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Simulation of water-energy fluxes through small-scale reservoir systems under limited data availability

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Abstract

We present a stochastic approach accounting for input uncertainties within water-energy simulations. The stochastic paradigm, which allows for quantifying the inherent uncertainty of hydrometeorological processes, becomes even more crucial in case of missing or inadequate information. Our scheme uses simplified conceptual models which are subject to significant uncertainties, to generate the inputs of the overall simulation problem. The methodology is tested in a hypothetical hybrid renewable energy system across the small Aegean island of Astypalaia, comprising a pumped-storage reservoir serving multiple water uses, where both inflows and demands are regarded as random variables as result of stochastic inputs and parameters.

Keywords: stochastic simulation; hybrid renewable energy systems; reservoir management; parameter uncertainty; pumped-storage system

1. Introduction

Small islands are regarded as promising areas for developing hybrid water-energy systems that combine multiple sources of renewable energy with pumped-storage facilities. The most essential element of such systems is the water storage component (reservoir), which implements both flow and energy regulations. Apparently, the representation

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of the overall water-energy management problem requires the simulation of the operation of the reservoir system, which in turn requires a faithful estimation of water inflows and demands of water and energy. Yet, in small-scale reservoir systems, this task is far from straightforward, since both the availability and accuracy of associated information is generally very poor. In contrast to large-scale reservoir systems, for which it is quite easy to find systematic and reliable hydrological data, in the case of small systems such data may be scarce or even missing, which introduces further uncertainty to the inherently complex water-energy simulation problem.

The stochastic approach is the unique means to account for the multiple uncertainties within the combined water-energy management problem. Using as pilot example the Livadi reservoir, which is a hypothetical pumped storage component of the small Aegean island of Astypalaia (Greece), we provide a stochastic simulation framework, where the time-varying reservoir inputs, i.e., inflows and demands, are subject to two different sources of uncertainty. The first source is the long-term hydrometeorological uncertainty, which is typically tackled by using synthetic time series that reproduce the statistical characteristics of the observed data, while the second source is associated with the complex dynamics of the rainfall-runoff transformation, expressed by means of conceptual parameters. Yet, due to the lack of historical runoff data, it is not possible to infer these parameters through the classical calibration procedure, thus obtaining a unique rainfall-runoff transformation model [1]. For this reason, we take advantage of the limited information about the hydrometeorological regime of the study area, to provide multiple “behavioural” parameter sets, resulting to multiple stochastic responses of the water-energy system. The proposed modelling scheme comprises stochastic and deterministic components, co-operating within a Monte Carlo simulation framework.

2. Study area and data

Astypalaia (*Αστυπάλαια*) is a small Greek island (total area 97 km^2) with 1334 residents (2011 census), that belongs to the Dodecanese complex (Fig. 1, left). The major water infrastructure of the island is the Livadi reservoir (Fig. 1, right), having a useful storage capacity of 875 000 m^3 (against a total capacity of 1 050 000 m^3) and extending over a maximum surface of 105 000 m^2. The reservoir, which operates from 1998, fulfills domestic, touristic and agricultural ware uses. The estimated annual demands are 210 000 m^3 for water supply and 230 000 m^3 for irrigation, most of which implemented during the summer period. The drainage basin upstream of the dam is 8 km^2, producing ephemeral runoff. Unfortunately, across the Livadi basin there are no available any hydrometric data, except for rough estimations about its hydrological regime. In particular, recent hydrological studies estimate that about 15% of the mean annual rainfall is transformed to surface runoff, about 11% are underground losses that are finally conducted to the sea, and the remaining quantity represents the evapotranspiration losses [2].

In the context of this pilot study, Livadi reservoir is assumed as the energy regulation component of a hypothetical hybrid renewable energy system across the island, aiming at ensuring full autonomy against the estimated electricity needs. In this respect, apart from the actual water uses, i.e., water supply and irrigation, we also consider a small hydropower plant, installed at the discharge outlet (with maximum head of 32 m, i.e., equal to the dam height) and a pump-storage tank, implementing daily regulations of energy surpluses and deficits, provided by other renewable resources.

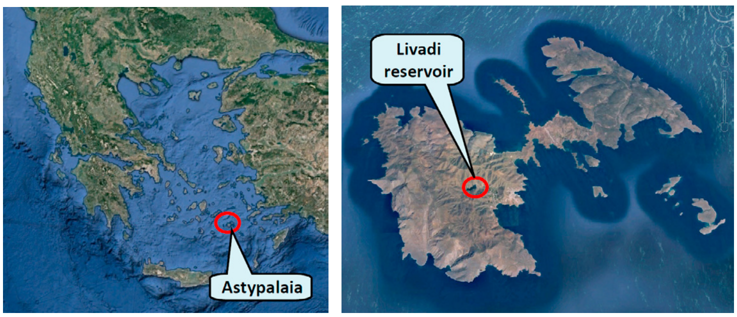

Fig. 1. Study area and location of Livadi reservoir (satellite images from Google Earth).

3. Stochastic simulation procedure of water-energy fluxes

3.1. Overview

The outline of the modelling procedure is illustrated in Fig. 2.The simulation scheme, implemented at the daily time scale, comprises of: (a) a stochastic model for generating synthetic rainfall and temperature time series; (b) a radiation-based model, which transforms temperature to evaporation and potential evapotranspiration (PET); (c) a stochastic rainfall-runoff model, whose parameters are represented as correlated random variables; (d) a stochastic model for estimating water supply and irrigation demands, based on simulated temperature, PET and soil moisture; and (e) a water management model of the reservoir system, providing stochastic forecasts of water and energy outflows. Herein are given brief descriptions of each individual modelling component.

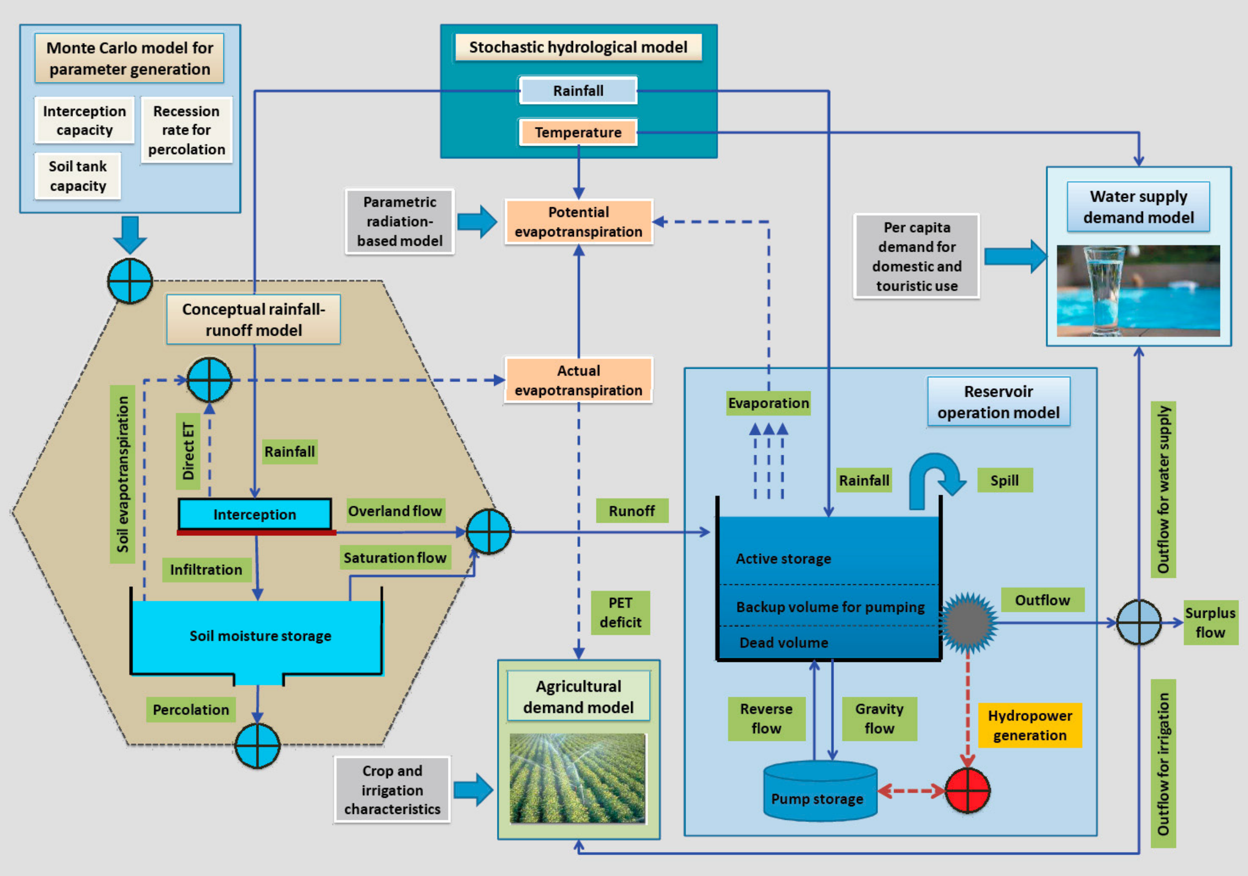

Fig. 2. Outline of the stochastic simulation procedure.

3.2. Stochastic simulation of meteorological drivers

The meteorological drivers of the simulation scheme are the daily rainfall and mean daily temperature. In particular, rainfall is input of the hydrological model and the reservoir management model, while temperature is input of the evaporation/PET model and the water demand model. Apparently, due to the intrinsically uncertain nature of meteorological phenomena and the limited lengths of the historical data, it is essential to employ stochastic approaches to represent the above non-deterministic inputs. On the one hand, this allows accounting for uncertainty and large variability of the associated processes, and on the other hand, the use of synthetic time series, instead of historical records, allows providing sufficiently large samples, in order to evaluate the system responses in statistical terms (e.g., by means of reliability), with satisfactory accuracy [3].

For the generation of statistically consistent synthetic rainfall and temperature data we employed the stochastic framework implemented within Castalia software [3]. This model uses state-of-the-art stochastic methodologies that ensure the preservation of the essential statistical characteristics (marginal and joint distributions) of the parent historical data at three time scales (annual, monthly, daily). Moreover, it reproduces the long-term persistence (Hurst-Kolmogorov dynamics) at the annual and over-annual scales, the periodicity at the monthly scale, and the rainfall intermittency (i.e., probability dry) at the daily scale.

3.3. Evaporation / potential evapotranspiration model

Theoretically, the evaporation from water surfaces, which is input of the reservoir management model, and the potential evapotranspiration (PET) from vegetated surfaces (also called reference crop evapotranspiration), which is input of the irrigation demand model, can be computed with high accuracy by the well-known Penman and Penman-Monteith approaches, respectively, using as inputs four meteorological variables (air temperature, solar radiation, relative humidity, wind velocity). However, in many cases, it is difficult to find simultaneous measurements of all variables of interest, thus favoring the use of simplified approaches, using as single input the temperature.

In the proposed simulation scheme, we employ the radiation-based expression:

$$E = a\, R_{\mathrm{a}} / (1 - c\, T) \tag{1}$$

where E is the evaporation (or potential evapotranspiration) in mm, R_{a} (kJ m^{-2}) is the extraterrestrial radiation, T (°C) is the mean air temperature, and a (kg kJ^{-1}) and c (°C^{-1}) are model parameters that are inferred through calibration, against “reference” data, which is estimated through the Penman (or Penman-Monteith) approaches [4]. We remark that the extraterrestrial radiation is an astronomic variable, which is a periodic function of latitude and time, thus the sole input of eq. (1) is the temperature, which can be easily obtained from a representative meteorological station.

3.4. Stochastic rainfall- runoff model

The key hydrological processes of the river basin upstream of Livadi dam, i.e., the transformation of rainfall to actual evapotranspiration, surface runoff and underground losses to the sea, are modelled through a lumped conceptual scheme, which uses three parameters. As illustrated in Fig. 2, the basin is vertically subdivided into two storage elements that represent the temporary interception processes on the ground and the soil moisture accounting across the saturated zone. Model inputs are the daily precipitation, P, and daily PET. All fluxes are expressed in units of water depth (i.e., mm) per unit time (day), while storages are expressed in terms of water depths.

The model parameters are: (a) the interception capacity, I_{a} (mm), representing a rainfall threshold for runoff generation, (b) the soil capacity K, (mm), and (c) the fraction, a of the soil storage that outflows to the sea, which acts as a recession parameter. Initial condition of the model is the soil storage at the start of simulation, which may be considered negligible (if the simulation starts at the end of the dry period) or expressed as fraction of K.

For given inputs and parameter values, the simulation procedure is the following. First, provided that P exceeds the interception capacity, I_{a}, we employ the well-known SCS-CN formula for estimating the overland flow, i.e.:

$$Q_{\mathrm{overland}} = (P - I_{\mathrm{a}})^2 / (P - I_{\mathrm{a}} + K - S) \tag{2}$$

where $K - S$ represents the so-called maximum potential soil retention (i.e., the empty space of the soil tank). The latter is the key input parameter of the SCS-CN method, for which three typical values are generally considered, depending on three antecedent soil moisture conditions. In the proposed model, this quantity is appropriately handled as a continuous variable, depending on the current soil moisture storage, S [5].

The remaining rainfall is by priority used for fulfilling the PET demand, thus generating direct ET, i.e.

$$\mathrm{ET}_{\mathrm{direct}} = \min\,(\mathrm{PET}, P - Q_{\mathrm{overland}}) \tag{3}$$

while the remainder enters the soil moisture tank, thus increasing its current storage, i.e.:

$$S = S_0 + P - Q_{\text{overland}} - \text{ET}_{\text{direct}} \tag{4}$$

where S_0 denotes the soil moisture storage at the beginning of the time interval.

The actual evapotranspiration losses through the soil are estimated via the conceptual formula:

$$\text{ET}_{\text{soil}} = (\text{PET} - \text{ET}_{\text{direct}})\tanh(S/K) \tag{5}$$

Next, a fraction a of the current storage moves vertically, thus generating underground losses to the sea, i.e.:

$$L = a\,(S - \text{ET}_{\text{soil}}) \tag{6}$$

Finally, we check whether there is enough empty space in the tank, otherwise saturation excess runoff is produced by means of spill, i.e.:

$$Q_{\text{excess}} = \max(0, S - \text{ET}_{\text{soil}} - L - K) \tag{7}$$

The total runoff is the sum of the overland and excess flow, while the total actual ET is the sum of the direct and soil ET. At the end of the time step, we recalculate the current soil moisture storage, i.e.:

$$S_0 = S - \text{ET}_{\text{soil}} - L - Q_{\text{excess}} \tag{8}$$

In case of missing observed runoff, the model is subject to major uncertainty, since it is not possible to identify its parameters through calibration. This uncertainty is expressed in terms of *a priori* distributions of parameters; for simplicity, I_a, K and a can be considered uniformly distributed within "reasonable" feasible ranges, specified via hydrological evidence. In this respect, the model is stochastic, since its parameters are random variables.

3.5. Stochastic water demand model

For the estimation of drinking and agricultural water demands on a daily basis, we have developed two modules. The first component, symbolized D_{supply}, comprises a deterministic term, which accounts for seasonally-varying per capita water needs and population projections (different for domestic and touristic use), and a stochastic term, which is a function of the daily temperature.

On the other hand, the agricultural water module estimates the irrigation demand for four major crop categories (arable, vegetable, orchard, and vineyard). The theoretical needs for each type are estimated on the basis of PET, obtained from eq. (1), and the corresponding crop coefficient (different per month), obtained from [2]. Next, the actual demand is estimated by considering the evapotranspiration deficit, i.e., the difference between PET and the simulated actual evapotranspiration, ET, and an efficiency factor, e, depending on the irrigation method, i.e.:

$$D_{\text{irrigation}} = (\text{PET} - \text{ET}) / e \tag{9}$$

We remark that the water supply component is only associated with the uncertainty of temperature, while the uncertainty induced in the estimated demand for irrigation is subject to more sources of uncertainty, namely the input uncertainty of rainfall and temperature, as well as the parameter uncertainty of the rainfall-runoff model.

3.6. Reservoir management model

For the representation of the daily operation of Livadi reservoir we consider the two aforementioned water uses, putting water supply in first priority and irrigation in second, and we also consider a hypothetical power plant, installed downstream of the intake; in case of abstractions for the fulfillment of drinking water or agricultural demands, the water passes through the turbines, thus also producing hydroelectric energy. Moreover, in case of storage surplus, and in order to avoid water losses due to spill, additional flow is conveyed through the turbines and next conducted to the Livadi stream. The management policy is subject to storage and discharge capacity constraints, as well as an external constraint, namely the preservation of a backup storage for employing energy regulations within the in-daily pumping-storage cycle. We recall that in the context of the hypothetical renewable energy system, the excess of energy produced by other renewable recourses (i.e., wind and solar parks) across the island is consumed by pumping water to an upstream tank, and retrieved later as hydropower. This hypothetical tank employs daily regulations, thus its capacity equals the backup storage of the downstream reservoir.

All inputs of the water management model are stochastic, i.e.:

- Catchment runoff, provided by the stochastic hydrological model, driven by synthetic rainfall and temperature and having uncertain parameters;
- Rainfall over the lake area, synthetically generated;
- Evaporation losses, estimated on the basis of synthetic temperature;
- Water demand for domestic and touristic use, also depending on synthetic temperature;
- Water demand for irrigation, estimated on the basis stochastic evapotranspiration deficits.

An explicit scheme is used to solve the reservoir simulation problem at the daily scale, assuming that at the beginning of each time step the current storage and head are known, the latter being function of the former. Initially, we add the net inflows (i.e., catchment runoff plus rainfall over the lake area minus evaporation losses) to the current storage, and next we implement the outflows through the reservoir. By priority, we aim fulfilling the water supply target, assuming that all active storage capacity is available for abstractions. Next, we fulfil irrigation demands, yet now considering the storage above the backup volume, which is the sole control variable of the problem. At the end, we check whether the current storage exceeds the reservoir capacity. In that case, we release additional water, until exhausting the discharge capacity of the intake pipe. Whenever we release water, either for satisfying the above uses or as surplus flow, for the sake of preventing water losses through the spillway, we produce hydroelectric energy.

All model outputs (simulated storage, water release, spill losses and energy production) are stochastic, since they depend both on stochastic inputs and the uncertain parameters of the rainfall-runoff procedure, which interrelate in a complex manner. The system performance is evaluated in terms of reliability (i.e., probability of fulfilment of the two water demands) and mean daily energy production. The reliability is estimated empirically as the percentage of time that the actual outflow equals the corresponding demand. Apparently, the reliability of meeting the agricultural demand depends on the value of the backup volume; the larger this value is, the lower the reliability.

4. Results and discussion

4.1. Generation of synthetic time series

Due to absence of reliable meteorological data in the island region, we obtained historical rainfall and temperature records from the neighbouring island of Kalymnos, covering the period from June 2009 to February 2017. Based on these data, we generated daily synthetic time series for a 100 year simulation period, through the Castalia stochastic weather generator model. The synthetic data preserve with high accuracy the statistical properties, at the annual, monthly and daily temporal scales. Indicatively, in Table 1 we contrast the monthly average and standard deviation values of the observed against simulated rainfall. Moreover, the increased length of synthetic data, exhibiting the so-called Hurst-Kolmogorov behaviour, allows for providing rich patterns of potential future realizations of the underlying processes and reproducing the changing behaviour of climate [6], which is impossible to detect in the limited historical information (Fig. 3).

Table 1. Comparison of monthly statistical characteristics (average, standard deviation) of synthetic vs. observed rainfall.

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Average, synthetic	42.0	88.3	160.6	153.4	98.7	58.8	40.8	16.2	4.5	7.1	0.6	11.1
Average, observed	37.4	77.4	143.7	143.5	98.5	56.0	34.8	14.3	3.8	0.0	0.5	10.0
St. dev., synthetic	27.4	89.9	102.7	44.0	47.9	31.1	38.3	10.3	6.5	0.7	1.1	13.2
St. dev., observed	26.9	80.8	110.0	48.6	43.4	33.0	33.6	9.7	6.7	0.0	1.3	13.5

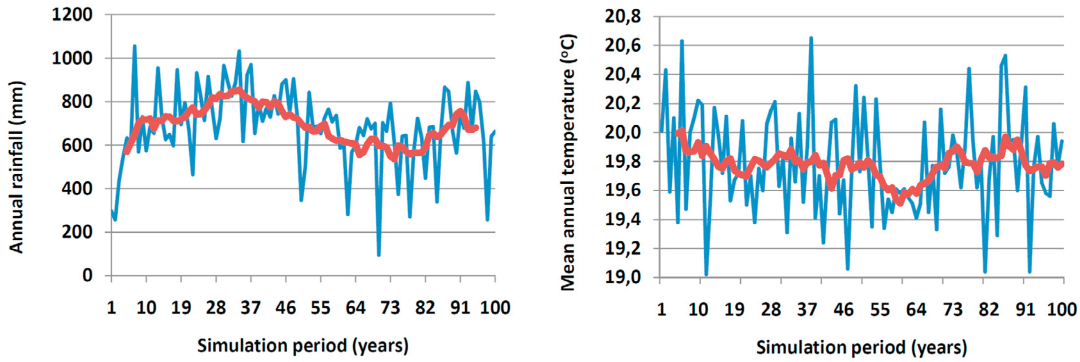

Fig. 3. Synthetic time series of annual rainfall (left) and temperature (right) and 10-year moving average for a 100-year horizon.

4.2. Rainfall-runoff model calibration under uncertainty

The rainfall-runoff model, detailed in Section 3.4, was used to provide stochastic estimations of the daily inflows to the Livadi reservoir and the actual evapotranspiration through the study area, which was essential for estimating the agricultural demands.

Model inputs were the 100-year daily synthetic rainfall, provided by Castalia model, and the daily synthetic PET, provided by the parametric expression (1), using synthetic temperature, extraterrestrial radiation estimated for the study area latitude (φ = 36 30′)and parameters a and c interpolated from a neighbouring station.

To calibrate the model, in the absence of any observed runoff data, we receded to the use of available 'soft' data, i.e., rough estimates of the mean annual water balance of the basin, obtained from local expert knowledge. We recall that a recent hydrological study estimated that the mean annual rainfall is partitioned into actual evapotranspiration, surface runoff, and underground losses at ratios of 74, 15 and 11%, respectively.

For an *a priori* quantification of uncertainty, we employed 300 000 Monte Carlo simulations with synthetic inputs (rainfall and PET), as resulting from 300 000 randomly generated parameter sets I_a, K and a. These were assumed to be uniformly distributed in vast 'feasible' ranges, particularly [0, 70] for initial abstraction (mm), [10, 700] for soil capacity (mm), and [0, 0.01] for recession rate for percolation. For each simulation experiment, we calculated the associated water balance estimates, i.e., the percentage of rainfall to actual evapotranspiration, surface runoff, and underground losses, and distinguished the parameter sets satisfying the aforementioned ratios with a 5% tolerance interval. This resulted to 2100 parameter sets, which are considered "behavioural", in the sense that they ensure a realistic representation of the macroscopic hydrological behaviour of this highly uncertain system [7].

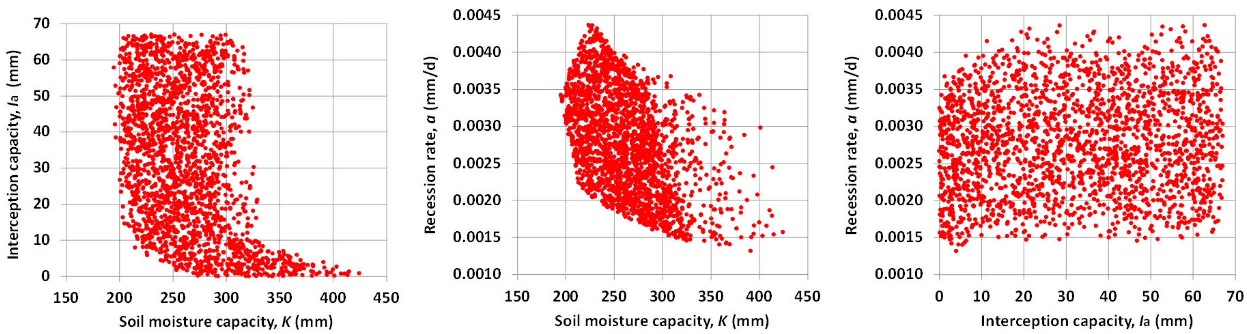

Fig. 4. Scatter plots of all pairs of acceptable (behavioural) parameter sets.

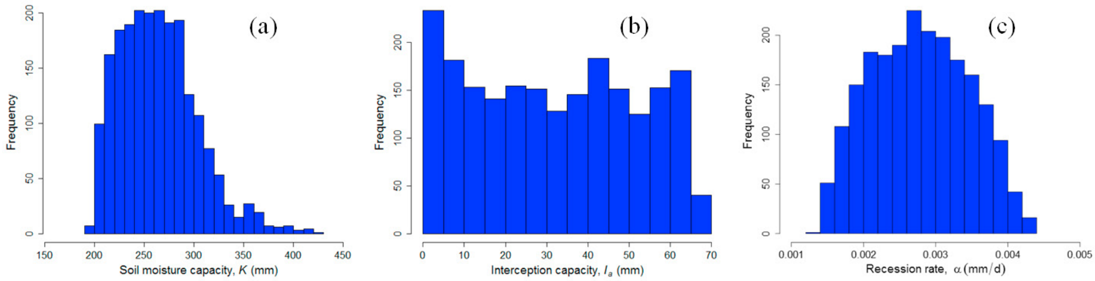

Fig. 5. Histograms of behavioural parameters (2100 sets).

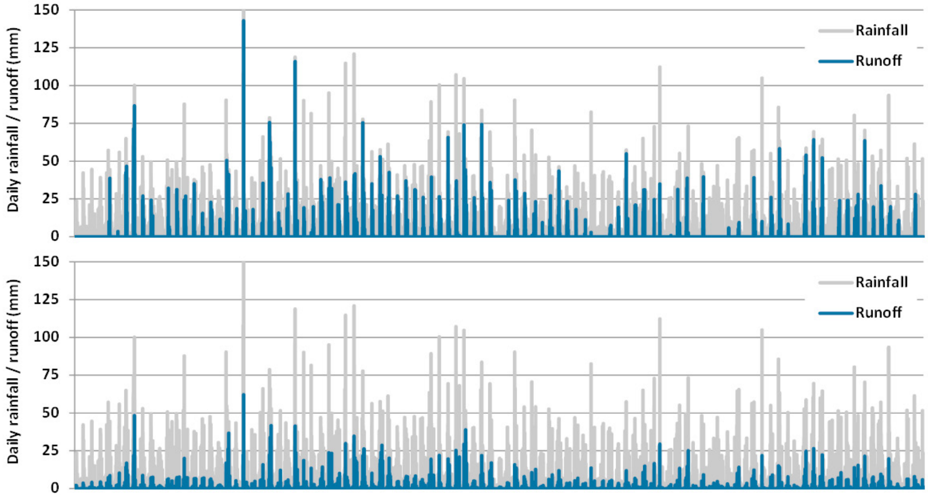

Fig. 6. Simulated runoff vs. synthetic rainfall assuming two extreme behavioural parameter sets (upper set: I_a = 57.8 mm, K = 194.7 mm, a = 0.00342; lower set: I_a = 0.8 mm, K = 424.2 mm, a = 0.00157).

This simple yet effective Monte Carlo procedure provided an *a posteriori* quantification of the model uncertainty, together with insights into the nonlinear dependencies among the behavioural parameters (Fig. 4). In general, the extent of the behavioural parameter space is quite large, and the dependency patterns are irregular. It can be seen that in order to preserve the estimated water balance within the acceptable tolerance, the interception capacity I_a, and the recession rate, a, should be both anti-correlated with the soil moisture capacity, K, which is reasonable. In Fig. 5 we also plot the histograms of the three parameters, which exhibit different statistical behaviour. We observe that K follows a heavy-tail distribution, I_a is uniformly distributed, while a is normally distributed.

Although the water balance information helped restricting somehow the tremendous initial parameter uncertainty, the remaining uncertainty is still very large. For instance, in Fig. 6 we contrast the simulated daily runoff from two totally different parameter sets, corresponding to the extreme values of soil capacity.

For all behavioural parameter sets, we ran the rainfall-runoff model in stochastic mode, thus providing 2100 scenarios of potential basin responses. The main outcomes of the model, i.e., synthetic actual evapotranspiration and runoff, were next used to feed to water demand and reservoir operation model, respectively.

4.3. Estimation of water demands

As explained in section 3.5, the simulated drinking water demand depends on temperature, which is provided by the Castalia model, while the irrigation demand depends both on temperature and the simulated actual evapotranspiration, which is output of the rainfall-runoff model. In this respect, for the former we generate a unique synthetic time series of 100 years length, while for the latter we generate 2100 scenarios, associated with the behavioural outcomes of the hydrological model. On mean daily basis, the water supply demand is 578 m^3, while the agricultural demand ranges between 550 and 675 m^3, reflecting the relatively small variability of actual ET. On the other hand, the seasonal variability of both processes is significant, due to climatic and socioeconomic reasons (substantial increase of summer population, due to tourism).

4.4. Simulation of Livadi reservoir

We ran the reservoir management model in Monte Carlo setting, considering 2100 runoff and irrigation demand scenarios, as well as a common scenario for synthetic rainfall, evaporation and water supply data. From this procedure, we obtained 2100 scenarios of the daily operation of the system for 100 simulated years, by setting a backup storage constraint up to 50 000 m^3. The key quantity of interest is the mean daily hydropower production, which was used for creating the energy mix of the island [8]. This variable should be represented by a bounded distribution, due to the existence of the head constraint. In Fig. 7, it is shown that the Beta distribution has a satisfactory fit to the mean daily hydropower production.

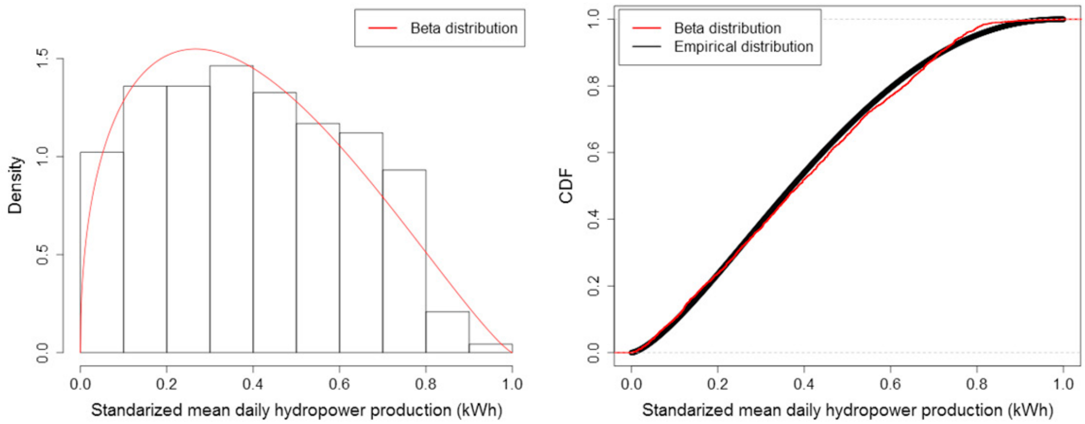

Fig. 7. Fitting of the Beta distribution to standardized mean daily hydropower production values.

4.5. Analysis of parameter and process dependencies

This analysis aims at investigating how the parameter uncertainty of the rainfall-runoff model is propagated to next simulations.Fig.8 shows scatter plots of the mean daily runoff, irrigation demand and hydropower production against the full range of behavioural values of soil moisture capacity, *K*. As expected on physical grounds, an increased soil moisture capacity is associated with less surface runoff and decreased irrigation demands. The mean daily energy production potential is also decreased for larger values of the *K* parameter, yet in a less unambiguous way as shown in Fig. 5(c). At this final modelling stage of hydropower simulation, the uncertainty that initiated from the rainfall-runoff simulations is propagated through the sequence of models used and amplified due to the inter-relation of the inputs in the different models. The increased complexity of the model at this stage -also enhanced by the set of operational rules imposed- together with the variability induced from the meteorological forcing makes tracing back the physical drivers more difficult than in the previous cases. For example, an increased soil moisture capacity would lead to less runoff, but also less irrigation needs, since more soil moisture can be retained in the unsaturated zone. In this respect, the unique approach to reveal and quantify such complex trade-offs is through Monte Carlo analysis.

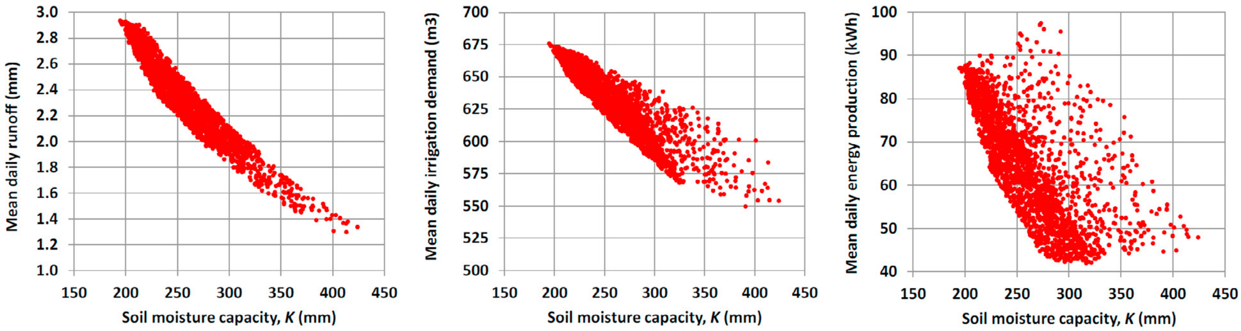

Fig. 8. (a) Mean daily runoff (output of hydrological model, input of reservoir model) vs. behavioural soil moisture capacity values; (b) Mean daily demand for irrigation (depends on simulated evapotranspiration deficits) vs. behavioural soil moisture capacity values; (c) Mean daily hydropower production vs. behavioural soil moisture capacity values

5. Conclusions

This study highlights the value of stochastic approaches to handle the different sources of uncertainty, both case-specific, i.e., data limitations in data-scarce regions, and inherent, i.e., emerging from the complexity of modelled systems (e.g., multi-purpose hybrid renewable energy systems). Actually, the improper representation of uncertainty is an intrinsic drawback of all deterministic hydrological and water management models, which are prone to limited information provided by historical data. Combinations of hard (observations) and soft (human evidence based on experience) information can help reducing yet never eliminating uncertainties. Moreover, complex water-energy management problems suffer from multiple sources of uncertainties, since many of their inputs are not directly obtained from in situ measurements but are generated through models or sequences of models, where uncertainties are propagated from model to model.

For this reason, stochastic approaches are unique means to quantifying uncertainties, yet they do require careful interpretation of their outcomes, since they may result to very large uncertainty bounds that seem difficult to take advantage in practice. On the other hand, the awareness of modelling limitations due to uncertainty is absolutely crucial to avoid overconfidence into deterministic approaches and to concentrate our efforts towards systematic and reliable data, which is the sole way to reduce uncertainty.

References

[1] Efstratiadis, Andreas, Ioannis Nalbantis, and Demetris Koutsoyiannis (2015) "Hydrological modelling of temporally-varying catchments: Facets of change and the value of information." *Hydrological Sciences Journal* 60.7-8 (2015): 1438–1461.

[2] Aegean Hydrosystems Joint-Venture (2005) "Astypalaia Island." In: *Development of Systems and Tools for Water Resources Management of Dodecanese Water District – Phase A*, Report 1, Ministry of Development.

[3] Efstratiadis, Andreas, Yiannis Dialynas, Stefanos Kozanis, and Demetris Koutsoyiannis (2014) "A multivariate stochastic model for the generation of synthetic time series at multiple time scales reproducing long-term persistence" *Environmental Modelling & Software* 62 (2014): 139–152.

[4] Tegos, Aristotelis, Andreas Efstratiadis, and Demetris Koutsoyiannis (2013) "A parametric model for potential evapotranspiration estimation based on a simplified formulation of the Penman-Monteith equation." In: Stavros Alexandris (ed.) *Evapotranspiration - An Overview*, 143–165, InTech.

[5] Efstratiadis, Andreas, Antonios D. Koussis, Demetris Koutsoyiannis, and Nikos Mamassis (2014) "Flood design recipes vs. reality: can predictions for ungauged basins be trusted?" *Natural Hazards and Earth System Sciences* 14 (2014): 1417–1428.

[6] Koutsoyiannis, Demetris (2011) "Hurst-Kolmogorov dynamics and uncertainty." *Journal of the American Water Resources Association* 47.3 (2011): 481–495.

[7] Beven, Keith. J., Andrew M. Binley (1992) "The future of distributed models: model calibration and uncertainty prediction." *Hydrological Processes* 6.3 (1992): 279-298.

[8] Stamou, Paraskevi, Sofia Karali, Maria Chalakatevaki, Vassiliki Daniil, Katerina Tzouka, Panayiotis Dimitriadis, Theano Iliopoulou, Panos Papanicolaou, Demetris Koutsoyiannis, and Nikos Mamassis (2017) "Creating the electric energy mix of a non-connected Aegean island." *EGU General Assembly 2017, Geophysical Research Abstracts, Vol. 19,* Vienna, EGU2017-10130-10, European Geosciences Union.