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Towards improving the calibration practice of conceptual hydrological models of extensive green roofs

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ABSTRACT

Conceptual rainfall-runoff models (CRRMs) can be used as a design tool for green roofs due to their simplicity and acceptable accuracy. This study showed how the uncertainty of CRRM parameters could be reduced by changing the calibration practice, which can enhance the interpretation and identifiability of CRRM parameters. A CRRM was developed and tested on a dataset of 14 extensive green roofs located in four Norwegian cities with different climatic conditions. Two calibration schemes were compared: a common scheme using runoff data as a basis for calibration (single-objective), and a scheme combining runoff and soil moisture data for the calibration (multi-objective scheme). The results confirmed the ability of the CRRM to simulate runoff from extensive green roofs across multiple climatic zones and different roof configurations (Kling Gupta Efficiency $>$ 0.75). The multi-objective calibration scheme was found to reduce the uncertainty of the CRRM parameters, especially the storage parameters, enhancing the physical interpretation of parameter values. The study attempted to give guidelines to estimate parameters of the CRRM which can be used by practitioners for new roof configurations under different climatic conditions.

1. Introduction

Urbanization converts the natural undeveloped areas into impermeable surfaces such as roads, parking lots, and rooftops. This results in decreased evapotranspiration and infiltration, and increased stormwater runoff on a catchment level. The ongoing climate change is causing an increase in the intensity of precipitation for many places around the globe (Sun et al., 2006), while global urbanization is growing rapidly (Luederitz et al., 2015). The combined effect of climate change and rapid urbanization is expected to increase the stormwater runoff in the future, as stated by Yazdanfar & Sharma (2015) among others. Green roofs have over the past decade become a popular solution to reduce stormwater runoff in urban areas. Green roofs have shown great potential in reducing runoff from rooftops, as concluded by many studies (Fassman-Beck et al., 2013; Johannessen et al., 2018; Stovin, 2010). Additionally, green roofs have been shown to improve runoff water quality, enhance urban biodiversity and improve visual amenities in urban areas (Czemiel Berndtsson, 2010).

Much of the current literature on green roofs pay particular attention to the performance of different green roofs under different climatic conditions through field measurements (Fassman-Beck et al., 2013; Hamouz et al., 2018; Johannessen et al., 2018; Stovin, 2010). Some studies applied hydrological models to test green roofs performance beyond the measured data and roof characteristics which is of great interest for planning future cities (Li & Babcock, 2016; Stovin et al., 2013). Hydrological models of green roofs can serve as a valuable tool for decision-makers and stormwater engineers for planning and design purposes. These practitioners prefer models that i) require less effort to set up, ii) run with low computation costs, and iii) give reliable results (Johannessen et al., 2019). Conceptual rainfall-runoff models (CRRM) fulfil these criteria as they are simpler and computationally cheaper than physically-based models. Additionally, their results are more generic and interpretable than data-driven models.

CRRMs have been applied successfully in many green roof studies (Palla et al., 2012; Soulis et al., 2017; Stovin et al., 2013; Vesuviano et al., 2014; Yio et al., 2013). The most common conceptualization is to represent the roof with a cascade of linear or nonlinear tanks representing the different roof layers (i.e., vegetation, substrate, and drainage layers). The storage and the flow of water between the tanks are controlled via parameters. Due to the simplification of these conceptual models, most of their parameters are not physically measurable, and hence calibration is needed to find their optimal values.

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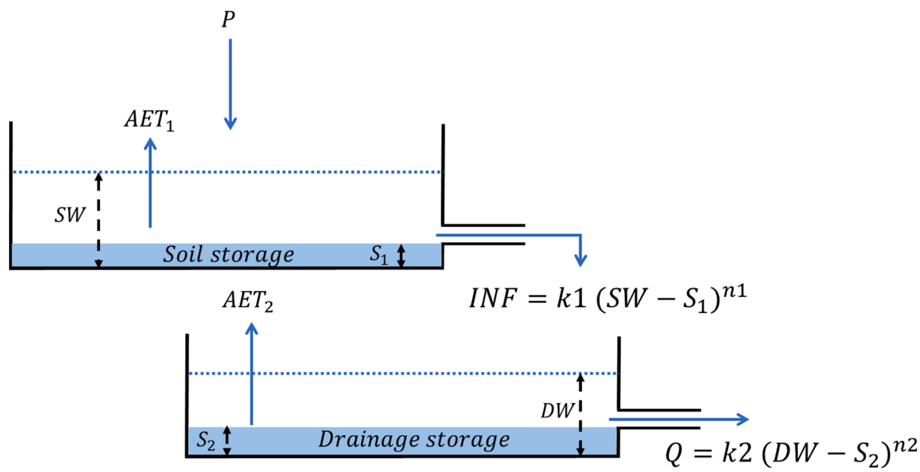

Fig. 1. The hydrological model used in this study.

Many studies have attempted to link the parameters of CRRMs and the physical characteristics of the green roofs. For instance, Stovin et al. (2013) explained how the storage parameters in their reservoir model could be estimated from the substrate's measurable physical properties (i.e., field capacity). Vesuviano & Stovin (2013) found the parameters of the drainage layers in their model to be independent of rain intensity, while correlated with the physical properties of the drainage layer and the slope of the roof. Yio et al. (2013) found the flow parameters of the substrate layer to be correlated to the depth of the substrate. Similarly, Soulis et al. (2017) described how the depth of the roof affected the flow parameter in their reservoir model. However, all the above-mentioned studies were conducted in lab-scale green roofs in which horizontal water flow through the roof structure is insignificant due to the short horizontal flow length compared to a full-scale roof. Hence, there is a need for further studies to estimate CRRM parameters for full-scale green roofs. Estimating parameters of green roof models has been done for other models than the reservoir routing based models. For instance, Johannessen et al. (2019) attempted to transfer parameters of a SWMM model (Rossman, 2015) between similar full-scale green roofs located in four Norwegian cities. The calibrated parameter sets for the same type of green roofs differed between the cities, limiting the performance of the transferred parameter sets.

The limited knowledge on how to estimate CRRM parameters of green roofs from climatic and roof characteristics can be attributed to the uncertainty of finding their optimal values. Many sources of uncertainties can affect parameter values, such as the uncertainty of model inputs, uncertainty due to the calibration practice, and the induced uncertainty due to the model structure. For instance, Sims et al. (2019) attributed the errors of their hydrological model to the uncertainty of initial soil moisture measurements. On the other hand, Hernes et al. (2020) found the lack of temporal storage in the drainage layer in the Mike-Urban model (DHI, 2017) to be compensated by the model by assigning unrealistic parameter values during calibration to fit with the observed discharge. In this study, we investigated the effect of the calibration practice on CRRM parameters values.

Many calibration practices can be found in green roof modelling studies, such as maximizing NSE between observed and simulated runoff (Hamouz & Muthanna, 2019; Liu & Fassman-Beck, 2017; Soulis et al., 2017), or minimizing the error between observed and simulated runoff (such as the sum of square error or the root mean square error) (Alfredo et al., 2010; Vesuviano et al., 2014; Yio et al., 2013). However, it was found that for all the studies, the measured runoff was the only quantity used as a basis of calibration in most green roof modelling studies. This was found despite the fact that using only one measured quantity (e.g., observed runoff) for model calibration increases the uncertainty of parameter values (Beven, 1989). This is because the parameters of the substrate and vegetation layers do not explicitly simulate the runoff process but other internal processes (i.e., infiltration, evapotranspiration, soil storage, plant storage, etc.). Hence, using one measured quantity (i.e., runoff) might cause convergence towards the wrong parameter set due to the compensation and interaction between model parameters which increase the equifinality (Beven, 1993), in which different parameter sets give similar results. Hernes et al. (2020) demonstrated this by presenting two different parameter sets of a green roof model that gave the same results due to the compensation between substrate and drainage parameters.

The benefits of constraining hydrological models by calibrating against more than one measured quantity, hereafter referred to as "multi-objective calibration", have been discussed frequently in general hydrological modelling studies. Seibert (2000) applied a multi-objective calibration scheme that combined measured groundwater level data and observed streamflow data to calibrate a CRRM for multiple catchments. The author found that the multi-objective calibration scheme significantly reduced parameter uncertainty compared to the typical scheme using streamflow measurements only. A similar finding was found by Beldring (2002), in which groundwater level data and runoff data were used to calibrate a physically-based model for a Norwegian catchment. Parajka et al. (2009) found a multi-objective calibration scheme combining soil moisture data with runoff data to provide a more robust parameter set for a CRRM compared to using only one measured quantity. Budhathoki et al. (2020) applied a multi-objective calibration scheme incorporating in-site soil moisture measurements with runoff data to calibrate a distributed hydrological model. The study found that the scheme to reduce parameter uncertainty while enhancing the simulation accuracy of the internal catchment storage in comparison to a calibration scheme that only used flow measurements.

In this study, a CRRM was developed and validated using a dataset of 14 full-scale extensive green roofs located in four Norwegian cities with different climatic conditions. In addition, the study investigated the advantages of multi-objective calibration (i.e., using soil moisture and runoff for calibration) in green roof CRRMs. The study sheds light on how the multi-objective calibration improves the model results by reducing the uncertainty of model parameters, enhancing their identifiability, and their physical interpretation. Moreover, the study attempted to develop a general guideline for estimating parameters for the CRRM from climate and physical roof characteristics simplifying the use of the model for practical applications.

Table 1
Roof geometries and configurations.

Category	City	Area (m^2)	Slope (o)	Substrate type and thickness	Drainage layer type and thickness
Thin1	BERG	7.84	16	VM (30 mm)	RF (3 mm)
	OSL	8	5.5	–	–
	SAN	8.48	27	VM (30 mm)	RF (3 mm)
	TRD	15	16	–	–
Thin2	BERG	7.84	16	VM (30 mm)	RF (10 mm)
	OSL	8	5.5	VM (30 mm)	RF (10 mm)
	SAN	8.48	27	VM (30 mm)	RF (10 mm)
	TRD	15	16	VM (30 mm)	RF (10 mm)
Medium	BERG	7.84	16	VM (30 mm)	MW (50 mm)
	OSL	8	5.5	–	–
	SAN	8.48	27	VM (30 mm)	MW (50 mm)
	TRD	15	16	VM (30 mm)	MW (50 mm)
Thick	BERG	7.84	16	VM (30 mm) + BS (50 mm)	EPS (75 mm) + RF (5 mm)
	OSL	8	5.5	VM (30 mm) + BS (50 mm)	HDPE (40 mm) + RF (5 mm)
	SAN	8.48	27	VM (30 mm) + BS (50 mm)	EPS (75 mm) + RF (5 mm)
	TRD	15	16	VM (30 mm) + BS (50 mm)	HDPE (25 mm) + RF (5 mm)
Valid	TRD	100	2	VM (30 mm)	RF (10 mm) + HDPE (25 mm)

VM = Pre-grown vegetation mats (sedum plants).
RF = Retention fabric.
MW = Mineral wool plate.
BS = Brick substrate (a mixture of Leca and bricks).
EPS = Plastic drainage layers of expanded polystyrene.
HDPE = Plastic drainage layers of high-density polyethylene.

2. Methods and tools

2.1. The hydrological model

The hydrological model is a simple two-stage reservoir model (Fig. 1), somewhat similar to the one applied in the study by Vesuviano et al. (2014) and to the FAVEUR model (Ramier et al., 2018). The model represents the roof layers by two tanks: an upper tank for the substrate layer and a lower tank for the drainage layer. The precipitation (P) enters the substrate and fills the available storage of the substrate layer (S1). Water infiltrates into the lower tank when the storage of the substrate layer is surpassed. The infiltration process is determined by Equation (1). The drainage layer stores the water (S2), and the water starts to flow from S2 (Q) after the storage of the drainage layer is filled (Equation (2)).

$$INF_t = k1(max(SW_t - S1, 0))^{n1} \tag{1}$$

$$Q_t = k2(max(DW_t - S2, 0))^{n2} \tag{2}$$

$$SW_t = max(SW_{t-1} + P_t - AET1_t - S1, 0) \tag{3}$$

$$DW_t = max(DW_{t-1} + INF_t - AET2_t - S2, 0) \tag{4}$$

Evapotranspiration is allowed from both storage tanks. Actual evapotranspiration (AET) (Equation (7) and Equation (8)) is determined from the potential evapotranspiration (PET) and the actual soil moisture. The Oudin equation (Equation (5)) was used to determine PET following recommendations from Johannessen et al. (2017). In the Oudin equation, PET is a function of the latitude and the Julian day as follows:

$$PET\left[\frac{mm}{day}\right] = \begin{cases} 0 \ if \ T_{mean} \leqslant 5C \\ \frac{Ra}{\lambda\rho} \times 0.01 \times (T_{mean} + 5) \ if \ T_{mean} > 5C \end{cases} \tag{5}$$

T_{mean} is the daily mean temperature [C*Ra* is extra-terrestrial radiation derived from the Julian day and latitude [MJ.m^{-2}], $\frac{1}{\lambda\rho} \approx 0.408$, λ the latent heat of vaporization [MJ.kg^{-1}], ρ is the volumetric mass of water [kg.m^{-3}]. The reduction factor (f_t) due to the moisture deficit was determined using a simple soil reduction function (Equation (6)).

$$f_t = min(1, \frac{SW_{t-1}}{S11}) \tag{6}$$

$$AET1_t = f_t \times PET_t \tag{7}$$

$$AET2_t = min(DW_{t-1}, PET_t - AET1_t) \tag{8}$$

S11 is a calibrated parameter representing a threshold of the soil moisture, after which the AET equals the PET.

2.2. The calibration schemes

The model has seven calibrated parameters: the storage parameters (S1, S2), the substrate flow parameters (k1, n1), the drainage flow parameters (k2, n2), and an evapotranspiration parameter (S11). Two calibration schemes were tested:

- Single-objective calibration: maximize KGE_Q (objective function 1 **OF1**)
- Multi-objective calibration: maximize $KGE_Q \times KGE_{SW}$ (objective function 2 **OF2**)

KGE_Q is the Kling-Gupta Efficiency (Gupta et al., 2009) between simulated and observed runoff and KGE_{SW} is the Kling-Gupta Efficiency between simulated and observed soil moisture. According to Thiemig et al. (2013), the KGE can be used to classify model results as follows:

- Good (KGE ≥ 0.75)
- Satisfactory (0.75 > KGE ≥ 0.5)
- Poor (unsatisfactory) (0.5 > KGE)

Multi-objective calibration techniques can be divided into Pareto-based and aggregated (Efstratiadis & Koutsoyiannis, 2010). The Pareto-based approach detects sets of non-dominated solutions using multi-objective evolutionary algorithms while the aggregated approach selects a unique parameter set by multiple criteria embedded into one aggregated objective function, making it a best compromise. In this study, the adopted multi-objective calibration scheme can be classified as an aggregated approach, similar to the work of Seibert (2000).

We evaluated two parameterization options of the CRRM; a linear parameterization in which the values of n1 and n2 were fixed to one during calibration (5 calibrated parameters), and a nonlinear parameterization in which n1 and n2 are calibrated (7 calibrated parameters). Both calibration schemes were applied to the linear and nonlinear parameterizations of the CRRM.

For calibration, the differential evolution algorithm (DE) (Storn & Price, 1997) was applied using the Deoptim library in R (Mullen et al., 2011). The algorithm solved the optimization problem by generating populations of candidate solutions. Each new population was generated from the previous one in such a way that the new objective function of each candidate was either improved or kept the same in the next generation. For each calibration scheme, 200 generations were done. The number of candidates in each population was selected as $the number of model parameters \times 10$. The best result of each generation was stored. The best solution of the 200th generation was considered as the optimized parameter set. Due to the lack of a snow routine in the current model, snow periods were excluded (1st of October – 31st of March) from the simulations. 2017 was used for model calibration while 2016 was used for model validation. The simulations were done using a 5-minute time step.

Fig. 2. Comparison between the two calibration schemes and the two parameterizations of the CRRM at Thin2 roofs.

3. Green roof data

Fourteen green roofs, located in four Norwegian cities: Bergen (BERG), Trondheim (TRD), Sandnes (SAN), and Oslo (OSL), were used in this study. BERG receives the highest amount of precipitation, followed by SAN, TRD, and OSL. The four cities cover three classes of the Köppen Geiger classification system (Kottek et al., 2006). TRD has a subpolar oceanic climate (Dfc) while OSL has the warm-summer humid continental climate (Dfb). The climate of Bergen and Sandnes cities is classified as temperate oceanic climate (Cfb). The green roofs were categorized into five groups based on their configurations: *Thin1* with a thickness of 33 mm, *Thin2* with a thickness of 40 mm, *Medium* with a total thickness of 80 mm, and *Thick* with a thickness higher than 100 mm. An additional category termed “*Valid*” includes an additional green roof located in Trondheim (TRD), described in Hamouz et al., (2018). The *valid* roof was used to verify the applicability of the developed guidelines to estimate the parameters of the reservoir model. The details of the roof configurations are presented in Table 1. Precipitation, temperature, and runoff were collected in 1-min resolution between 2015 and 2017 at BERG, SAN, and TRD, while OSL roofs have eight years of records from 2011 to 2017. The roof “*Valid*” has a data record of 11 months collected between May 2017 to April 2018. Details about field measurements and data processing are documented by Johannessen et al. (2018) and Hamouz et al. (2018).

4. Results and discussion

4.1. Parameterization of the CRRM

The *Thin2* roofs in the four cities were used to compare linear and nonlinear parameterizations of the CRRM, as shown in Fig. 2. The result confirmed the ability of the two parameterization options to simulate

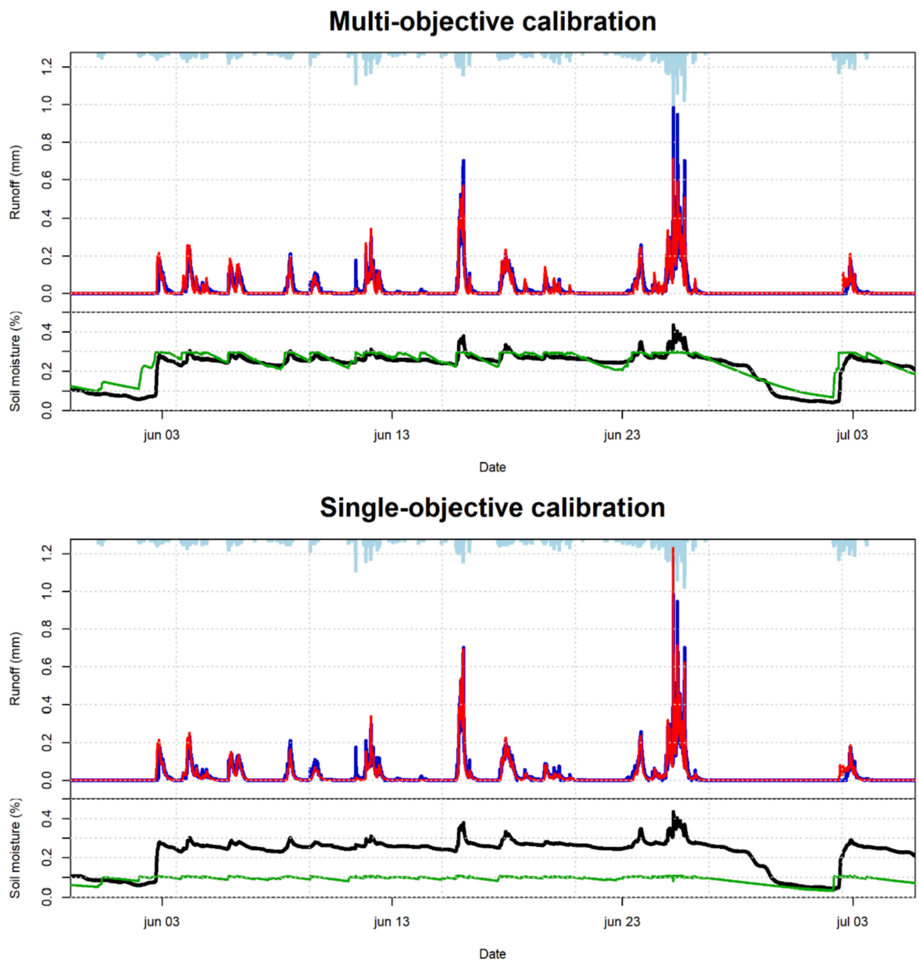

Fig. 3. Comparison between the two calibration schemes in simulating runoff and soil moisture (Thin2-BERG) for one month (calibration period).

observed and simulated discharges in both calibration and validation periods ($KGE \geq 0.75$). The nonlinear parameterization of the CRRM produced slightly better runoff simulations (higher KGE values) than the linear option, especially in BERG and OSL roofs. Similarly, Skala et al. (2019) found a nonlinear model in their study to yield more accurate results than a linear cascade model. This can be attributed to the higher degree of freedom for the nonlinear parameterization due to the number of calibrated parameters, which improves the calibration (Schoups et al., 2008). However, the reduced number of calibrated parameters and the fact that the results produced by the linear parameterization of the CRRM model are still classified as good, based on the KGE criteria (Thiemig et al., 2013) make the linear parameterization of the CRRM more favourable over the nonlinear one. Models with few parameters are widely recommended in the hydrological modelling literature over models with higher model parameters (Kay et al., 2006; Oudin et al., 2008; Tsegaw et al., 2019) due to the reduced model parameter interactions and uncertainties.

4.2. Calibration schemes and parameter values

The comparison between the two calibration schemes is presented in Fig. 2. By considering runoff data only as a basis for calibration, it is possible to produce good results of runoff simulations ($KGE > 0.75$) for both the calibration and validation data. However, by applying the single objective calibration, there is a high risk of yielding unsatisfactory soil moisture simulations. Fig. 3 and Fig. 4 present one month of runoff and soil moisture simulations from calibration and validation periods at *Thin2*-BERG roof using the two calibration schemes. The results show how it is possible, by applying the single-objective scheme, to achieve satisfactory runoff calibration in both the calibration and validation periods with a large deviation on the simulated internal state of the roof (i.e., soil moisture), which in this case was underestimated. This demonstrated the need for alternative calibration strategies which account for the internal state and runoff response. In this case, it was found that the optimizer converged to optimal solutions by splitting the total roof storage between the substrate and the drainage layer in an unrealistic way which resulted in erroneous soil moisture simulation results. A consequence of this approach was a high correlation between the storage parameters (S1 and S2) which could result in equifinality, where different parameter sets yield similar results. Similar correlations were found by Locatelli et al. (2014) between the storage parameters when only runoff was used as a basis for calibration. Applying the multi-objective calibration strategy, the model produced satisfactory results for both flow and soil moisture simulations. Budhathoki et al. (2020) found the same, that multi-objective calibration produced better soil-moisture simulations than single-objective calibration. Similarly, Seibert (2000) reported better runoff and groundwater level simulations by following a multi-objective calibration compared to a single-objective scheme. It should be noted that the TRD and SAN roofs have large gaps in soil moisture measurements in the validation year, which resulted in low values of KGE for the simulated soil moisture.

The results presented in Fig. 5 and Fig. 6 illustrate the parameter sets of the best solution in each of the 200 generations identified by the DE algorithm for the nonlinear and linear parameterization of the CRRM, respectively. It can be noted that the calibration scheme highly affects the uncertainty of parameter values in the two parameterizations of the CRRM. This can be seen in Fig. 5 and Fig. 6 by the range of parameter values giving the same modelling results. The single-objective

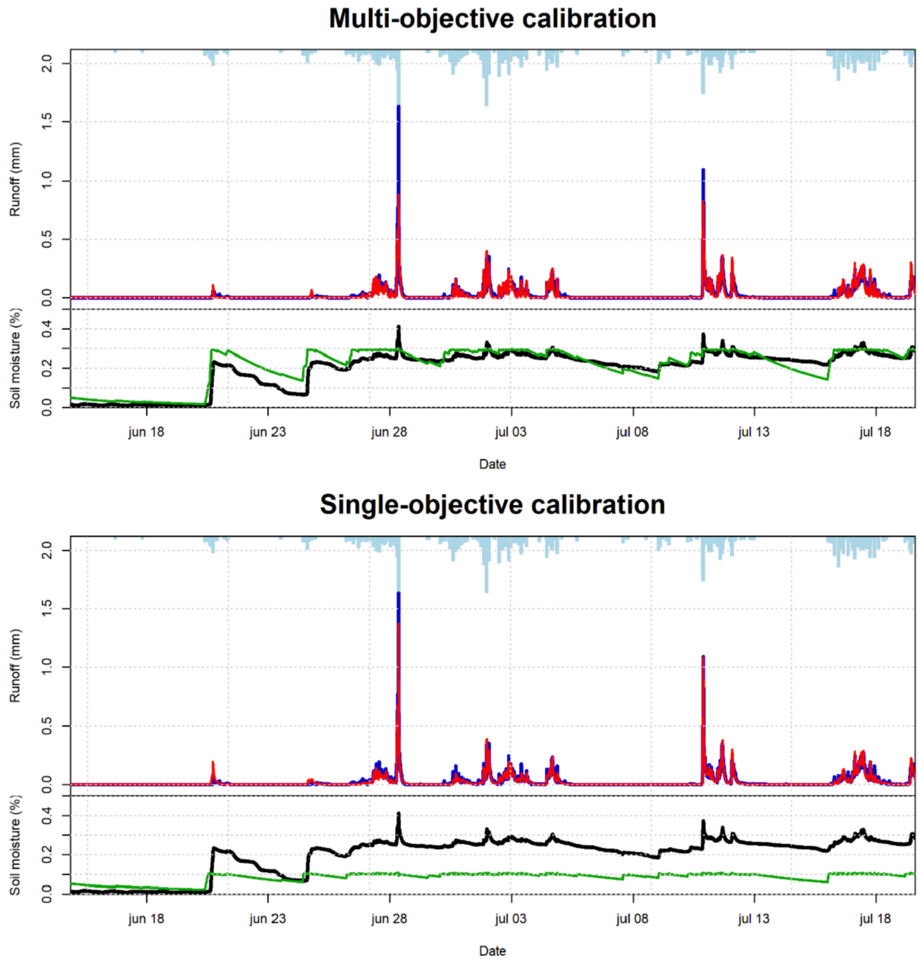

Fig. 4. Comparison between the two calibration schemes in simulating runoff and soil moisture (Thin2-BERG) for one month (validation period).

calibration made it difficult to conclude on the optimal set of parameters, especially the storage parameters, if no prior knowledge about the system is utilized. For instance, Soulis et al. (2017) applied runoff only for calibrating a reservoir model. However, the storage parameters in the model were fixed following the result of lab measurements and the calibration results of a physical-based model. As presented in Fig. 5 and Fig. 6, the multi-objective calibration scheme resulted in unique clusters of solutions for most parameters that were easier to interpret than the solutions of the single-objective scheme. For instance, S1 values of the *Thin2* roofs clustered around 10 mm and ranged between 7 mm and 11 mm, accounting for 23% to 36% of the substrate thickness. Likewise, Locatelli et al. (2014) concluded a similar value of S1 when they applied a reservoir model for a green roof with 30 mm substrate depth, similar to the *Thin2* roofs.

In addition, minor differences between S1 values in the four cities were noted. For instance, the roofs at OSL and SAN had a higher S1 value than those at BERG and TRD. This can be attributed to the different geometries of the roofs, particularly the slope. The OSL roofs have a mild slope of 5.5%, and TRD and BERG roofs have a slope of 16% and SAN has a slope of 27%. Through lab measurements, Getter et al. (2007) found the green roof retention (i.e., available permanent storage) to increase by decreasing the roof's slope. The S1 values at the SAN roof location were slightly higher than those at BERG and TRD, despite the 27% slope. Though this was somewhat contradictory to expectation, it is difficult to evaluate accurately the value of S1 due to the quality of the soil moisture dataset, which can be seen in the model performance during validation. Another factor that could explain the minor differences of S1 values is the difference of vegetation types and densities amongst the roofs, as reported by Johannessen et al. (2018). TRD and BERG have lower vegetation coverage and percentages of Sedum plants, in comparison to SAN and OSL roofs which results in different substrate properties (i.e. porosities) due to roots development.

Another interesting finding was the S11 parameter, the threshold at which the actual evapotranspiration equals the potential. The parameter had a unique value for each city, which can be explained by the difference in local climatic conditions (e.g. wind exposure, air humidity, solar radiation) and the vegetation types and densities. As reported in Johannessen et al. (2018), TRD roofs were the most wind-exposed, which increased the evapotranspiration resulting in a lower value of S11 than the other roofs. In comparable studies, S11 has been fixed to the maximum holding capacity of the roof (Stovin et al., 2013). Arguably, fixing S11 to the maximum holding capacity might lead to an overestimation of green roof retention for locations without enhanced evapotranspiration conditions (e.g., low wind exposure). In addition, the differences of vegetation types and densities between the roofs as reported in Johannessen et al. (2018) study could partly explain the geographical difference of S11. *Thin2* roofs at TRD and BERG have higher percentages of local vegetation than OSL and SAN roofs, which enhances evapotranspiration, resulting in lower values of S11 parameter. Johannessen et al. (2018) reported higher values of event-based retention of *Thin2* roofs at TRD and BERG in comparison to SAN and OSL cities.

The value of S2, the permanent storage in the drainage layer, varied between the four cities. At OSL and SAN roofs, S2 was found to vary between 1 mm and 2 mm, whereas the value of S2 in TRD and BERG was found to higher and to vary in a wider range, as shown in Fig. 6. The model used in this study does not explicitly account for the storage due to the plant interception. Therefore, the parameter S2 represents the

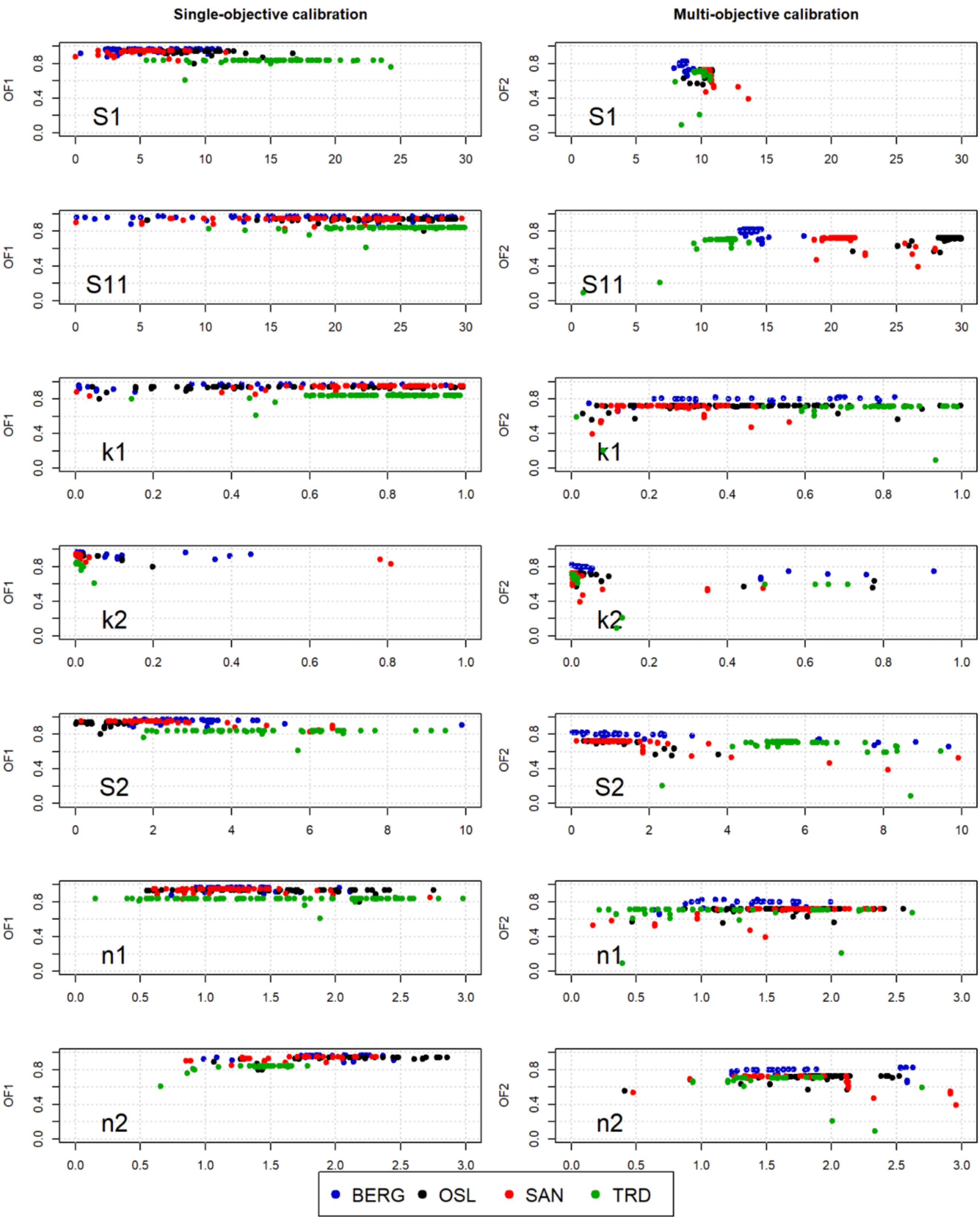

Fig. 5. Calibration results of the two schemes at Thin2 roofs (the nonlinear parameterization of the CRRM).

permanent storages in the drainage and vegetation layers. Hence, the variation of S2 amongst the roofs can somewhat we explained by the differences of vegetation densities and types (Johannessen et al., 2018). Locatelli et al. (2014) developed a CRRM for extensive green roofs with an additional layer representing the plant interception. They found the storage parameter of the vegetation layer to be 0.8 mm.

The sensitivity of S2 was investigated by running grid simulations in which S2 was changed by a fixed step (1 mm) while fixing the other

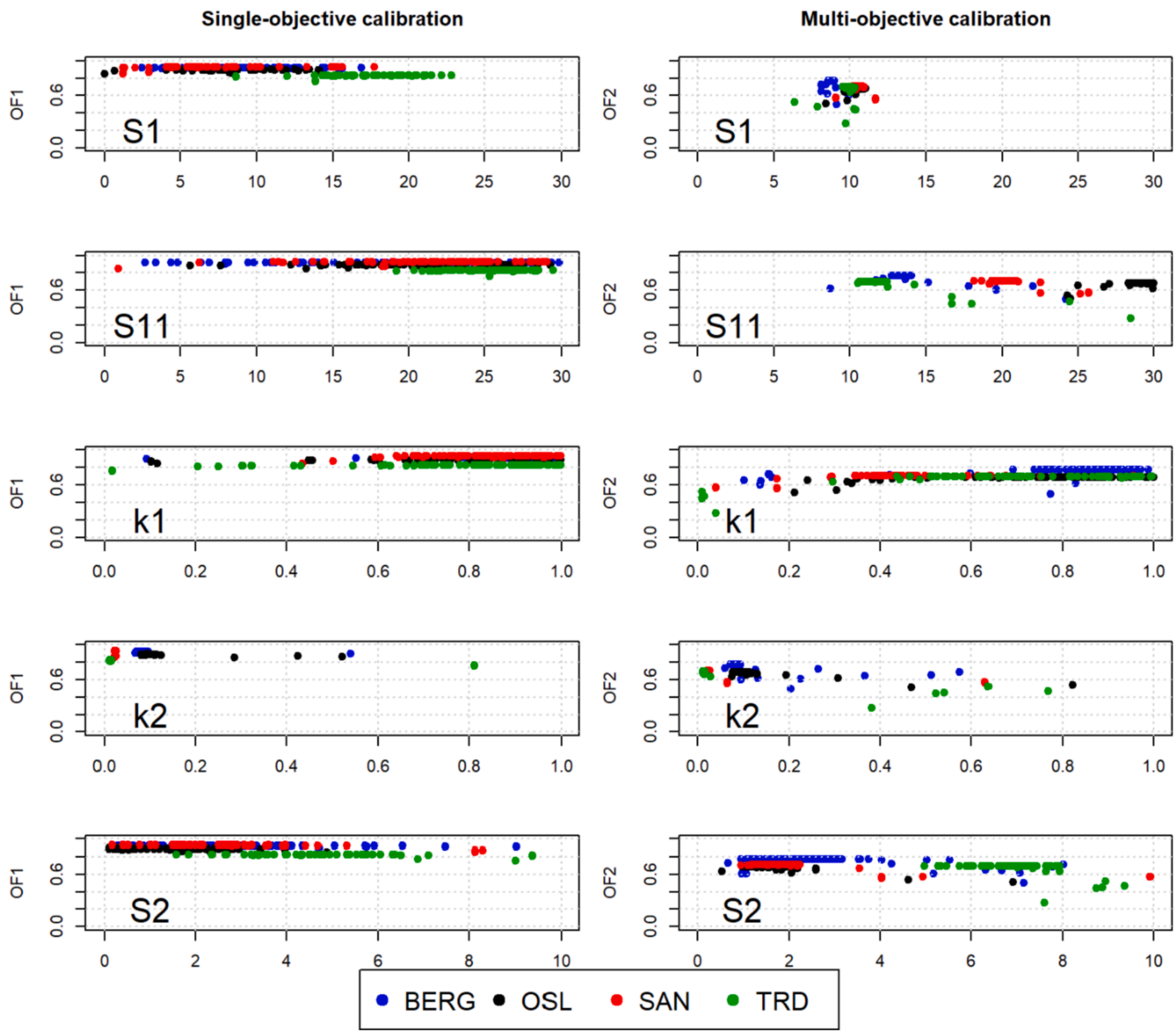

Fig. 6. Calibration result of the two schemes at Thin2 roofs (the linear parameterization of the CRRM).

model parameters to their optimal values. The results of these simulations are illustrated in Fig. 7. Changing the value S2 parameter was found to have no effect on the simulated soil moisture (KGE_{SW}) and to have a little impact on the quality of runoff simulation (KGE_Q), except for the *Thick* roofs at TRD and OSL and the Medium roof at TRD. In addition, the range of S2 between (1 mm – 2 mm) could yield good modelling results ($KGE_Q > 0.75$) in most of the roofs in the study.

The parameters n1 and n2 showed unpredictable variations for both calibration schemes, probably due to compensation with other model parameters, further strengthening the conclusion of using the linear parameterization of the CRRM. Similarly, Vesuviano et al. (2014) suggested fixing the value of n in their reservoir model due to the compensation between the n and k parameters.

By following the multi-objective scheme, the parameter k1 showed a wide range of variation in the linear parametrization of the CRRM (Fig. 6). We investigated how k1 and k2 are related in all roofs in the study. This was done by running grid simulations (Fig. 8) in which k1 and k2 were changed by a small step (0.01) while fixing S1, S2, and S11 parameters. The result presented in Fig. 8 suggested a unique k1-k2 relationship for each green roof thickness that was influenced by the local climatic conditions as well. The k1 and k2 values can be interchangeable for *Thin* roofs (*Thin1* and *Thin2*). This means that a model with high k1 and low k2 can achieve the same response as a model with low k1 and high k2 values. However, this is not valid for *Thick* roofs where the k2 value must be lower than k1 for optimal performance. The parameter k1 represents the portion of water above field capacity that flows into the drainage layer, representing the vertical infiltration of water through the substrate. The k2 parameter represents the horizontal movement through the drainage layer (i.e., the portion of water that leaves the roof system). Green roofs substrates are designed with high porous materials to avoid surface ponding, and thus quickly moving from the substrate to the drainage layer after reaching field capacity. Additionally, the horizontal flow distance (i.e. roof length) is typically higher than the vertical flow distance (i.e. substrate) by orders of magnitude in extensive green roofs Hence, the vertical movement of water is typically faster than the horizontal movement (Johannessen et al., 2018). Therefore, it can be concluded that the value of k1 should be higher than k2, which is illustrated in Fig. 8. It was found that the k1 value can be fixed between 0.75 and 1 for all roofs in the study.

After fixing the k1 value to 0.75, the variation in the k2 value can be attributed to the location, and to, some extent, the roof depth (Fig. 9). Similar relations between roof flow parameters and the substrate depth were described by Yio et al. (2013) and Soulis et al. (2017). TRD and SAN roofs were found to have lower k2 values, in comparison to the roofs at BERG and OSL cities. This is can be partly explained by the difference in rainfall events characteristics amongst the four cities. For instance, BERG city receives rainfall events with higher amount and intensity and has shorter anticipant dry weather periods (ADWP), in

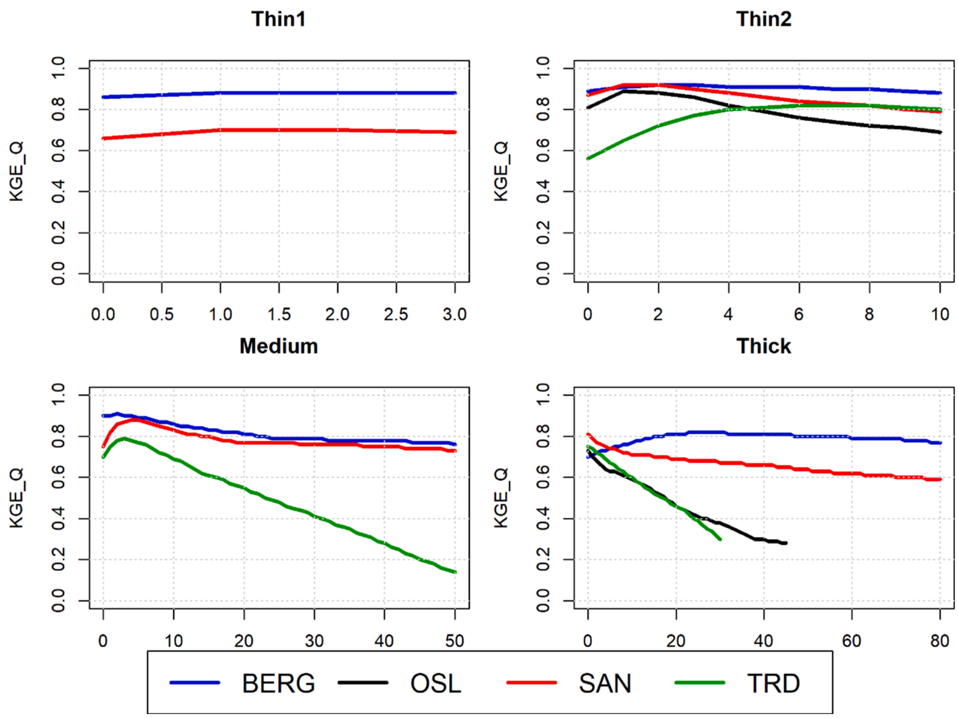

Fig. 7. Effect of varying the value of S2 (mm) on the value of Kling-Gupta efficiency (KGE_Q) of the simulated discharges at the four cities for the four roof configurations and for the linear parameterization of the CRRM.

comparison to TRD and SAN cities (Abdalla et al., 2021). Consequently, the green roofs located at TRD and SAN have, in most of the time, lower soil moisture contents than the green roof at BERG. As a result, the green roofs at BERG were found to have higher k2 values (more outflow) in comparison to the roofs at TRD and SAN, as illustrated in Fig. 9.

It should be noted that OSL roofs have the mildest slope and the highest k2 values. This is somewhat contradictory to expectation as k2 values are expected to be higher for steep roofs and lower for roofs with mild slopes. One possible explanation is the differences of rainfall-events characteristics amongst the four cities, which influence the value of k2 parameter as explained earlier. Hence, it is expected to observe a higher impact of roof slope on the value of k2 if roofs with different slopes are tested in the same location.

4.3. Calibration and validation of the CRRM model

Following the multi-objective calibration, the linear CRRM was calibrated and validated for all the green roofs at the four locations in the study. The results are shown in Table 2.

The result confirmed the CRRM's ability to produce good runoff modelling results ($KGE_Q > 0.75$) in most cases. Some of the soil moisture simulations results were unsatisfactory ($KGE_{SW} < 0.5$), especially for the TRD and SAN roofs which were attributed to large gaps in soil moisture measurements.

The value of S1 for *Thin1*, *Thin2*, and Medium roofs was found to be 9.56 ± 1.44, accounting for 27–36% of the substrate depth. For *Thick* roofs, the S1 value was found to be 29.3 ± 1.44, which is equivalent to 34% to 38% of the substrate depth. These are consistent with the reported literature values of the maximum holding capacities of vegetation mats (Johannessen et al., 2018; Locatelli et al., 2014) and brick-based substrates (Stovin et al., 2013). It can be noted that the variation of S1 values was larger for *Thick* roofs. One possible explanation could be the different drainage layer configurations for the roofs in this category (Table 1).

4.4. Practical applications of the CRRM

The hydrological performance of green roofs is typically assessed by estimating retention and detention. The former is the permanent reduction of stormwater due to evapotranspiration, and it is typically determined from flow accumulation curves (Stovin et al., 2013). On the other hand, the detention is the delay and attenuation of drainage outflows due to the temporal storage of water within the green roof layers. Detention is typically estimated via several indicators such as peak reduction rate, peak delay, and centroid delay (Stovin et al., 2017) or by using flow duration curves (Hernes et al., 2020). The model developed in this study can be used by practitioners (e.g., stormwater engineers, city planners, etc.) to plot flow accumulation curves and flow duration curves from long-term simulations to estimate retention and detention performance. Fig. 10 presents the simulated and observed flow accumulation curves and flow duration curves for *Thin2* roofs. Flow accumulation curves illustrate the cumulative reduction of precipitation water due to the evapotranspiration of the green roof. As shown in Fig. 10, the model gave accurate estimations of flow accumulation curves at the different climatic regions. On the other hand, flow duration curves show the values of runoff from green roofs and durations when these runoff values are exceeded. Therefore, they represent the practical implication of green roof detention (i.e. peak delay and attenuation). For instance, Hernes et al. (2020) showed how the implementation of green infrastructures at the catchment scale could reduce the duration of drainage flows above a critical value that triggers combined sewer overflow events. As presented in Fig. 10, the CRRM estimated accurately the flow duration curves at the four cities except for high runoff values (duration < 1hr) and low values (duration > 1000 hr).

4.5. Guidelines to estimate parameters of the linear CRRM

Well-calibrated CRRM yielded satisfactory runoff and soil moisture simulations across different climatic regions and can be used to estimate green roof retention and detention performances. Based on the results of this study, we attempted to give guidelines that can be used to estimates

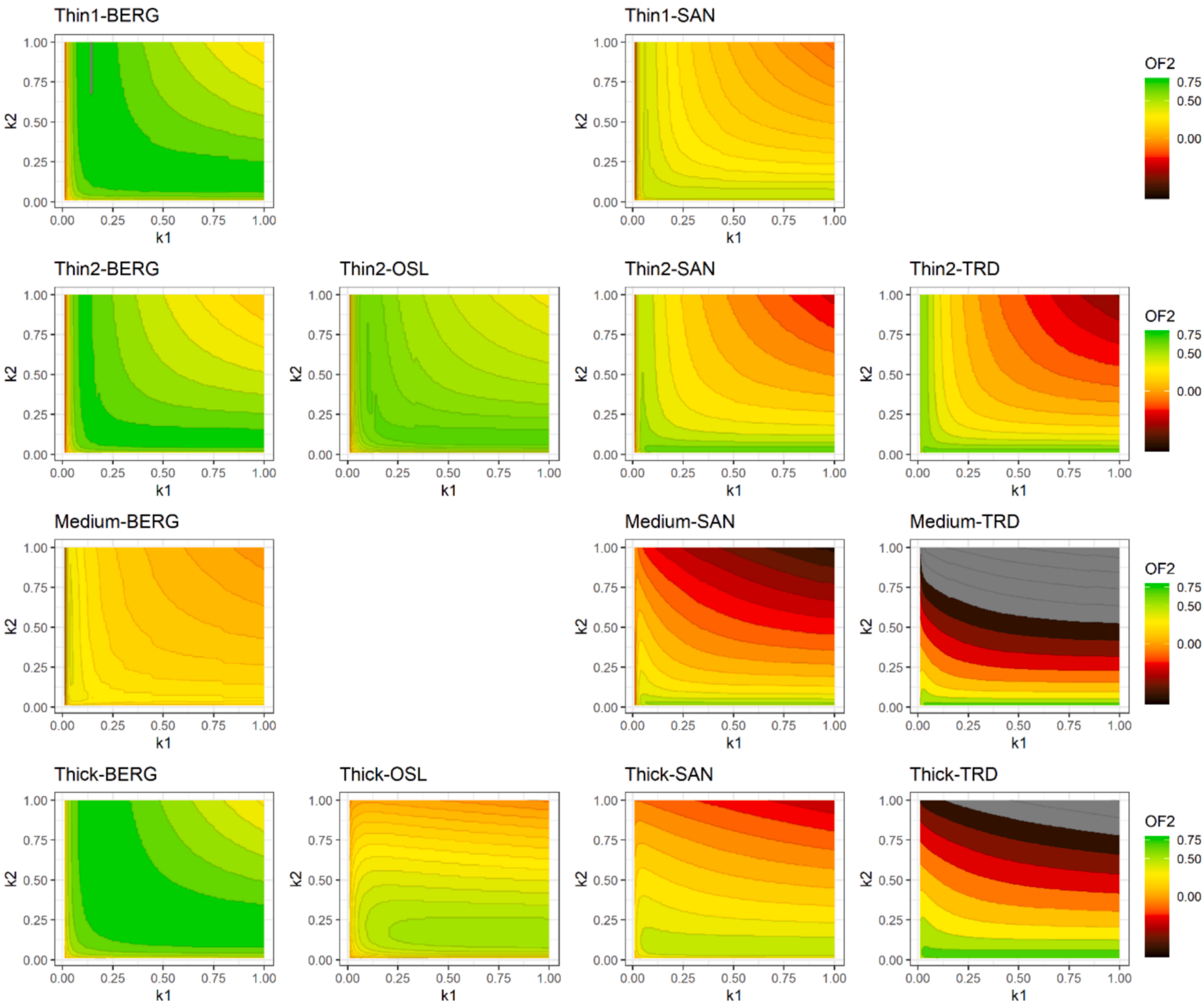

Fig. 8. Effects of changing k1 and k2 parameters (using the linear parameterization of the CRRM).

the linear CRRM parameters, when observations are not available for model calibration:

- S1 represents the available permanent storage in all substrate layers. Vegetation mats were found to have around 23% to 36% of their total depth, while brick-based substrates have around 40% of total substrate depth.
- The optimal range of the parameter S2 was found to be (1 mm–2 mm) in most of the roofs. This parameter represents the permanent storages of the vegetation (i.e. interception) and drainage layers.
- S11 varies according to local climatic conditions and the vegetation characteristics of the green roof but it is typically less than the total substrate thickness. S11 is lower for locations with enhanced evapotranspiration conditions (wind exposure, humidity, vegetation density, etc.). Further studies are needed to relate the S11 value with local climatic conditions and vegetation characteristics.
- The value of k1 represents the vertical movement of water, which is typically faster than the horizontal movement. A k1 value of 0.75 was found to fit with the different roof characteristics and climatic regions.
- The value of k2 ranges between 0.01 and 0.15 in all roofs in our study. It depends mainly on the climatic conditions and slightly on the roof thickness. A low k2 value is expected in dry locations, and a high k2 value is expected in wet locations and mild-sloped roofs.

These guidelines were tested on a month-long simulation for the *Valid-TRD* roof (July 2017) (Fig. 11). High KGE values were obtained for soil moisture and runoff simulations ($KGE_Q = 0.77$, $KGE_{sw} = 0.82$), indicating good simulation results (Thiemig et al., 2013).

The value of S1 was initially selected as 10 mm yielding a good runoff simulation but overestimated the soil moisture. By reducing the value of S1 to 6 mm it resulted in a good fit with the *Valid-TRD* roof. This can be attributed to the difference in substrate age between *Valid-TRD* roofs and the other roofs in the study. De-Ville et al. (2017) found the holding capacity of a crushed brick-based substrate of an extensive green roof to increase by 7% over five years. The modelled period of *Valid-TRD* was during the third month of operation of the roof, which might explain the reduced S1 value compared to other roofs. It should be noted that the type of substrate in the study by De-Ville et al. (2017) was different from the substrate of *Valid-TRD*. The value of S11 was taken as 30 mm, which was estimated from the value of S11 at OSL. This because the roof is almost flat (2 degree) which affects its exposure to wind and hence reduce the evapotranspiration. k1 was fixed to 0.75 following the general guidelines, while the value of k2 was estimated as 0.02 from Fig. 8 by following the curves of TRD. S2 was taken as 1.5 mm, following the general guidelines.

5. Conclusions

This study developed a CRRM reservoir model that can be used to estimate the hydrological performance of green roofs. The study highlighted the benefits of the multi-objective calibrations, in which soil moisture measurements are used for calibration together with runoff data in green roof CRRMs. Based on the results, the following

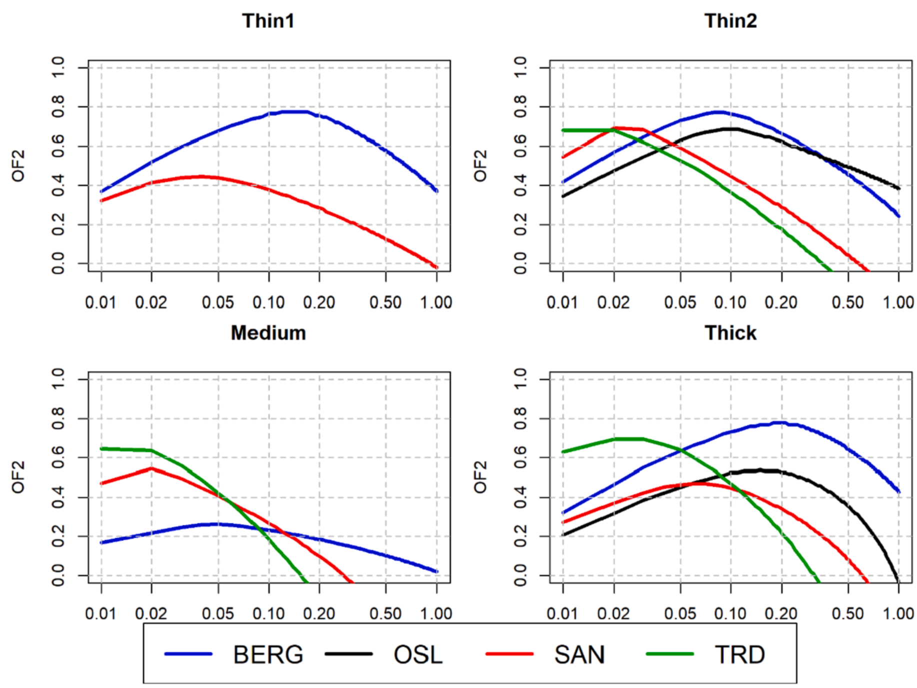

Fig. 9. Effect of varying the value of k2 on the value of the objective function (OF2) at the four cities for the four roof configurations (k1 = 0.75) and for the linear parameterization of the CRRM.

Table 2
Optimal parameters for the roofs (Linear model/calibration scheme 2).

Category	City	S1	S11	k1	k2	S2	Calibration		Validation	
							KGE_Q	KGE_{SW}	KGE_Q	KGE_{SW}
Thin1	BERG	9.66	16.44	0.14	0.82	1.51	0.88	0.91	0.88	0.8
	OSL									
	SAN	10.65	23.15	0.16	0.04	1.74	0.7	0.64	0.81	0.52
	TRD									
Thin2	BERG	8.74	13.58	0.81	0.08	2.82	0.92	0.84	0.89	0.87
	OSL	10.96	29.64	0.67	0.10	1.38	0.89	0.77	0.83	0.77
	SAN	10.40	19.66	0.48	0.02	1.79	0.92	0.77	0.82	0.38
	TRD	9.75	11.96	0.96	0.01	7.07	0.82	0.85	0.75	0.44
Medium	BERG	6.38	9.42	0.04	0.36	2.10	0.91	0.4	0.89	−0.4
	OSL									
	SAN	10.68	24.24	0.35	0.02	3.16	0.88	0.63	0.89	0.52
	TRD	8.46	12.45	0.73	0.01	2.60	0.79	0.84	0.79	0.58
Thick	BERG	29.43	17.65	0.86	0.20	28.50	0.82	0.95	0.84	0.88
	OSL	31.46	30.98	0.87	0.15	0.01	0.73	0.74	0.72	0.82
	SAN	29.53	30.06	0.76	0.07	0.00	0.81	0.58	0.73	−0.41
	TRD	27.24	24.36	0.90	0.03	0.06	0.75	0.94	0.78	0.09

conclusions were drawn:

- The results confirmed the ability of the CRRM to simulate runoff from extensive green roofs across multiple climatic zones and different roof configurations
- The multi-objective calibration scheme reduced the uncertainty of the CRRM model parameters, especially the storage parameters, which enhances the physical interpretation of CRRM parameters values. The scheme results in comparable runoff simulations as the single-objective scheme while yielding satisfactory soil moisture simulations.

This study attempted to give practitioners guidelines to estimate the linear CRRM model parameters for new roof configurations. However, we acknowledge the difficulties of identifying k2 and S11 parameters solely from the green roof characteristics. The variation of the parameter k2 amongst the cities was attributed to the rainfall characteristics of each city (i.e. amount, intensity, ADWP). The variation of the parameter S11 was attributed to the local climatic conditions (i.e. wind exposure, air humidity, solar radiation, etc.) and vegetation characteristics of the green roof (density and type).

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.

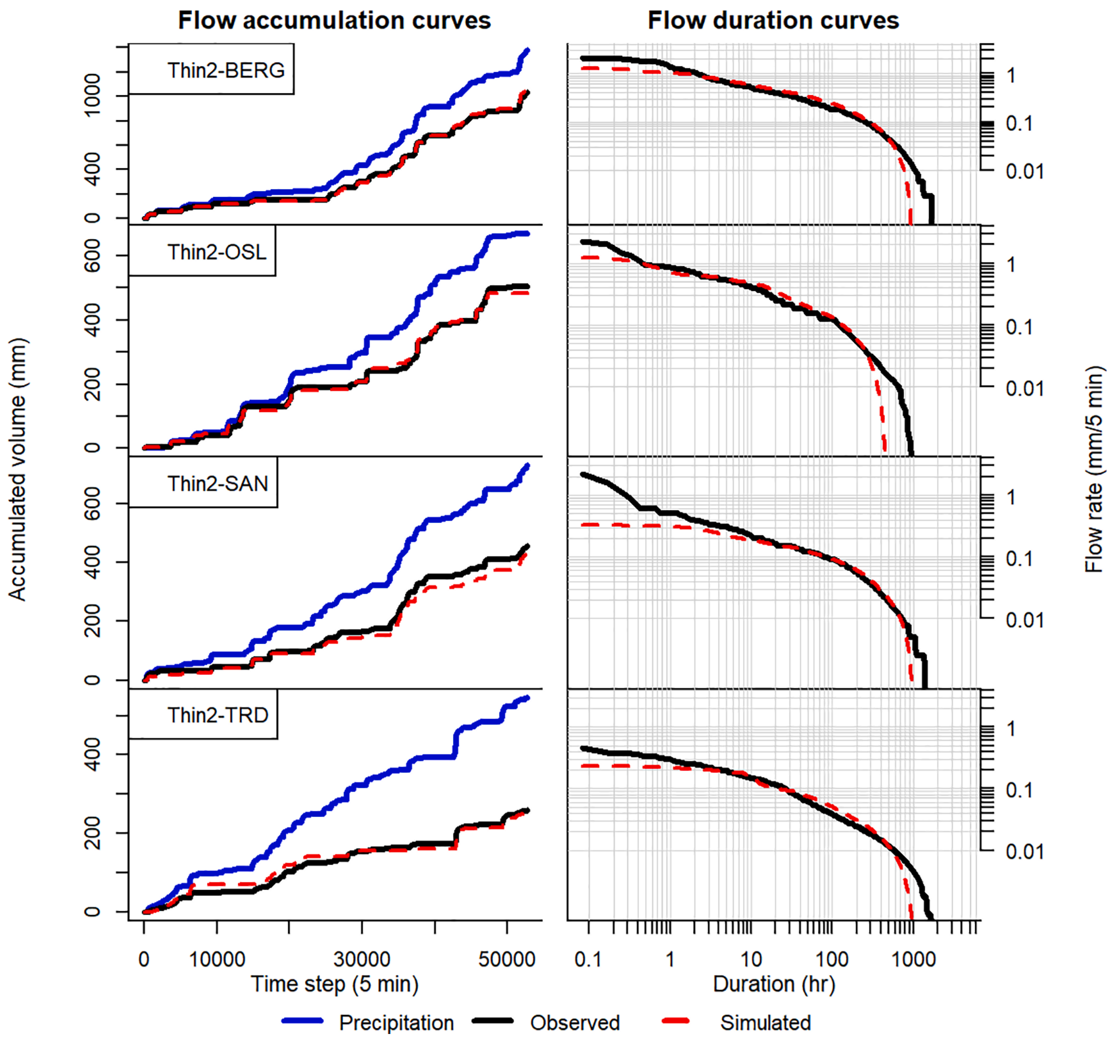

Fig. 10. Observed and simulated flow accumulation curves and flow duration curves for Thin2 roofs (validation periods).

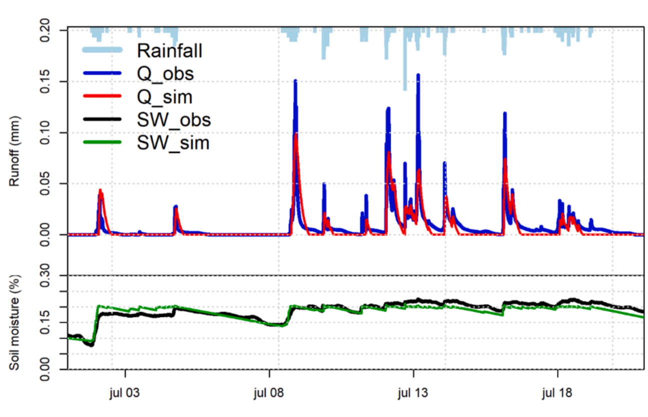

Fig. 11. Validation of the general guidelines at VALID-TRD roof.

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