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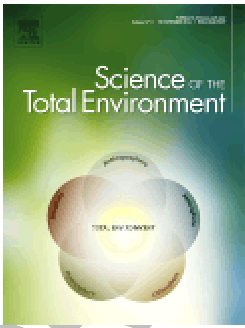


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# Using data from monitoring combined sewer overflows to assess, improve, and maintain combined sewer systems

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## Abstract

Using low-cost sensors, data can be collected on the occurrence and duration of overflows in each combined sewer overflow (CSO) structure in a combined sewer system (CSS). The collection and analysis of real data can be used to assess, improve, and maintain CSSs in order to reduce the number and impact of overflows. The objective of this study was to develop a methodology to evaluate the performance of CSSs using low-cost monitoring. This methodology includes (1) assessing the capacity of a CSS using overflow duration and rain volume data, (2) characterizing the performance of CSO structures with statistics, (3) evaluating the compliance of a CSS with government guidelines, and (4) generating decision tree models to provide support to managers for making decisions about system maintenance. The methodology is demonstrated with a case study of a CSS in La Garriga, Spain. The rain volume *breaking point* from which CSO structures started to overflow ranged from 0.6 mm to 2.8 mm. The structures with the best and worst performance in terms of overflow (overflow probability, order, duration and CSO ranking) were characterized. Most of the obtained decision trees to predict overflows from rain data had accuracies ranging from 70 to 83%. The results obtained from the proposed methodology can greatly support managers and engineers dealing with real-world problems, improvements, and maintenance of CSSs.

## KEYWORDS

CSO; CSS; wastewater; management; maintenance; performance; low-cost

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## 1. INTRODUCTION

A combined sewer system (CSS) collects rainwater runoff, domestic sewage, and industrial wastewater in the same pipe. Normally, these systems will transport the total volume of sewage to a wastewater treatment plant (WWTP) for treatment. However, some rain episodes result in volumes of runoff that, when mixed with domestic and industrial waste, can exceed the capacities of a CSS. When capacity is exceeded, a combined sewer overflow (CSO) occurs, which is the discharge of untreated sewage (mixed with urban runoff) from a CSO structure directly into surface water.

Because CSOs contain untreated domestic and industrial waste, toxic materials, and debris, they impact the physicochemical, biological, hydraulic, and aesthetic status of receiving water bodies. For example, overflows can result in oxygen depletion, increased turbidity, and higher concentrations of micropollutants, heavy metals, and pathogenic and faecal organisms in surface waters (Passerat et al., 2011). Since the adoption of the Water Framework Directive 2000/60/EC by the European Union in the year 2000, Member States must apply local measures to address pollution affecting their surface waters. Most historic European cities, such as London, Paris and Rome, are drained by CSSs. In the United States, over 40 million people in 770 cities are served by CSSs, which release approximately 850 billion gallons of untreated wastewater and stormwater each year (EPA, 2004; EPA, 2014). Thus, decreasing the occurrence of overflows is an important part of reducing pollution in surface waters and requires accurate monitoring of CSO structures to provide reliable performance data to managers and engineers.

In previous studies, usually only a few CSO structures within a CSS were monitored (e.g. Gruber et al., 2005; Tetzlaff et al., 2005). Simultaneously monitoring all of the structures within one system would provide more useful information about the performance of the CSS as a whole but was until today cost prohibitive. Thus, researchers and engineers have resorted to using mathematical sewer models, calibrating the models with flow or level measurements taken in the sewer system (e.g. Kleidorfer et al., 2009; Gamerith et al., 2011). The main drawback of this modelling approach is that the real behavior of CSSs may not be accurately represented if the model was not calibrated properly. Schroeder et al. (2011) used real data to study the relationship between rainfall height and overflow activity, but the data was from only a few CSO structures within a network. More recently, Montserrat et al. (2013) developed and validated a low-cost method to measure the occurrence and duration of overflows using temperature sensors, which makes measuring all of the CSO structures within a CSS economically feasible.

Just as important as data collection, however, is the analysis and application of data. Municipalities, industries, and research centers regularly collect large amounts of data using the vast array of measurement technologies available today. The ability to analyze and learn from collections of data is essential to making informed decisions. Managers of CSSs must make important decisions concerning the maintenance and upgrade of CSO structures. The maintenance of sewer systems is a large cost to a municipality. For instance, the EPA estimated that for one CSO structure containing a screen facility, 10 overflows per year would have an annual operation and maintenance cost of approximately $10,000 USD (EPA, 1993). With a 50-year lifespan, CSSs eventually need to be replaced or upgraded (Center for Sustainable Systems, 2013). In the United States, the upgrades could cost approximately $64 billion USD over the next 20 years (EPA, 2008). Many municipalities cannot afford to pay for upgrades without federal and state aid, but federal spending on sewage infrastructure is falling (Tibbetts, 2005). Thus, municipalities or companies that manage sewers need to make

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the best use of the money that is available to them for maintenance and upgrades.

If managers could monitor and analyze data on the occurrence and duration of overflows within each and every CSO structure of a CSS, then they could assess how the structures perform, pinpoint where the weak spots are within the system, and then make decisions accordingly. The structures in which overflows occur most often are prime candidates for maintenance and upgrades, and conversely, structures that have low frequencies of overflow need less attention. Ideally, managers would have access to a tool that assesses or predicts which structures are likely to overflow as a result of rain. Such a tool would help to coordinate post-rainfall maintenance tasks, and costs could be decreased by spending less time and effort checking on those structures that, through assessment, have been recognized as unlikely to overflow. Similarly, managers could focus on updating only those structures whose improvement would yield the greatest reduction of CSOs, which can best be determined through monitoring and assessment. Using data from monitoring overflows can, therefore, help CSS managers to decide on the most appropriate and cost-effective strategies for maintenance and improvement, which is crucial when budgets for sewer infrastructures are decreasing.

To the best of our knowledge, no prior studies have evaluated the performance of a CSS based on data from monitoring the occurrence and duration of overflows in all or most of the CSO structures within the system. The recent development of low-cost CSO-monitoring methods (e.g. Montserrat et al., 2013) offers an excellent opportunity for the thorough evaluation of CSSs. The insight gained from such an evaluation can be used to improve their overall performance while reducing the negative impacts of overflows. The objective of this study was to develop a methodology to evaluate the performance of CSSs using data from low-cost monitoring. This methodology has four components: (1) assessing the capacity of a CSS, (2) characterizing the performance of CSO structures, (3) evaluating the compliance of a system with government guidelines, and (4) providing support for managers to make decisions about system maintenance. The methodology is demonstrated with a case study of a CSS in La Garriga, Spain.

## 2. MATERIALS AND METHODS

### 2.1 Data collection

We used a case study to demonstrate the methods described in this section, though they can be applied to any CSS. The case study is in La Garriga, a village in the northeast of Spain. This system collects urban and industrial wastewater from La Garriga, as well as a portion of the wastewater from two adjacent municipalities. The drainage area of the whole urban catchment is 370 Ha. The wastewater is conveyed to the La Garriga WWTP by gravity-induced flow through 7.3-km-long circular pipes. Diameters of the pipes range from 300 to 800 mm. The CSS consists of a total number of 14 CSO structures, of which 8 are the side-flow type and 6 are the transverse type. Structure 14 is located at the entrance of the WWTP. A map of the system with the labeled CSO structures is illustrated in Fig. 1.

We monitored the occurrence and duration of CSOs in the La Garriga CSS over the course of 11 months (from July 2011 through May 2012). CSO Structures 1 through 14 were monitored using low-cost temperature sensors, as described by Montserrat et al. (2013). Briefly, an abrupt shift of temperature from a sensor installed at the overflowing structure indicates the start of a CSO event, and the recovery of the signal back to the baseline temperature corresponds to the end of the event. The data used in this study concerning the duration of the

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CSO events and overflowing order for each structure, as well as the information on the rain episodes, is provided in Supp. Data in the file 'Rain_CSO_Information.xlsx'. More information about the materials and methods used to collect the data is given in Montserrat et al. (2013). Of the 14 CSO structures that were monitored, we analyzed data from 12 structures; data from Structures 9 and 13 were not considered in the study due to the poor quality (high background noise) of the gathered data.

During the evaluated period 53 independent rain episodes occurred and were monitored. The inter-episode time between independent rain episodes was calculated as the average time the system needs to return to dry weather flow conditions (6 hours in the La Garriga system).

(Figure 1)

## 2.2 Methodology for CSS evaluation

### *2.2.1 Assessing the capacity of a CSS*

We assessed the capacity of a CSS by plotting the duration of overflows versus rain volume for each rain episode and each individual structure. Fig. 2 shows two examples of how the capacity of the CSS can be assessed by evaluating the behavior of individual structures using overflow duration and rainfall data. The first example, Fig. 2A, belongs to a structure with high activity in which overflows occur even with rain volumes as low as 2 mm. This example indicates that the CSS does not have the capacity to assimilate the increased flow from rain episodes. The second example, Fig. 2B, shows a CSS in which the structure starts to overflow only after rainfall reaches a volume greater than 25 mm. In case A, data were fitted by a linear curve ($R^2$: 0.98), while data in case B were fitted better by a quadratic curve ($R^2$: 0.95). We also determined the *breaking point* of each CSO structure, defined as the rain volume at which the structure starts to overflow, shown as dashed line in Fig. 2B. The lower the slope and the greater the *breaking point*, the higher the capacity of the system or the better the stormwater retention capacity of the catchment. These cases are examples of two extreme scenarios and qualitatively show how CSS behavior changes as storage capacity increases.

Figs. 2A and 2B were generated using a numerical model example of a subcatchment of the case study, and afterwards the methodology was applied to the collected field data. The model was developed using the Storm Water Management Model version 5.0.022 (Rossmann, 2007), and details about the model development and the making of the CSO duration-rain volume curves are provided in Supp. Data.

(Figure 2)

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*2.2.2 Characterizing the performance of CSO structures*

We developed a detailed statistical analysis on the data we collected of the occurrence and duration of CSO events. To characterize system performance, we calculated and plotted the following parameters for each CSO in the network over the entire data collection period: (i) total number of overflows, (ii) total duration of overflows (sum of the durations of all overflows in the period), (iii) average overflow duration, (iv) the average chronological order that a CSO structure begins to overflow compared to all the other structures in the network, and (v) overflow probability. These parameters are indicators of the performance of each CSO structure and can be used to compare different structures within the same system. To calculate the total number of overflows, we counted any number of overflows that occurred during one independent rain episode as a single, independent CSO event. 53 independent rain episodes occurred during the study period, so the maximum number of CSO events per structure would be 53 for this case-study.

We developed ranking curves to provide information about the order in which a structure overflows with respect to the other structures in a CSS. For each rain episode, we identified which structure overflowed first and assigned a value of 1 as its overflow position; then we assigned consecutive values of overflow positions to the other structures in the order that they overflowed. For a particular structure ($z$) and for each overflow position ($i$), we used Eq. (1) to calculate the *CSO ranking index* – the fraction of CSO events in which the structure overflowed in position $i$ or lower.

$$CSORanking_{(z,n)} = \frac{\sum_{i=1}^{n} C_{i,z}}{\#_z} \qquad \text{Eq. (1)}$$

where $\#_z$ is the total number of times during the monitored period that $z$ overflowed, $C_{i,z}$ is the number of times that $z$ overflowed in $i^{th}$ position, and $n$ is the number of CSO structures in the CSS. The maximum value of $i$ is equal to $n$.

The ranking curves are obtained by plotting the ranking index of each CSO structure with respect to overflow position $i$ and reach a maximum y-axis value of 1. To compare the performance of different structures, each curve was fitted by a power function ($F(x)=X^b$), and the exponent $b$ of the function was used to rank the structures according to their ranking index.

Confidence intervals were calculated to see whether significant statistical differences existed among the parameter values of the different CSO structures. The confidence interval (*Ci*) (Eq. (2)) gives the range of values in which the true average is located.

$$Ci = Avg \pm E\frac{SD}{\sqrt{n}} \qquad \text{Eq. (2)}$$

where *Avg* is the average value of the sample, *SD* is the standard deviation of the sample, $n$ is the number of samples, and $E$ is a statistical value that depends on the size of the sample and the confidence limits. The value for $E$ is found in the *T-table* (for $n< 25$) or *Z-table* (for $n \geq 25$). The *Ci* with 95% confidence limits was calculated for each parameter. In the case of parameters that represent proportions, the $Ci_p$ was calculated as

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$$Ci_p = p \pm E\,\frac{\sqrt{p(1-p)}}{\sqrt{n}} \qquad \text{Eq. (3)}$$

where $p$ is the proportion of the studied variable.

The confidence interval $Ci$ was calculated for the variables *average overflow duration* and *average chronological order*, while the $Ci_p$ was calculated for the *overflow probability*. The calculated confidence intervals are valid for normally distributed variables, such as those calculated here, since they represent averages or proportions over a sample of data from each variable.

*2.2.3 Evaluating the compliance of a CSS with government guidelines*

The number of overflows per year per CSO structure is a common emission standard referred to in CSO regulation guidelines. Hence, we can evaluate the compliance of a CSS with government guidelines by comparing the number of overflows measured in each CSO structure of a CSS to the maximum number of overflows suggested by the guidelines. Table 1 gives some examples of the permitted number of overflows per year in six countries. In some cases, such as in Belgium, Denmark, or the Netherlands, the permitted number of overflows is dependent on the sensitivity of the receiving waters (Zabel et al., 2001). Sometimes, the threshold is estimated using models fed with representative pluviometric data of the region (e.g. the ITOGH in Spain described in Hernáez et al., 2011). It is worth noting that the guidelines are site-dependent and differ in the permitted number of overflows. Furthermore, the definition of overflow frequency is crucial. For instance, overflows can be counted as events (or spills), or as overflow days (which can be calendar days or running days). Taking one definition or another significantly changes the results (Dirckx et al., 2014).

(Table 1)

*2.2.4 Providing support to managers for CSS maintenance*

Decision trees are predictive models based on supervised machine learning. In supervised learning, a teacher (the user) gives a computer program example input data and their desired or known outputs, and the program learns a general rule that maps inputs to outputs. The map is known as a decision tree, which can then be used to predict the results of input data with unknown outputs. If trained on high-quality data, decision trees can make accurate predictions (Kingsford and Salzberg, 2008). The output of decision trees visually and explicitly represent predictions and can therefore be an important tool for decision making.

Because of their power and utility for aggregating diverse types of data and making predictions, decision trees have become very popular in a variety of fields, such as environmental engineering, medicine, and bioinformatics (Kingsford and Salzberg, 2008; Rudin, 2012). In the field of wastewater treatment, decision trees have been used to design and develop tools to cope with highly complex environmental problems such as wastewater plant supervision or the selection of wastewater treatment systems (Poch et al., 2004), aimed at assisting in the decision-making process to find an optimal solution.



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In this study, we constructed decision trees for CSO structures as part of a tool to help managers make decisions about CSS maintenance. A decision tree consists of nodes connected by branches. There are two types of nodes in a decision tree: (1) internal nodes that represent explanatory variables, and (2) terminal nodes, or leaves, which give the response variable. Branches extend from internal nodes, with each branch defining a range of values for the internal node. The appropriate branch will be selected depending on the value for the internal node input by the user, leading to the next node. The process of branch selection continues until a prediction (leaf) is reached.

The specific technique used to induce the decision trees was the *J48 algorithm*, which is based on the *C4.5 algorithm* (Quinlan, 1993). Waikato Environment for Knowledge Analysis (WEKA) Version 3.6.0 was used to generate the trees. The input data, or explanatory variables, were rain characteristics (total volume, duration, maximum intensity, and time since the previous rain episode), and the output, or response variable, was whether or not the CSO structure overflowed. Data on rain episodes and CSO occurrence and duration were used to build each decision tree through a *k*-fold cross-validation procedure; the data set is randomly split into more or less equal *k* folds (or subsets), and the algorithm is run *k* times. At each time, *k-1* folds are used as training data to generate the tree, while the remaining fold is used as validation data. The prediction error (i.e. the accuracy) of the trees is calculated from the validation data. A thorough description of the cross-validation procedure is given in Rokach and Maimon (2008). This technique is especially suited for relatively small data sets ($n$<1000; De'ath, 2007), since the trees are trained on all the data sets. In this study, $k$=10 folds was used. Furthermore, we developed a user-friendly computer application to visualize the different decision trees that are obtained with known characteristics of a rain episode. The application was programmed in JScript and is available in Supp. Data in the 'CSO_application' zip file.

## 3. RESULTS AND DISCUSSION

### 3.1 Assessing the capacity of a CSS

For each of the 12 structures evaluated, we plotted the CSO duration versus rain volume for each rain episode during the 11-month study period. The rain episodes ranged in volume from 0.4 to 51.4 mm. Fig. 3 illustrates two examples with different behaviour obtained from the collected data. Fig. 3A refers to Structure 11 and shows that for rain volumes lower than 20 mm only a few overflow events occurred, with durations between 6-27 min. Even for rain volumes larger than 20 mm all but one of the overflow durations were less than 50 min. In this case, the rain volume *breaking point* at which the structure starts to overflow was established at 2.2 mm. For that case, non-linearity holds between the rain volume and the overflow duration ($R^2$: 0.31). Fig. 3B corresponds to Structure 7, for which the *breaking point* of the system was also set at 2.2 mm. However, after a rain volume of 15 mm, increasing rain volumes resulted in longer CSO durations, reaching saturation around 200 min. The data were fitted by a sigmoidal curve ($R^2$: 0.86). The rain volume *breaking points* for the other structures ranged from 0.6 mm to 2.8 mm (provided in Supp. Data).

(Figure 3)

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Plotting overflow duration versus rainfall volume and fitting the data is useful to assess the behavior of each CSO structure and evaluate the efficacy of the CSS's design. CSSs are typically designed with a target value for the capacity of the system, for instance two times the mean dry weather flow (De Toffol, 2006). Whether or not the target capacity is achieved by the CSS can be determined from collecting and analyzing data as described here.

### 3.2 Characterizing the performance of CSO structures

By applying our characterization method to the case study, we were able to gain an understanding of the performance of each CSO structure in the La Garriga CSS and highlight the system's weak points. Structures 7 and 14 each had the greatest numbers of overflow events, 36 and 49 respectively, during the 11-month study period. By far, Structure 14 (at the inlet of the WWTP) had the greatest total overflow duration, with close to 10,000 minutes (about 7 days) for the 53 rain episodes (see Supplementary Data, Fig. SD2). The other CSO structures had total overflow durations ranging from 294 to 2,113 minutes.

Fig. 4 shows the averages of the variables that we evaluated with a 95% *Ci*. For *overflow probability*, Structure 14 had a probability of overflowing (avg = 0.9) during any given rain episode that was significantly greater than the probabilities of all the other CSO structures. Structure 7 had the second highest average overflow probability (avg = 0.7), but not significantly different than other structures. Structure 11 had the lowest probability (avg = 0.3). As for *average overflow duration*, Structure 14 had a significantly higher value (avg = 186 min) than the other structures, and Structure 11 had the lowest overflow duration on average (5.5 min). The overflow durations of the other structures in the network were between 10 and 40 minutes, with no significant difference among them. Finally, analysis of the *average order of overflow* showed that Structure 7 tended to overflow first (average order of overflow = 2.6), with a significant difference between the order of overflow of most of the other structures. Structure 10 had the second average value for overflow order (avg = 3.1), and Structures 1, 11, and 12 tended to overflow last (averages around 7).

The inclusion of the *Ci* in the average allows us to state with 95% confidence whether or not there is significant difference among the evaluated variables of the different CSO structures. In addition to the obvious importance of Structures 14 and 7 for the performance of this CSS, comparisons can be made between select groups of structures in order to find significant differences between them. For instance, Structures 2 and 11 had on average less *overflow duration* than Structures 5 and 7, and Structures 7 and 10 overflowed on average before Structures 1, 5, 6, 11, and 12.

(Figure 4)

Each CSO structure can be characterized by a *ranking index*, based on the orders in which a structure overflows during rain episodes. Fig. 5 shows the *ranking* curves for each CSO structure and its corresponding exponent *b*. The vertical axis of the plot is the ranking index and the horizontal axis is the $i^{th}$ place of overflow in the network. For example, in the case of Structure 7, almost 80% of the times that it overflowed, it was in the first 3 places (1$^{st}$, 2$^{nd}$, or 3$^{rd}$ structure in the network to overflow). Structure10 had a similarly high ranking. On the other hand, Structure 11 overflowed in the first three places only around 7% of the times that it overflowed. Looking at the ranking curves, Structures 7 and 10 had curves with the lowest value for exponent *b* (0.26 and 0.31, respectively), while Structures 1 and 11 had the highest exponents (1.3 for each). Structures 7 and 10 overflowed in the first 4 places around 80 to



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85% of the time – more than any other structures, and Structures 1 and 11 overflowed in the first 4 places the least – approximately 20% of the time. The lower the value of *b*, the sooner the structure is likely to overflow within the network.

(Figure 5)

Using these methods for characterizing system performance, Structures 14, 7, and 10 stand out as problematic, at least compared to the other structures. Characterization of the structures highlighted those with the best and worst performance in terms of overflow. It should be noted that for a CSO structure that overflows often, the problem may not be with the structure itself but may originate from other, more distant factors, such as the overloading conditions downstream from the system. A proper investigation must be carried out to determine the true cause of frequent overflows. Nonetheless, from the characterization information, management strategies can be devised and implemented, such as seeking out the cause of overflows or installing upgrades or extra reinforcements. Without this analysis, it would not have been possible to know which of the CSO structures were most reactive to rain episodes.

### 3.3 Evaluating the compliance of the CSS with government guidelines

Fig. 6 is a schematic of the CSS of La Garriga and includes the number of CSOs measured during the 11-month study for each CSO structure. We compared the number of overflows for each CSO structure in the La Garriga CSS during the study period to the number of overflows per CSO structure per year permitted by Spain's ITOHG, which is 15-20 overflows. We are aware of the specificity of ITOHG to the Galician region with a very particular pluviometric regime. Hence, the results obtained here are for illustration purposes only. The 11 months of study accumulated a rainfall volume of 525 mm. The analysis of the rainfall series from 2009 to 2013 registered in the La Garriga rain gauge resulted in an average annual precipitation of 642 mm. Considering a 95% confidence interval, the precipitation of the evaluated period was assumed to be representative of an average pluviometric year. Our study period was only 11 months, and we recognize that a 12-month study period would have been best for comparison with government guidelines for annual overflows. Most of the structures in our 11-month case study exceeded the number of recommended overflows per year. Only three out of the 12 CSO structures (Nos. 2, 11, and 12) in the La Garriga CSS meet or closely meet the ITOHG guidelines. None of the CSO structures in La Garriga would comply with the CSO guidelines of the countries outside of Spain shown in Table 1.

The CSO structures with the least overflows were CSO 2, 11, and 12 (≤ 21 overflows). CSO 2 is a lateral structure that receives discharges from a residential neighborhood with a highly pervious surface. CSOs 11 and 12 are located at the beginning of the system. Moving further down the system, the number of overflows is higher. CSO 5 (30 overflows) and 7 (36 overflows) are lateral structures located at the outlet of densely urban areas. CSO 4 (29 overflows) is located along the main sewer trunk and receives most of the runoff from La Garriga and contributing areas (all the urban and part of the industrial areas). CSO 3 (32 overflows) is a lateral structure at the outlet of a recently developed industrial area with a mostly impervious surface. CSO 1 (29 overflows) is a lateral structure that receives wastewater from part of a neighboring municipality. Given that CSO 1 is located towards the end of the system, backwater effects could be increasing the number of overflows at this point. At the very end of the system and at the entrance of the WWTP is CSO 14, which had by far the highest number of overflows (49) of all the CSO structures.

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Evaluating the compliance of a CSS with government guidelines can help to define appropriate CSS management strategies, which can range from upgrades to improve CSS performance, to measures aimed at increasing the stormwater retention capacity of the catchment, so that local overflow recommendations are met. However, as addressed in section 2.2.3, compliance with standards is a major issue in which site-specific regulations have to be considered.

(Figure 6)

**3.4 Providing support to managers for CSS maintenance**

For our case study of the La Garriga CSS, we constructed a decision tree for each CSO structure. Supp. Data Table SD2 gives a summary of the configurations and accuracies of the decision trees constructed for the La Garriga CSS. Overall, the trees had simple configurations. The number and types of explanatory variables needed to make predictions differ among the CSO structures. In other words, different rain characteristics will cause different structures to overflow more than others. For instance, Structures 3, 7, 8, and 10 need only one explanatory variable to reach the response variable. Rain volume will be the primary determinant of whether or not Structures 3 and 7 overflow, while the maximum intensity of a rain episode will mainly control whether or not Structures 8 and 10 overflow. The more complex a tree is, the more explanatory variables are involved. An exception was the tree for Structure 7, which had 8 branches, 4 nodes, 5 leaves, and only one explanatory variable (rain volume). As an example, a description of the decision tree made for Structure 14 is included in Supp. Data, Fig. SD3. Structure 14 had the highest accuracy (91%) and Structure 2 the lowest (57%). The accuracy of the other trees ranged between 70 and 83%.

Fig. 7 shows both the successful and the incorrect overflow predictions made by the model for each CSO structure during 53 rain episodes. In this example, the trees predicted whether or not a CSO structure would overflow with given rain volumes of each rain episode, which were sorted from highest to lowest rain volume along the *x*-axis. The white spaces in the figure denote correct predictions of structures that did not overflow during a particular rain episode, while the black spaces represent correct predictions of the occurrence of overflow. Grey squares show where the model's predictions did not match observations (real data from monitored CSOs). For all the rain episodes and structures, the prediction succeeded in 89% of cases.

(Figure 7)

We developed a computer application, called "La Garriga CSO Network Simulator", to visualize the different decision trees that are obtained with known characteristics of a rain episode. The application has a user-friendly interface that allows predictions to easily be made and clearly understood for the La Garriga CSS. Though this particular application was made for the La Garriga CSS, the same application format can be developed for any CSS and used by managers, engineers, or maintenance crew. For a description of the interface and to open the application, see the 'CSO_application' zip file in Supp. Data.

Typically, sewer maintenance crew have to visit each CSO structure in a CSS after rainfall to check if overflow occurred and to do any maintenance work that might be necessary. Structures that don't overflow usually would not require checking or maintenance post-

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rainfall. Maintenance time, and therefore money, would be better spent by focusing on the structures that have a tendency to overflow. Thus, the CSO prediction tool described here could save time and money for sewer managers and crew by indicating the CSO structures that need to be checked after a rain episode with given characteristics. This is especially true for large CSSs with high numbers of CSO structures, when one sewer management company must manage several CSSs in one or more municipalities, or when maintenance crew is limited. The prediction of overflows through decision trees would also present an advantage for real-time control of CSSs. By means of weather forecast information (rain volume, duration and max. intensity), it would be possible to identify which structures overflow and take actions to maximize the usage of CSS volume (Schütze et al., 2004).

## 4. CONCLUSIONS

In order to assess, improve, and maintain CSSs, we developed a comprehensive methodology to analyze data collected from the low-cost monitoring of CSO structures. Monitoring was in the form of measuring rainfall data and the occurrence and duration of CSOs using temperature sensors.

CSS capacity is assessed by analyzing the relationship between the overflow duration and rain volume for each single CSO structure and each rain episode. In the case study, the La Garriga CSS was found to have a capacity in which overflows occur with rain volumes as little as 2 mm. To characterize the performance of each structure within a CSS, a statistical analysis is used. Through the statistical analysis, we determined the overflow probability and ranking index of each structure in the La Garriga CSS, which highlighted the structures that were most problematic. To evaluate compliance with legislation, the measured number of overflows for each CSO structure was compared to the annual permitted number of overflows per structure recommended by government-issued guidelines. Finally, to predict which structures in a CSS will overflow after a rain episode, we constructed a predictive model using decision trees, which can be used to optimize post-rainfall maintenance of CSSs. The decision trees for the La Garriga CSS had accuracies ranging from 70 to 83%, with two exceptions – one tree with an accuracy of 91% and another with 57%.

The methodology presented in this study is an effective and affordable package for municipalities and companies that manage sewer systems, as well as for engineers and scientists who need to gain a better understanding of the CSSs they are providing services for or in which they are conducting studies. Each of the analyses included in the methodology is based on the direct, simultaneous measurements of overflows in all of the CSO structures within a CSS. In this study, data was collected from sensors by manually downloading the data onto a computer once per month. To make CSO monitoring even more efficient and effective, future studies should use online sensors that collect and transmit data to online data storage in real time. A program could be set up to analyze the raw data as it is transmitted. Real-time data collection and analysis would negate the need for predictive models and could further reduce maintenance costs. Online sensors are the future of monitoring and are recommended for municipalities that can afford to install them.

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## 5. ACKNOWLEDGMENTS

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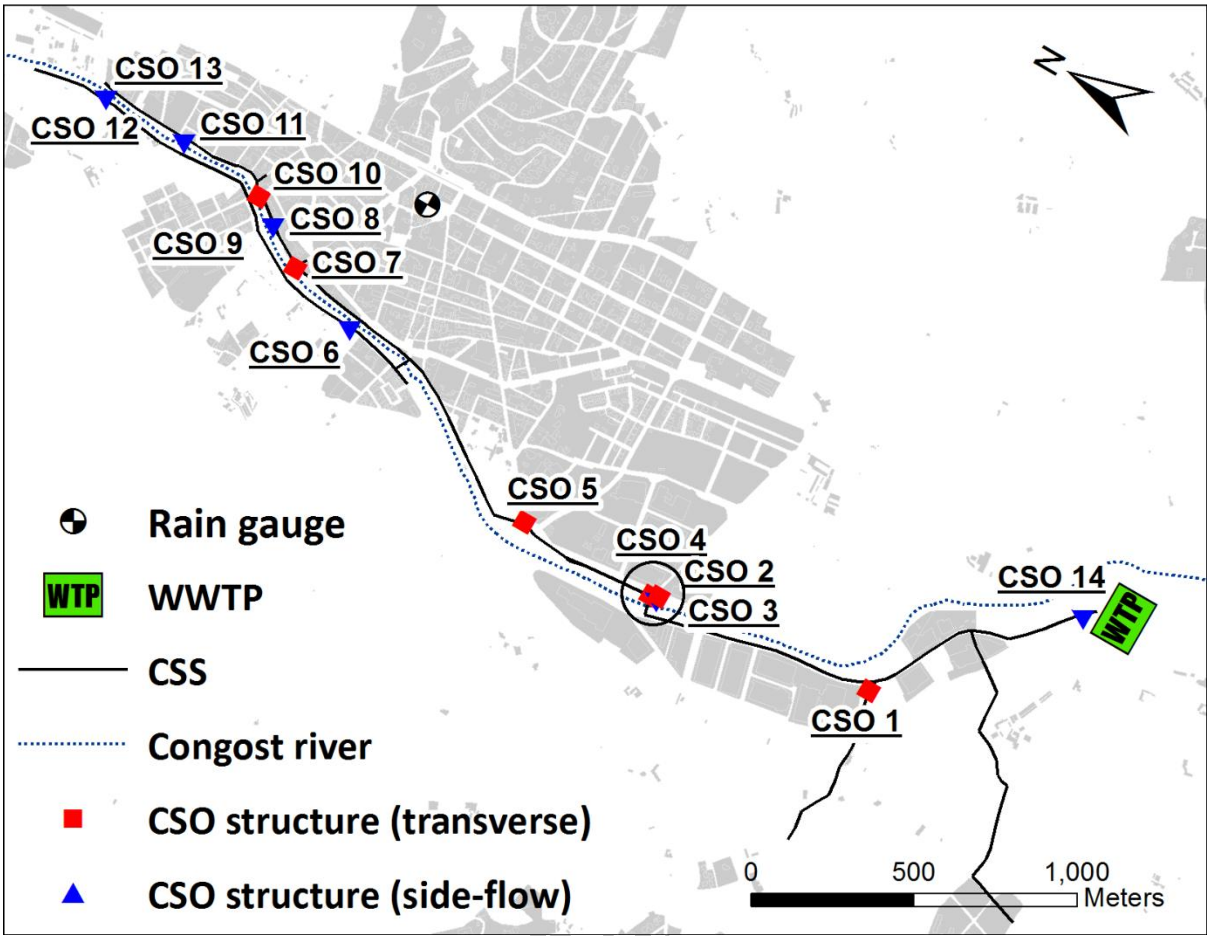


**Fig. 1.** Overview of the La Garriga catchment with the CSO structures numbered. The analyses were conducted using data from all of the CSO structures except Structures 9 and 13.

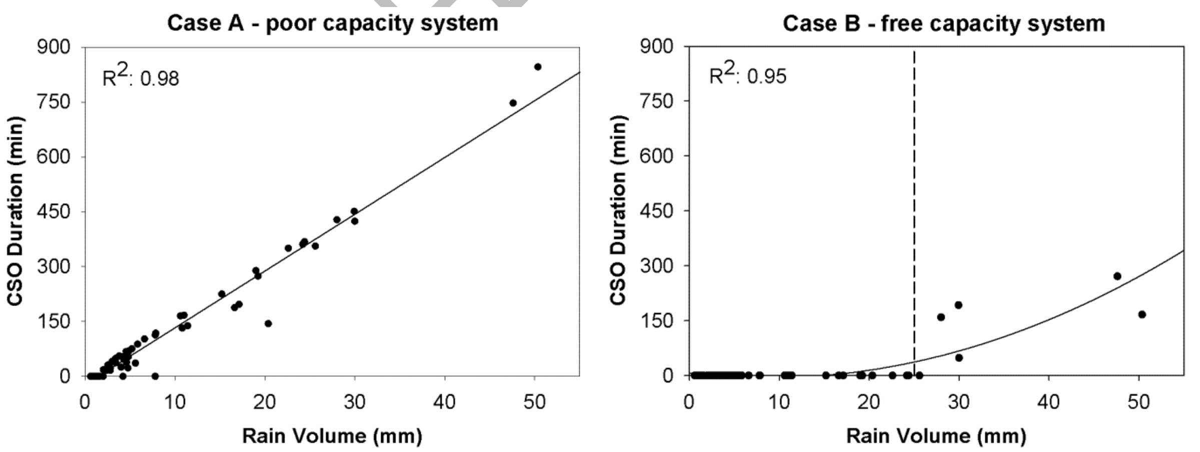


**Fig. 2.** CSO duration versus rain volume for two hypothetical CSSs. Fig. 2A shows data from a poorly-designed CSS with high CSO activity, while Fig. 2B shows data from a system with higher capacity. In Fig. 2B, the vertical dashed line indicates approximately the maximum volume of rain (about 25 mm) that the system can assimilate before it begins to overflow.

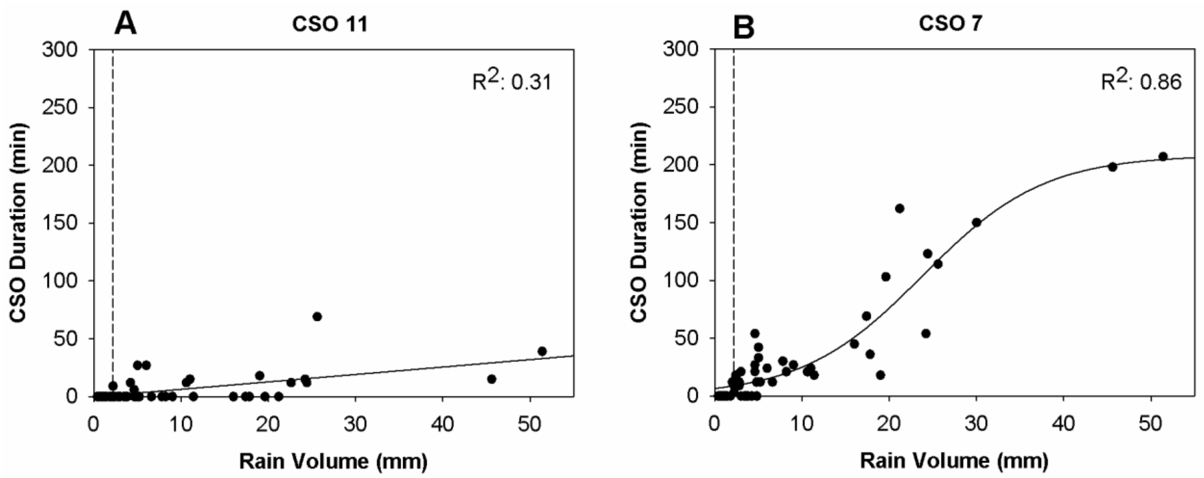


**Fig. 3.** Rain volume versus overflow duration obtained for CSO Structures 11 and 7 during the studied period (53 rain episodes). The vertical dashed line indicates approximately the maximum rain volume that the system can assimilate before it begins to overflow, which was 2.2 mm in both cases.

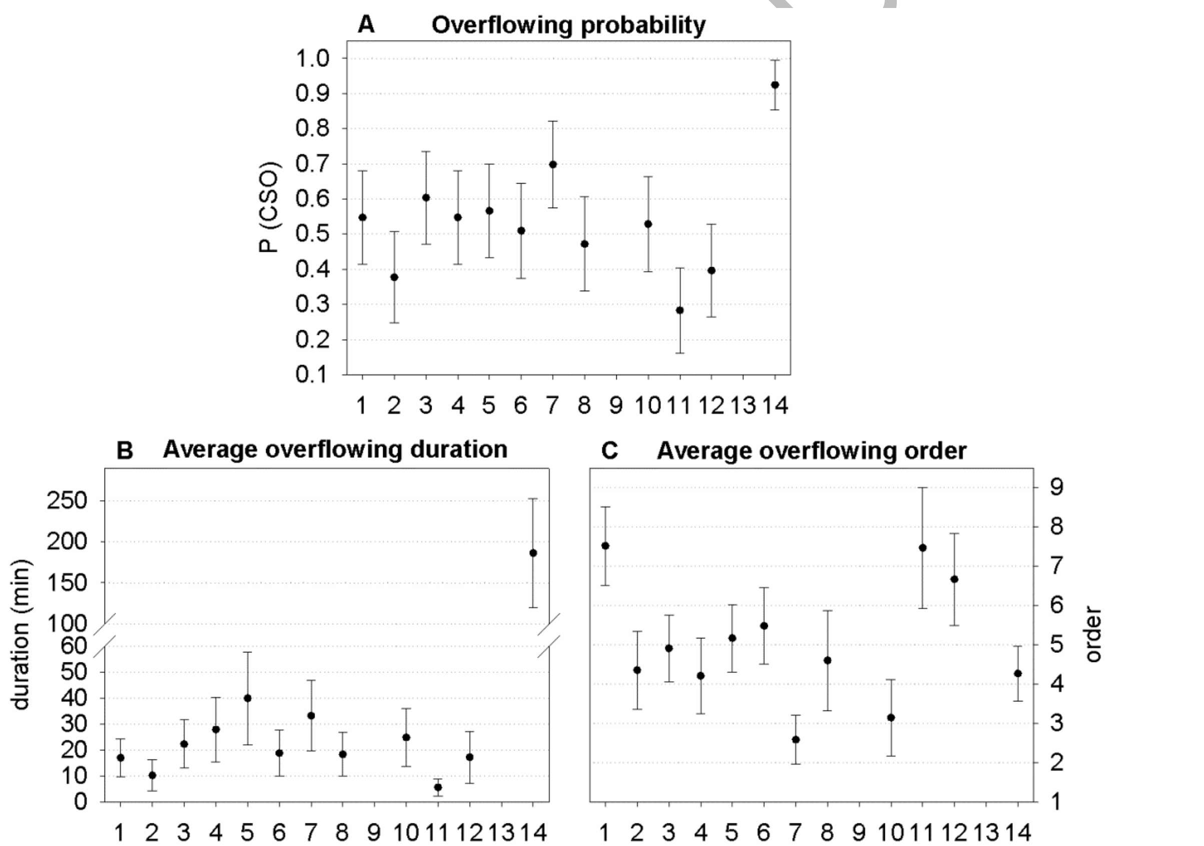


**Fig. 4.** Evaluated parameters of the CSO structures (dots represent the average value, and the lines represent the 95% *Ci*). The x-axis is each structure of the CSS (note that Structures 9 and 13 do not have values because they were not used in this study).

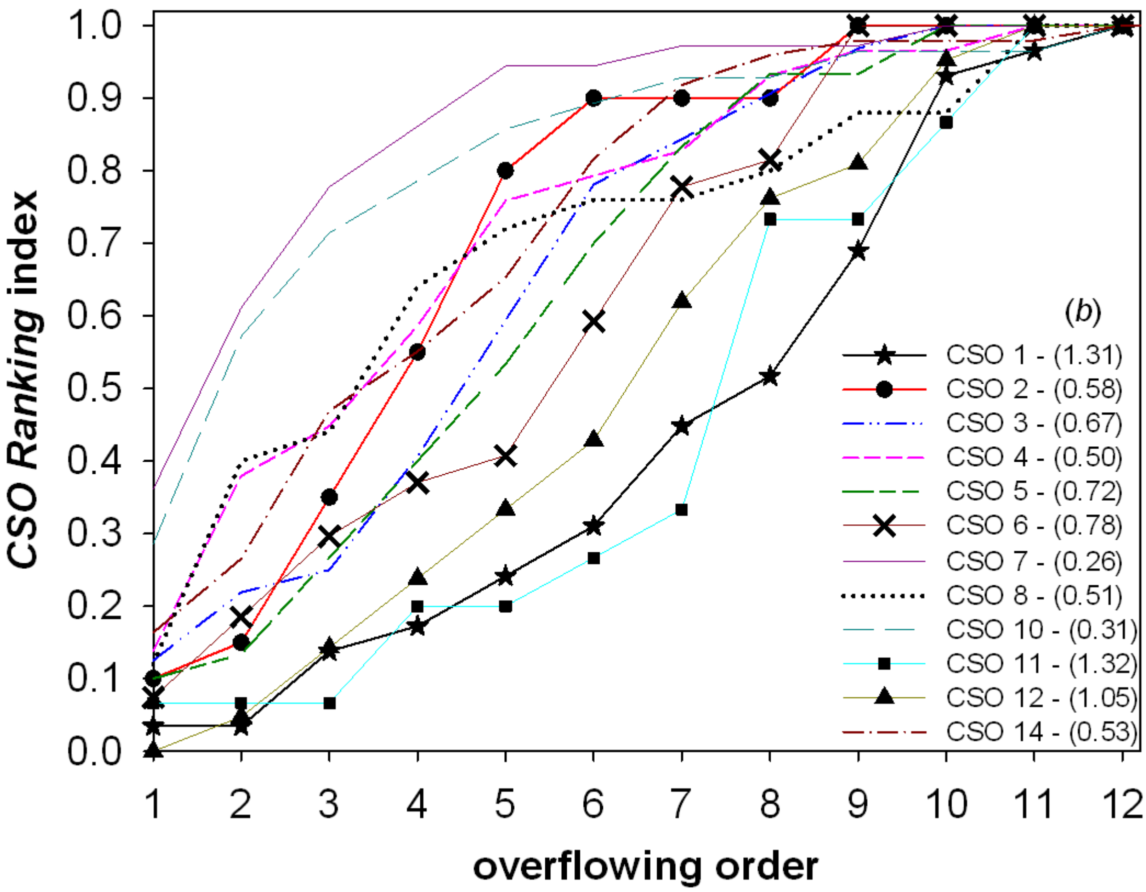


**Fig. 5.** *Ranking* curves for each CSO structure. The y-axis is the ranking index, and the x-axis is the $i^{th}$ place of overflow in the network. In the legend shows in parentheses the value of exponent $b$ of the power function fitted to each curve.

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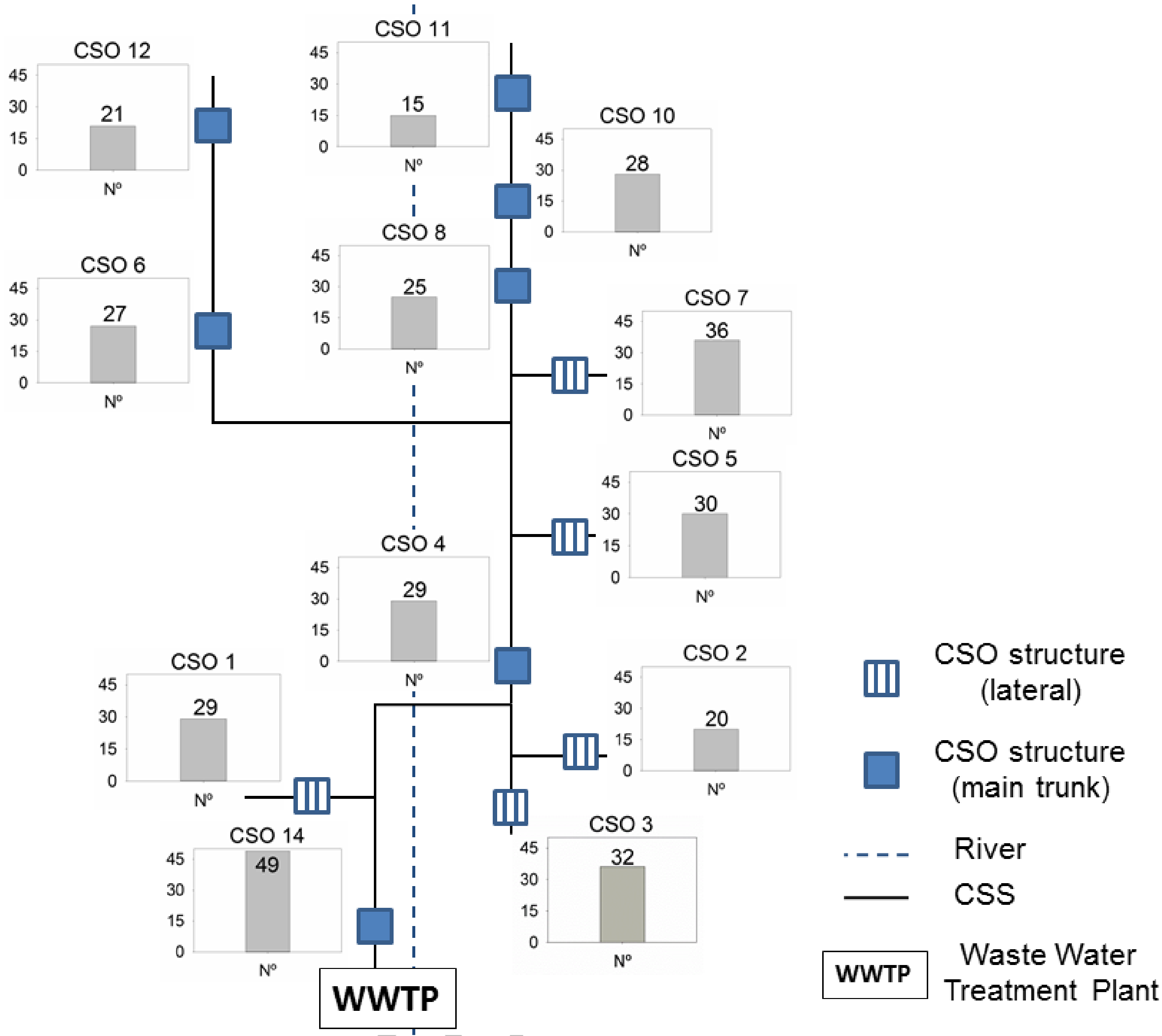


**Fig. 6.** Schematic of the La Garriga CSS. The number of overflows that occurred in each CSO structure during the 11–month study is graphed.

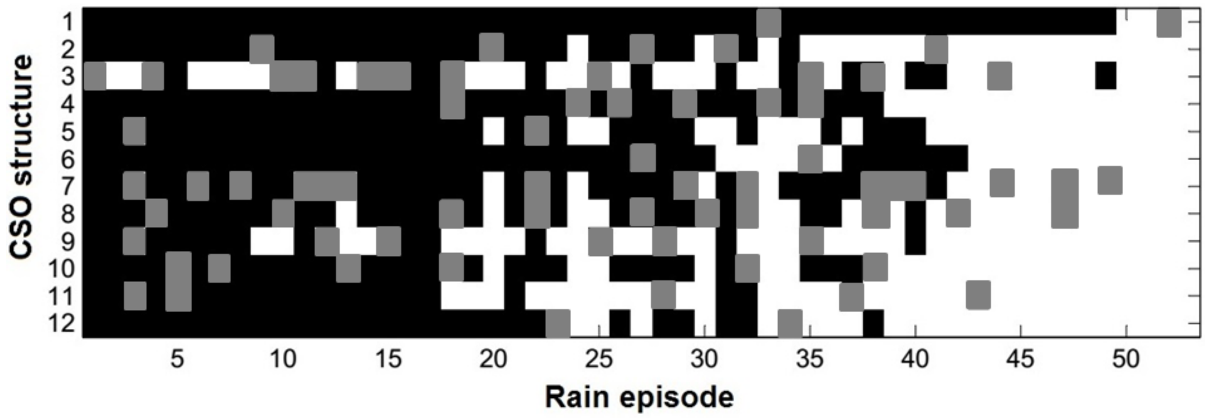


**Fig. 7.** A plot of the predicted and observed responses of each CSO structure in the La Garriga CSS for 53 rain episodes that occurred in La Garriga. The black squares indicate instances where the model correctly predicted overflow (the prediction matched observation), the white squares indicate when the model correctly predicted that an overflow did not occur, and the grey squares show where the model incorrectly predicted overflow or no overflow (the prediction did not match observation).

**Table 1.** Permitted number of overflows proposed by CSO regulation guidelines in different countries (adapted from De Toffol, 2006; Hernáez et al., 2011; FWR, 2012).

| Country | Belgium (Flanders) | Denmark | Netherlands | USA | U.K. | Spain (Galicia) |
|---|---|---|---|---|---|---|
| **Nº CSOs per year** | 7 | 2-10 | 3-10 | 4-6 | 3-10 | 15-20 |

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