



Available online at www.sciencedirect.com



Procedia Engineering 154 (2016) 868 - 876

Procedia Engineering

www.elsevier.com/locate/procedia

# 12th International Conference on Hydroinformatics, HIC 2016

# A BMA Analysis To Assess The Urbanization And Climate Change Impact On Urban Watershed Runoff

V. Notaro<sup>a,</sup> \*, L. Liuzzo<sup>b</sup>, G. Freni<sup>b</sup>

<sup>a</sup>Dipartimento di Ingegneria Civile Ambientale Aerospaziale e dei Materiali, Università degli Studi di Palermo, viale delle Scienze Ed. 8, Palermo 90128, Italy <sup>b</sup>Facoltà di Ingegneria e Architettura, Università degli Studi di Enna Kore, Cittadella Universitaria, Enna 94100, Italy

## Abstract

A reliable planning of urban drainage systems aimed at the mitigation of flooding, should take into account the possible change over time of impervious cover in the urban watershed and of the climate features. The present study proposes a methodology to analyze the changing in runoff response for a urban watershed accounting several plausible future states of new urbanization and climate. To this aim, several models simulating the evolution scenario of impervious watershed area and of climate change were adopted. However, it is known that an evolution scenario represents only one of all possible occurrence and it is not necessary the true future state, therefore it is needed to find the plausible forecast of the future state by taking into account and combining several possible evolution models. According to this aim, in the present study the Bayesian Model Averaging (BMA) approach was applied to several evolution models for climate variables. The Bayesian Model Averaging is a statistic multi-model method that computes a weighted average of the series of available competing models forecast overcoming the problem of arbitrary selecting of single best model and, consequently, the relative requirements of uncertainty analysis. The weighted average is the probability density function (pdf) of the quantity to be forecasted, while the weights correspond to the comparative performance of the models over training period of observation. After the application of BMA, for a given probability, the impervious area extension and the design rainfall event were identified and used as input data for a numerical model based on the SWMM software which was adopted to simulate the behavior of the urban drainagesystem adopted as case study. Particularly, the proposed procedure was applied with reference to the Sicilian climate regions (southern Italy).

\* Corresponding author. *E-mail address:*  © 2016 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/). Peer-review under responsibility of the organizing committee of HIC 2016

Keywords: BMA analysis; climate change; urbanization; urban drainage system design.

#### 1. Introduction

There is strong evidence that, due to the global warming, the probabilities and risks of sewer surcharge and flooding are changing [1]. Nevertheless, flooding in urban areas is not just related to the increase of intensity and frequency of extreme rainfall related to climate change, but also to changes in the built-up areas. Indeed, the increased imperviousness, due to vegetation removal, is cause of high flow peaks and fast response to even minor precipitation events [2]. Therefore, extreme rainfall variations, coupled with the increasing of urban areas, could intensify the pressure on urban drainage systems, making the cities more vulnerable to flood risk. For this reason, some recent studies focused on the assessment and quantification of the impacts of climate change and urbanization on urban drainage systems [1-3].

Detection of climate trends at the local scale is a critical issue due to the high inter-annual variability of local weather and confounding factors such as land-use change or urbanization effects [4]. Non-parametric techniques, such as the Mann-Kendall test [5, 6] have been frequently used to assess the presence of a trend in rainfall series [7, 8] Following the temporal analogues approach [9], the detected trends can be used to assess the future variations of variable [10]. In fact, climate scenarios can be generated by supposing that the detected changes will proceed in the future with the same pattern, assuming a linear trend. Nevertheless, the use of a single model often leads to overestimates the confidence in the model response and increases the statistical bias of the forecast [11]. For this reason, in recent years, multi-model methods have been developed and applied. The Bayesian model averaging (BMA) is a statistical procedure that has been developed in order to overcome the limitations of a single model and improve the prediction skill by combining multiple model output into a single new model forecast [12]. The BMA predictions are based on likelihood measures used as model weights. These weights depend on the success frequency of the predictions, such as weather forecasting [14], hydrological modelling [12] and flood damage estimation modelling [11] and, in a great number of cases of study, this approach has shown to provide more accurate and reliable predictions than other multi-model techniques [15, 16].

In order to assess the impact of changes to climate and urbanization on urban drainage systems, the Paceco sewer system has been simulated for current conditions and for future scenarios of climate change and urbanization using the SWMM software. The BMA approach has been used in order to update the parameters of the Depth-Duration-Frequency (DDF) curves in climate change scenarios, while the future increase of impervious areas has been deduced from the urbanization trend of the last 30 years. Specifically, three scenarios have been investigated: the climate change projection to 2050, the urbanization projection to 2050 and a projection to 2050 that involves both factors.

#### 2. Case of study

The case of study involves the urban drainage system of Paceco, a small town with a population of approximately 12,000 inhabitants, located in the north-western part of Sicily (Southern Italy). Sicily is an island of about 25,700 km2, characterized by a Mediterranean climate with mild winters and hot and generally dry summers, mainly influenced by hot winds blowing from the North African coast. Figure 1a shows the location of Paceco. Annual maxima rainfall series were not available for this site. Therefore, rainfall data recorded in the Trapani rain gauge has been collected and used. The available historical annual maxima rainfall series of durations 1, 3, 6, 12 and 24 h for the period from 1950 to 2008 were elaborated and provided by Osservatorio delle Acque-Regione Siciliana (OA-RS).

The Paceco watershed is highly urbanized, with an area equal to 18 ha, consisting of about 75% impervious areas (mainly including buildings, roads and squares) and some small pervious areas. The entire catchment is drained by a combined sewer system (designed in 2004), which has a total pipe length of about 10 km. The analyzed network also receives storm drainage from upstream watersheds, having a total area equal to approximately 30 ha. The

concentration time of the whole urban watershed is less than 1 h. The network pipes are made of high density polyethylene (HDPE), with diameters ranging between 400 and 1500 mm. The network has been designed considering a return period of 5 years. The DDF curve used for design purpose has been evaluated by means of univariate statistical analysis of the annual maxima series recorded at the Trapani rain gauge during the 1953-1991 period. In order to simulate the hydraulic behaviour of the urban drainage system of Paceco, both for the design conditions and the climate change and urbanization scenarios, the Storm Water Management Model SWMM 5.1 model [17] has been used. Figure 1b shows the network schematic employed in the SWMM model to simulate the hydraulic behaviour of the analyzed drainage system.



Fig. 1. (a) Location of Paceco and Trapani; (b) Network schematic employed by means of the Storm Water Management Model SWMM 5.1 model.

# 3. Methodology

# 3.1. Estimation of DDF curve parameters

The DDF curves are widely used in engineering applications to evaluate the design storm for a specified return period and duration. Thus, reliable estimations of the DDF curves parameters are required for the optimal design of hydraulic infrastructures. The DDF relationship for the return period T often takes the form of a power law relationship:

$$h(d)_T = a_T \cdot d^{n_T} \tag{1}$$

where  $h(d)_T$  is the rainfall depth at the specified return period *T*, duration *d* and  $a_T$  and  $n_T$  are parameters. According to previous studies the annual maxima rainfall trends occurring in Sicily are cause of variations of the  $a_T$  parameter [10, 11]. This analysis focused on the estimation of the  $a_T$  parameter by means of a BMA procedure, while in this phase the effect of the  $n_T$  parameter variations has been neglected, requiring for further investigations. The BMA provided the  $a_T$  predictions for the definition of the design storm in a future climate change scenario.

#### 3.2. The Bayesian Model Averaging (BMA)

The Bayesian Model Averaging (BMA) is a statistical methodology aimed at combining inferences and predictions of several different models and to jointly assess their predictive uncertainty [18]. If  $M = \{M_1, ..., M_K\}$  denotes a set of K models and y is the quantity of interest, according to the given observed data D, the model ensemble posterior density function (PDF) of y is given by the BMA method as:

$$p(y_{BMA} \mid D) = \sum_{k=1}^{K} p(y \mid M_k, D) \cdot p(M_k \mid D)$$
<sup>(2)</sup>

where  $y_{BMA}$  is the BMA prediction,  $p(y | M_k, D)$  is the posterior distribution of y on the condition of the given sample D and model  $M_k$  and  $p(M_k | D)$  is the posterior model probability of  $M_k$  or the probability that the model  $M_k$ is the optimal model on the condition of the given data D. This probability represents the likelihood of model  $M_k$  being the correct model or the weights  $w_k = p(M_k | D)$  of model  $M_k$ . Based on the Bayes' law, the weight  $w_k$ , related to  $M_k$  can be expressed as follow:

$$w_{k} = p(M_{k} \mid D) = \frac{p(D \mid M_{k}) \cdot p(M_{k})}{\sum_{k=1}^{K} p(D \mid M_{k}) \cdot p(M_{k})}$$
(3)

where  $p(M_k)$  is the prior probability of the model  $M_k$  and  $p(D|M_k)$  is the marginal likelihood of the model  $M_k$ . The posterior mean and the variance of the BMA prediction  $y_{BMA}$  can be calculated as follows [12]:

$$E[y_{BMA}|D] = \sum_{k=1}^{K} p(M_k|D) \cdot \int_{-\infty}^{+\infty} y \cdot p(y|M_k,D) \, dy = \sum_{k=1}^{K} w_k \eta_k \tag{4}$$

$$Var[y_{BMA}|D] = \sum_{k=1}^{K} w_k \cdot \left(\eta_k - \sum_{k=1}^{K} w_k \eta_k\right)^2 + \sum_{k=1}^{K} w_k \sigma_k^2$$
(5)

where  $\eta_k$  and  $\sigma_k^2$  are the expectation and the variance of y, respectively, on the condition of the given sample D and model  $M_k$ . In this analysis, the log-likelihood function has been evaluated, that is more convenient to compute than the likelihood function itself [12]. The log-likelihood function can be approximated as:

$$l(\theta) = \log\left(\sum_{k=1}^{K} w_k \cdot p_k(y|M_k, D)\right)$$
(6)

where  $\theta = [\{w_k, \sigma_k, k = 1, 2, ..., K\}]$ . In order to obtain an analytical solution of  $\theta$ , an iterative procedure is required. To this aim, in this analysis the Expectation-Maximization (EM) algorithm has been used [14].

The difference between observed and modelled variables provides the residuals. The application of the Eq. (6) requires the hypothesis that residuals are homoscedastic, independent and identically distributed in time. This hypothesis need to be verified considering that the probability distribution of hydrological variables is commonly non-Gaussian. Therefore, the variable, both modelled and obtained by observed data, has to be pre-processed, in order to make them more normal distribution-like. In this study the Box-Cox transformation has been applied to  $a_T$  before the application of the BMA procedure [19].

In order to evaluate the performance of model predictions, two measures associated with accuracy and forecast skill were computed, and specifically:

$$ABSE = \frac{\sum_{i=1}^{K} \left( a_T^i - a_T \right)}{N} \tag{7}$$

$$RMSE = \frac{\sum_{i=1}^{N} (a_T^i - a_T)^2}{N}$$
(8)

where *ABSE* is the Absolute Error, *RMSE* is the Root Mean Square Error,  $a_T^i$  is the estimation of  $a_T$  provided by the *i*-th model  $M_i$ ,  $a_T$  is the parameter appraisal obtained from historical dataset, N is the number of  $a_T$  estimations. ABSE and RMSE have been calculated for the expected BMA predictions and for the simple model average predictions (SMA). Since, verification statistics are less meaningful when used in absolute terms, the performances of the BMA and the SMA have to be compared with the best individual model prediction. Then, in order to verify if the predictions of the BMA and SMA are better or worse than that provided by the best model, the following quantities (%) have been computed:

$$ABSES = \frac{ABSE}{ABSE_{host}} \cdot 100 \tag{9}$$

$$RMSES = \frac{RMSE}{RMSE_{best}} \cdot 100 \tag{10}$$

where *ABSE*<sub>best</sub> and *RMSE*<sub>best</sub> are the *ABSE* and the *RMSE* related to the best model respectively.

#### 3.3. Urbanization model

In Sicily a chaotic urbanization has led to a considerable increase in the percentage of impervious surfaces and, consequently, to a decrease in water infiltrated into the soil to the deep aquifers. In order to assess the effects of urbanization on the urban drainage system of Paceco, the dynamic of the expansion of urban areas has been investigated. For the analysis of the impacts of urbanization on the drainage system performance for the subject area, an assessment of the potential future development of the urban areas has been carried out starting from the comparison of the available orthophotographs of Paceco. Namely the images for the years 1988 (Figure 2a), 1994, 2000, 2006, 2012 and 2016 (Figure 2b) have been analyzed, evaluating for each year the total impervious area.



Fig. 2. (a) Orthophotograph of Paceco in 1988; (b) orthophotograph of Paceco in 2016; (c) impervious area (km<sup>2</sup>) from 1988 to 2016 and related linear regression

The comparison allowed to define a mathematical law that describes the variation of the impervious areas over time (Figure 2c). This area was equal to  $0.64 \text{ km}^2$  in the 1988. In current conditions the urban area has a surface of  $0.95 \text{ km}^2$ . Using the linear regression in Figure 2c, the impervious area in the 2050 has been calculated, resulting equal to  $1.2 \text{ km}^2$ . The consistency of this result has been confirmed by the planned urban expansion reported in the Development Plan of the town of Paceco.

#### 4. Results and discussion

Starting from the historical series of annual maximum rainfall depth for given duration, a series of the  $a_T$  parameter has been obtained, including years one by one to a initial subdataset of 12 years (1950-1961). Once the  $a_T$  values have been evaluated, it has been assumed that the series could be affected by a positive, null or negative trend. Therefore, K linear regressions, representing the increasing trend, the decreasing trend and the no trend conditions. Each linear regression represents an individual model  $M_k$ . For each value of  $a_T$ , the BMA procedure allowed to attribute the weight  $w_k$  to the  $M_k$  models, ascribing the highest weight to those models that provide the best predictions of  $a_T$ . The expected BMA prediction is the average of individual model predictions weighted by the likelihood  $w_k$  that the individual model  $M_k$  is the optimal model on the condition of the given data D. The  $w_k$  are the result of a weighted average of their current forecast performance weighted by the conditional probabilities of the previous step.

As previously mentioned, the models are represented by a wide range of linear regressions, for which the intercept is the first datum of the  $a_T$  series. Figure 3a shows the  $a_T$  series and the positive, null or negative trend. The solid red line represents the BMA estimations of the  $a_T$ . Starting from the first value of  $a_T$ , the BMA predictions of  $a_T$  improve year after year, due to the effect of the updating approach of the  $w_k$ . In Figure 3a the SMA is showed as well. The comparison between BMA and SMA points out that the BMA prediction performance is better that that of SMA, meaning that simply averaging the original ensemble predictions would not necessarily lead to improve accuracy of the predictions.

The posterior mean of the BMA prediction is used as quantitative forecasting and it is obtained by weighting the individual model predictions  $\eta_k$  by the likelihood  $w_k$  that the individual model  $M_k$  is the optimal model on the condition of the given data D [14]. In Figure 3b, the posterior variance of the models and of the ensemble BMA model are shown. It can be observed that the variance of the BMA is lower than the large majority of the single models. Since the posterior variance represents an important measure of uncertainty, the BMA predictions of  $a_T$  are affected by a lower uncertainty if compared with the predictions of the models. Indeed, the BMA outperforms the majority of single models, due to the attribution of lower  $w_k$  to models that underestimate or overestimate the  $a_T$ .



Fig. 3. (a) Historical and modelled aT estimates; (b) models and BMA variances

To evaluate the performance of model predictions, the *RMSES* and the *ABSES* have been evaluated. Figure 4 shows the *RMSES* (Figure 4a) and *ABSES* (Figure 4b) of the expected BMA predictions, together with that related to the SMA. The *RMSES* and the *ABSES* statistics of the expected BMA predictions are better than that of the best individual predictions. These results further supports that the BMA predictions are more accurate than those that can be obtained by simply averaging the original ensemble predictions.

By means of the BMA, the future variations of the  $a_T$  parameter can be assessed. In this study, in order to obtain the prediction of  $a_T$  for a climate projection to the 2050, the predictions of the *K* models to 2050 have been weighted using the  $w_k$  related to the last  $a_T$  estimation (2008). For the 2050, the procedure provided a value of  $a_T$  equal to 38.61 mm.



Fig. 4. (a) RMSES statistics of BMA and SMA predictions; (b) ABSES statistics of BMA and SMA predictions

In the last step of the analysis, the implications of the annual maxima rainfall trend and the increase of urbanization were investigated to provide an evaluation of the drainage system performance in climate and urbanization change scenarios. Four simulations have been carried out, assuming a Chicago hyetograph with a duration of 120 min as the rainfall input, with a time-to-peak of 50 min. Rainfall values were sampled from different 5-year return period DDF curves with the following values of  $a_T$  and  $n_T$  parameters:

- $a_T = 30.75$  mm and  $n_T = 0.28$  (design conditions and urbanization scenario);
- $a_T = 38.61$  mm and  $n_T = 0.28$  (climate change and urbanization + climate change scenarios).

The hydraulic performance of the drainage system for the different considered rainfall inputs has been compared in terms of the network pipe volume percentage related to several maximum pipe capacity range.

Max Pipe Capacity	Network Pipe Volume			
	Current climate and urbanization conditions (2008)	2050 scenario		
		Urbanization	Climate Change	Urbanization + Climate Change
0%-20%	21.3%	6.6%	19.8%	5.6%
20%-40%	20.4%	33.6%	17.8%	28.8%
40%-60%	22.0%	21.5%	14.0%	16.9%
60%-80%	27.2%	28.3%	34.7%	31.5%
80%-100%	9.6%	9.9%	13.6%	17.1%

Table 1. Network pipe volume percentage related to several maximum pipe capacity ranges.

As shown in Table 1, for the current climate and urbanization conditions, the maximum pipe capacity reached ~64% of the network pipe volume, which is lower than the design threshold (60%). Only the 27.2% of the network pipe volume shows a maximum pipe capacity higher than 60%, and the 9.6% of the pipes is surcharged. The 21.3% of the network pipe volume is overdesigned, reaching a maximum capacity lower than 20%. With regard to the urbanization scenario, the potential future increase of the impervious areas assumed for the 2050 has not produced remarkable changes in the system performance, if compared with current conditions. Specifically, the maximum pipe capacity reached about the 62% of the network pipe volume, while the 9.9% of the pipe is surcharged. In the climate change

scenario the system performance worsens, indeed the 34.7% of the network pipe volume shows a maximum pipe capacity higher than 60% and the surcharged network pipe volume is equal to the 13.6%. In this scenario, the increase of the runoff volumes drained by the system, due to the positive rainfall trend, results in a reduction of the oversized network pipe volume. In the 2050 scenario that includes urbanization and climate change, the combined effect of the two factors produces a slight worsening of the drainage system performance, if compared with the climate change scenario. The maximum pipe capacity reached the ~51.4%. The 31.5% of the network pipe volume has a maximum pipe capacity higher than the design threshold, while the 17.1% of the pipes is surcharged.

### 5. Conclusion

In this study, a procedure based on the BMA approach has been developed and applied in order to evaluate the  $a_T$ parameters of DDF curves in future climate change scenarios. As regards to urbanization, the comparison of the available orthophotographs for the area of study provided an estimation of the future development of the impervious areas. The proposed procedure was applied to estimate the DDF curves in climate change and urbanization scenarios for a case study in the northwestern part of Sicily, in the town of Paceco. The application of the procedure for the  $a_T$ estimation showed that the expected BMA predictions are better or comparable to the best individual model predictions. Moreover, the BMA prediction performance was clearly better than that the SMA predictions, meaning that simply averaging the original ensemble predictions would not necessarily lead to improved accuracy of the predictions. After the application of BMA, the imperviousness area and the design rainfall event for future scenarios were identified and used as input data for a numerical model based on the SWMM software which was adopted to simulate the behavior of the urban drainage system of Paceco. Results highlighted that the implications of extreme rainfall variations on the drainage system of Paceco are more significant than those due to urban area increase. The surcharge probability is expected to increase in the future due to the climate change; therefore, current design standards should be updated and improved in order to allow the network to maintain the surcharge return period target till the end of its expected life. As an alternative, storm water source control techniques (such as Best Management Practices or generally local storage tanks) may be implemented in the future in order to reduce the runoff volume and the peak discharge reaching the sewer network thus reducing the risk of surcharge.

## References

- Willems, P., Arnbjerg-Nielsen, K., Olsson, J., Nguyen, V.T.V. Climate change impact assessment on urban rainfall extremes and urban drainage: methods and shortcomings. Atmos. Res. 103 (2012), 106-118.
- [2] Semadeni-Davies, A., Hernebring, C., Svensson, G., Gustafsson, L. G. The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Combined sewer system. J. Hydrol. 350(1) (2008), 100-113.
- [3] Astaraie-Imani, M., Kapelan, Z., Fu, G., Butler, D. Assessing the combined effects of urbanisation and climate change on the river water quality in an integrated urban wastewater system in the UK. J. Environ. Manage. 112 (2012)., 1-9.
- [4] Wilby, R.L.A review of climate change impacts on the built environment. Built Environment 33(1) (2007), 31-45.
- [5] Mann, H.B. Nonparametric tests against trend. Econ. J. Econ. Soc. 1945, 13, 245-259.
- [6] Kendall, M.G. Rank Correlation Methods, 3rd ed., Hafner Publishing Company, New York, NY, USA, 1962.
- [7] Brunetti, M., Maugeri, M., Nanni, T. Changes in total precipitation, rainy days and extreme events in northeastern Italy. Int. J. Climatol. 21(7) (2001), 861-871.
- [8] Liuzzo, L., Bono, E., Sammartano, V., Freni, G. Analysis of spatial and temporal rainfall trends in Sicily during the 1921–2012 period. Theor. Appl. Climatol.1-17 (2015).
- [9] Arnell, N.W. Climate change and global water resources. Global environmental change 9 (1999), S31-S49.
- [10] Liuzzo, L., Freni, G. Analysis of extreme rainfall trends in sicily for the evaluation of depth-duration-frequency curves in climate change scenarios. J. Hydrol. Eng., 20(12) (2015), 04015036.
- [11] Notaro, V., Fontanazza, C.M., Freni, G., La Loggia, G. Assessment of Modelling Structure and Data Availability Influence on Urban Flood Damage Modelling Uncertainty. Proceedia Engineering 89 (2014), 788-795.
- [12] Duan, Q.Y., Ajami, N.K., Gao, X., Sorooshian, S. Multimodel ensemble hydrologic prediction using Bayesian model averaging. Adv. Wat. Resour. 30 (2007) 1371-1386.
- [13] Ajami, N. K., Duan, Q., Sorooshian, S. An integrated hydrologic Bayesian multimodel combination framework: Confronting input, parameter, and model structural uncertainty in hydrologic prediction. Water Resources Research 43(1) (2007).
- [14] Raftery, A.E., Geneiting, T., Balabdaoui, F., Polakowski, M. Using Bayesian model averaging to calibrate forecast ensembles, Mon. Weather Rev. 133 (2005) 1155-1174.

- [15] Clyde, M. A. (1999), Bayesian model averaging and model search strategies, in Bayesian Statistics, vol. 6, edited by J. M. Bernardo et al., pp. 157-185, Oxford Univ. Press, New York.
- [16] Ellison, A. M. Bayesian inference in ecology, Ecol. Lett. 7 (2004), 509-520.
- [17] Rossman, L.A. Storm Water Management Model: User's Manual 5.1; U.S. Environmental Protection Agency: Cincinnati, Ohio, USA, 2009.
- [18] Woling, T., Vrugt, J.A. Combining multiobjective optimization and Bayesian model averaging to calibrate forecast ensemble of soil hydraulic model. Water Resour. Res. 44 (2008) doi: 10.1029/2008WR007154.
- [19] Box, G.E.P., Cox, D.R. An analysis of transformations, Journal of the Royal Statistical Society, Series B 26 (1964), 211-252.