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Water supply sensitivity to climate change: An R package for implementing reservoir storage analysis in global and regional impact studies

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ABSTRACT

Whilst there are numerous global and regional studies of climate impacts on water resources, relatively few authors have incorporated reservoir storage into their earth system models. Consequently, such studies are unlikely to provide coherent estimates of how changes in climate might affect water supplies globally. This short communication describes an R package, named *reservoir*, which has been designed for rapid and easy routing of runoff data through storage. The package comprises tools for capacity design, release policy optimisation and performance analysis—allowing users to specify realistic reservoirs and then assess performance in terms of meeting water delivery targets. We demonstrate some of the capabilities of *reservoir* using 271 runoff records from the Global Runoff Data Centre. The package is freely available through the Comprehensive R Archive Network (CRAN).

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Software availability

Name of software: *reservoir*
Version: 1.0
Developers: S.W.D. Turner and S. Galelli
Contact email: swd.turner@gmail.com
Year first available: 2015
Available from: The Comprehensive R Archive Network (CRAN) (https://cran.r-project.org/web/packages/reservoir); development versions available on GitHub (https://github.com/swd-turner/reservoir).

1. Introduction

Global and regional studies of climate impacts on water resources are seen as part of a critical endeavour towards understanding and preparing for global environmental change. Typically, these studies are based on modelled runoff. For instance, one might propagate climate scenarios through hydrological models to simulate runoff, which is then used to infer impacts on water availability in the broadest sense (e.g., Milly et al., 2005; Jun et al., 2011; Hagemann et al., 2013; Yang et al., 2013; van Vliet et al., 2013; Schewe et al., 2014). One limit to this approach is that water users rarely rely on natural, uninterrupted runoff to meet their water needs—reservoirs play a vital role in most of the world's large river systems (Nilsson et al., 2005) and are instrumental in sustaining water supplies for municipal, industrial, agricultural and environmental purposes. The regulation of runoff by engineered water storage reservoirs must therefore be modelled in order to study the effects of climate change on global water supplies.

One way of tackling this problem is to use a global dataset of reservoirs (ICOLD, 2009; Lehner et al., 2011) and then model the storage dynamics using stylised operating rules tailored to each reservoir's primary function (Nazemi and Wheater, 2015). This approach has been followed in a handful of studies to estimate global and regional impacts of water resources management practices on river discharge (e.g., Haddeland et al., 2006; Hanasaki et al., 2006, 2008; Döll et al., 2009; Haddeland et al., 2014). These studies have advanced the field of earth systems modelling, demonstrating the importance of incorporating reservoir storage in global and regional impact assessments. A further useful development would be to apply the operating methods used widely by

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practicing engineers and then assess performance in terms of water supply to consumers (as opposed to focussing on impacts on downstream discharge or the water cycle more broadly). To help the field advance toward this goal, we present a software package that draws together some of the well-established methods of reservoir storage analysis. The package, named *reservoir*, allows users to design realistic, single-storage systems that can be simulated to evaluate water supply performance in terms of meeting water delivery targets (Turner and Galelli, 2015).

2. Software characteristics and capabilities

2.1. Software environment

We sought to make the software easy to obtain, use and manipulate, so as to expose it to a large community of potential users. We use the statistical computing environment 'R', which runs on all major platforms and is freely-available under the GNU General Public Licence (R Core Team, 2015). Many hydrologists use R because its libraries (packages developed by the R user community) hold thousands of functions for implementing a wide range of statistical techniques. There are also various packages and add-ons designed specifically for hydrological and water management applications (Thyer et al., 2011; Joseph and Guillaume, 2013; Reichert et al., 2013; Zambrano-Bigiarini and Rojas, 2013; Andrews et al., 2011; Fuka et al., 2014; Srivastav and Simonovic, 2014; Wu et al., 2014; Horsburgh and Reeder, 2014; Zambrano-Bigiarini, 2014; Mehrotra et al., 2015; Metcalfe et al., 2015; Whateley et al., 2015). Since *reservoir* is available on CRAN, it can be downloaded and installed directly from the R console using the one-line command install.packages("reservoir").

2.2. Package basics

Version 1.0 of *reservoir* comprises six functions for reservoir analysis, which can be divided into three main categories: capacity design, release policy design and performance analysis (Table 1). A seventh function estimates the Hurst coefficient of a runoff time series. The capacity design functions could be used in instances where users wish to specify realistic, stylised reservoir models based on inflow and demand data. If actual reservoir data are available, then they can be set up as inputs for running policy design and performance analysis functions across multiple sites. In addition to reservoir and demand data, all functions require as input a single vector or time series of runoff data, which is assumed to represent the natural inflow to the reservoir. These data must be in the format of inflow totals for each time step (e.g., Mm^3/month) rather than as average flow rates (e.g., m^3/s). Any desired temporal resolution and time series length can be handled, although a minimum of 30 years of continuous observations is recommended to capture interannual streamflow variability. We anticipate that users of our software would either apply their own hydrological models to compute runoff (which would then be fed into our functions) or use baseline and/or projected runoff scenarios from global runoff data sets. Full details of data and parameter inputs for each function can be found in the documentation accompanying the package. Underlying algorithms can be displayed on screen by entering the relevant function name into the R console.

The reservoir analysis functions apply basic mass balance (Eq. (1)) to simulate storage behaviour:

$$S_{t+1} = S_t + Q_t - R_t \quad \text{s.t. } 0 \leqslant S \leqslant S_{cap} \tag{1}$$

where S_t, Q_t and R_t represent the volume of water held in storage, the inflow and the controlled release at time step t. S_{cap} is the storage capacity of the reservoir. Evaporation can be accommodated by subtracting from the inflow time series, so that Q_t becomes the effective inflow (runoff minus evaporation and other losses). This approach allows the analyst to capture the varying role played by evaporation across different climates.

2.3. Capacity design

The package offers two capacity design functions, named *Rippl* and *storage*. The Rippl function returns the minimum storage required to meet specified water demands without allowing supply shortfall (occurring when the reservoir empties) when fed by the recorded inflow time series (Rippl, 1883). The resulting design capacity is known as the 'no-fail storage,' which is found computationally using the sequent peak algorithm (Thomas Jr and Burden, 1963).

The *storage* function offers a more nuanced approach to capacity design, basing the design on both the desired yield and target reliability of supply. The yield is the maximum demand that the system can meet without violating the reliability criterion, and can be modelled as either a constant demand or by assigning an interannual demand profile—useful for representing summer urban water demand peaks or crop water demands, for instance. We use the time-based reliability, which is the ratio of non-fail periods to total number of periods in the simulation (McMahon et al., 2006). The design storage is computed iteratively using the bisection method, which converges on the target reliability by varying the modelled storage capacity (users may specify a maximum number of iterations to reduce computational time if required). Setting the reliability to 1 will return the no-fail storage (as determined by the Rippl function), although the Rippl function remains useful for situations where rapid determination of the no-fail storage is desired.

Both the *Rippl* and *storage* functions allow the user to double-cycle the inflow time series, which avoids bias in cases where the

Table 1
Functions of *reservoir*.

Category	Function	Purpose	Notable features
Capacity design	Rippl	Determine no-fail storage capacity for specified demand time series.	Double-cycle option; constant or time-varying release target.
	storage	Determine storage capacity for specified time-based reliability and yield target.	Double-cycle option; interannaul demand profile option.
Release policy design	dp	Determine the optimal sequence of releases to minimise a penalty cost function based on water supply deficit	Flexible supply deficit penalty cost function; optional reporting of reliability, resilience and vulnerability
	sdp	Estimate the optimal policy look-up array (based on storage, inflow and within-year time period).	Inflow persistence embedded; flexible supply deficit penalty cost function; optional policy simulation.
Performance analysis	yield	Determine the yield for specified reservoir capacity and time-based reliability.	Double-cycle option; interannual demand profile option
	rrv	Determine reliability, resilience and vulnerability for a specified reservoir capacity and target release.	Standard operating policy or optimised releases; annual, time-based and volumetric reliability measures.
_	Hurst	Estimate the Hurst coefficient of an annualised streamflow record.	

critical drawdown period is cut short at the end of the simulation (Vogel and Stedinger, 1987). The initial storage on the onset of simulation defaults to full capacity, but can be redefined by the user in the storage function. Both functions adopt 'standard operating policy,' which assumes that the operator supplies the target demand in full unless constrained by the physical water availability in storage and current period inflow (McMahon and Adeloye, 2005).

2.4. Release policy design

Two functions are available for water release policy design: deterministic dynamic programming (*dp*) and stochastic dynamic programming (*sdp*). Both approaches optimise release decisions to minimise the sum of penalty costs incurred in long-term operation of the reservoir. Penalty costs are a function of the volume of water delivered relative to the demand, as given by Eq. (2):

$$C_t = [1 - (R_t/D)]^{\tau} \tag{2}$$

where D is the demand, or target release, and τ is the penalty cost exponent, which, when greater than one, drives reservoir hedging—the deliberate cutback of release so as to avoid any reservoir failure that would result in larger, more damaging supply shortfalls. To exemplify, this type of policy is applied when a water authority decides to impose demand restrictions in response to drought. The larger the exponent τ, the greater the impetus for hedging. Academic studies often apply a squared term ($\tau = 2$) (e.g., Reddy and Kumar, 2006; Celeste and Billib, 2009), but there is no reason not to allow for a range of possible exponents. The exponent should ultimately reflect the cost curve that a given water authority would encounter as it mobilises increasingly expensive supply augmentation and demand management measures as drought progresses (Draper and Lund, 2004). The release policy design functions in *reservoir* allow the user to specify the loss exponent, providing a degree of flexibility in setting the performance criteria for different water supply reservoirs.

The *dp* function returns the optimal sequence of releases for the input inflow time series by solving Eq. (3) using the backwards recursive procedure (Loucks et al., 2005).

$$f_t(S_t) = \min_{R_t} \{C_t(S_t, Q_t, R_t) + f_{t+1}(S_{t+1})\} \quad \forall\ S_t \text{ and } t \in \{1, \ldots, H\} \tag{3}$$

where H is the final time step of the inflow time series. The water release decision R_t is selected to minimize the current period cost $C_t(S_t, Q_t, R_t)$ plus future cost $f_{t+1}(S_{t+1})$. The *dp* function is useful as a benchmarking tool for determining the upper bound performance of a reservoir. Alternatively, the user might fashion monthly release rules from the optimised time series of releases (Bhaskar and Whitlatch, 1980).

Stochastic dynamic programming returns a look-up table of releases based on information that would be available to the operator at the time of making the release decision—namely the storage level, current inflow and time of year. The *sdp* function solves Eq. (4) (adapted from Eq. (6) of Faber and Stedinger (2001)) using the backwards recursive procedure.

$$f_t(S_t, Q_t) = \min_{R_t} \left\{ C_t(S_t, Q_t, R_t) + \mathop{E}_{Q_{t+1}|Q_t} [f_{t+1}(S_{t+1}, Q_{t+1})] \right\} \quad \forall\ S_t, Q_t \text{ and } t \in \{1, \ldots, T\} \tag{4}$$

where T is the system period (for instance, $T = 12$ for a monthly operating scheme). The state of the reservoir at each decision-making time step t is described by the storage S_t and the current period inflow Q_t. For each state and time step, the release decision R_t is selected to minimize the current period cost $C_t(S_t, Q_t, R_t)$ plus future cost expectation $f_{t+1}(S_{t+1}, Q_{t+1})$, which depends on the resultant state of the system at time step $t + 1$. The persistence

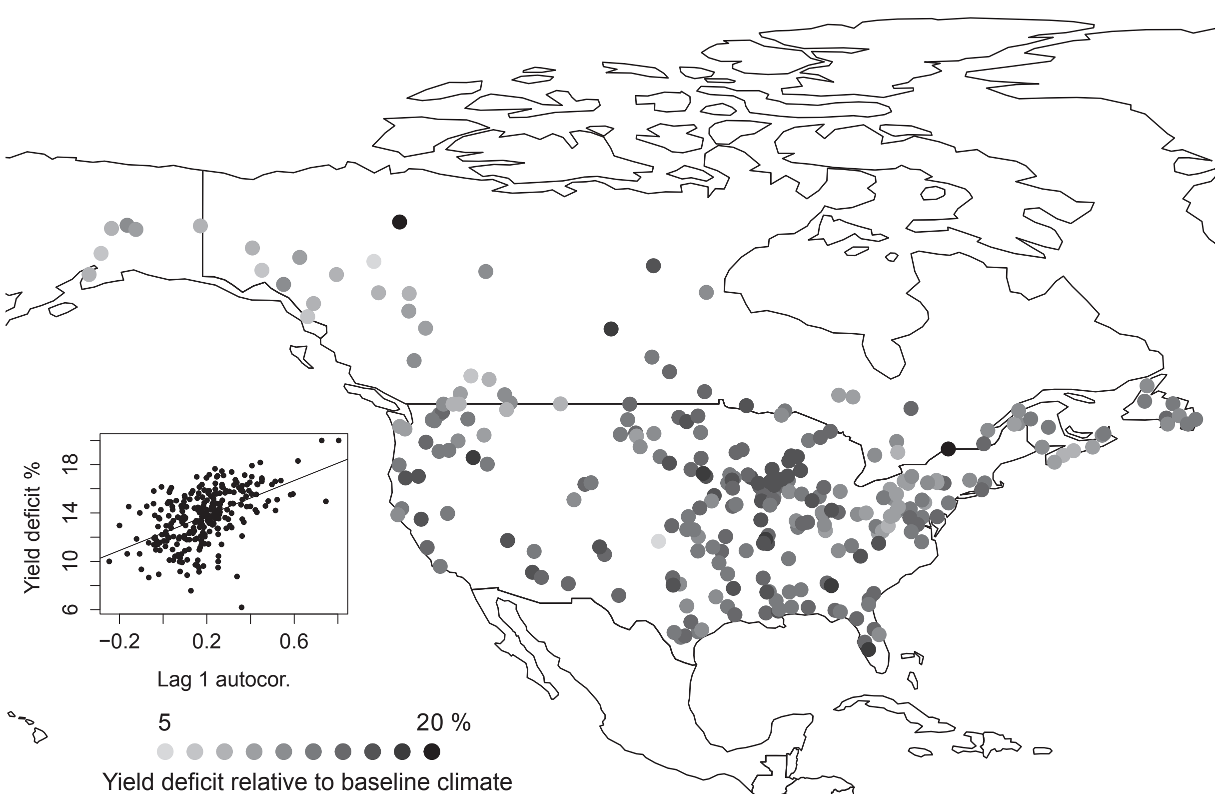

Fig. 1. Impact of 'climate projection' on yield for 271 stylised reservoirs in North America (reservoirs designed to 90% reliability under recorded flows).

structure of the inflow process is described using a periodic, first-order Markov chain, which provides transition probabilities for computing the future cost expectation in the equation (Loucks et al., 2005).

Dynamic programming methods require that the decision and control variables be discretised so that the problem can be solved numerically (Soncini-Sessa et al., 2007). In *reservoir* the storage and release are discretised to 1000 and 10 uniform states respectively by default, although these parameters can be set by the user. The *sdp* function also requires inflow discretisation. The default setting classifies the inflow data separately for each within-year period (e.g., calendar month) and according to bounding quantiles of 1.00, 0.95, 0.7125, 0.4750, 0.2375, and 0.00 (Stedinger et al., 1984).

The algorithms underlying *dp* and *sdp* employ the family of apply functions in R, which substitute inefficient loop structures by assigning computational tasks to array margins. This means that the release policy design functions execute rapidly—see Appendix A.

2.5. Performance analysis

The ability of a reservoir system to uphold service levels and meet water delivery targets is commonly analysed using either a yield-based or risk-based approach. Yield-based methods estimate the maximum supply that can be sustained over a period of time without violating specific performance criteria (e.g., Kuria and Vogel, 2014; Turner et al., 2014b; Peel et al., 2015). Risk-based methods focus on estimating the likelihood and severity of water supply shortfalls or restrictions (e.g., Asefa et al., 2014; Borgomeo et al., 2014; Turner et al., 2014a). Both approaches can be applied using *reservoir*.

For the *yield* function, we adopt a method that can compute both the 'no fail' yield (also known as 'firm yield') and the 'reliability yield.' The latter is the maximum supply that can be sustained without violating a specified time-based reliability (McMahon and Adeloye, 2005). The 'no fail' yield is simply the reliability yield with a required reliabilty of 1 (meaning zero supply shortfalls incurred). The yield is computed iteratively using the bi-section method as in the *storage* function introduced above.

Risk-based methods for evaluating water supply performance include reliability, resilience and vulnerability (Hashimoto et al., 1982). The *rrv* function in *reservoir* computes annual reliability, time-based reliability, volumetric reliability, resilience and dimensionless vulnerability (see definitions in McMahon et al., 2006) based on simulations of reservoirs with specified capacity and target release, which can be constant or time-varying. All of these metrics are computed from the output supply time series of the reservoir simulation. The default simulation mode assumes standard operating policy, although optimised operating policies can also be specified using the output of the *sdp* function, allowing reanalysis of water supply performance under alternative operating schemes.

3. Example applications

3.1. Data

The following examples demonstrate two possible applications of *reservoir* using records of average monthly streamflow obtained from the Global Runoff Data Centre (alternative sources of observed global runoff data are listed in Nazemi and Wheater (2015)). We used stations located in the North American continent filtered for records with 50 or more years of unregulated runoff without gaps of more than 12 months in duration. This left 271 streamflow records. Remaining short-duration gaps in the data were interpolated using the StructTS function in R. Units were then converted from average monthly streamflow (m^3/s) to monthly inflow totals (Mm^3). In R, we convert these records to date-stamped time series objects using the ts function and then store the records in a list object with the name GRDC_list. For the sake of this simplified demonstration let us assume that these data represent a baseline climate and that a perturbed version of the same set of records represents expected flows under some climate projection. Here the 'projection' is simply the recorded time series multiplied by 0.8; in an actual application users might apply baseline and projected runoff time-series generated from Global Climate Models and downscaled to the relevant catchments or grid squares.

3.2. Reservoir capacity design

For the purposes of this demonstration, we use a capacity design function to create hypothetical reservoirs for analysis. We shall assume that the reservoirs must supply a constant demand equal to 0.75 of the mean of the inflow time series with a time-based reliability of 0.9. The following code computes the design storages for these criteria using the *storage* function, retaining the results in a vector named S:

```
for(i in 1:271){
 Q <- GRDC_list[[i]]
 demand <- 0.75 * mean(Q)
 S[i] <- storage(Q, yield = demand, reliability = 0.9)
}
```

These storages can be used to assess sensitivity of water supply performance to climate change.

3.3. Impact of climate change on reservoir yields

The following code loops through each inflow record, perturbs the inflow to our hypothetical projection, selects the stylised design storage from vector S and then calls the *yield* function to determine the yield under the projected climate scenario.

```
for(i in 1:271){
 Q <- GRDC_list[[i]] * 0.8
 S_cap <- S[i]
 Y[i] <- yield(Q, capacity = S_cap, reliability = 0.9)
}
```

Results are displayed in the map in Fig. 1 as a percentage reduction in yield (or yield deficit) from the yield of the baseline climate (75% of the mean inflow). Despite the uniform change function applied across all inflow data, we can see from this analysis that the resulting yield deficit ranges from 5 to 20% depending on location. The impact on reservoir yield is greatest in the southern, western and mid-western United States; reduced runoff has less impact on water supply performance in western Canada and the north-eastern United States. There are significant positive correlations between the measured yield deficits and the lag-1 autocorrelation ($r^2 = 0.27$, $p < 2.2 \times 10^{-16}$) and coefficient of variation of annualised inflows (log–log regression: $r^2 = 0.11$, $p < 1.7 \times 10^{-8}$). High variability and high persistence leads to longer critical drought periods, and so the yield is controlled by fewer, longer droughts in these systems, which appear to be more sensitive to reductions in the runoff. These results highlight the importance of modelling reservoir storage in water supply impact assessments as opposed to drawing conclusions directly from runoff.

3.4. Impact of reservoir hedging on vulnerability

In the next experiment, the same set of reservoirs is used to assess the impact of release policy on vulnerability. First, the *rrv* function is used to compute the vulnerability of each system

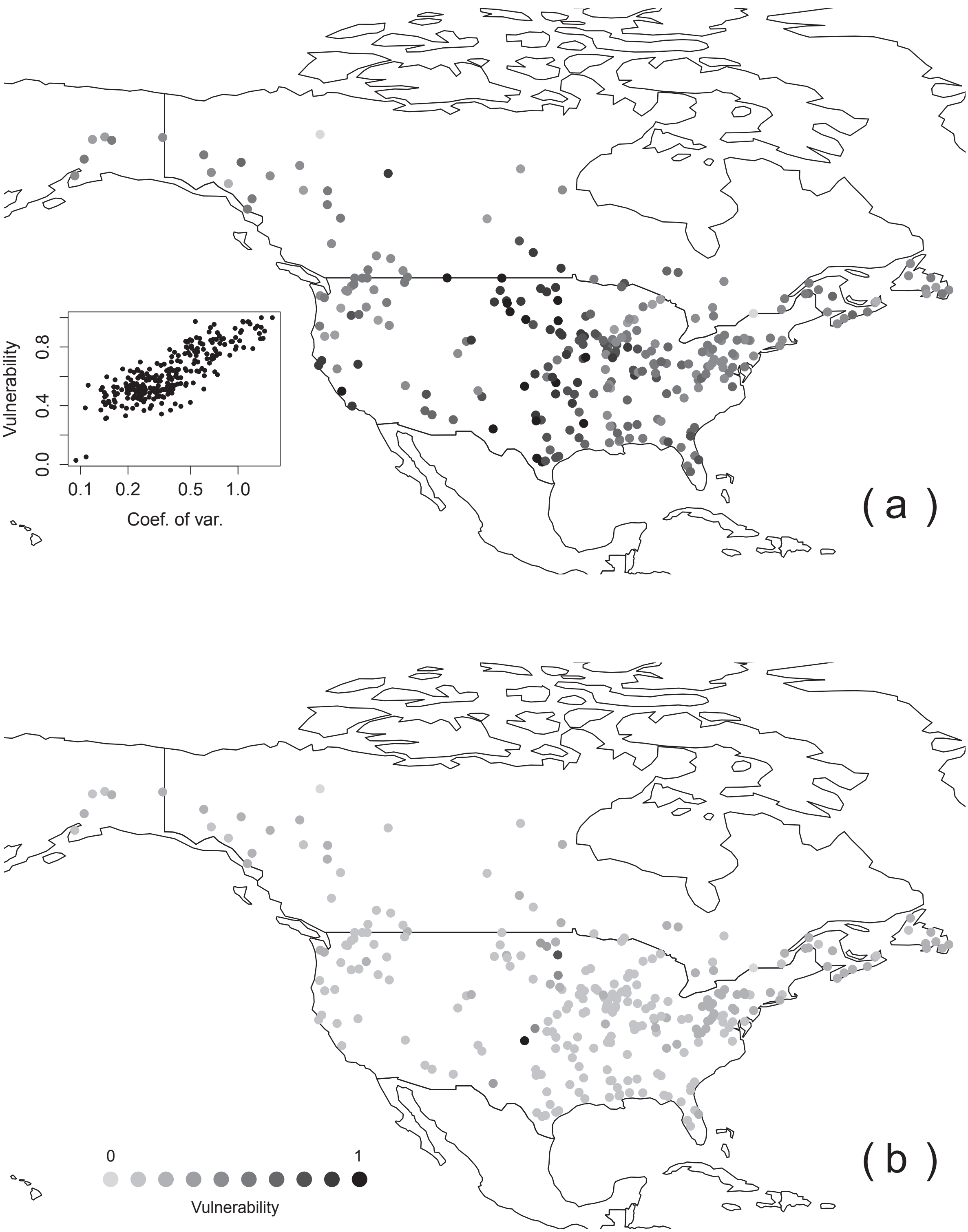

Fig. 2. (a) Dimensionless vulnerability of reservoirs designed to 90% reliability under historical recorded inflows and assuming standard operating policy. (b) Dimensionless vulnerability of the same reservoirs but operated according to an offline policy derived by Stochastic Dynamic Programming.

assuming standard operating policy. The final line of code pulls out the vulnerability result from the list of outputs generated by *rrv*.

```
for(i in 1:271){
 Q <- GRDC_list[[i]]
 S_cap <- S[i]
 demand <- 0.75 * mean(Q)
 RRV <- rrv(Q, R_target = demand, capacity = S_cap)
 Vulnerability[i] <- RRV$vulnerability
}
```

In an impact assessment it would perhaps be unwise to assume standard operating policy, particularly when examining water shortage risks. The reason is that reservoir operators will seek to hedge against reservoir failure by cutting back the release on the onset of drought. They thereby accept reduced reliability (higher likelihood of shortfall) for improved resilience and vulnerability (lower severity of shortfall)—an operating approach that can be simulated using the *sdp* function. When calling the *sdp* function, there are two ways in which the reliability, resilience and vulnerability can be re-examined. One approach is to simply generate the policy using the *sdp* function and plug the output directly into the *rrv* function using the policy parameter. This would be useful in instances where the user wishes to validate the optimised policy under alternative inflow data. Here, however, we can simply instruct the *sdp* function to simulate the optimised policy and report reliability, resilience and vulnerability. This is achieved by setting the rep_rrv parameter to TRUE:

```
sdp(Q, target = demand, capacity = S_cap, rep_rrv=TRUE)
```

In this procedure we accept the function default values for the loss exponent τ and discretisation of storage, release and inflow. Results are given in Fig. 2. The analysis shows how strongly the operating policy affects the vulnerability of water supply reservoirs—an insight that cannot be drawn easily from a direct analysis of runoff. The nested scatter plot shows that the variability of the annualised inflow predicts the vulnerability of these reservoirs when modelled assuming standard operating policy ($r^2 = 0.69$, $p < 2.2 \times 10^{-16}$).

4. Outlook

We intend to maintain and improve *reservoir* in response to user suggestions and demands. Imminent updates may include: bathymetry relationships (i.e., storage-depth and storage-surface area curves), which would allow for varying the evaporation as a function of volume held in storage; alternative performance criteria for release policy design, such as for flood control and hydropower generation; and capability for modelling multi-reservoir systems with climate-independent supply sources. Whilst we realise that there are various commercial and open-source software packages available for water resources system analyses at the river-basin level (e.g., Soncini-Sessa et al., 2003; Sieber and Purkey, 2011; Kelly and O'Brien, 2012; Whateley et al., 2015), we believe that *reservoir* can find broad application in global climate impact assessments and generalised reservoir studies.

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Appendix A. Computation times

Table A.2 gives elapsed run times for looping each function across the same 271 stations used in this paper. These tests were executed using a 64-bit operating system with Intel(R) Core(TM) i7-4790 CPU (3.60 GHz) processor and 16.0 GB installed memory (RAM).

Table A.2Computation times for functions of *reservoir* for 271 monthly runoff records of approximately 50 years' length

Function	Elapsed time (s)	Parameter settings (where deviating from default)
Rippl	4.14	double_cycle = TRUE, plot = FALSE
Storage	68.39	double_cycle = TRUE, plot = FALSE
dp	107.54	S_disc = 100, rep_rrv = TRUE, plot = FALSE
sdp	51.30	S_disc = 100, rep_rrv = TRUE, plot = FALSE
Yield	64.04	double_cycle = TRUE, plot = FALSE
rrv	5.04	double_cycle = TRUE, plot = FALSE
Hurst	0.07	

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