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Published in:
Journal of Hydrology

DOI (link to publication from Publisher):
10.1016/j.jhydrol.2021.126776

Publication date:
2021

Document Version
Publisher's PDF, also known as Version of record

Journal of Hydrology 602 (2021) 126776

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

CLIMACS: A method for stochastic generation of continuous climate projected point rainfall for urban drainage design

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ARTICLE INFO

This manuscript was handled by Emmanouil Anagnostou, Editor-in-Chief

Keywords:
Urban drainage design
Climate projection
Stochastic rainfall generation
Continuous rain series
Storm detention water pond
Ensemble modelling

ABSTRACT

Climate projected continuous rain series are required for urban drainage design and analysis. Outputs from regional climate models are yet insufficient in quality and resolution for this purpose. Here, we introduce a novel method, *CLIMACS* (CLImate projection of MeAsured preCipitation Series) for stochastic climate projection of point rain series for urban drainage design. It is developed and evaluated to represent current climate conditions as well as projections for the period 2071–2100 with RCP scenarios 4.5 and 8.5. *CLIMACS* includes seasonal stochastic resampling of individual rain events and rainfall intermittency as well as climate scaling. Fifteen climate variables representing multiple changes in the future rainfall are selected and projected to target future conditions. Realizations of the resampled and stochastically generated rain series are ranked and selected according to the minimum relative error between realization and target. To give an insight into the uncertainty of the climate projection as well as year-to-year variability of precipitation climate variables, an ensemble of the top 100 realizations for each climate scenario is selected for further analysis. It is concluded that the ensembles represent the future conditions well, however, with a large variability due to the uncertainties in climate projection. With the aim of showing the impact in urban drainage system design, a stormwater detention pond design with multiple design parameters and climate scenarios is demonstrated. The pond design results show a significant difference in required pond volume depending on the design parameters and the choice of climate scenario, which emphasizes the need for climate projected continuous rain series for urban design purposes as an alternative to design storms.

1. Introduction

In design and planning of urban drainage systems, it is crucial to be able to give an estimate of the future loading of the drainage system in order to certify a long lifetime of the designed systems. The impacts of how global warming changes precipitation patterns, therefore, have to be taken into account. In the projection of climate change for Northern Europe, it is well-known that the most high-intensity rainfall will increase and that the average annual precipitation will increase. This is the case for all RCP scenarios (Kovats et al., 2014). The climate changes might also cause a shift in the annual precipitation patterns. One example for Denmark is that the summer precipitation is expected to decrease or remain at the same level in 2071–2100 as in the current climate conditions (1981–2010). At the same time, the heavy rain events are expected to increase by some 30–40 % - resulting in longer drought periods between events (Thejll et al., 2020).

Small or upstream parts of drainage systems are most commonly designed with IDF-curves or design storms, where rain intensities for a given short duration with a given return period are multiplied by a contributing area to assess a maximum flow corresponding to the specified return period, cf. the *rational method* (Kuichling, 1889). The design rainfall can easily be climate projected by multiplying the rainfall intensity with a climate factor that represents the increase in rainfall intensity for short heavy rain events. For larger systems or downstream parts where branches confluence and flow are regulated by pumps, detention ponds, weirs, etc., flow patterns become more complex. The assumption of unity between the return period of the rain and the return period of the flow is therefore not necessarily in agreement. Rather than using design storms, design and impact analysis of complex drainage systems are therefore often done with numerical models that simulate flow with inputs from continuous rain series (Schaarup-Jensen et al., 2009; Thorndahl, 2009; Thorndahl et al., 2008). The return periods of flow or water levels exceeding specified thresholds can hereby be estimated as part of the design process. Where the design does not only

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https://doi.org/10.1016/j.jhydrol.2021.126776

Available online 2 August 2021

depend on the peak rainfall intensity of the rain over a specified duration, but on multiple combinations of rain intensities with different durations as well as regulated flows, the linear scaling with regard to climate change also falls short. It is necessary to produce continuous rain series that represent the future rain patterns, e.g., by scaling the extremes and less intensive rain differently from each other. Moreover, it is important to represent how the dry periods between events change with changing climate conditions. This applies in situations where runoff, peak flows, etc. dependent on the antecedent soil moisture conditions (Nielsen et al., 2019; Pathiraja et al., 2012), or the design of stormwater detention ponds where the emptying time between rain events is crucial for required volumes.

In a broader urban drainage context, it is essential to be able to calculate loads on receiving waters either from combined or separate sewer systems. To do this correctly, the yearly and seasonal precipitation amounts also have to match future climate conditions. This can only be achieved by developing climate-projected continuous rain series.

Global circulation models with different forcings of climate gas concentrations can represent future global warming and thereby changes in climate. By deriving relevant boundary conditions from the global models, regional climate models can be applied to simulate the impacts of climate change on regional scales. This includes the projection of the changes in precipitation. In comparison with the observations or rainfall statistics used for urban drainage design or impact analysis, the regional climate models are however biased and in course temporal and spatial resolutions. It is therefore widely recognized to apply outputs from regional climate models to statistically downscale climate changes to sufficient scales (Willems et al., 2012).

There are different approaches to statistical downscaling, e.g., weather typing (Van Uytven et al., 2020a; Willems and Vrac, 2011), stochastic rainfall generation (Burton et al., 2008; Chen et al., 2021; Haberlandt et al., 2015; Kim and Olivera, 2011; Park et al., 2021), or methods that modify or perturbate time series (often referred as change factor-based methods, e.g. Ntegeka et al., 2014; Olsson et al., 2009; Sørup et al., 2017; Sunyer et al., 2015). Van Uytven et al. (2020b) argued that the change factor-based methods have advantages over rainfall stochastic rainfall generators since they do not contain stochastic elements and therefore can produce one single perturbation of a rain series rather than a stochastic ensemble. In this paper, we argue for the opposite, namely, those stochastic rainfall generators have the advantage to simulate an ensemble that can represent the uncertainty in the climate projections of rain series and due to the stochastic features they, can be targeted through specific applications in urban drainage design and impact analyses.

We present a stochastic rainfall generator procedure, *CLIMACS* (CLImate projection of MeAsured preCipitation Series) that can generate a continuous climate projected rain series for urban drainage design and impact analyses. A former version is presented in the HESS publication "Event-based Stochastic Point Rainfall Resampling for Statistical Replication and Climate Projection of Historical Rainfall Series" by Thorndahl et al. (2017) and has been evaluated along with other methods in Sørup et al. (2018) and De Niel et al. (2019).

Compared to Thorndahl et al. (2017), the procedure is further developed and improved with regards to simulating yearly variability, implementation of uncertainties in climate projections as well as new stochastic generation and evaluation procedures that make the stochastic procedure faster and more consistent. In addition to the targeting of rain series to statistically represent climate variables relevant for precipitation, *CLIMACS* also features validation on the dry weather periods between rainfall events. *CLIMACS* applies new processing of climate model ensembles from the EUROCORDEX database for both RCP 4.5 and 8.5. Here, we aim to present and evaluate the new features of the improved procedure.

CLIMACS produces ensembles of stochastically sampled rain events. The idea is not to produce rain series that match the true climate and precipitation pattern for a given period but to create rain series that statistically represent rainfall for a given period and which can be used for the design of hydrological systems, e.g. urban drainage systems. *CLIMACS* can provide rain series representing current climate conditions as well as future conditions projected by different climate scenarios. The former is considered as a validation of the procedure when the reference rain series and a resampled rain series statistically are in agreement. It is important to emphasize that each stochastic realization of a rain series is different. The objective of this paper is therefore also to investigate the ensemble variability between generated rain series and to assess how large an ensemble is required in a given design process.

To investigate and compare the generated rain series under different hydrological design conditions and climate conditions, we apply a simple stormwater detention pond design routine that estimates the required pond volume for a given unit area and return period. By varying the outlet flow rate from the detention pond, the design volume becomes differently dependent on the continuity of the rain series and thus the time between rain events. The difference in detention pond design volume is investigated and compared for both current and future climate conditions.

Other applications of CLIMACS rain series as inputs to urban hydrological models of integrated systems, e.g. to simulate flooding, surcharge, combined sewer overflow, is also tested as part of the evaluation of CLIMACS, but not reported here.

The paper is structured as follows. In section 2.1 the stochastic procedure and the novel features are presented. In Section 2.2, the method for evaluating the generated time series in detention pond design is presented. The rainfall data and climate model projections applied to exemplify the procedure are presented in section 3. Results of the evaluation of both rainfall statistics and detention pond design are presented in Section 4. Section 5 features a discussion of the ensemble size related to urban drainage design. Conclusions are provided in Section 6.

2. Methods

2.1. Stochastic generation and evaluation of rain series

The procedure for generating both resampled rain series (representing the current climate) and climate projected rain series (representing a given future climate scenario), is presented in the following section. For specific details on the procedure, you can refer to Thorndahl et al. (2017) and the explanations are limited here to present a general understanding of the procedure's steps (Fig. 1) as well as emphasize and detail the improvements of the method.

CLIMACS can run in two modes: *Single station mode*, where rain events are sampled from a single historical rain series (referred as the reference rain series from hereon) and fitted to the statistics or projections of the same rain series; or in a *multiple station mode* (Thorndahl and Andersen, 2021), where events are resampled from multiple historical rain series and fitted to regional rainfall statistics and climate projections. Where the *single station mode* will generate a rain series representative for the location of the reference rain series, the *multiple station mode* can generate a rain series to represent a random location as long as the regional rainfall statistics and climate projections are available as targets. In this paper, we limit the description to the *single station mode*. The stochastic generation procedure therefore exclusively samples rain events from the original reference rain series.

It is a key feature in *CLIMACS* that the stochastic sampling and climate scaling are split into individual seasons (winter, spring, summer, and autumn), which allows for different climate projections depending on the season. We apply brute force sampling of rain events, interevent time, and climate scaling which is stochastic and unconditional on the past. *CLIMACS* will generate numerous rain series and the concept is that the posterior evaluation procedure determines if each individual realization should be accepted or rejected based on the statistics of a number of target climate variables. These target climate variables are solely

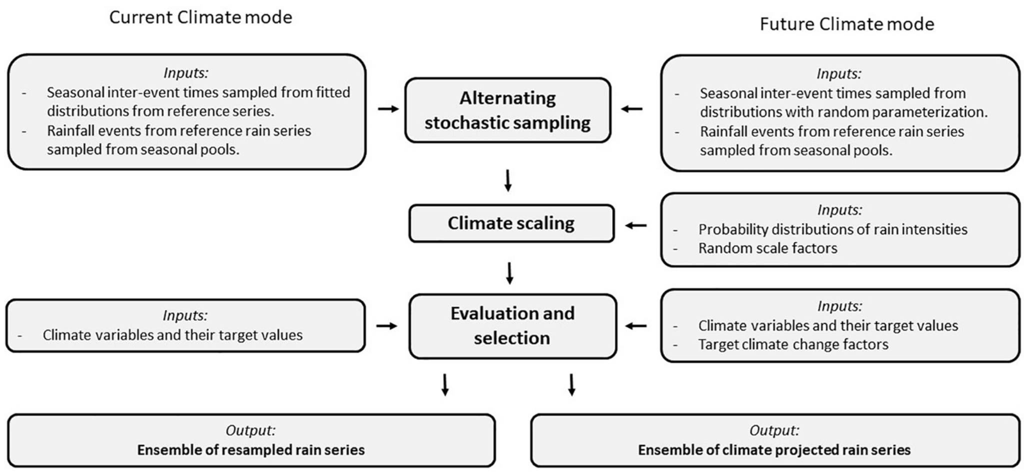


Fig. 1. Flow diagram of the procedure and inputs of *CLIMACS*.

related to precipitation and serve as evaluation indicators throughout the paper. Due to the brute force randomization, the greater majority of series are rejected due to too large errors on one or more of the target variables. The evaluation and accept/reject procedure is based on relative errors between realization and targets related to both annual and seasonal statistics as well as extreme statistics. This ensures that the minority of the generated series that in fact comply with the acceptance criteria has low errors on multiple statistical parameters and therefore can represent real rainfall statistics for either the current climate or projections of the future climate.

2.2. Alternating stochastic sampling of single rain event and interevent time

Rainfall intermittency (interevent time) is stochastically sampled from a two-component mixed exponential probability density function for each season (Thorndahl et al., 2017). The probability distribution has three parameters for each of the four seasons. For replicating the current climate, the parameters are assessed by fitting the reference rain series. In order for the climate projected rain series to include different interevent time distributions, the three parameters for each season are sampled randomly from a uniform distribution with fixed upper and lower boundaries. This allows for a shift in interevent times, e.g., to accommodate for longer drought periods or periods with an increased frequency of event occurrences in the future climate. Rain events are sampled randomly from the pool of seasonally grouped historical events from the reference rain series, and each event is treated as an independent event. Other studies have applied Markovian processes (e.g. Basinger et al., 2010; Fowler et al., 2005) or even more complex weather generators (e.g. Kim and Onof, 2020; Peleg et al., 2017) to introduce or simulate interevent dependency. Since the objective of *CLIMACS* is to produce continuous rain series which are statistically valid for urban drainage design, and not to reproduce real rainfall, the interevent dependency is neglected, and the continuity of the individual rain events and interevent times are evaluated seasonally by the target climate variables. The discrete stochastic sampling of individual rain events to produce continuous rain series is stochastic and unconditional on the past and can thus be described as a non-markovian process. Therefore, it is crucial to statistically evaluate the generated series and to reject realizations that do not comply with the acceptance criteria for each climate variable.

We allow for random sampling of the same event multiple times. Unlike other studies, (e.g., Sørup et al., 2017), there is no grouping by rainfall intensity or total rain depth of the individual events prior to the random sampling. This makes the method flexible in terms of sampling from the complete distribution of events without introducing assumptions on the grouping. The disadvantage of this approach is that many generated rain series have to be rejected due to low-performance scores (or high relative errors) on one or more target climate variables. This is elaborated in section 4.1. The alternating sampling of rain events and interevent times is repeated until the desired length of the generated rain series is obtained.

2.3. Climate scaling

In the generated continuous rain series, climate scaling is implemented by a linear scaling of the rain intensity (i). A scale factor (c) for each season is calculated using a first-order function with a contribution from a scale factor (β) which is drawn randomly from a uniform distribution for each season and a contribution (α, also sampled from a seasonal uniform distribution) depending on the fitted two-component mixed exponential cumulative probability (F(i)) of rain intensity for the season in question:

$$c(i) = \alpha F(i) + \beta \tag{1}$$

The scaling with regard to intensity allows for different change factors for different intensities and gives more variability between the generated rain series. An example of a scale factor from a set of randomly selected parameter values for a given season could be $\beta = 1.09$ and $\alpha = 0.05$. The scale factor c would therefore range between 1.09 (for F(i) = 0) and 1.14 (for F(i) = 1) The scaling factor (c) is different from the climate factor (cf) defined in the “evaluation procedure” and given in Table 1. The latter serves as the projection of the individual target variables, whereas the former serves as a stochastic input to the climate scaling.

The linear scaling of rain intensities is inspired by the delta change method, as applied in Olsson et al. (2009) in which the scaling depends on the intensity distribution. Compared to a static climate projection (e.g. Sørup et al, 2017), which might have been implemented using selected climate factors from Table 1, directly as scaling parameters, the linear scaling creates a dynamic climate projection. It allows for the climate scale factor, $c(i)$ to be both smaller and larger than 1, and since parameters, α and β are drawn randomly for each season, there is a very large flexibility in the scaling procedure. The climate scaling, however, is very dependent on the succeeding evaluation and rejection of series with too large relative errors. The brute force approach, in which event sampling and scaling parameters are consistently randomized, requires the generation of many realizations to obtain a few that comply with acceptance criteria.

Table 1
Mean and standard deviation (SD) of absolute values and climate factors, *cf*, for the 15 selected climate variables.

Target climate variable	Notation	Absolute values		Climate factor		Climate factor		Weight
		Current climate		RCP 4.5		RCP 8.5		
		Mean	SD	Mean	SD	Mean	SD	
Annual precipitation	ap (mm)	660	131	1.07	0.10	1.14	0.09	0
Seasonal precipitation, winter	spwi (mm)	132	59	1.12	0.11	1.24	0.13	0.125
Seasonal precipitation, spring	spsp (mm)	121	40	1.12	0.11	1.20	0.13	0.125
Seasonal precipitation, summer	spsu (mm)	185	69	1.05	0.20	0.98	0.23	0.125
Seasonal precipitation, autumn	spau (mm)	184	56	1.04	0.09	1.10	0.13	0.125
Annual number of events above 10 mm per day	n10mm (#)	16.5	5.6	1.15	0.18	1.29	0.13	0.06
Annual number of events above 20 mm per day	n20mm (#)	3.0	1.9	1.31	0.33	1.61	0.31	0.04
Annual Maximum daily precipitation	mdp (mm)	33.6	12.2	1.13	0.11	1.23	0.16	0.05
Annual Maximum 5-day precipitation	m5dp (mm)	55.7	15.8	1.09	0.10	1.18	0.11	0.05
Rain intensity for 10 min, T = 2 years	d10T2 (mm/h)	52.9		1.18	0.16	1.31	0.20	0.06
Rain intensity for 10 min, T = 10 years	d10T10 (mm/h)	69.2		1.23	0.20	1.38	0.29	0.04
Rain intensity for 60 min, T = 2 years	d60T2 (mm/h)	16.6		1.18	0.16	1.31	0.20	0.06
Rain intensity for 60 min, T = 10 years	d60T10 (mm/h)	20.9		1.23	0.20	1.38	0.29	0.04
Rain intensity for 360 min, T = 2 years	d360T2 (mm/h)	5.0		1.18	0.16	1.31	0.20	0.06
Rain intensity for 360 min, T = 10 years	d360T10 (mm/h)	6.1		1.23	0.20	1.38	0.29	0.04
								1

2.4. Evaluation procedure

A central part of the stochastic generation of rain series is the evaluation of the generated series according to the specified target climate variables, and how the weights of the different targets are applied to calculate the metrics for each individual rain series realization. The criterion for accepting a rain series realization is twofold. Initially, each individual target variable has to fit within a specified range of each target defined by the relative error; and secondly, the overall weighted relative error of the realization must satisfy a specified acceptance criterion.

The applied target variables are presented in Table 1 along with the applied weights. The developed methodology has no upper limit with regard to the number of target variables and other variables might be added or replaced if other or better climate variables become available. In this paper, however, we limit the target climate variables to the ones presented in Table 1. The climate variables presented in Table 2 are related to the dry weather periods between rainfall. In this case, they are used as validation variables, but could also have been equally implemented as targets and weights. The interevent times that we sample as part of the alternating procedure are fully stochastic and therefore independent from the projections of dry weather periods. Furthermore, the interevent times are at a minutely timescale as the rain series. The dry weather periods are estimated in days. Although interevent times and dry weather periods indeed represent the same, we choose to distinguish between them, since the interevent times are used as part of the input for generating rain series and the dry weather periods are used as part of the validation procedure.

Table 2
Mean and standard deviations (SD) of absolute values and climate factors, *cf*, for the 8 selected validation variables related to dry weather periods.

Validation variables	Notation	Absolute values		Climate factor		Climate factor	
		Current climate		RCP 4.5		RCP 8.5	
		Mean	SD	Mean	SD	Mean	SD
Number of dry days, winter	nddwi (days)	53.8	10.4	0.98	0.05	0.99	0.04
Number of dry days, spring	nddsp (days)	65.4	7.8	0.98	0.03	0.97	0.04
Number of dry days, summer	nddsu (days)	59.9	7.8	1.01	0.07	1.07	0.09
Number of dry days, autumn	nddau days)	53.6	7.8	1.02	0.05	1.03	0.08
Maximum dry period, winter	mddwi (days)	9.5	4.6	0.98	0.15	0.92	0.12
Maximum dry period, spring	mddsp (days)	12.5	4.7	0.98	0.12	0.95	0.13
Maximum dry period, summer	mddsu (days)	12.8	4.1	1.04	0.12	1.11	0.17
Maximum dry period, autumn	mddau (days)	11.0	4.3	1.02	0.15	1.08	0.18

Compared to the methodology presented in Thorndahl et al. (2017) an improved metric of defining the acceptance range for each target variable is developed. It is hereby possible to include both variabilities from year to year (for the target variables defined annually) as well as the uncertainty estimates of the climate projections of the individual target variables.

For each climate variable (m) the relative error (RE) for each realization (n) is calculated as:

$$RE_{m,n} = \frac{|T_m - R_{m,n}|}{T_m} \tag{2}$$

In which T is the target value and R is the corresponding value based on the realizations.

In the present climate simulations, the target value is an absolute value for a given climate variable, e.g. the mean summer precipitation. In the case of the evaluation of climate projected rain series, the target value is the absolute value multiplied by the climate factor, cf of the climate variable in question. For climate variables defined with annual values (e.g., seasonal precipitation, number of days with precipitation over a specific threshold, etc.), the relative error term is calculated both as a mean for the period of the rain series as well as the standard deviations of the annual values. The target and the realization value related to the means are calculated by:

$$T_m = \bar{X}_m cf_m \tag{3}$$

$$R_{m,n} = \bar{Y}_{m,n} \tag{4}$$

In which X and Y are the annual climate variable estimates for the reference rain series, and the realization rain series respectively.

The target (T) and the realization value (R) related to the standard deviations are calculated by:

$$T_m = \left(s_{X_m}^2 \sigma_{cf_m}^2 + s_{X_m}^2 cf_m^2 + \sigma_{cf_m}^2 \bar{X}_m^2 \right)^{1/2} \tag{5}$$

$$R_{m,n} = s_{Y_m} \tag{6}$$

In which s is the sample standard deviation of the annual climate variable estimates and σ_{cf} is the standard deviation of the climate factor. The target is equal to the standard deviation of a product of two Gaussian distributions. In this way, we can both include the year-to-year variability as well as uncertainty estimates on climate factors.

With regard to the extreme target climate variables (defined here as variables that are not estimated on an annual basis, but with respect to a return period or frequency (f)), the target and realization values are calculated by:

$$T_m = i(d, f, X_m)cf_m \tag{7}$$

$$R_m = i(d, f, Y_{m,n}) \tag{8}$$

where i is the rainfall intensity for a specific duration d and frequency f.

To fulfill the acceptance criterion each target variable must fulfill:

$$RE_{m,n} \leq \frac{2\sigma_{cf,m}}{cf_m} \tag{9}$$

where $\sigma_{cf,m}$ is the standard deviation of the climate factor, cf, for climate variable m. Acceptance is thus allowed if the relative error is within the 95 % confidence interval of the climate factor assuming a Gaussian distribution.

The first step of the evaluation procedure certifies that each individual climate variable of each individual realization rain series complies with the acceptance criterion. In the second step, the average relative error based on the weighted mean of all climate variables is calculated by:

$$\overline{RE}_n = w_1 RE_{1,n} + w_2 RE_{2,n} + \cdots + w_m RE_{m,n} \tag{10}$$

w_m are the weights for each individual climate variable, m.

By ranking the estimated average relative errors, the realizations with the lowest overall errors are identified and selected for further application. The accepted realizations for each climate scenario are referred as an ensemble. Weights can be changed depending on the application of the generated rain series, e.g. by weighting some seasons higher than other seasons, or by weighting extremes higher than annual estimates.

The brute force sampling and evaluation procedure of *CLIMACS* based on an initial acceptance criterion for each climate variable and the succeeding ranking by the weighted errors is inspired by the *GLUE* methodology (Beven and Binley, 1992; Thorndahl et al., 2008).

2.5. Stormwater detention pond design

We use a stormwater detention design to exemplify the application of continuous climate projected rain series as this design is dependent on both the peak rain intensity over as specific rainfall duration as well as the antecedent conditions. This mutual dependency displays the importance of the application of continuous rain series rather than single design events in estimating required storage volumes.

In the procedure for designing stormwater detention ponds we evaluate and compare the ensemble of generated rain series representing current and future climate conditions in order to investigate how both changes in rain intensities as well as interevent times affect the required design volumes.

The procedure furthermore serves the purpose to investigate the variability between the accepted realizations in each climate scenario ensemble and to explore differences in design volumes depending on the design parameters and choice of the climate scenario.

For the detention pond design, a simple mass-balance box model is formulated as a first-order differential equation (as e.g. presented in Hvitved-Jacobsen et al., 2010):

$$\frac{dV(t)}{dt} = i(t)F_r - Q_{out}(t) \tag{11}$$

where $dV(t)/dt$ is the increase in pond volume per time step, dt, $i(t)$ is the rain intensity, F_r is the contributing catchment area, and $Q_{out}(t)$ is the outlet flow from the pond. The time of runoff in the catchment is neglected since this is most often insignificant to the emptying time of the pond.

Eq. (11) is solved explicitly using backward Euler:

$$V(t+1) = V(t) + (i(t)F_r - Q_{out})\Delta t \tag{12}$$

In which V is the stormwater pond volume and Δt is a fixed time step. The outlet flow is for simplicity reasons assumed to be a constant defined by an outlet flow rate, a ($l\ s^{-1}\ ha^{-1}$), hence $Q_{out} = a\ F_r$.

The simulation of detention pond volumes is executed by a continuous simulation over the total period of each generated rain series. Thereby, it is possible to simulate how the detention pond volume depends on antecedent rainfall and thereby by the emptying of the pond between rain events. If the outlet flow rate is low, the pond will empty at a slower pace, and the antecedent rainfall period becomes relatively more important for low outlet flow rates than for larger ditto.

The storage pond volume corresponding to a specific return period is found by ranking the event-separated volumes applying the California method (as cited in e.g. Rakhecha and Singh, 2009) and a linear interpolation between discrete return periods. Events are separated by the maximum emptying time (or drain time) of the pond.

3. Data

The reference rain series applied exclusively for the stochastic generation of rain series in the present study is based on tipping bucket rain gauge recordings from a station in Viby (Aarhus) Denmark. The rain gauge is part of the rain gauge network of the Danish water pollution committee (Sarup, 2020). It covers the period from 1979 to 2018. The total observation period is 38 years when the rain series is corrected for outages. Rainfall data is filtered and quality controlled in regard to the recommendations in Publication no. 26 of the Danish Water Pollution Committee (WPC, 1999). The rain series contains 9253 individual rain events separated by at least one hour of dry weather and a minimum rain depth of 0.4 mm. The temporal resolution of the rain series is 1 min. The total observed rain depth corresponds to an average of 660 mm per year. Individual years with more than 30 days of total downtime are excluded from the annual statistics to remove potential biases in the annual and seasonal statistics. Individual rain events from the discarded years are however included in the pool of events similar to data from the approved years. The calculated absolute mean and standard deviation values for the selected target climate variables (as described in the following section) are shown in Table 1 with respect to the reference rain series. Correspondingly, Table 2 presents the same values, however for the validation climate variables related to dry weather periods.

The selection of climate variables and climate factors for each individual climate variable is based on a processing of 20 EURO-CORDEX 0.11° ensembles for RCP 4.5 and 57 EURO-CORDEX 0.11° ensembles for RCP 8.5, (Jacob et al., 2014; Kotlarski et al., 2014; Prein et al., 2016; Thejll et al., 2020). From this processing, it is possible to derive the climate variables that relate to the annual and seasonal values of Table 1 and 2. The derived climate factors and their uncertainty estimates represent means and standard deviations for the ratio between the projected period 2071–2100 with RCP 4.5, RCP 8.5 and the reference period (1981–2010). The climate projections are available from the Danish Climate Atlas at (https://www.dmi.dk/klima-atlas/data-i-klimaatlas/). In *CLIMACS*, only the relative projections between the reference period and the projected period are used. It is also possible to use absolute climate variables as targets. This is covered further in Thorndahl and Andersen (2021).

The climate factors that relate to the extreme rainfall intensities and their durations and return periods (Table 1) are based on derived scenarios from the Danish design practice (WPC, 2014). The derived climate factors from herein have their origin in the A1B climate scenario from the ENSEMBLES project (Van Der Linden and Mitchell, 2009) supplemented by other single RCP4.5 and RCP8.5 simulations (reported in Gregersen et al., 2014; Sørup et al., 2016). Due to problems of simulating in very fine timescales with climate models, they are based on downscaled values from courser models. The climate factors are derived to represent Danish conditions and are in general agreement with the more recent and EURO-CORDEX- 0.11° findings of Berg et al. (2019), which includes simulations at an hourly timescale.

The climate variables of Table 1 are chosen to represent different rainfall conditions. In comparison with Thorndahl et al. (2017), more climate variables are added to cover a wider range of applications within urban drainage design. The annual maximum 5-day precipitation is added to include a target related to changes in consecutive rainfall days. In an urban drainage context, the 5-day precipitation has an impact on the continuous filling and thus the emptying time of stormwater detention ponds with low outflow rates. Furthermore, rain intensities for very short durations of 10 min with return periods 2 and 10 years are added along with rain intensities over 360 min for the same return periods. By introducing both shorter and longer durations than the original 60 min, we accommodate a range of durations that covers most drainage system pipe design values in Denmark.

In the generation of rain series representing the current climate, climate factors corresponding to $cf = 1$ are applied and the standard deviations of the climate factors (used in Eq. (3), 5, 7, and 9) are derived from the absolute values.

The validation climate variables (Table 2), represent both the total number of dry days per season as well as the maximum contiguous number of dry days per season. In this way, the dry weather periods are parameterized to represent average seasonal values as well as seasonal extremes. The absolute values are indeed sensitive to rain gauge station downtime and filtering of defective data. Therefore, some potential uncertainty is associated with estimating these variables solely on the reference series as we do with the target climate variables. To overcome this problem, we establish the absolute values as well as the climate factors on average regional values from the Danish Climate Atlas (Thejll et al., 2020).

The weights applied to estimate the average relative error are also presented in Table 1. In this case, we assign equal weights to the seasonal rainfall totals and weigh them with a total of 50 % (12.5 % for each season). The rest of the climate variables are given weights of 6 % (for the climate variables with the highest occurrence) and 4 % (for climate variables with the lowest occurrence). This weighting certifies that both seasonal and extreme values are represented. However, if one season or one specific extreme value is more important for particular applications, there is the opportunity to change the weights accordingly. It is important to notice that the weights are merely applied to rank the realizations that are already accepted based on the individual climate variable criterion (Eq. (9)).

In the stochastic generation of rain series, we assume stationarity over the period of a climatological normal corresponding to 30 years. It is assumed that the period of the reference series (1979–2018) is climatological equivalent to the period of the current climate as applied in the EUROCORDEX database (1981–2010). Despite the findings by Gregersen et al. (2015) and Willems (2013), any potential gradually increasing effects of climate change during the 38 years of the observed reference rain series is thus not considered.

4. Results

4.1. Generation and evaluation of rain series

A total of 50,000 rain series realizations are generated with seasonally variable random parameter values for interevent time distribution, climate scaling, and event sampling. Each of the generated rain series covers 39 years, which is the same period as the approved period of the historical reference rain series.

For each of the climate scenarios, the realizations that fulfill the relative error acceptance criteria are selected for further analyses. Concerning the current climate conditions (resampled historical), 1,049 of the 50,000 realizations fulfill the relative error criteria (Eq. (9)) for all of the 15 climate variables (Table 1). Equivalently, 145 and 253 realizations are accepted for the realizations of RCP 4.5 and 8.5 respectively. The acceptance ratios are indeed low, which is because we define an ultimate acceptance criterion that Eq. (9) must be kept for all 15 target variables. Many of the generated rain series are rejected because maybe one or two target variables are outside the acceptance range. This is definitely a disadvantage of *CLIMACS* which leads to more than 98 % of the realizations being rejected. On the positive side, we do not compromise results by lowering the acceptance criteria and therefore maintain the stochasticity of each generated series as well as the statistical agreement with targets.

Fig. 2 shows time series plots of the historical reference series as well as the realizations of current climate and RCP 4.5 and 8.5 with the lowest weighted relative errors (RE, Eq. (10)). These time series serve as examples of the generated series.

We rank the top 100 realizations by the smallest weighted average relative errors (Eq. (10)) and append them to an ensemble for each climate scenario. The weighted relative errors of the 100-member ensembles for the current climate and projections to 2100 with RCP 4.5 and 8.5 are presented in Fig. 3. The weighted average relative errors of the ensemble of the top 100 realizations are between 5.5 and 8.6 %for the resampled current climate conditions (resampled hist.), and 3.6–7.9 % and 6.2–11.3 % for RCP 4.5 and 8.5 respectively. RCP 8.5 has larger relative errors due to larger standard deviation of the climate factors compared to RCP 4.5. The relative errors of winter and summer precipitation are generally larger than the relative errors of spring and autumn precipitation. This is due to uncertainties related to solid precipitation in winter (see further discussion of this below) and more occurrences of extreme intensity events and larger climate factors in summer compared to the other seasons.

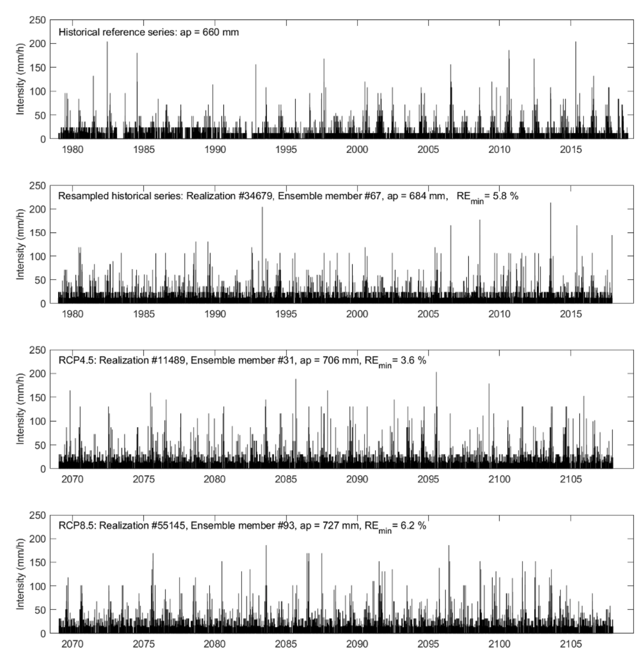


Fig. 2. Rainfall intensity time series plots of historical reference series and realizations of generated rain series with the lowest weighted relative errors (RE, Eq. (10) and Fig. 3) for current climate (resampled historical series) and RCP 4.5 and 8.5. *ap* is the mean annual precipitation of the displayed rain series.

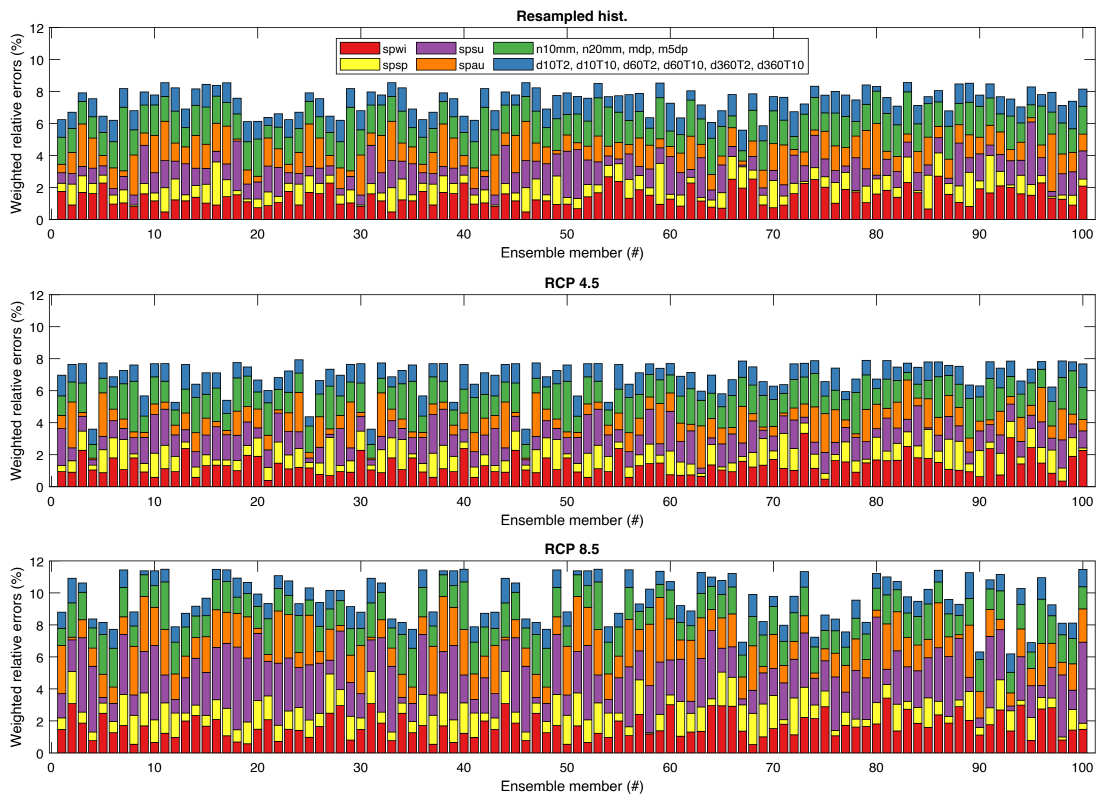


Fig. 3. Weighted relative errors of 100 ensemble members for each climate scenario. The grouped relative errors indicated by the different colors correspond to the notation of climate variables in Table 1.

The absolute values for the targets and realization results of the rain series generation are presented in Fig. 4 as boxplots for the different climate parameters and climate scenarios. The boxplots in muted colors represent the projection of each climate variable with mean and standard deviation of climate factors and absolute values from Table 1 assuming Gaussian distributions. The boxplots in vivid colors display the results of the top 100 realizations for each climate scenario. The boxplots show medians (horizontal lines), 25 % and 75 % quantiles, and whiskers as 5 % and 95% quantiles. All top 100 realizations for each climate scenario and climate variable are pooled, such that the boxplot illustrates the aggregated results of all realizations. Each boxplot span thus represents both the year-to-year variability, the uncertainty related to the climate scenarios as defined by equations (5) and (6), as well as the variability between the realizations. The year-to-year variability and the variability from ensemble member to ensemble member are discussed further in section 4.3.

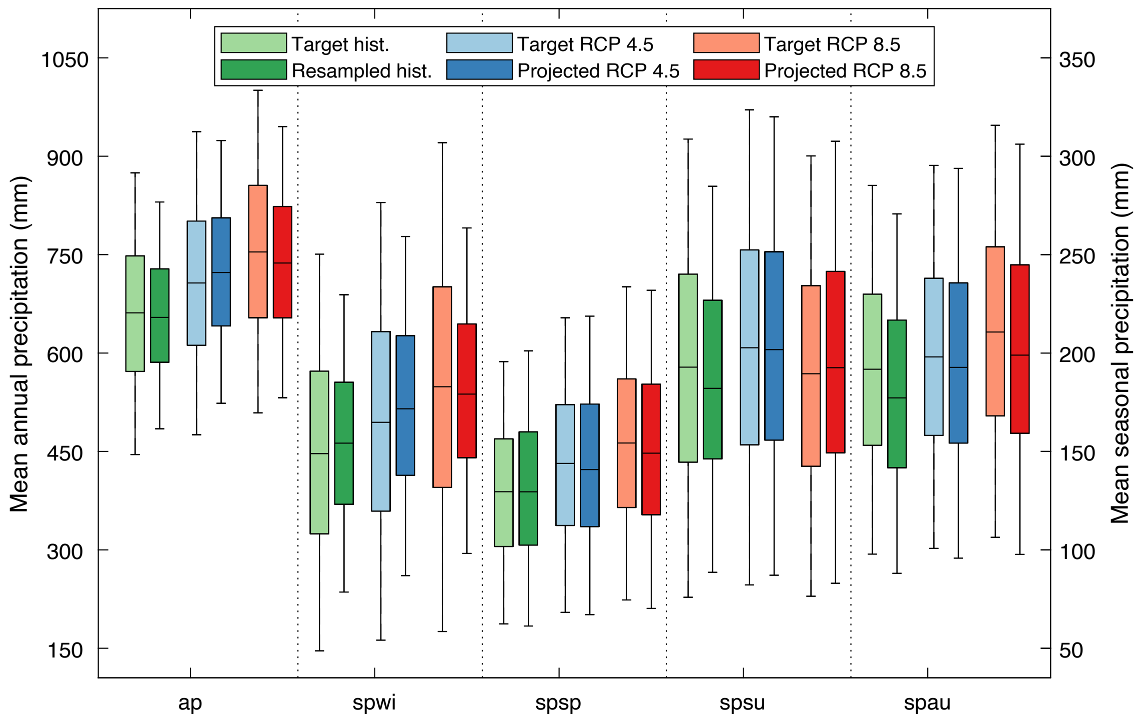
In general, there is a good agreement between the median values of targets and realizations and the equivalent quantiles for all climate variables. The realizations of winter precipitation have a smaller range than the target values, which to some extent also appear in the realizations of annual precipitation. This is most certainly due to larger uncertainties in winter precipitation observations due to the occurrence of solid precipitation in this period. In an earlier attempt, solid precipitation is removed from the reference rain series by temperature filtering. Unfortunately, that leads to a severe underestimation of winter precipitation in the reference rain series and subsequent difficulties in fitting and accepting the realizations. Based on these evaluations, it is decided to keep the data with potential solid precipitation in the reference data and accept larger uncertainties related to winter precipitation.

The statistics of dry weather periods, which we do not apply as targets for the acceptance criteria, but only serve as a validation of the accepted rain series for each climate scenario, are presented in Fig. 5 as similar boxplots as in Fig. 4. As also shown in Table 2, the climate change impacts on dry weather periods are generally less than +/- 5 % in both RCP 4.5 and 8.5. The most significant changes are the increase in the maximum dry summer period (mddsu) in RCP 8.5 which increases by 11%, and the decrease in the maximum dry winter period (mddwi) of 8 % in RCP 8.5.

Dry weather periods are generally larger in spring and summer than in autumn and winter both in current and future climate conditions. By acknowledging the rather large year-to-year variability, we consider, the generated rain series to represent both current and future climate conditions well both with regards to the total number of dry days per season as well as the maximum dry periods per season. This is also expected since we get good fits of the seasonal precipitation amounts (Fig. 4). If it was the case, that we obtained a bias in the seasonal precipitation between target and realization, it would also show as a bias in the dry weather periods. This justifies the exclusion of the dry weather periods as direct target variables.

Fig. 6 shows *IDF*-relationships for the top 100 realizations and targets of the extremes defined by return periods. The *IDF* relationships of the historical rain series (reference) are well represented by the realizations of the current climate (hist. resampled) for the 2- and 10-year return levels. There is a larger variability of the data concerning return periods larger than 10 years (not shown, but exemplified in the stormwater pond design, Fig. 8). This generally is due to the sparse occurrence of the highest-ranked events (rank 1–4) in the observation/simulation periods of 38 years.

From Fig. 6, it is also clear that there is a general increase in rain intensity from the current climate situation to the two future climate



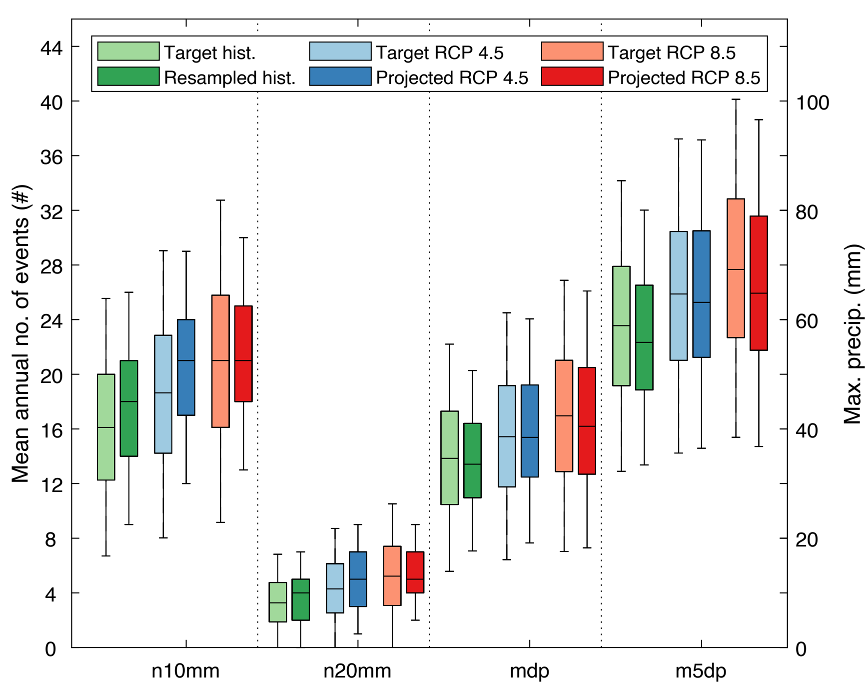
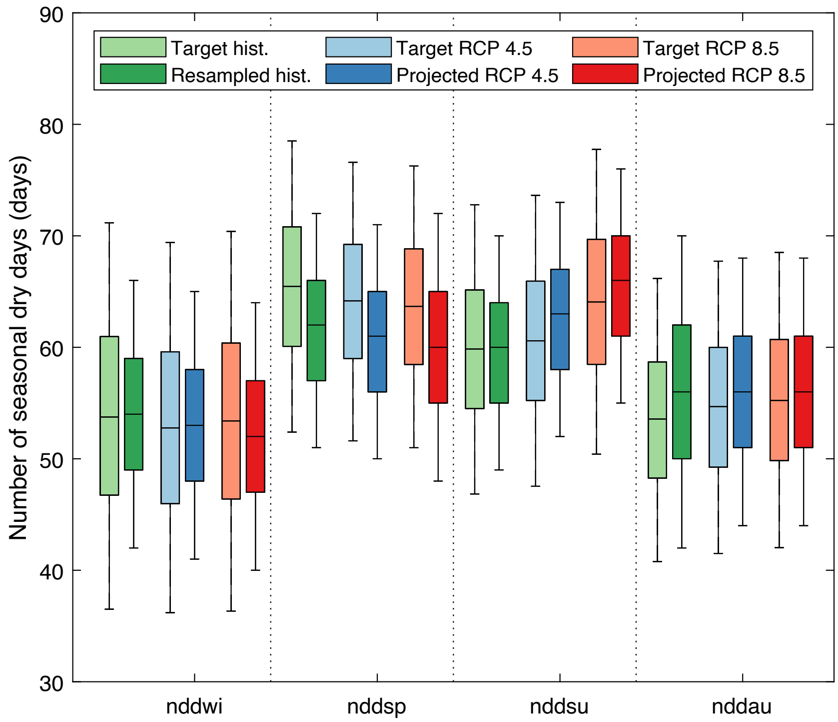


Fig. 4. Boxplots of target distributions (developed from Eq. (3) and (5)) for each climate scenario and climate variable (green: current climate, blue: RCP 4.5, and red: RCP 8.5, in muted colors) and boxplots of the top 100 realizations (based on Eq. (4) and (6)) for each climate scenario and climate variable (in vivid colors). The climate variables are: Top: Annual precipitation (ap, left ordinate axis), seasonal precipitation for winter (*spwi*), spring (*spsp*), summer (*spsu*), authmn (*spau*) on the right ordinate axis. Bottom: Annual number of events above 10 and 20 mm per day (*n10mm* and *n20mm*) on left ordinate axis, and annual maximum daily and 5-day precipitation (*mdp* and *m5dp*) on the right ordinate axis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



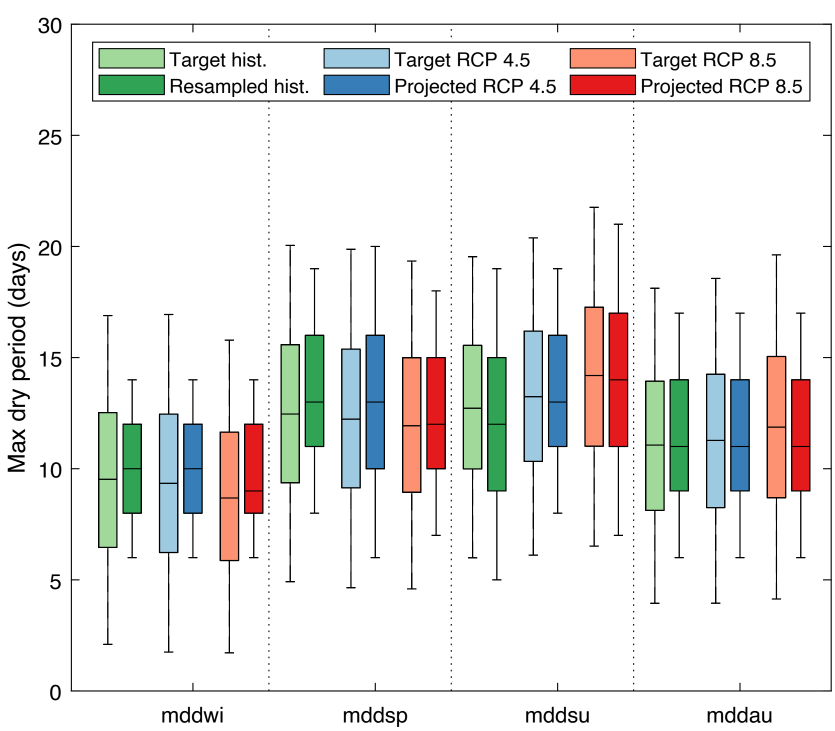


Fig. 5. Boxplots of variables related to dry weather periods for each climate scenario and validation variable (green: current climate, blue: RCP 4.5, and red: RCP 8.5, in muted colors) and boxplots of top 100 realizations for each climate scenario and validation variable (in vivid colors). The validation variables are: Top: Number of dry days per season (ndd) and bottom: maximum contiguous number of dry days per season (mdd). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

scenarios. The top 100 realizations for each climate scenario present a substantial variability, which is caused both by the stochasticity in the generation of rain series as well as the representation of uncertainties in climate projections. This is analyzed further in the response analysis (Section 4.2).

In conclusion, the specified climate variables and their target values for both means, standard deviations as well as extremes are well transferred to the stochastic realizations of current and future climate. The generated rain series therefore statistically represent both current and future climate conditions to the degree that fulfill the acceptance criteria

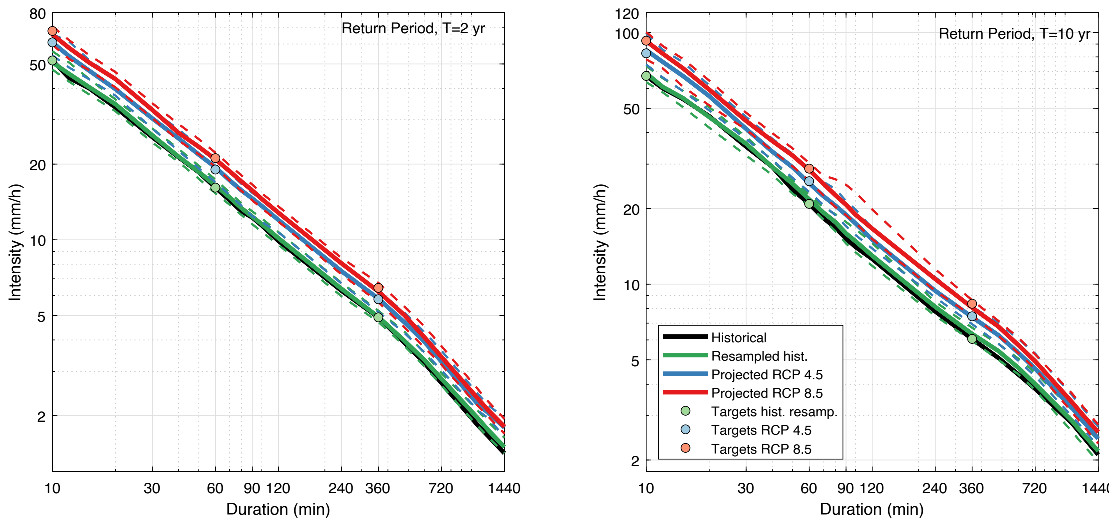


Fig. 6. 2-year (left) and 10-year (right) IDF relationships for the historical (reference) data as well as the three different climate scenarios. Solid lines denote the median of the 100 realizations and dashed lines represent 5 % and 95 % confidence intervals. Target values from table 1 are shown as circles for 10, 60, and 360 min. durations.

we define in *CLIMACS*.

4.2. Evaluation of rain series ensembles in stormwater detention pond design

The detention pond design is completed for a pond with a unit area of 1 ha of contributing catchment. We apply the historical reference series as well as each member of the three ensembles representing current and future climate conditions as continuous inputs to the calculations of pond volumes (Eq. (12)) and rank the calculated volumes to estimate the volumes corresponding to specific return periods. Fig. 7 presents an example of a continuous simulation of detention pond volume with the RCP8.5 rain series with the lowest weighted relative error (same rain series as shown on the bottom panel of Fig. 2). The highest-ranking design volumes are indicated by their respective return periods.

The return period for the design volume is initially selected as 5 years corresponding to the engineering practice of many Danish municipalities (WPC, 2007). The required pond volume is estimated for the different rain series with an outlet flow rate of 0.5, 1.0, and 5.0 $\mathrm{l\,s^{-1}\,ha^{-1}}$ corresponding to 0.18, 0.36, and 1.8 mm/h, respectively. These values represent typical outlet flow rates specified in regulatory permits given by Danish water authorities when discharging to receiving waters with different sizes and capacities (Jensen et al., 2020). A maximum outlet flow rate of 0.5 $\mathrm{l\,s^{-1}\,ha^{-1}}$ will typically be permitted discharging to a small stream, whereas 5.0 $\mathrm{l\,s^{-1}\,ha^{-1}}$ will represent a robust large stream or river.

Fig. 8 shows the calculated detention pond volumes for the different climate scenarios and the three initially selected outlet flow rates and for a fixed return period of 5 years. The ranges of the boxplots represent the ensemble variability.

Generally, there is little difference between the volumes obtained from historical (reference) and median of the resampled, which indicates that the resampled rain series on average represent the current climate well. The increase in rain intensity is evident for the two climate scenarios. The reason that the required volumes are smaller for increasing outlet flow rates is that the detention pond with a larger outlet flow rate will empty faster than with a smaller outlet flow rate. The design with smaller outlet rates will therefore consist of many succeeding coupled smaller rain events, whereas the pond design with larger flow rates is constituted by larger-intensity single events. This is also reflected in the emptying time of the ponds (Table 3), which are shown to last up to more than 20 days for very low outlet flow rates.

There is significant variability of the detention pond volumes for the top 100 realizations (Fig. 8). This variability also depends on the return period and to illustrate this, the required pond volumes are estimated as a function of return periods with a fixed outlet flow rate of 1 $\mathrm{l\,s^{-1}\,ha^{-1}}$ in

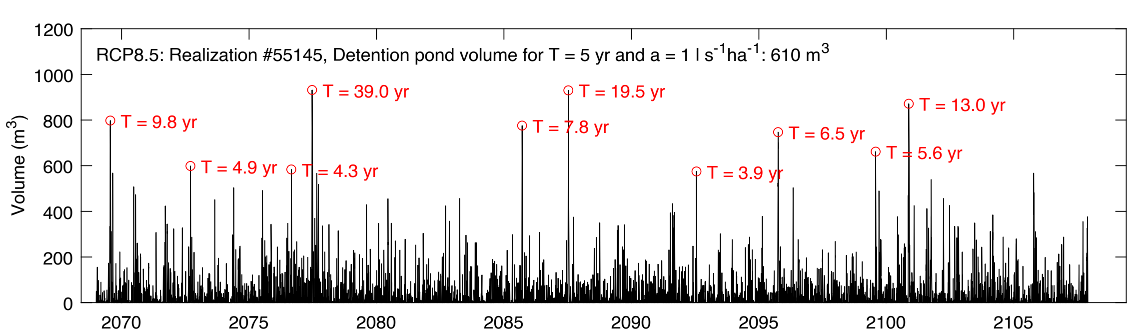


Fig. 7. Example of continuous simulation of detention pond volume with the generated RCP8.5 rain series from Fig. 2. The ten highest ranks of pond design volumes corresponding to return periods from 39 to 3.9 years are indicated by red markers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

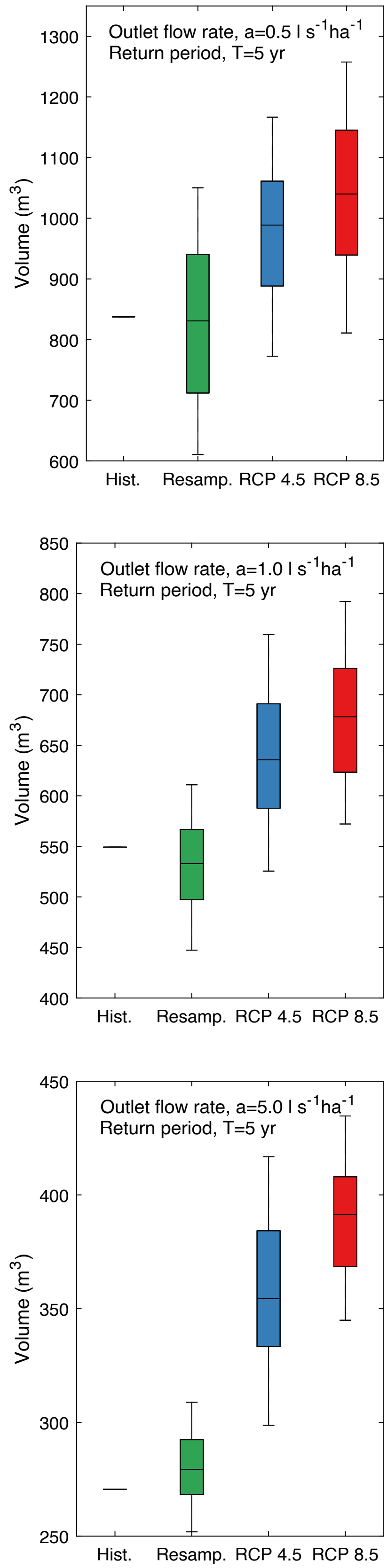


Fig. 8. Boxplots of required stormwater detention pond volumes with outlet flow rates of 0.5 l s^{-1} ha^{-1} (top), 1.0 l s^{-1} ha^{-1} (middle) and 5.0 l s^{-1} ha^{-1} (bottom) for return periods of 5 years.

Table 3
Mean emptying time of stormwater ponds as a function of outlet flow rate and climate scenario.

Outlet flow rate (l s^{-1} ha^{-1})	Mean detention pond emptying time (h)			
	Historical	Resampled	RCP 4.5	RCP 8.5
0.5	465	465	553	595
1.0	153	148	177	189
5.0	15	16	20	22

Fig. 9. As typically seen in extreme event analysis, there is an increase in variability as a function of return periods due to the ranking procedure and less data with increasing return periods. This illustrates the importance of having an ensemble of rain series to apply in the detention pond design process to evaluate the uncertainty related to the design.

In Fig. 8, it is observed that with an increase in outlet flow rate, the difference between the current and the future climate projections becomes larger. This is studied further in Fig. 10, where the mean increase in required detention pond volumes between current (represented by the mean of the resampled rain series) and future climates are plotted as a function of outlet flow rate. This shows an increase in required volume from current to future climate conditions of approx. 18 % (RCP 4.5) and 27 % (RCP 8.5) for outlet flow rates of 0.5 l s^{-1} ha^{-1} up to 29 % (RCP 4.5) and 44 % (RCP 8.5) for outlet flow rates of 8 l s^{-1} ha^{-1}. The fact that the impact of climate change is less for the smaller outlet flow rates is found in the change of distribution of rain in future climate. It is primarily the summer rainfall that constitutes the design rainfall. The total summer rainfall changes little in the future climate and at the same time, the extremes will become significantly larger (this is even more significant in RCP 8.5 than in RCP 4.5). These changes in rainfall patterns will allow for more time between individual events, which is also shown by the climate factors of the summer dry weather periods. A larger inter-event time will work in favor of smaller outlet flow rates. Since the pond design with larger outlet flow rates is more dependent on single events, the impact of the projected extreme events becomes more significant. RCP 8.5 has larger changes in peak intensity and even less total summer rainfall, compared to RCP 4.5, and therefore the mean increase-curves of Fig. 10 diverge as a function of increasing outlet flow rate.

5. Discussion

Based on the evaluation of the generated rain series on climate variables (Section 4.1) and the application of rain series ensembles in stormwater pond design (Section 4.2), it is interesting to consider and discuss the ensemble size. In many practical design applications, it might be too comprehensive to apply ensembles with 100 members for each climate scenario - especially if these practical applications are using integrated model simulations of large and complex drainage systems. It is, however, difficult to recommend a smaller ensemble of rain series or to select individual rain series that represent a specific quantile without considering each climate variable or other derived variables relevant for the application in question. Since the generated rain series are stochastic, a single ensemble member rain series might represent the upper distribution quantile for one climate variable and a lower quantile for another climate variable. A selection of an ensemble with fewer members, or even a selection of ensemble members to represent, e.g., the mean or a specific quantile, must rely on a specific derived rainfall variable. If, for example, the 60 min. rainfall intensity is identified as the most critical rainfall duration for a specific part of a drainage system, the reduction of the ensemble, or the selection of specific members should be done based on the statistics of the 60 min. rainfall. If, on the other hand, the application depends on multiple variables, or critical variables that have not been identified beforehand, it is recommended to apply the full ensemble to propagate the uncertainty of the climate projections through the application. Statistics of the simulated model response can

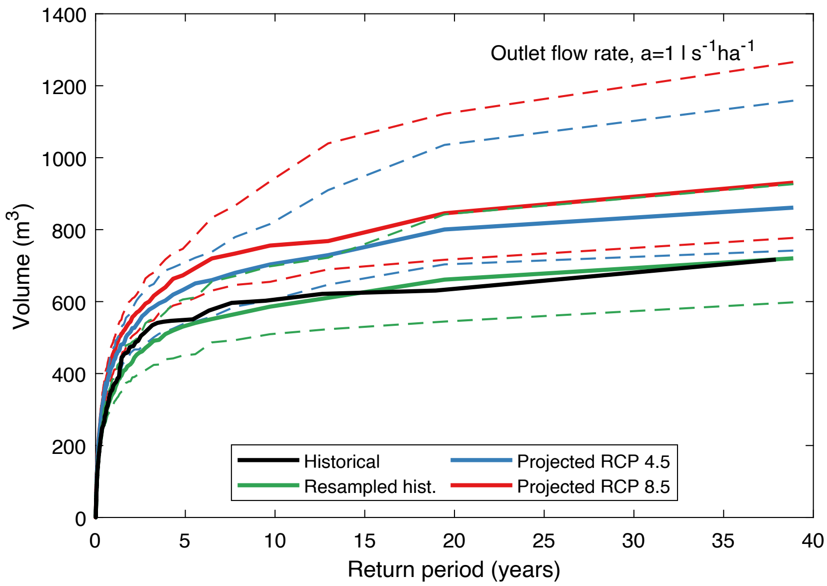


Fig. 9. Stormwater detention pond volume as a function of return period for a fixed outlet flow rate of 1.0 l s^{-1} ha^{-1}. Solid lines are median values and dashed lines are the 5 % and 95 % confidence bands of each simulated ensemble.

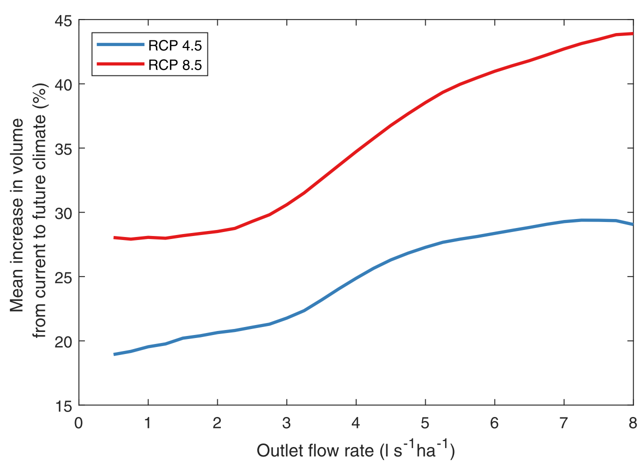


Fig. 10. Mean increase in required storage volume from current to future climate as a function of outlet flow rate.

then subsequently be derived and design decisions can be made based on the uncertainty evaluation of the system response rather than on the rainfall input.

6. Conclusion

The current need for climate projected continuous long-term rain series for urban drainage design is provided by the development of *CLIMACS*. The method provides a novel stochastic resampling of individual rain events, interevent time, and climate scaling. Based on one single historical reference rain series, three ensembles, each with 100 members are developed to represent current climate conditions as well as projections to the period 2071–2100 with RCP 4.5 and 8.5, respectively. The ensemble members are selected according to a minimization of the relative error between the 15 target climate variables and realizations of generated rain series. It is possible to generate rain series that fit both seasonal precipitation and dry weather means and standard deviations as well as extremes considering both year-to-year variabilities as well as the uncertainty of climate projections of climate variables. Due to large uncertainties in the projections of the 15 climate variables, the variability of the generated rain series also becomes large. In the application of the generated rain series for urban drainage design purposes, it is therefore important to consider the ensemble variability to evaluate the uncertainty related to the design and climate projection.

CLIMACS has a general application within urban drainage design that requires long-term continuous rain series to represent the complexity of drainage system response based on rainfall loads. This is illustrated by the design of stormwater detention ponds where continuous rain series are needed as inputs to simulate the effects of antecedent rainfall conditions, that is, the emptying of the pond between rain events. By varying the outlet flow rate from the detention pond, the design volume becomes differently dependent on the continuity of the rain series. With a large outlet flow rate, the design volume is more or less dependent on single events. For smaller outlet flow rates, the pond does not empty between events and therefore becomes more dependent on multiple successive events and the interevent time. In the future climate, the pond volume, therefore, becomes dependent on the projection of dry weather periods as well as the increase in the design rainfall intensity. This complexity illustrates the need for a continuous climate projected rain series that can include heterogeneity in the projection of rainfall to represent multiple climate variables, seasonal variability, representation of extremes, and changes in interevent time (or dry weather periods).

CRediT authorship contribution statement

Søren Thorndahl: Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Christoffer Bang Andersen:** Data curation, Methodology, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The paper is developed as part of the KLIMAKS projected funded by VUDP, DANVA grant no. 1162.2017 and Aarhus Water Utility, Denmark. The authors would like to acknowledge project partners: Aarhus Water Utility (Lene Bassø Duus), NIRAS (Lene Lykke Kraglund and Preben Dam Simonsen), and Danish Meteorological Institute (Fredrik Boberg) for contributions to inputs, applications, and testing.

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