Can small reservoirs be used to gauge stream runoff?

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Abstract

Understanding stream runoff generation processes requires distributed stream runoff estimates ; however the acquisition of such estimates remains challenging in hydrology, especially in remote areas. In regions with a high spatial density of small reservoirs, those reservoirs could be employed to gauge stream runoff (Liebe *et al.*, 2009). Using a water balance approach, the stream runoff flowing into a reservoir from a drainage catchment could be estimated. Accordingly, this work aims to address the following two questions: i) what is the error in the estimated stream runoff and ii) what are the main estimation uncertainty factors? Based on a case study of the Kamech catchment, Tunisia, stream runoff was estimated at different temporal resolutions (1-32 days), and a global sensitivity analysis was performed to estimate the contributions of the reservoir water balance terms (evaporation, rainfall, percolation, reservoir water level and level-area-volume relations) to the estimated stream runoff uncertainty.

The results reveal that stream runoff can be reliably estimated based on small reservoirs using a mass balance approach. The error and global stream runoff estimation uncertainties decrease as the temporal resolution increases. The bathymetric relationships (level-area and level-volume relations) constitute a strong factor of uncertainty for all temporal resolutions, and even the dominant factor for temporal resolutions ranging from 4 to 23 days. The estimation uncertainty for the shortest temporal resolutions (1-8 days) mainly originates from reservoir level uncertainty. As the temporal resolution increases, the contribution of percolation uncertainty increases. The general (not site-specific) conclusions of this study are that stream runoff gauging based on small reservoirs requires the determination of the bathymetric relations and that small reservoirs could be used as reliable stream runoff gauges at short temporal resolutions if the reservoir level is measured with limited uncertainty and at long temporal resolutions as long as the percolation rate from the reservoir is known with limited uncertainty.

keywords

gauging stream runoff, reservoir water balance, uncertainty, global sensitivity analysis,

Highlights

- Small reservoirs could be used to gauge catchment stream runoff
- Stream runoff is estimated based on a small reservoir using the water balance approach
- High stream runoff are better estimated than low ones
- The performance of estimation improves as the temporal resolution increases [1d-32d]
- Bathymetric relations, percolation and reservoir level estimation are the main sources of uncertainty

Introduction

Stream runoff time series constitute basic and critical data in hydrology that are needed to better understand the mechanisms underlying the variability and generation of stream runoff and are essential for quantifying the status of water resources and planning and implementing management operations. Stream runoff data are important for hydrological modelling performed for both scientific and operational objectives. These time series are also necessary for understanding the biogeochemical cycles and ecological functioning of streams. However, acquiring either local (at a point) or spatially distributed stream runoff time series data remains a real challenge in hydrology; this challenge is particularly acute in remote areas, such areas in arid and semi-arid environments.

Small reservoirs have been erected in arid and semi-arid locales for supplying water (often for agriculture) and preventing downstream flooding. Despite the lack of a formal definition, a small reservoir is commonly characterised by a storage capacity smaller than 1 Mm^3 (Habets *et al.*, 2018). A small reservoir often consists of a small dam built across a valley to intercept and store stream runoff. For decades, small reservoirs have been increasingly constructed in many countries. Consequently, in some catchments,, such as those in Australia (Schreider *et al.*, 2002 ; Nathan & Lowe, 2002) and in South Africa (Hughes & Mantel, 2010), the density can exceed 1 reservoir/km^2. The idea to use small reservoirs as stream gauges has already been examined (Albergel & Rejeb, 1997 ; Mekki et al., 2006 ; Liebe *et al.*, 2009). Liebe *et al.* (2009) used a simple hydrological model coupled with the remote monitoring of a small reservoir to simulate daily stream runoff time series for a catchment in Ghana. Furthermore, using the water balance approach, the water levels in small reservoirs have been continuously monitored to estimate stream runoff, for instance, in Tunisia by Albergel and Rejeb (1997) and Mekki *et al.* (2006). The technological development of automatic water level sensors and remote data transmission and the development of community-based approaches (Starkey *et al.*, 2017), could enhance the availability of data for the evaluation of the water balance and thus improve the use of small reservoirs as stream runoff gauges.

The objective of this study is to examine the relevance of regarding small reservoirs as stream gauges based on the water balance approach. This study relies on the Kamech catchment, Tunisia, which is a research catchment draining into a small reservoir. We followed a two-step approach. In the first step, the stream runoff was estimated at different temporal resolutions based on the reservoir water balance; then, the estimated time series data were compared with stream runoff measurements obtained from a classic stream gauge station. To evaluate the adding value of the reservoir method, we also estimated, as a comparison, stream runoff based on a more straightforward method used in engineering hydrology which is the runoff coefficient. In the second step, a global sensitivity analysis was performed to identify and quantify the main sources of uncertainty in the stream runoff estimated using the reservoir water balance approach. Based on these results, the feasibility of considering small reservoirs as stream gauges is discussed.

1. Study catchment and data

The Kamech catchment is a small catchment (2.63 km²) located in northern Tunisia. The Kamech catchment is one of the two catchments in France and Tunisia of the observatory OMERE (an acronym for Mediterranean Observatory of Rural Environment and Water or « Observatoire Méditerranéen de l'Environnement Rural et de l'Eau », in French) (Molénat *et al.*, 2018); the catchment also belongs to the French network of critical zone observatories called OZCAR (Gaillardet *et al.*, 2018). The catchment characteristics, equipment and monitoring are extensively described in Molénat et al. (2018). Climatically, the region is semi-arid to sub-humid, and the 25-year mean annual rainfall and reference evaporation are 645mm and 1366mm, respectively.

In 1992, a dam was built across the wadi at the catchment outlet to prevent siltation in a large downstream dam. The reservoir has a capacity of 135,000 m³ (Figure 1). The reservoir intercepts runoff from the wadi and lateral surface runoff along its banks. The water within the reservoir may be withdrawn for irrigation in spring and summer, and water can also be released when the reservoir reaches its capacity to ensure the safety of the dam's infrastructure. In the present study, we chose the water year 2011-2012 during which releases and withdrawals were either null or negligible.

Hereafter, we present the available data by estimating the relative or absolute errors in each measurement, as these errors are particularly important for the global sensitivity analysis performed in this work. Rainfall in the catchment is measured using a tipping bucket gauge located on the dam. In this work, the hourly mean rainfall rate is used. The relative error in a rainfall measurement acquired by a tipping bucket depends on many factors, such as the rainfall intensity and volumes of the compartments within the bucket; consequently, the relative errors vary considerably in the literature (Habib *et al.*, 2001 ; Wang *et al.*, 2008). In this work, we assumed a relative error of 20% in the rainfall measurements corresponding to the highest values of an hourly time step reported in previous studies (Wang *et al.*, 2008). Pan evaporation is measured daily using a pan located on a bank of the reservoir near the dam. The hourly evaporation rate was derived from daily records considering a sinusoidal hourly variation each day. Evaporation from the reservoir water free surface e_{fs} in the reservoir was derived from pan evaporation e_{pan} considering a pan coefficient, k, of 0.65 (Bouteffeha *et al.*, 2015) according to $e_{fs}=k.e_{pan}$. In general, the k factor can vary across reservoirs and within a given reservoir over time. Regarding lake or reservoir evaporation, k is generally found to be lower than 1.0 with wide variations ranging from 0.5 to 1.2 (e.g. Fu et al., 2004; Martinez Alvarez et al., 2007). In this work we considered both the error associated with pan evaporation measurements, e_{pan}, and the error associated with the determination of the pan coefficient, k. By applying a logarithmic transform of the latter relation and then deriving, we can deduce that $de_{fs}/e_{fs}=dk/k+de_{pan}/e_{pan}$ where de_{fs}, dk and de_{pan} are the derivatives of e_{fs}, k and e_{pan}, respectively, that are assimilated in the absolute error. Thus, the relative error in e_{fs}, de_{fs}/e_{fs}, is the sum of the relative errors in e_{pan} and k. Following Winter (1981), the relative errors in the pan evaporation and pan coefficient estimation were considered to be 20% and 10%, respectively, yielding to a relative error of 30% in the reservoir water evaporation estimation. The reservoir water level is measured every 5 minutes by a continuous pressure probe compensating for atmospheric pressure fluctuations. The absolute error in the water level measurement was estimated at 20 mm independent of the level. This error includes the error due to the sensor considered as independent of the level according to the manufacturer and the error resulting from wind-induced variations which was considered empirically at approximately 15 mm and independent of the level. The reservoir water volume can be derived from the relations between the water volume and level and between the water area and level, hereafter named the level-volume (L-V) and level-area (L-A) relations, respectively. These relations were determined based on a bathymetric survey performed in August 2008. The bathymetric survey produced bipoints of L_i-

V_i and L_i-A_i . The relations L-V and A-V were fitted on the bi-points as $V=aL^b$ and $A=cL^d$. Error in the relations are derived from different sources as follows: data source error derived from the topographic survey of the reservoir bed elevation (error in measurement, sampling interval and DEM building) and error in the volume and area calculations. For each bi-point, *i.e.*, L_i-V_i, or L_i-A_i , we considered that the volume V_i, or area A_i, was estimated with a relative error of 20%.

The percolation from the reservoir was estimated according to Bouteffeha *et al.* (2015), who estimated the percolation rates at some reservoir water levels. A linear regression was performed, allowing us to estimate the percolation rate at each reservoir water level. Thus, the relation between the percolation rate and water level, hereafter named the percolation relation, was based on different data than those used in the present study to estimate stream runoff. The error in the percolation estimation was fixed from the 99% confidence interval. In a linear regression, the confidence interval depends on the value of the regressor and is not theoretically constant; in our case, the errors in the percolation rates within the range of reservoir water levels varied between 2.18 and 2.19 mm/day. Consequently, the error in the percolation rate estimation was assumed to be constant at 2.185 mm/day.

In the Kamech catchment, the wadi runoff is monitored with a gauging station located upstream of the reservoir mouth (wadi station in Figure 1). The station is located sufficiently upstream of the reservoir mouth to avoid or minimize backwater effects (Figure 1). The station is equipped with a U-shaped concrete flume. The water level in the flume is measured once per minute by a pressure transducer sensor and recorded in a data logger. Then, a stage-discharge relationship is used to estimate stream runoff based on the water level. A set of ten stage-discharge values was used to establish the stage-discharge relationship. For every stage-discharge value, the discharge was estimated by the velocity-area method. Velocity in the wet section was measured with a velocimeter every 2 cm of depth and at lateral intervals proportional to water level. Hourly runoff averages were used in this work, and the total runoff entering the reservoir was calculated as the area-scaled specific runoff measured in the wadi.

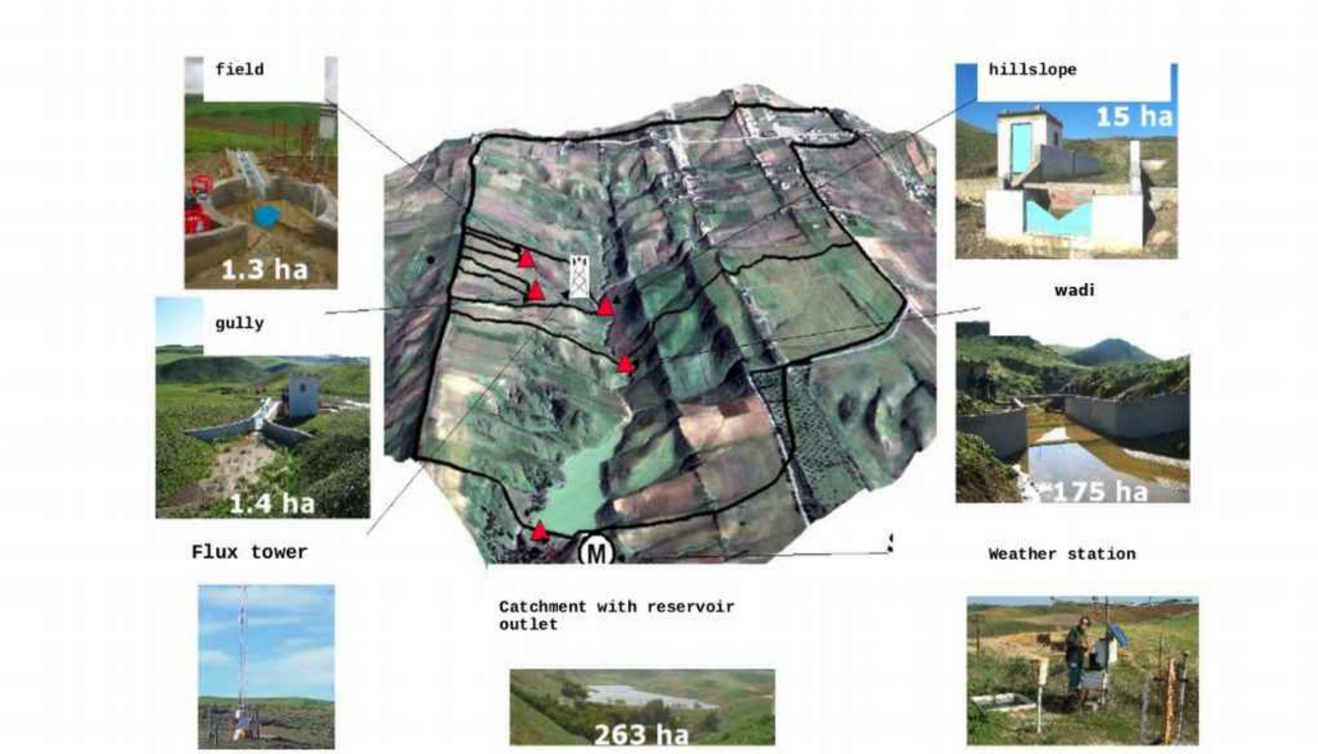

Figure 1 : Aerial view of the Kamech catchment showing the reservoir and locations of the weather station and wadi gauge station.

2. Estimated stream runoff and associated error and uncertainty

2.1. Estimation of stream runoff

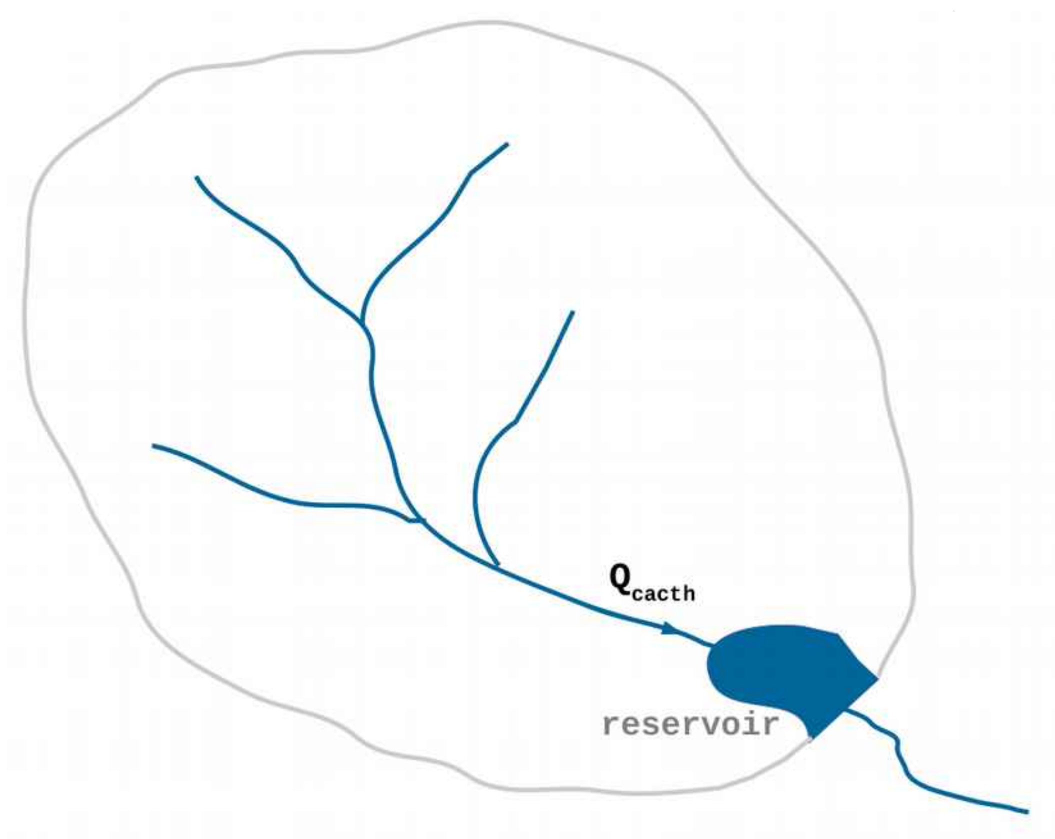

Figure 2 : Schematic view of a catchment draining into a small reservoir. Q_{catch} represents the catchment stream runoff flowing into the reservoir.

The small reservoir considered here captures the stream runoff draining from an upstream catchment (Figure 2). Hence, the temporal variations in the reservoir water volume depend on the upstream stream runoff and other inflows (rainfall directly impacting the surface water) and outflows (evaporation from the surface water and seepage through the reservoir bed and dam). Here, water abstraction is assumed to be null or negligible. The variation in the reservoir water volume at a temporal resolution of *Δt* [T] can be expressed based on the water balance as follows:

$$\frac{\Delta V}{\Delta t} = q \cdot A_c - E + R - S_p \qquad \text{Equation (1)}$$

where *ΔV* is the variation in the reservoir water volume L^3 over the given time step *Δt*, q is the catchment-specific runoff [L/T] flowing into the reservoir over the given time step, E is the evaporation flux [L^3/T] from the reservoir surface water over the given time step, R is the mean rainfall flux [L^3/T] at the reservoir surface water over the given time step, S_p is the mean percolation flux [L^3/T] from the reservoir water surface as infiltration occurs through the reservoir bottom or wall dams, and A_c is the catchment area [L^2] drained by the reservoir. From Equation (1), the specific stream runoff over a given time step Δt_i is estimated as:

$$q_i^{est} = \frac{1}{A_c}\left(\frac{\left(V_i^{fin} - V_i^{ini}\right)}{\Delta t_i} - R_i + E_i + Sp_i\right) \qquad \text{Equation (2)}$$

where V_f^{fin} [L^3] and V_i^{ini} [L^3] are the final and initial water volumes in the reservoir, respectively, at the end and the beginning of the given time step and q^{est}_i, E_i, R_i and Sp_i are the estimated specific stream runoff [L/T], rainfall flux [L^3/T], evaporation flux [L^3/T] and percolation flux [L^3/T], respectively, over the given time step Δt_i. The percolation was calculated based on a linear regression of the reservoir water level and percolation rate. At each time step of a given temporal resolution, the evaporation, rainfall and percolation fluxes were estimated as the product of the water surface area of the reservoir and the cumulative evaporation, rainfall and percolation, respectively, over the time step. The surface area and volume of water in the reservoir were calculated based on the water level measurements and the L-A and L-V relations, respectively. The average surface area over a given time step was considered to be the mean of the initial and final surface areas of the time step.

The specific stream runoff in one hydrologic year ranging from 01 September 2010 to 31 August 2011 was calculated. The stream runoff times series were calculated for 32 temporal resolutions Δt ranging from 1 day to 32 days with a one-day increment. The length of the stream runoff time series ranged from 365 steps at the 1-day resolution to 11 steps at the 32-days resolution.

The interest of using the small reservoir method to estimate stream runoff was analysed based both on performance criteria of estimation (see the following section) and on a comparison with a simple method. The runoff coefficient method was used as the simple method, since it is particularly relevant to Hortonian runoff catchments, such as Kamech catchment (Hingray et al., 2014). According to this method, the stream runoff is estimated at a constant fraction of the rainfall. We explored the values of runoff coefficient ranging from 0.01 to 0.5. For every value and at every time resolution (1 to 32 days), the Nash-and-Sutcliffe efficiency was calculated from the observed and estimated stream runoff. We retained the value of 0.09 as runoff coefficient, which provided the highest efficiency mean calculated from the efficiencies of all the time resolutions.

2.2. Estimation error, uncertainty and performance

The following two types of uncertainty sources were considered in the analysis of uncertainty in the stream runoff estimation based on Equation (2): the measurement uncertainty and the derived data uncertainty (McMillan et al., 2018). The measurement uncertainty was associated with errors in the direct and local measurements of the pan evaporation, rainfall rate by rain gauging and reservoir water level by a pressure sensor. The derived data uncertainty in the reservoir water volume and area, the evaporation flux and the percolation flux was considered. The derived data uncertainty in the water volume and area (V_i and A_i in Equation 2) was assumed to result from the uncertainty in the L-V and L-A relations. The uncertainty in the percolation rate (Sp_i in Equation 2) was assumed to mainly originate from the uncertainty in the percolation relation. At least, the derived data uncertainty associated with the evaporation flux (E_i in Equation 2) was assumed to originate from the uncertainty in the pan coefficient. Each uncertainty was assumed to vary from time step to time step when applying Equation 2.

As a consequence of the measurement uncertainty and the derived data uncertainty, each variable in Equation (2) was considered a random variable characterised by a probability density function (pdf). The range of values defined by the pdf of a given term corresponds to the range of possible values due to the errors potentially occurring in the estimation of that term

The stream runoff at each Δt_i was also considered a random variable with possible values. Therefore, for each time step Δt_i during a given simulation period (*e.g.*, a water year), we defined the following: q^{est}_i, a possible value of the stream runoff during Δt_i ; $\overline{q_i^{est}}$,the estimated stream runoff during Δt_i as the mean of all possible values; and U_{qi}, the uncertainty in the estimated stream runoff at Δt_i, where the true value q_i is in the interval $[\overline{q_i^{est}} - U_{q_i} ; \overline{q_i^{est}} + U_{q_i}]$ with a certain level of confidence. With the 99% level of confidence we chose, the uncertainty is equal to 3.0 $\sigma_{qi}/\sqrt{n}$, where σ_{qi} is the standard deviation of *n* possible values.

The error in the estimation, ε_{qi}, was considered the difference between the mean estimated stream runoff, $\overline{q_i^{est}}$, and the *unknown true stream runoff*, q^{catch}_i. Then, the mean error (ME) and the mean uncertainty (MU) of the catchment stream runoff over the given simulation period are the averages of the errors, ε_{qi}, and uncertainties, U_{qi}, respectively, where i ranges from 1 to *n* with n being the total time step considered during the given period. The Nash-Sutcliffe efficiency was calculated as the estimation performance criterion considering the stream runoff (*NSE*) and the square root of the stream runoff (NSE_{sqrt}). The motivation to consider the square root transform is to reduce the weights of the high stream runoff values in the analysis of the stream runoff estimates.

2.3. Global sensitivity analysis

A global sensitivity analysis (GSA) was performed based on Sobol's method, which is a variance-based method (Sobol *et al.*, 2001). The output of a model with a discrete time step can be expressed as follows:

$$y = f(x, \theta) \qquad \text{Equation (3)}$$

where *y* is the output variable of the model, *x* is the input variable and *θ* is the parameter set. The variables *y* and *x* and the parameter *θ* can be scalar or vectors. Sobol's method evaluates the variance of *y* caused by changes in the input, *x*, and the parameter set θ. Therefore, both the input variables and the parameters can be factors in the sensitivity analysis. Typically, the direct model output, *y*, is replaced by a model performance measure of the stream runoff prediction (Tang *et al.*, 2007). Thus, a sensitivity analysis applies a measure of the error between the observed and simulated values. In the present work, the root mean square error (RMSE) between the observed and estimated stream runoff was chosen as the performance measure. Considering *y* a random variable described by a pdf *Y*, the total variance of *y* can be decomposed as follows:

$$Var(y)=\sum_{i}^{p} Var_i+\sum_{i<j=1}^{p} Var_{ij}+\sum_{i<j<k=1}^{p} Var_{ijk}+\ldots+Var_{1,2,\ldots p} \quad \text{Equation (4)}$$

where *Var(y)* is the total variance of the output variable, *y*, due to *p* factors, p is the number of factors, and Var_i is the variance attributable to the principal effect of factor *i*, while the factors are the input variables x and/or parameters θ, and the other terms corresponding to the fraction of the total variance attributable to the interaction effects between the factors. The interaction reflects how the factors intensify, cancel, or compensate for the effects of the other factors in the model outputs (Razavi and Gupta, 2015). Based on the variance decomposition of *y*, the following two indices are defined:

$$S_i=\frac{Var_i}{Var(y)} \quad \text{Equation (5)}$$

and

$$S_{Ti}=1-\frac{Var_{-i}}{Var(y)} \quad \text{Equation (6)}$$

where S_i and S_{Tii} are the first-order Sobol index and total Sobol index, respectively, and Var_{-i} is the variance attributable to all factors except for *i*.

The GSA aims to study the sensitivity of the model simulation to various factors. In contrast to the usual GSA, where the model parameters are the factors (*e.g.*, Tang et al., 2007), in our study, the factors are the variables used in Equation (2) to simulate stream runoff. Actually, each variable used in Equation (2) corresponds to a vector, i.e., a time series. Therefore, the Sobol indices were calculated from a large number of simulations of stream runoff time series, and each simulation was performed with a sampled time series of each variable in Equation (2). In practice, considering a given temporal resolution *Δt,* a large number of sampled time series of the initial water level at the beginning of each time step, the final water level at the end of each time step, the rain, the evaporation and the percolation were generated. Furthermore, for each simulated time series of stream runoff, we considered a possible L-A relation and a possible L-V relation (see the following section). Ultimately, the following six factors were considered in the GSA : i) initial water level ii) final water level, iii) rain, iv) evaporation, v) percolation and vi) bathymetric relations (L-A and L-V relations).

2.4 Implementation of estimations

For each temporal resolution *Δt*, we estimated *n=10,000* possible time series of stream runoff. As a result, we obtained *n* estimations of the stream runoff, q^{est}_i, for each given time step Δt_i. Each possible time series of runoff was obtained with all possible time series of all terms on the right side of Equation (2). To generate a possible time series for each term on the right side, we proceeded as follows. For each variable or derived variable used in Equation (2) and associated with uncertainty, a possible value at each time step was drawn from a pdf. We assigned a pdf to each variable associated with measurement uncertainty and derived data uncertainty. A given pdf characterised by a mean and a standard deviation was considered at each time step for each term. Following previous studies (Horner *et al.*, 2018), the error associated with water level measurement was assumed to follow a Gaussian distribution. The mean was considered the measured value and the standard deviation was fixed at the absolute error in the measurement. The percolation rate was also assumed to follow a Gaussian distribution with a mean equal to the value derived from the percolation relation and a standard deviation corresponding to the prediction error at the 99 % confidence interval in the linear regression used as the percolation relation. Regarding the other terms (rainfall and evaporation), due to lack of real distribution or tangible evidence of the shape of the pdf, we chose a uniform distribution. This choice, leads to maximizing the uncertainty compared to that of other distributions. At each time step, the mean was considered the measured value, and the standard deviation was derived from the relative error associated with the rainfall measurement and evaporation estimation. The relative errors were fixed at 20% for rainfall and 30% for the evaporation rate (see section 1).

To estimate n possible time series of stream runoff, n possible L-V and L-A relations were also established randomly by considering the uncertainty in these relations. To establish each possible relation, we considered that each V_i and A_i measurement used to fit the L-V and L-A relations is characterised by a specific uniform pdf with a mean corresponding to the measured value and a standard deviation derived from the standard error in the measurement (section 1). To estimate each possible time series of stream runoff, we first randomly drew each V_i and A_i and then fitted the possible L-V and L-A relation to the generated L_i-V_i and L_i-A_i bipoints.

Then, the estimated stream runoff at a given time step was calculated as the mean of all 10,000 simulated possible values. The uncertainty in the estimated stream runoff was calculated based on the standard deviation of the 10,000 simulated possible values. Then, the error in the simulated stream runoff at a given time step corresponded to the absolute difference between the observed value and the simulated mean value. In each temporal resolution, the mean error and mean uncertainty were calculated, corresponding to the means of the errors and uncertainties, respectively, of each simulated stream runoff in the time series. The Nash-Sutcliffe efficiency metrics (NSE and NSE_{sqrt}) were also calculated based on the observed values and simulated mean values.

3. Results

3.1 Error and total uncertainty

Considering the simulation performance, stream runoff is fairly well estimated based on the water balance approach regardless of the temporal resolution considered (Figure 3). The Nash-Sutcliffe criteria are greater than 0.87 at all temporal resolutions and greater than 0.91 at Δt≥27 days. The RMSE decreases as the temporal resolution increases up to 6 days, and then the RMSE slightly decreases. The largest RMSE (at a temporal resolution of 1 day) is 1.88×10^{-4} m/day, while the smallest RMSE is 5.8×10^{-5} m/day at a temporal resolution of 32 days.

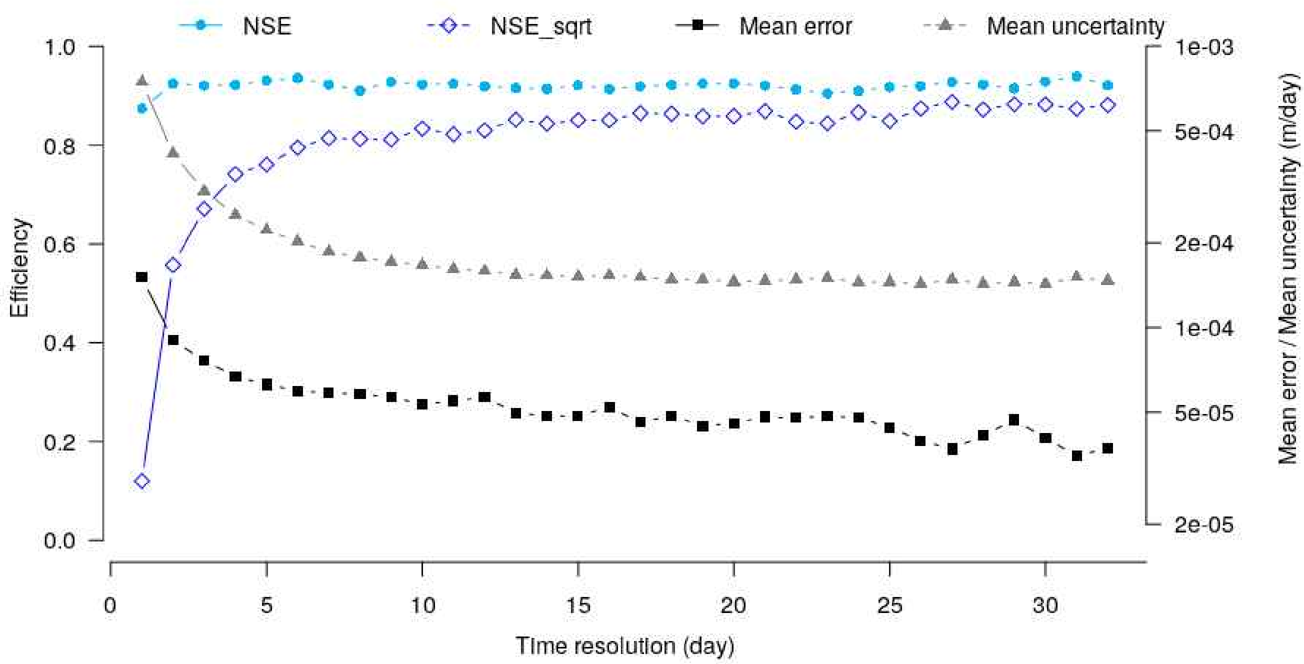

Figure 3 : Nash efficiencies calculated based on the stream runoff values NSE (blue points) and the square roots of the values NSE_{sqrt} (blue diamonds) on the left y-axis and the RMSE (black squares) and mean uncertainty in the stream runoff estimation (grey triangles) on the right y-axis at temporal resolutions ranging from 1 day to 32 days.

The NSE_{sqrt} criteria are more variable than the common *NSE* depending on the temporal resolution. NSE_{sqrt} increases from 0.12 to 0.88 as the resolution increases from 1 day to 32 days, implying that low stream runoff is globally simulated the worst at the finest temporal resolution. A comparison of the simulated and observed stream runoff values at varying temporal resolutions (Figure 4) confirms these results. A large discrepancy is observed in the lowest stream runoff values (smaller than $5.0x10^{-4}$ m/day) at fine temporal resolutions (1 day and 2 days). Regarding larger temporal resolutions (greater than 8 days), the discrepancy in the same range of stream runoff values is much smaller.

The mean uncertainty exhibits a strong decreasing trend at temporal resolutions between 1 day and 8 days but remains relatively constant at resolutions longer than 8 days. The relative mean uncertainty was calculated for each estimated stream runoff as the quotient of the mean of the estimated values over the standard deviation of the estimated values ; then, we derived the mean relative uncertainty corresponding to the mean of all relative uncertainty values during the simulation period. The mean relative uncertainty decreases from 1.16 to 0.51 as the temporal resolution increases from 1 day to 32 days. Furthermore, the relative uncertainty of low stream runoff seems to be greater than for that of the highest stream runoff as illustrated by the spread of the grey squares in Figure 4. To quantify the visual interpretation of Figure 4, the mean relative uncertainty was also calculated considering the following two classes of stream runoff values: one class corresponding to stream runoff values smaller than the threshold of $5x10^{-4}$ m/day, *i.e.*, low stream runoff, and one class corresponding to stream runoff values larger than this threshold, *i.e.*, values considered representative of medium to high stream runoff. At all temporal resolutions, the mean relative uncertainty of the low stream runoff class is much greater than that for the medium/high stream runoff class. In both classes, the mean relative uncertainty decreases as the temporal resolution increases. The mean relative uncertainty of the low stream runoff class is 1.21 (121%) and 0.55 (55%) at temporal resolutions of 1 day and 32 days, respectively. Regarding the high stream runoff values, the mean relative uncertainty is 0.67 (67%) and 0.12 (12%) for temporal resolutions of 1 day and 32 days, respectively.

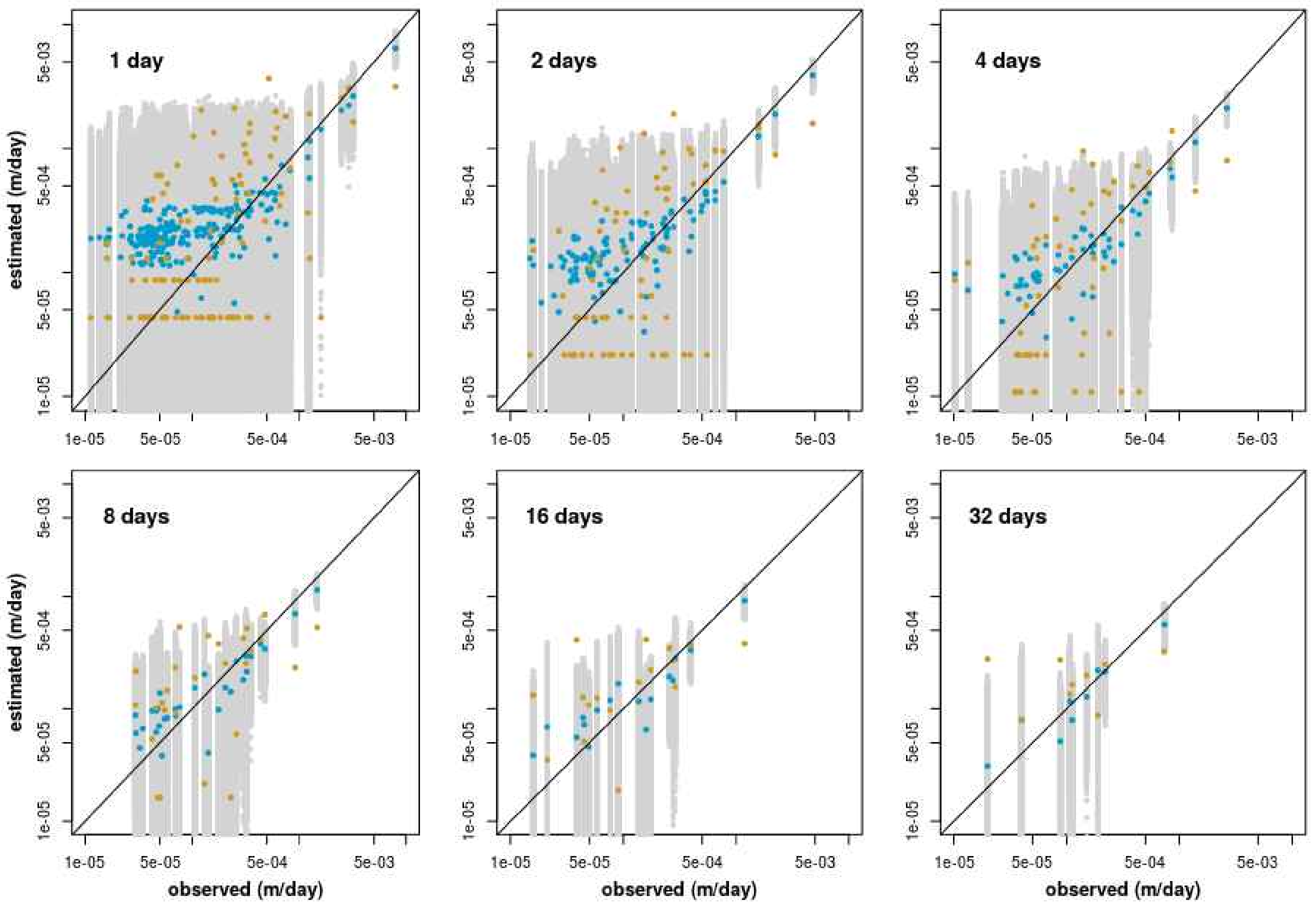

Figure 4 : Estimated versus observed stream runoff [m/day] at six time steps ranging from 1 to 32 days. The estimated value by the reservoir method correspond to the blue points. The estimated values with the runoff coefficient method correspond to the golden points. Each light grey point corresponds to one estimation. The 1:1 line is indicated in black.

The stream runoff was also estimated using the coefficient runoff method. The best performance in the estimation was obtained with a runoff coefficient of 0.09. Based on this value, the NSE ranged from 0.27 (found at 1 day temporal resolution) to 0.54 (found at 24 days). The variation in the NSE_{sqrt} with the temporal resolution followed the same pattern as that observed using the small reservoir method. However, the values obtained using the coefficient runoff method were lower than those obtained using of the small reservoir method, ranging from 0.06 at the 1 day temporal resolution to 0.5-0.7 at temporal resolutions greater than 9 days. The discrepancy between observations and simulations with the runoff coefficient method was found for the full range of values at all time steps (Figure 4). Unlike the reservoir method, the runoff coefficient method tended to overestimate the medium flow values ranging from 5.0 10^{-5} to 5.0 10^{-4} m/day. The reservoir method simulated also better than the coefficient runoff method the highest values larger than 5.0 10^{-4} m/day.

3.2 Global sensitivity analysis

Regarding the lowest time resolution, the S_T of the initial and final volumes are especially large with values exceeding 0.55 (Figure5). The other factors, namely, bathymetric relations, evaporation, rainfall and percolation rates, have very low to almost null S_{Ti}. Regarding the highest time resolution, as illustrated by the plot at the temporal resolution of 32 days in Figure 5, the percolation rate is the dominant factor in the estimation with S_{Ti} greater than 0.50. The bathymetric relation is a factor with a large S_{Ti} (>0.3) for temporal resolution greater than 2 days. This is even the dominant factor for resolutions between 4 and 23 days. The evaporation and rainfall rates have very low S_{Ti}, lower than 0.02, for all resolutions. The variation shows a progressive decrease in the S_{Ti} for the initial and final water levels as the temporal resolution increases (Figure 6). This decrease is particularly sharp up to a temporal resolution of 10 days, and then, the decreasing trend is slow. Regarding the percolation, the increase in S_{Ti}l is sharp up to 10 days, after which the rate of increase is slow. Notably, the cumulative S_{Ti} of each of the six factors is lower than 1.1 at the temporal resolutions greater than 2 days. Thus, the interactions between the factors are particularly weak at these temporal resolutions.

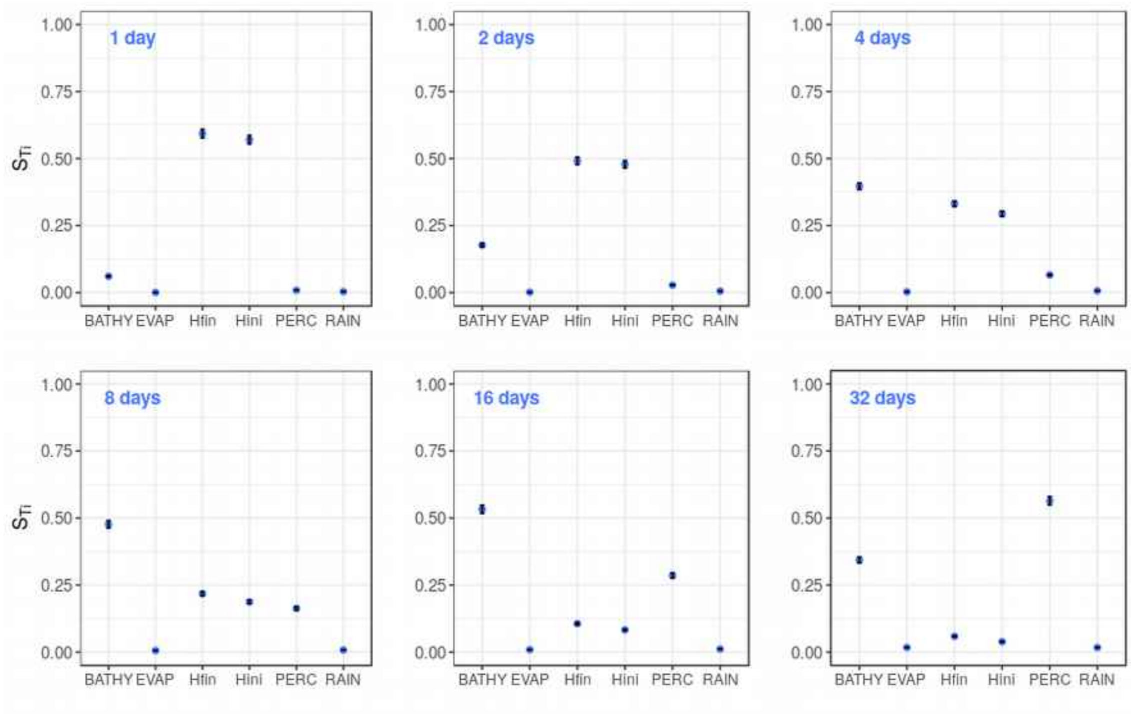

Figure 5 : S_{Ti}s at six time steps from (a) 1 to (f) 32 days. The S_{Ti} of the following estimated factors are provided: bathymetric relations (BATHY), evaporation (EVAP), final and initial reservoir water levels (Hini and Hfin), percolation (PERCOL) and direct rainfall (RAIN).

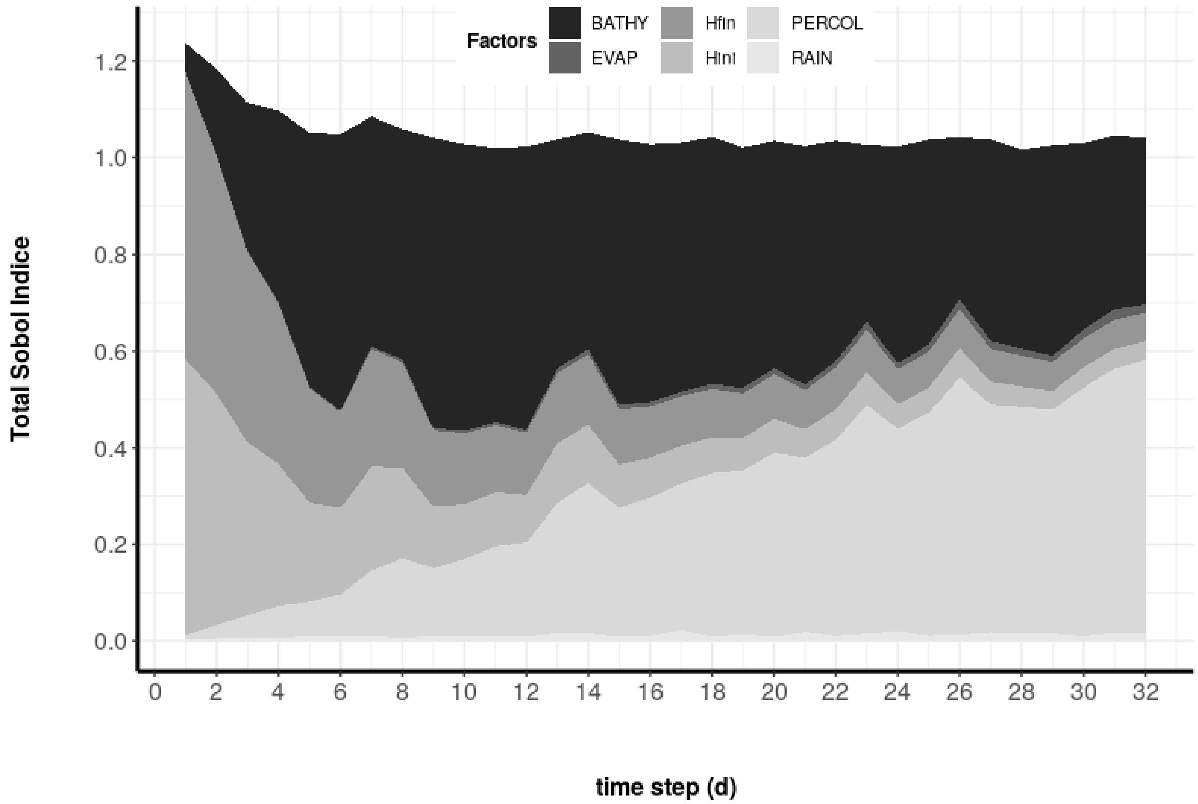

Figure 6 : S_{Ti} at continuous time steps from 1 to 32 days. The S_{Ti} of the following estimated factors are provided: bathymetric relations (BATHY), evaporation (EVAP), final and initial reservoir water levels (Hini and Hfin), percolation (PERCOL) and direct rainfall (RAIN).

<u>4. Discussion</u>

The relevance of using small reservoirs as stream gauges is analysed in this study. The analysis is developed based on a specific case study of the Kamech small reservoir, which drains a 2.64 km² catchment in northern Tunisia. Nevertheless, general rather than only site-specific outputs can be drawn and emphasized based on the results.

4.1 Using small reservoirs to gauge stream runoff

Using small reservoirs as stream gauges leads to globally reliable estimations of stream runoff at each time step, as illustrated by the estimation performance. However, the reliability must be nuanced according to the temporal resolution and stream runoff range. The reliability increases as the temporal resolution increases, as reflected by the variations in the mean errors and Nash efficiencies with the resolution. Furthermore, regarding the lowest temporal resolutions [1-8 days], the highest stream runoff values are estimated better than the lowest values, as indicated by the low NSE_{sqrt} (Figure 3) and the differences between the observed and estimated stream runoff values lower than $5x10^{-4}$ m/day (Figure 4). Two explanations can be offered for this phenomenon. The first explanation is provided by the uncertainty analysis. Indeed, we showed that the relative estimation uncertainty due to the uncertainties in the mass balance terms (Equation 2) is higher in low stream runoff than high stream runoff (*e.g.*, up to 116% at a 1-day temporal resolution). The second reason is that the observed stream runoff is also affected by errors. In the Kamech catchment, the stream runoff is derived from water level measurements performed in a channel at the outlet gauge station (Figure 1). Low water levels (a few millimetres in the Kamech gauge station) may be affected by errors. Furthermore, water level measurements are performed with a pressure sensor whose error is absolute and not relative; consequently, the error in the water level measurement is higher at low water levels than high water levels.

As stream runoff is estimated more reliably in large stream runoff than small stream runoff, using small reservoirs as stream gauges appears particularly relevant in arid and semi-arid environments. In environments such as the Mediterranean, excess infiltration overland flow (Hortonian flow) is recognized as the main mechanism responsible for stream runoff (Ribolzi *et al.*, 2000, 2007 ; Ludwig et al., 1999).

The stream runoff in these environments is very intermittent. Furthermore, storm flow usually constitutes the predominant fraction of stream runoff, while the baseflow fraction is small and even null in some areas. In the Kamech catchment, the baseflow was estimated to account for 11% to 28% of the total stream runoff depending on the year (Raclot *et al.*, 2010). Accordingly, our results show that the implementation of small reservoir water monitoring as a stream gauging network could be particularly suitable for this type of hydrological function encountered in arid and semi-arid environments, such as the

Mediterranean, where the volume of stream runoff is mainly due to large storm events. In contrast, estimating stream runoff based on small reservoir monitoring during low flow periods is associated with relatively large uncertainties and errors and appears much less appropriate. In the Kamech catchment, this situation is clearly illustrated by the low values of NSE_{sqrt} at the shortest temporal resolutions (<8 days) (Figure 3). Interestingly, the stream runoff was better estimated with the small reservoir method compared to a simpler method, namely, the runoff coefficient. The runoff coefficient method, which is a simple method used to estimate stream runoff, appears to be particularly appropriate for arid and semi-arid catchments where Hortonian runoff is often the dominant process as in Kamech catchment (Hingray et al., 2014). Therefore, the difference in the performance criteria values between the two methods shows the added value that could be provided by the small-reservoir method.

Automatic devices, such as those employed in the Kamech catchment, are valid methods for obtaining water level measurements to estimate stream runoff. However, in remote areas, the financial cost of such devices and the maintenance needs and long-term reliability of the equipment are real concerns. Crowdsourcing has been developing in recent years in hydrology to produce new data through the involvement of citizens (Lowry et al., 2019 ; Strobl et al., 2020). As a part of the development of crowdsourcing in hydrology, collaborative and community-based approaches could be an efficient way to obtain reliable measurements while strengthening the relationships with the local populace. In the Kamech catchment, for instance, along with automatic measurements, a villager performs daily manual measurements of pan evaporation, rainfall and water levels in the reservoir.

4.2. Uncertainty in the stream runoff estimation

The conditions that must be met to obtain reliable stream runoff estimations differ depending on the temporal resolution. At short temporal resolutions, the main uncertainty in stream runoff estimations is caused by uncertainty in the water level measurements. Decreasing the uncertainty in the estimated stream runoff could imply decreasing uncertainty in reservoir water level measurements. In the present study, the water level measurement error was fixed at 20 mm to incorporate equipment errors (the error due to the pressure sensor as given by the manufacturer) and errors arising from environmental conditions (mainly due to small wind-generated water waves). Reducing the error due to in situ sensors may be accomplished in the future by improving the measurement technology. Moreover, the errors due to wind-induced waves could be reduced by performing high-frequency measurements (once every minute or less) to provide an estimate of the magnitude and filtering high-frequency variations in water level measurements. Such filtering could be achieved by applying a moving average with a window of a few minutes.

At large temporal resolutions (longer than 23 days in the present case), the percolation estimation is the main source of uncertainty. In many small reservoir water balance approaches, percolation is often neglected, mainly because it is difficult to estimate (Oblinger *et al.*, 2010). Nevertheless, we show that percolation estimations appear crucial for using small reservoirs as stream gauges at decadal or longer temporal resolutions. Regarding the percolation issue, the Kamech catchment is likely representative of many small reservoirs in arid and semi-arid regions. In dams built to enhance groundwater recharge, the percolation rate indeed represents a major flux in the reservoir water dynamics, as this enhancement is the aim of the reservoir. In contrast, the engineering of other reservoirs does not prevent unwanted percolation due to leaking dam walls or permeable reservoir beds. To resolve this issue, pragmatic approaches have been proposed and applied in previous studies to estimate the percolation under small reservoirs (Oblinger *et al.*, 2010 ; Fowe *et al.*, 2015). The most straightforward method is to quantify percolation from the reservoir water balance on many non-rainy days and non-flowing days, *i.e.*, days when the runoff entering the reservoir is null or negligible, and by considering the evaporation (Sharda *et al.*, 2006). Under such conditions, the percolation volume can be estimated as the reservoir volume decrease minus the evaporation volume. A relation with these estimations and corresponding water levels can often be developed and employed to estimate the percolation rate as a function of the reservoir water level.

Bathymetric relations (L-A and L-V) constitute a strong factor of uncertainty at all temporal resolutions and may even serve as the dominant factor at temporal resolutions ranging from 4 to 23 days. Bathymetric relations are involved in the estimation of nearly all terms in Equation 2 used for the runoff estimation. Evaporation, rainfall, and percolation volumes are area-dependent, and thus dependent on the L-A relations ; the estimation of the initial and final volumes is directly related to the L-V relations. In this study, the relations were established based on an in situ topographic survey of the reservoir bed. Performing a topographic survey for several reservoirs would not be trivial and would be a major constraint in deploying the methods to many reservoirs in a region. However, the different avenues currently explored could at term overcome this constraint and provide information necessary for the estimation of the bathymetric relations. The use of a geomorphic predictor, such as that used by Sobek et al. (2014), to estimate lake water capacity and depth could be such an avenue. Developments in methodological procedures based on remote sensing and image analysis techniques at fine spatial resolutions represent another avenue. Satellite image analyses have been used to detect and estimate the water storage and surface area of small water bodies, such as reservoirs (Miahle et al. 2008; Eilander et al., 2014; Ogilvie et al., 2019). The analysis of digital elevation models could be another avenue in a context of the increasing availability of fine spatial resolution DEM. As conducted by Alcantara et al. (2010) at a large reservoir, integrating historical and Shuttle Radar Topography Mission (SRTM) topographic data prior to the reservoir construction could allow the establishment of bathymetric relations in small recent reservoirs.

Many studies investigating the hydrology and water balance of small reservoirs have focused on and emphasized the importance of direct evaporation from the reservoir water surface and the need to obtain reliable estimates of such flux. As evaporation is a form of water loss, knowing and preventing evaporation are indeed major concerns in the water management of small reservoirs. However, with the objective of estimating stream runoff, estimating evaporation is less crucial because it is far from a major source of uncertainty. Hence, the weight assigned to the percolation rate in the water dynamics and water balance of the Kamech reservoir in relation with water levels or bathymetric relations can justify the small sensitivity of the stream runoff estimation to the evaporation estimation uncertainty.

Conclusion

We analysed the relevance of using small reservoirs to gauge stream runoff. The estimations of high stream runoff are more reliable than those of low stream runoff and the performance of estimation improves as the temporal resolution increases from 1 to 32 days. Using a small reservoir to gauge stream runoff appears appropriate for arid and semi-arid environments, in which stream runoff mainly comprises high magnitudes of infrequent storm runoff due to excess infiltration runoff. In addition, the uncertainty factors change depending on the temporal resolution. The main source of uncertainty is the reservoir water level at the shortest temporal resolutions, while at the longest temporal resolutions, the uncertainty in the percolation rate is the major source of uncertainty in the stream runoff estimation. The L-A and L-V relations constitute a major factor of uncertainty at temporal resolutions greater than 1 day. Therefore, using reservoirs to gauge stream runoff requires determining these relations, which currently appears to be a strong constraint in the perspective of deploying this method over a large area with a large number of reservoirs. Recent and on-going developments in procedures based on remote sensing and image analysis techniques could help liminate this constraint. An obvious limitation of this study is that it is based on only one catchment. The same analysis could be conducted in other catchments with a wealth of data comparable to that of the Kamech catchment. At least, using small reservoirs to gauge stream runoff requires water level, rain and evaporation measurements. Acquiring such measurements can be a real challenge, especially in remote areas, due to financial costs and the maintenance and long-term reliability of monitoring infrastructures. Crowdsourcing by local villagers of these hydrological data could be a way to address this challenge and to involve the public in water resource evaluations.

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