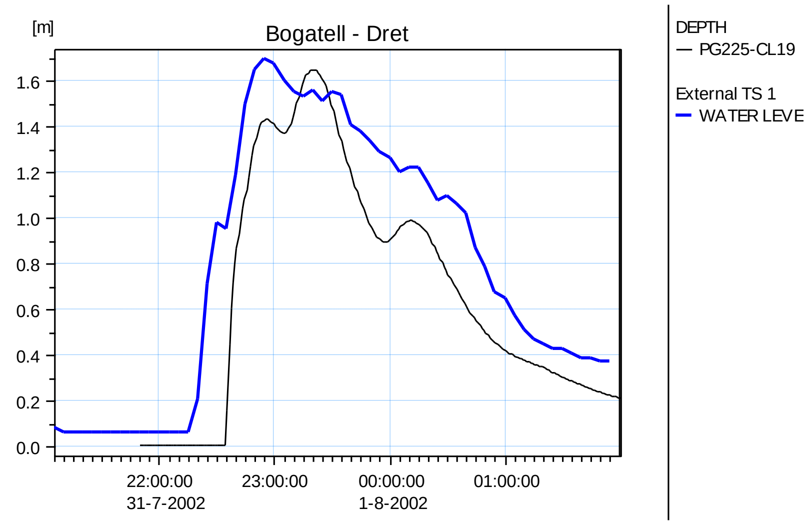
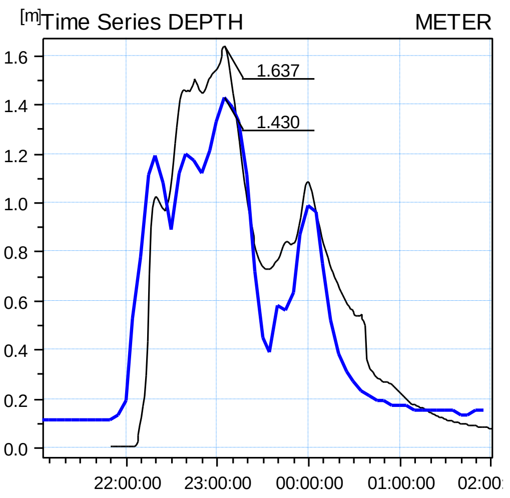



**Figure 5 1D sewer model calibration results for the event 31/07/2002 at Bogatell Seafront. Flow depths measured and calculated by the model are shown respectively in blue and black lines (Barcelona Case Study).**



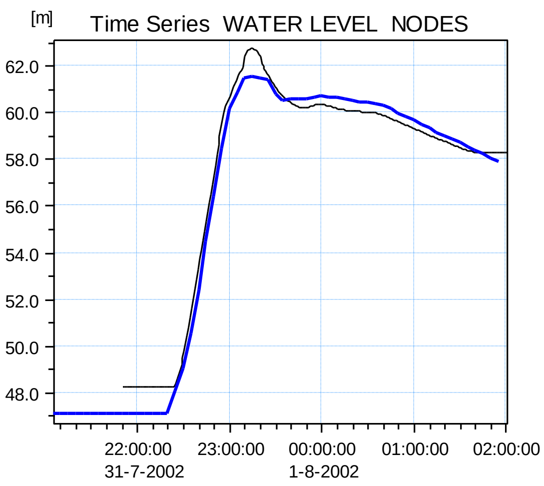




**Figure 6 1D sewer model calibration results for the event 31/07/2002 at Balmes-Travesera de Gracia (on the left) and in the Bori i Fontestá storage tank (on the right). Flow depths measured and calculated by the model are shown respectively in blue and black lines (Barcelona Case Study).**

The figures above (Figure 6) illustrate that the availability of graphs simultaneously showing model results and field measurements are useful in quick visual assessment of the performance of the model.

Manual trial and error calibration adjustment was also employed for the 1D/2D model for the Barcelona Case Study. The (old) 1D sewer model for the area was used in building the new 1D/2D coupled model, and local head losses in the previous 1D model were translated to the new model. Moreover, a big effort was made to adjust local head losses and hydraulic descriptions of several elements (i.e. storage tank entries, jumps, frontal and lateral weirs, gates, etc.). Some calibration plots are shown in Figure 7 below.

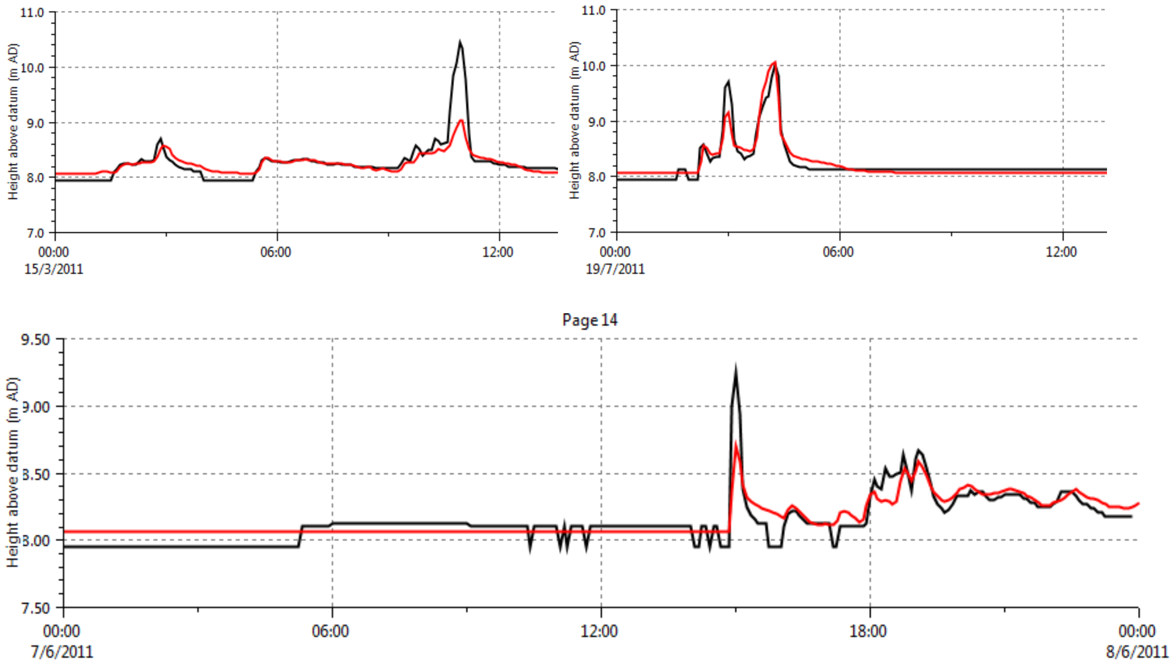



**Figure 7 Calibration results (for the three selected events) regarding a monitored manhole (P-AV65) located in Parallel Street (Raval District). Black lines show recorded flow depths, while red ones show simulated flow depths.**

Values for various hydrological parameters were determined with the calibrations. In the following table (Table 3), some of these parameters are summarized.

**Table 3 Hydrological parameters for the 1D/2D coupled model used for the Barcelona Case study**

| Surface classification type | Roughness factor | Hydrological losses model | Surface type | Initial loss value | Initial infiltration rate $f_0$ | Residual infiltration rate $f_\infty$ | Decay constant k | Recovery constant k' |
|---|---|---|---|---|---|---|---|---|
| | *$s \cdot m^{-1/3}$* | | | *m* | *mm/h* | *mm/h* | *1/h* | *1/h* |
| Road | 0.013 | Fixed | Impervious | 0.000071 | | | | |
| Roof | 0.013 | Fixed | Impervious | 0.000071 | | | | |
| Pervious | | Horton | Pervious | | 20 | 7.2 | 0.043 | 0.108 |

## 2.4.4 Automatic parameter optimization

Automatic parameter optimization involves having the computer run a numerical algorithm to find the extremum of a given numerical objective function on its own. The model parameters are adjusted automatically according to the algorithm without intervention from the modeller. The purpose of automatic parameter optimization is to search through as many combinations and permutations of parameter values as possible to achieve the set which is the optimum or "best" in terms of satisfying the selected criterion of accuracy.

The main advantages of automatic parameter adjustment are that it is faster and less subjective than the trial-and-error method. Its adjustment of parameters requires much less human intervention and does not greatly depend on visual inspection and the subjective judgement of the modeller. Instead, the evaluation of goodness-of-fit is mostly based on numerical objective functions. However, this is also the main disadvantage of automatic calibration in that it is dependent on the formulation of the numerical functions to be optimised.

The procedure involves the formulation of an objective function according to the selected performance measure for the model's goodness-of-fit to observations (e.g. good peak flow simulation), and the selection of a numerical algorithm that the processor should implement in order to optimize the objective function and obtain the targeted parameter set for the model.

Some examples of performance measures and corresponding numerical functions used in automatic calibration are:

- Agreement between the average simulated and observed runoff: overall volume error.

$$F_1(\theta) = \sum_{i=1}^{N} \left(Q_{obs,i} - Q_{sim,i}(\theta)\right) \cdot \Delta t$$

- Where θ is the set of model parameters to be calibrated.
- Agreement of peak flows: volume error of peak flow events.

$$F_2(\theta) = \frac{1}{M_p} \sum_{j=1}^{M_p} \left| \frac{1}{n_j} \sum_{i=1}^{n_j} \left(Q_{obs,i} - Q_{sim,i}(\theta)\right) \right|$$

- Where $M_p$ is the number of peak flow events in the calibration period and $n_j$ is the number of time steps in peak event number j. Peak flow events are defined as periods where the observed discharge is above a given user-specified threshold level.
- Overall agreement of the shape of the hydrographs: overall root mean square error (RMSE).

$$F_3(\theta) = \frac{1}{N} \left[ \sum_{i=1}^{N} \left[Q_{obs,i} - Q_{sim,i}(\theta)\right]^2 \right]^{1/2}$$

- The coefficient of determination ($R^2$) is a transformed and normalised measure of overall RMSE, and thus the minimisation of the above function corresponds to maximising $R^2$.
- Agreement of peak flows: average RMSE of peak flow events.

$$F_4(\theta) = \frac{1}{M_p} \sum_{j=1}^{M_p} \left[ \frac{1}{n_j} \sum_{i=1}^{n_j} \left[Q_{obs,i} - Q_{sim,i}(\theta)\right]^2 \right]^{1/2}$$

- Agreement of low flows: average RMSE of low flow events.

$$F_5(\theta) = \frac{1}{M_l} \sum_{j=1}^{M_l} \left[ \frac{1}{n_j} \sum_{i=1}^{n_j} \left[Q_{obs,i} - Q_{sim,i}(\theta)\right]^2 \right]^{1/2}$$

- Where $M_l$ is the number of low flow events in the calibration period and $n_j$ is the number of time steps in low event number j. Low flow events are defined as periods where the observed discharge is below a give user-specified threshold level.

Numerical optimisation problems are expressed as follows:

$$\theta_{opt} : \underset{\theta}{Min}\{F(\theta)\}, \theta \in \Theta$$

Where, for this case, minimisation of the objective function F(.) is the aim and θ are the model parameters to be optimised. The expression also indicates that a constraint has been applied to the optimisation by restricting θ to a feasible parameter space Θ. These limits should be chosen according to physical and mathematical constraints in the model and from modelling experiences. If no restrictions are imposed on θ then the optimisation is said to be unconstrained.

The use of just a single objective function during optimisation as is expressed in the previous equation is common in automatic calibration. But this brings the method under criticism as being pure curve-fitting in danger of giving unrealistic model parameter estimates. Multi-objective optimisation techniques have been developed, which involve simultaneous optimization of several performance measures or objective functions instead of just one. In this way, different aspects of the model response can be considered even with this automated procedure.

The multi-objective optimisation problem can be formulated as follows:

$$Min\{F_1(\theta), F_2(\theta), \dots, F_p(\theta)\}, \theta \in \Theta$$

Where, again, minimisation of the objective functions is the aim and θ are the model parameters to be optimised. The optimisation is also constrained by restricting θ to the parameter space Θ. The parameter is defined as a hyper-cube by specifying lower and upper limits for each parameter. The result of multi-objective optimisation is not a single unique set of parameters but consists of the so-called Pareto set of solutions (non-dominated solutions) according to various trade-offs between the different objectives.

The numerical algorithm is the procedure that is implemented in order to achieve or solve the optimization problem that has been laid out. An example of this is the shuffled complex evolution (SCE) algorithm (Duan, et al., 1992). It is what is termed a global search method especially designed for locating the global optimum of a multi-modal objective function and avoiding being trapped in local optima. It is an evolutionary algorithm that evolves a population of solutions. At the beginning of the iteration loop, the initial population selected randomly within the feasible parameter space is divided into complexes. Each complex is then evolved using the Simplex Method (Nelder & Mead, 1965), which is a local search method. Finally, the evolved complexes are combined or shuffled to form a new population to be evolved. The shuffling of the complexes promotes the overall effectiveness of the algorithm because it allows for simultaneous sharing of information among the solutions during the search for the best solution. Another example of automatic parameter optimization is the use of the Preference ordering genetic algorithm (Khu et al., 2006).

### 2.4.5 Combination parameter adjustment

The method for parameter adjustment during calibration may be a combination of both manual trial-and-error and automated procedures. For example, manual adjustment may be initially applied to obtain rough estimates of parameter values, and then an automatic optimization routine is used to fine-tune the estimates within the range of physically realistic values. Likewise, automatic optimization may be first used to perform sensitivity analysis in order to identify the important model parameters, and then these parameters are afterwards adjusted by manual trial-and-error.

Another way that the two approaches are combined is through expert systems. These are computer systems that simulate the decision-making process of a human expert, i.e. a well-trained and experienced modeller in the case of model calibration (Madsen, et al., 2010). It is essentially semi-automated wherein the process by which the human expert does calibration is automated. Being able to keep human knowledge process in the procedure is a strong point of expert systems. However, they are model-specific and need to be developed for each model.

Combination parameter adjustment methods allow the modeller to take advantage of the strong points of both manual and automated approaches, which is advantageous because although many studies have demonstrated the great benefits of automatic calibration and recommend its use (Madsen, et al., 2010), there are still those of the opinion that automated methods cannot replace the interactive process of manual parameter adjustment.

## 2.5 Verification

Verification is a process following calibration where the results obtained by the simulation of an independent event/period from those used during calibration are analysed and the model performance evaluated. It is an essential part of the modelling because it is the source of evidence than can help establish the soundness of the calibrated model for performing reliably in its intended application. An estimate of the model's actual accuracy can be obtained from the verification as it can essentially be thought of as an initial application run for the model.

At this stage no more changes to the model are made in order for simulation results to fit observed measurements. If needed, any changes to the model should be only when it is for physical aspects such as changes in weir crest levels, pump operation based on actual records, etc.

The verification event(s) must be independent of the data used for calibration, and this must be considered during the collection of measurement data. The results of verification may be less accurate than those from calibration if the range of input data for the two do not correspond well to each other. So, the close association between the calibration and verification processes is very apparent.

Different schemes are available for model verification (Madsen, et al., 2010):

- Split-sample test. The split-sample test is essentially the classical way of doing model calibration and verification. It involves splitting the available data into two sets, with one set used for model calibration and the other used for verification. It is performed within the same system/domain as the calibration as well as under similar conditions as the calibration period. The data must be divided in such a way that both sets cover the same range of magnitudes both temporally and spatially with respect to the different model responses being considered. The limitation of this verification scheme is that it is only able to support the good performance of the model for a similar range of conditions as those used for calibration.
- Differential split-sample test. This test involves performing the calibration and verification using data for differing conditions. Calibration is done with data for normal/existing conditions while verification is done using changed conditions. In the process, some

parameters may need to be re-adjusted because of physical system changes like changed land-use conditions. This type of test may be used in extreme event modelling, for example, where verification data are extreme event data not encountered in the calibration. This verification method is said to be more powerful than the split-sample test because it can ensure good performance of the model for a wider range of conditions.

- Proxy-basin test. In the proxy-basin test, only verification of the model is performed using measurement data from the area. Calibration of the model is not really performed but instead estimates for model parameters are based on experience from actual calibration of other models of similar characteristics.
- Proxy-basin, differential split-sample test. As the name implies, this test combines the proxy-basin and differential split-sample tests. No direct calibration of the model of interest is performed, and the model parameters for both “normal” and changed conditions are estimated from other similar models. The model is then verified using data for the area for both normal and changed conditions.

As in the parameter adjustment process , evaluation of numerical performance measures is performed to assess whether the model which had just gone through calibration performs consistently well even for a new set of input data/conditions. The selected performance measures in verification should be consistent with the ones selected for calibration.

If the verification reveals deviations significantly outside the range established by calibration, the calibration may be extended by including the verification event and selecting another event for repeated verification. It must be considered whether more data should be collected, or if the model that has been selected is truly appropriate for the modelling objective. The modeller should go back to the initial stages of the calibration process and reconsider model parameterisation/schematics and selection of the calibration parameters. It may be determined that another type of model would be more appropriate for the exercise, or even that the modelling must be stopped as it is not possible to achieve satisfactory results from it.

The early 1D sewer model of the Barcelona Case Study was verified using the split-sample test where one event out of the 3 available event data sets were used in the model verification. Examples of plots of results from their model verification are shown in the following figures (Figure 8 and Figure 9).

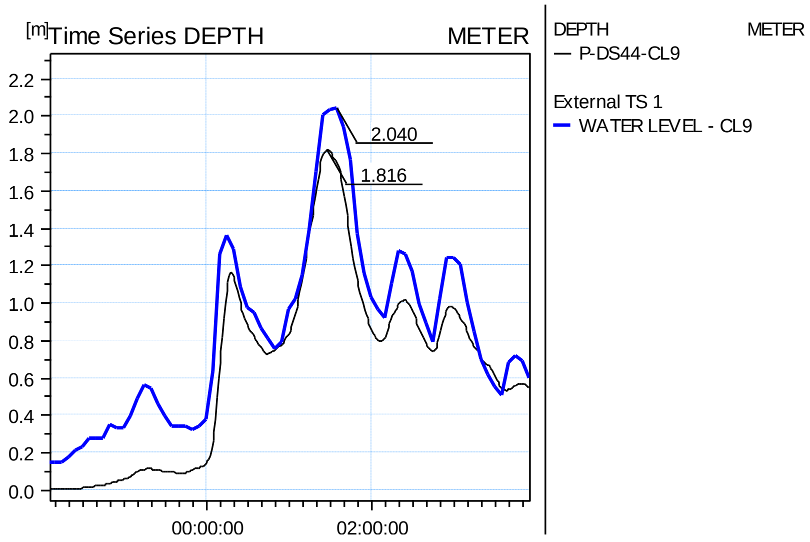



**Figure 8 1D sewer model verification results for the event 9/10/2002 at Diagonal – Pg. Sant Joan. Flow depths measured and calculated by the model are shown respectively in blue and black lines (Barcelona Case Study).**

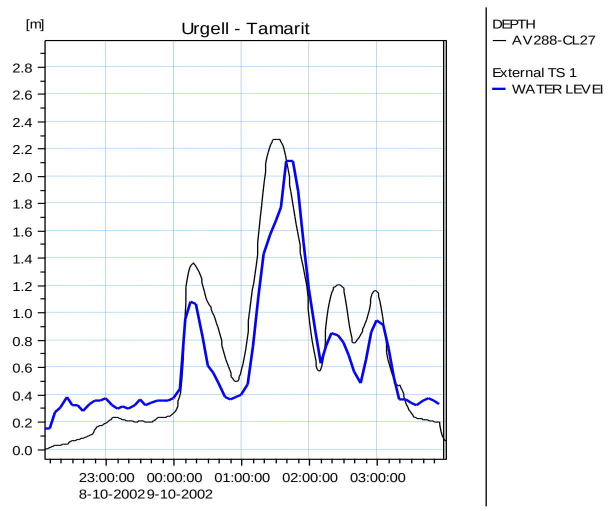



**Figure 9 1D sewer model verification results for the event 9/10/2002 at Urgell-Tamarit. Flow depths measured and calculated by the model are shown respectively in blue and black lines (Barcelona Case Study).**

Qualitative verification of the model was also performed through analysis of the general hydraulic behaviour of the network and the plan of the manholes that suffered overflows during the 09/10/2002 verification event (Figure 10 and Figure 11). Reports showed that 3 different zones suffered pipe inefficiency during the event and all these problems were detected by the 1D sewer model even if for one section of the model (Parallel Avenue) the model simulated a more critical situation compared to reality.

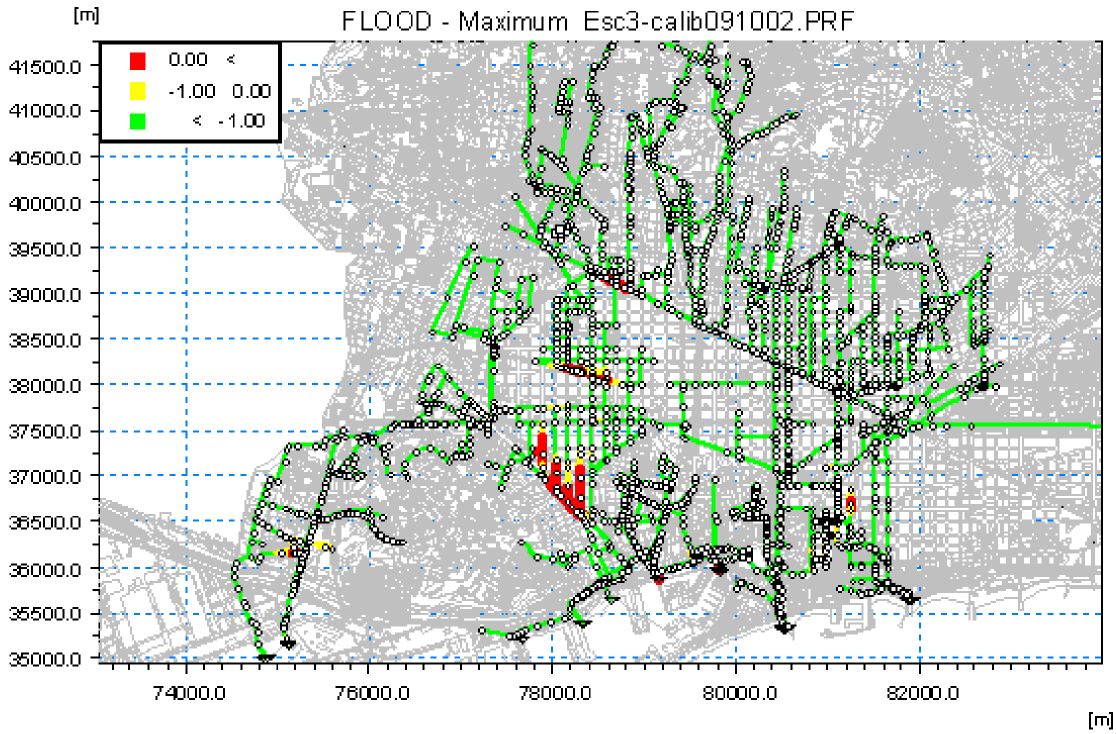



**Figure 10 1D sewer model verification plan for the event 9/10/2002 considering the results of the model for the whole analyzed domain (Barcelona Case Study).**

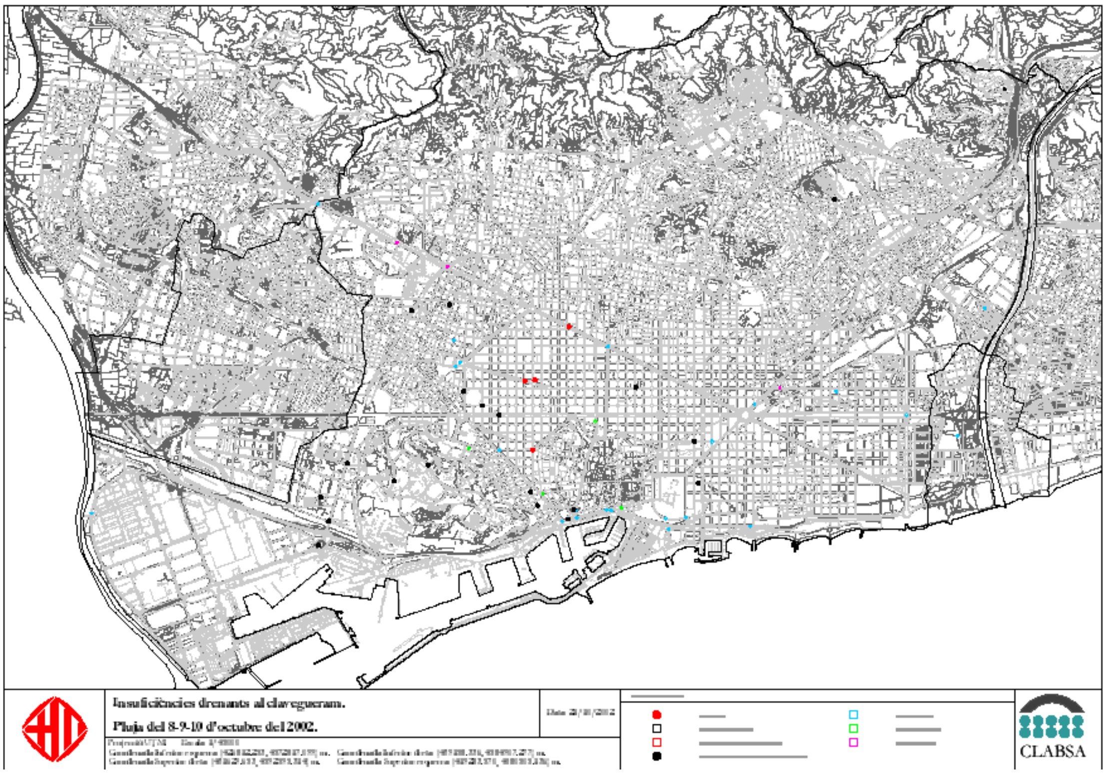



**Figure 11 1D sewer model verification plan for the event 9/10/2002 considering (in red) the manhole covers lifted by the flow pressure (Barcelona Case Study).**

Validation of the 1D/2D coupled model was carried out based on data for the 30 July 2011 event. 1D sewer model verification was done based on the agreement between recorded and simulated flow depths in several manholes and pipes (Figure 12).

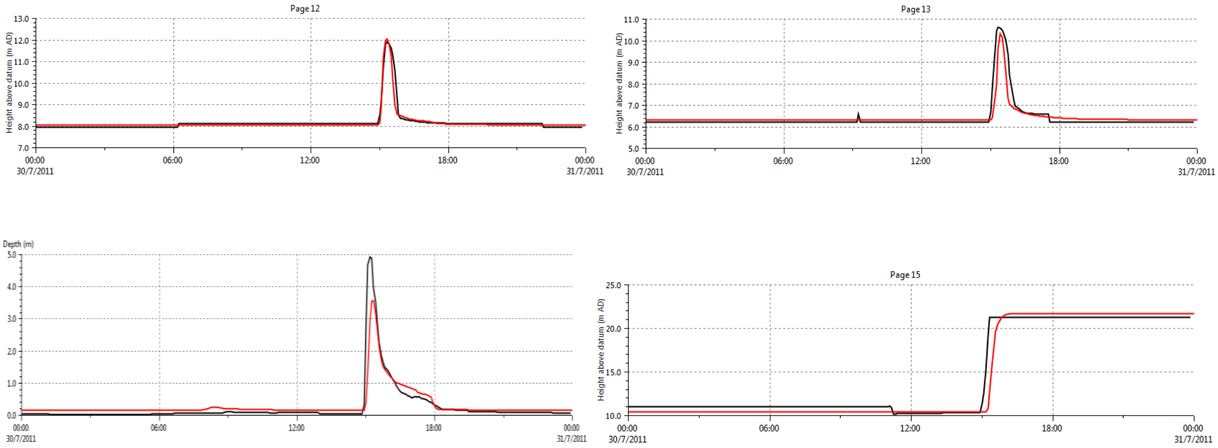



**Figure 12 Validation results (event of 30 July 2011) for two manholes (P-AV65 and BR-CL205) in the Raval District (upper part of the figure), a pipe in Diagonal Avenue (P-IV35.1) and Urgell storage tank (P-YD32) upstream the Raval District (in the bottom part of the figure). Black and green lines show recorded flow depths, while red ones show simulated flow depths.**

In addition, flood information from the model (perimeter of flooded areas, flow depths of the overland flow, etc.) were compared to observed data collected in post-event emergency reports of policemen and firemen, amateur videos and photos recorded during the selected storm events (Figure 13). In this way, it was possible to compare overland flow depths to reference elevations of objects located on surface (e.g. walls, cars, urban features, etc.).


**Figure 13 Validation results for Sant Pau Street (Raval District).**

In Figure 13, flow depths provided by the model for the event of 30 July 2011 were compared to images and videos recorded during this event. Specifically, in the bottom of the figure, it is possible to observe the calculated peak flow depth (34 cm) in a cell near the Pharmacy located in the Sant Pau Street. In the upper part of the figure, on the left a wall 40 cm high separates the street from the Sant Pau Church, while on the right, there was an amateur video showing the overland flow during the event.


**Figure 14 Validation results for the crossroad between Diagonal Avenue and Casanova Street.**

Figure 14 shows a comparison between the profile representing surcharged pipes shown with ICM (Infoworks Integrated Catchment Modeling) software and a photo taken during the event of 30 July 2011. Specifically, the maximum calculated flood depth corresponding to the photographed surcharged manhole was 46.6 cm.

# 3 Calibration According to Model Type

The main consideration and techniques used in calibration differ for different types of models. For example, conceptual models require more attention in calibration than the physically based models for which many parameters can be directly estimated from measurements and thus generally require less parameter adjustment.

In urban drainage modelling, the focus is usually on the conceptual hydrological model component, while the hydrodynamic model component for pipe flows typically requires only minor adjustments for accurate performance. In practice, the ability to calibrate an urban drainage model depends mainly on the ability to calibrate the rainfall-runoff model component and the calibration of an urban drainage model is reduced to the calibration of the rainfall-runoff model. As catchment slopes increase, the significance of pipe network flows diminish.

For integrated urban flood models, such as coupled 1D/2D systems combining 1D pipe network flow models with 2D overland flow models, multiple sources and types of information are used in the calibration. For example, the pipe flow model could be calibrated against flow and water level measurement time series, while the 2D model component could use flood extent maps for calibration. For the case of these types of integrated/coupled models, a two-step calibration approach may be used by first calibrating one component and then the other. For example, the runoff model component may be calibrated first, and subsequently and pipe flow and surface flow models. This type of approach can be followed if the model parameters that are relevant for specific processes where measurement data are available can be isolated. This is however seldom the case, and so a one-step calibration approach is recommended where all available information is used in a single step including all parameters, and thereby better constraining the model calibration

# 4 Calibration Using Remotely-Sensed Data

Flood modelling techniques continue to develop along with computing power and better understanding of flood mechanisms. Techniques now range from 1D dynamic pipe network models able to simulate the interaction of rainfall and flooding, to coupled 1D-2D pipe-overland flow models (Mark, et al. 2004), to physically-based distributed coupled hydrologic-hydraulic models able to simulate the full water cycle for flood modelling in urban catchments. Data requirements are also increasing with the complexity of flood modelling techniques being developed. However, the availability of data for modelling and calibration is more limited and continues to be an issue for many areas around the world.

Meanwhile, there has been great advances in remote sensing technology (Schumann, et al., 2009). For large-scale flood forecasting applications, the link to remote-sensing technology has become stronger over the last decade especially due to advances in synthetic aperture radar (SAR) remote sensing techniques, which allow image capturing during all meteorological conditions, day and night.

However, there has generally been limited use of remotely-sensed data in urban flood model calibration applications. This is because of difficulties encountered in the development of techniques for using remote sensing images in calibration (Schumann 2009), such as:

- Limited availability of remotely-sensed images for flood events due to revisit times of radar satellites
- Too coarse spatial resolutions of the images for urban area applications
- Inability of SAR to record flooding in urban areas due to coarse resolutions and the corner reflection principle causing inaccurate images around buildings
- High complexity of techniques for extracting flood extend and stage information from the images

A continuation of the review and possible testing and development of methods for the use of remote sensing data in urban flood model calibration will be undertaken in the project, especially within the activities for the various case studies. If not for the calibration process, the utilisation of these types of data for other hydraulic flood modelling components such as derivation of distributed model parameters like imperviousness, surface roughness and the like used for flood model setup will be explored.

# 5 Sources of Uncertainty in Calibration

The processes of computer modelling and calibration are illustrated by Figure 15 below (Parkinson & Mark, 2005). The main component of the process is the built mathematical model, which, as the figure illustrates, is a conceptualized mirror of the physical system (shown on the left side of the figure). Models are simplified representations of reality, and the schematization of the physical system and associated processes introduces errors in the modelling. Moreover, model input and parameters are quantified by measurements that contain some uncertainty. Furthermore, the model's output will contain the effects of the input uncertainties. The model is then calibrated and verified where its output is compared with measurements, which also contain uncertainties due to the way the measurements were carried out.

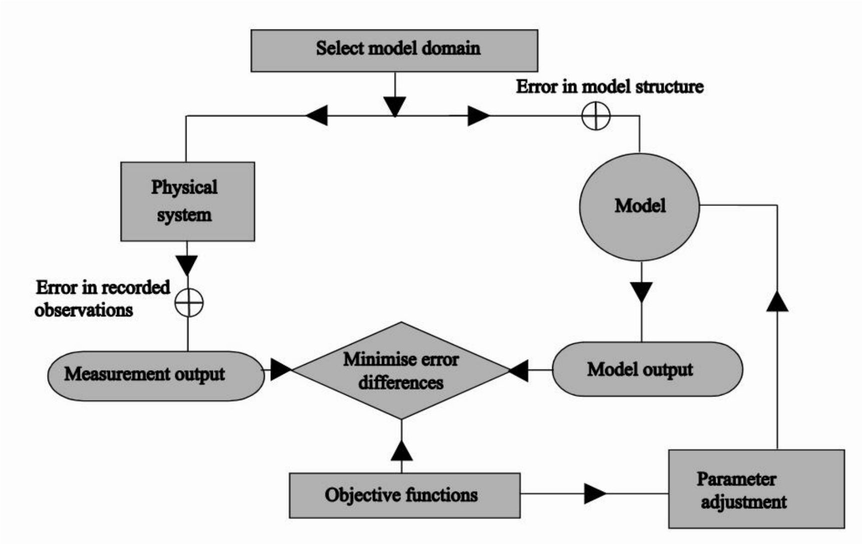



**Figure 15. The concept behind modelling and calibration (Refsgaard, 1995) as seen from (Parkinson & Mark, 2005).**

Therefore, in the modelling exercise, the differences between observations and model simulations can then be thought of as a combined effect of these different sources of errors and uncertainty (Parkinson & Mark, 2005):

1. Input model data.
2. Recorded observations (e.g. flow and water levels) used for calibration of the model.
3. Non-optimal parameter values in the model.
4. Anomalies inherent in the model, such as numerical dispersion from the solution of differential equations.
5. Invalid model structure.

The error from non-optimal model parameters (3) are the ones minimised during model calibration. In calibration, major sources of uncertainty are the input data (1), the output and measured data used (2), and the model conceptualization and structure (4 and 5). If the errors with the input and measurement data (1 and 2) are unacceptably large, either a new model type has to be chosen or an additional measurement exercise must be undertaken to collect more data for further calibration.

It is important that the different error sources are identified and accounted for in the calibration so that compensation for errors from one source by making adjustments with another source is not attempted. Otherwise the calibration will degenerate to curve-fitting and result into biased model parameter estimates.

## 5.1 Rainfall records

Rainfall measurement is an example of a possible source of error related to input data in modelling. The data is usually available as recorded rain at one or several locations within or in the vicinity of the model area.

The instruments used for rainfall records might be of different type and accuracy. Also they may be a part of an established meteorological service or might be installed for the purpose of the on-going project. Generally, the quality of rainfall records depends on:

- Gauging instrument sensitivity and precision
- Micro-location of the instrument (e.g. elevation from the ground, position of surrounding buildings and trees, exposure to wind, etc.)

It can be the case that the density of the rain gauges with respect to the study area is not enough. This limits the description of the spatial variability of the rain, and a very simplified representation of the rainfall surface could introduce error in the modelling. It must be considered that rain intensities may be very different even for locations that are relatively close to each other. The usual assumption is of uniform rainfall intensity over the catchments according to the recorded rainfall. This may cause over-or under-estimates of rainfall volume and bring about water balance errors in the modelling. Radar-based rainfall measurements may provide good spatial coverage but they also introduce uncertainties in the transformation of radar data into rainfall amounts for the models.

Users of numerical models must also be aware of the way in which the selected model uses and interprets the input rainfall time series. Incorrect interpretation of the data by the model may be the cause for serious systematic errors.

In Barcelona, CLABSA has built an extensive network of 23 rain gauges in order to study in an accurate way the spatial and temporal variation of the rainfall pattern in the city (Figure 16). The availability of this dense network of rain gauge stations in and around the study area is an advantage for their Case Study as it helps minimize the error and uncertainty associated with rainfall distribution.

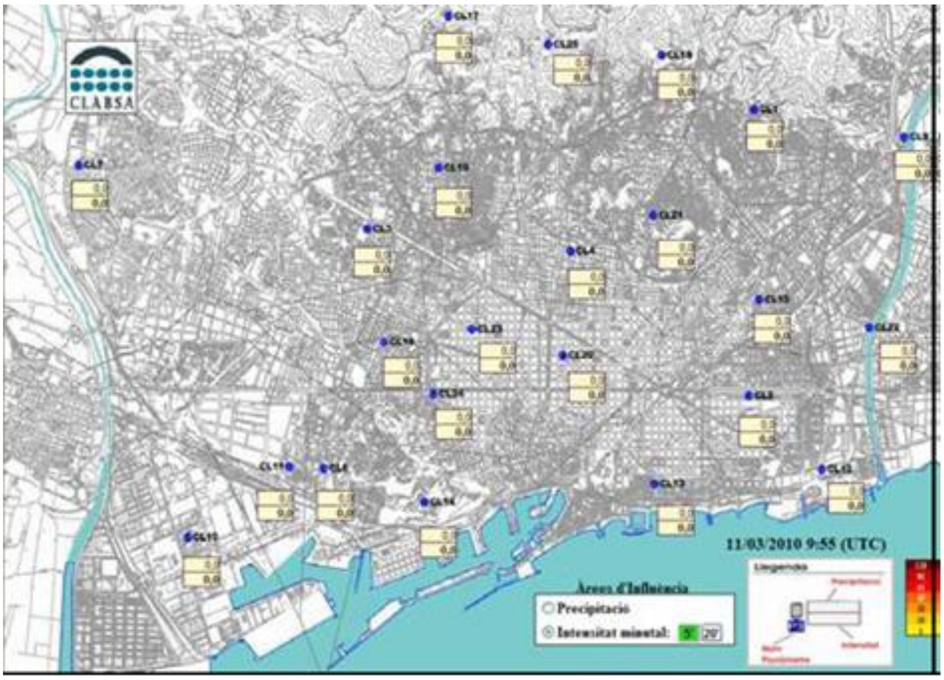



**Figure 16 Location of the CLABSA rain gauges in Barcelona (Barcelona Case Study).**

## 5.2 Flow and water level measurements

Errors in calibration and modelling may be introduced through the flow and water level measurements used for comparison with model results. The measurement of flows is a technical discipline reserved to specialists due to the very specific physical conditions that must be taken into consideration in order to obtain as accurate data as possible. Some difficulties that may be encountered in taking flow measurements are:

- The very large variation of water levels and flows, ranging from a few centimetres in depth up to surcharged conduits
- Inappropriate hydraulic conditions at the operationally preferred sites
- Large quantities of debris carried by water potentially affecting the instruments

Flow quantities are computed from water level and velocity measurements using the continuity equation. For locations with normal flow conditions, flow can be calculated from the measured levels and conduit geometry using uniform flow equations (e.g. Manning). The errors in measurements are usually caused by data processing, velocities being out of optimal range for the instrument, incorrect calibration of the instrument, unconsidered sediment deposits in the conduit, sensor clogging, etc. Misuse of the flow equation (e.g. under backwater or drawdown conditions) can also be the reason for incorrect records. For water level measurement inaccuracies are usually associated with an unstable water surface (ripples and or waves), the sensor drift or degradation of measuring properties , external noise, clogging, etc. Aside from processing, instrument and measurement errors, there are also uncertainties with the use of point measurements in making comparisons with model responses.

Apart from obviously illogical results and missing data it is difficult to detect monitoring errors by only looking at a single instrument data. Flow measurement data consistency and accuracy can be best controlled by combining and comparing the flow with rainfall records and establishing an initial rainfall-runoff volume balance. Volume balance can be established for individual sub-areas and for the entire system if data from several measurement stations are available for the area.

For the Barcelona Case Study, in addition to the dense network of rain gauge stations that they have, more than 100 limnimeters measuring flow depths series have also been installed in the city's sewer system (Figure 17). Rainfall data, flow depths series and devices functioning during rainfall events are measured and recorded by CLABSA. The abundance of data types and sources available for the Barcelona Case Study as well as the apparent control that they have with respect to data collection give considerable advantages for the study in terms of minimizing input and measurement data errors and promoting complete implementation of the calibration process.

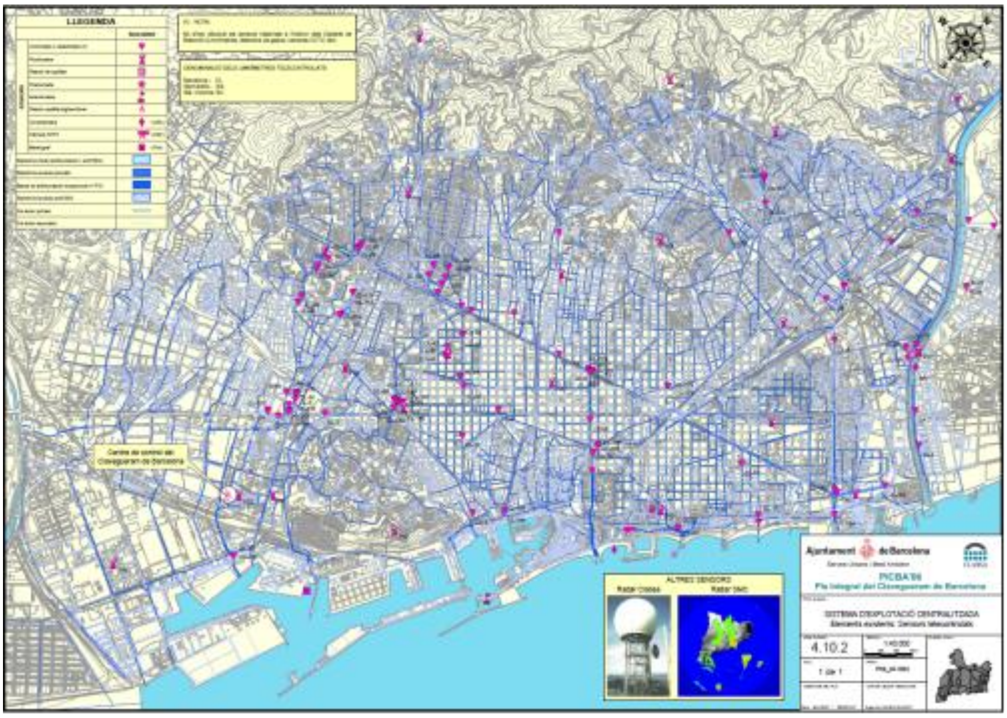



**Figure 17 Location of limnimeters in Barcelona's sewer system (Barcelona Case Study).**

## 5.3 Numerical models

Modelling and calibration uncertainties are introduced by the nature of the numerical models themselves, which are only rough approximations of the actual system. The representation of these physical processes into models introduce uncertainty as real-world processes are conceptualised and simplified into combinations of mathematical expressions.

For most rainfall-runoff models, the gap between the technical conceptualization and reality can be especially wide. Typical rainfall-runoff models for urban catchments are of the "black-box" type where the runoff process is described by a series of mathematical relations without real connection to actual physics of the runoff process. Hydraulic models, on the other hand, are so-called "white-box" types based on differential equations describing the flow process that are more relatable to the actual system physics. When using traditional rainfall-runoff models, some examples of typical errors encountered are the inability of the models to account for hydrological history, i.e. the initial or precedent hydrological conditions that may produce different catchment response under the same rainfall, and inability to account for non-linear catchment response with increasing rainfall intensity (e.g. due to runoff contribution from pervious surfaces).

A re-evaluation of the initial urban flood modelling scheme was made in the Barcelona Case Study, which revealed that a 1D sewer network model was not enough to accurately simulate surface flooding in detail in the district they have selected as a study area. The early 1D sewer model of Barcelona could provide a comprehensive knowledge of the hydraulics of the pipes, but poor information was provided in terms of surface flooding. Moreover the possibility to simulate surface flows, characterizing hydraulically all the connections (manholes and drain inlets) between surface and underground systems allows to improve the estimation of pipe flows during a storm. They determined that area characteristics such as very high imperviousness, dipping terrain, and quick catchment hydrological response limit traditional 1D sewer models from simulating flooding during storm events. For all these reasons a shift to the coupled approach (surface flow coupled to sewer flow) was decided to more accurately represent flooding problem in complex topographies of their study area. As illustrated by the case, different flood modelling schemes and types are available and depending on the study area characteristics and modelling purpose, an appropriate model must be selected that minimizes conceptualization and simplification errors as much as possible.

# 6 Summary

Computer models are expected to simulate the behaviour of the real system with a reasonable level of accuracy. This is ensured through the process of calibration. This is an essential process in modelling that involves not only the adjustment of model parameters but also other steps such as model structural and functional validation, data checking and preparation, sensitivity analysis, and model verification, which support and fortify the calibration process as a whole.

The main objective in calibration is the minimization of differences between model simulated results and observed measurements. This is normally achieved through a manual iterative parameter adjustment process but automatic calibration routines are also available. Combination parameter adjustment methods also exist, which is advantageous as many maintain that automatic calibration cannot replace interactive parameter adjustment where the user's expert experience and judgement are employed. The focus of the model calibration exercise is not the same for all types of models. But regardless of the model type, good modelling practice should involve thorough model verification before its application.

At the end of the calibration process one would have a model that is either calibrated or not calibrated. A well-calibrated model can give the assurance that, at least for a range of tested conditions, the model behaves like the real system, and that based on the calibration and verification results the model may be used as a tool for further analysis and application. However, the process could also reveal that the model cannot be calibrated and the correctness of the model and its suitability as a tool for analysis and management could not be proven.

The conceptualisation and simplification of the real-world system and associated processes in modelling inevitably lead to errors and uncertainty in the modelling exercise. Various modelling components introduce uncertainty, such as the input parameters, the model concept, scheme and corresponding output, and the observed response measurements. Ultimately, the quality of the model as quantified by how much it deviates from reality is an aggregate of the errors that have been brought into it during the modelling. Thus, it is important to be able to identify the different error sources and also account for and quantify them as part of the modelling. However, how to properly include all the different uncertainty sources in modelling is a complex and yet unsolved problem (Madsen, et al., 2010).

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