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To cite this article: Víctor Parra, Patricio Fuentes-Aguilera & Enrique Muñoz (2018): Identifying advantages and drawbacks of two hydrological models based on a sensitivity analysis: a study in two Chilean watersheds, Hydrological Sciences Journal, DOI: [10.1080/02626667.2018.1538593](https://doi.org/10.1080/02626667.2018.1538593)

To link to this article: <https://doi.org/10.1080/02626667.2018.1538593>



Published online: 13 Nov 2018.



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Identifying advantages and drawbacks of two hydrological models based on a sensitivity analysis: a study in two Chilean watersheds

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ABSTRACT

Hydrological modelling has undergone constant growth with the increase in information processing capabilities. Hydrological models have traditionally been used to study the effects of climate change on management and land-use changes and for water resources planning, among other purposes. The aim of this study was to determine and analyse the advantages of the HBV and HYMOD models, which are commonly used in hydrology on daily and monthly time scales. A regional sensitivity analysis was used to compare the processes that take on greater importance at different time scales in the two models. As a result, it was found that quick precipitation-runoff processes prove to be better represented in the HBV model, while slow, time-aggregated processes are better represented by the HYMOD model. This study confirms that both models are adequate for rain-dominated basins, such as those of the study area. Additionally, the HBV model proved to be more robust in comparison to HYMOD.

ARTICLE HISTORY

Received 14 November 2017
Accepted 29 August 2018

EDITOR

R. Woods

ASSOCIATE EDITOR

S. Weijs

KEYWORDS

water balance model
comparison; flow simulation;
sensitivity analysis

1 Introduction

Hydrological models are an effective tool for water and basin management. They are meant to represent hydrological processes at the basin level (e.g. precipitation, evapotranspiration, infiltration, snowmelt) and evaluate conditions for purposes of water resources management and administration.

The use of water balance models to solve hydrological problems has increased in recent times (Rusli *et al.* 2015), especially in areas such as climate change impact studies (Solomon 2007) and the simulation and prediction of different environmental processes (Wagener *et al.* 2001).

Normally, conceptual hydrological models are developed for different time scales and the specific conditions of a basin or hydro-climatic area; thus, using them under conditions different from those for which they were created can be challenging and yield unsatisfactory results. Staudinger *et al.* (2011), for example, mentioned that hydrological models usually poorly simulate minimum streamflows since they are traditionally designed to address maximum streamflow situations; therefore, the applicability of a model in low-streamflow conditions will depend on how the relevant hydrological processes are represented (Nicolle *et al.* 2013).

Some of the advantages of conceptual models are the simple manner in which they represent and simulate processes and allow users to understand what is being simulated. They can also support prediction- and management-related decision-making processes; for example, they can be used to estimate projected hydropower generation under climate change conditions (Chilkoti *et al.* 2017), predict the hydrological components of ungauged watersheds (Ibrahim *et al.* 2015, Sun *et al.* 2015), and evaluate the effects of wildfires (Moussoulis *et al.* 2015) or land-use changes (Younis and Ammar 2017), among other activities. However, despite their advantages, hydrological models also have limitations, such as not normally considering the groundwater exchange (Pellicer-Martínez *et al.* 2015) or oversimplifying the real world (Martina *et al.* 2011), simplifying the processes simulated and sometimes reducing their importance in the simulated water balance.

Each model should provide a clear statement of its limitations and proper guidance along with a description of dominant processes (Devia *et al.* 2015). Usually, the more complex the model, the broader the characteristics of the basins and climates in which it is applied; however, the more parameters it has, the less understandable the simulated processes become. On

the other hand, the simpler the model (such as a conceptual model), the easier it is to understand and calibrate; nonetheless, it proves necessary to know its limitations and advantages for different purposes, time scales and climates.

Due to the growing use of hydrological models to simulate processes in a basin, and the differences among them (e.g. in structure, the conceptual representation of the system and processes and the amount of model parameters), there is a need to evaluate them and assess their results and capabilities (e.g. the capacity to simulate different basins and climatic limits of applicability). te Linde *et al.* (2007) suggested that one way to evaluate a model is to implement two or more of them in a basin in order to compare their results. Jiang *et al.* (2007) quantified the differences between six hydrological models (Thorntwaite-Mather, VUB, Xinajiang, Guo, WatBal and Schaake) in order to evaluate the impact of climate change on the Donjiang River basin, China. Although very similar results were obtained regarding the streamflow data in that study, differences in the soil moisture model and, therefore, in the processes represented, were found. Thus, evaluating not only model capabilities but also the capabilities of their sub-models and their effects on the main model results may contribute to a better understanding of the simulated system and the processes that occur in it.

Two widely used models are HBV (Bergström 1972) and HYMOD (Boyle 2001). Both have been applied in a variety of basins and climates (e.g. the MOPEX database (Kollat *et al.* 2012), a continental climate with cold winters and relatively warm summers (Staudinger *et al.* 2011), a subarctic climate (Seibert 1997), a dry-continental climate (Przeczek *et al.* 2009), a subtropical climate (Rusli *et al.* 2015), and in the Asian monsoon region (Li *et al.* 2009), among others) with different characteristics in terms of precipitation, temperature, size, slope and aridity index.

The choice of a model for particular watershed characteristics and desired modelling time scales requires an understanding of model sensitivity to representative processes. In this study, the processes that take on greater importance according to the characteristics of models, watersheds and time scales are identified through a Regional Sensitivity Analysis (RSA). In order to identify the main characteristics of hydrological models, their advantages and drawbacks are evaluated. Different simulation time scales (daily and monthly) and watersheds are analysed to provide information that may contribute to the a priori selection of a model as a function of the processes to be modelled.

2 Study area and hydro-meteorological data

The study area comprises the watersheds of the Diguillín (207 km²) and Quino (298 km²) rivers up to the San Lorenzo and Longitudinal stream gauge stations, respectively, located in south-central Chile (Fig. 1). The Diguillín River (Fig. 1(a)) springs from the western slope of the Andes and drains toward the southwest of the *Nevados de Chillán* volcanic complex. The area is difficult to access; therefore, hydrological data are limited. The watershed presents a volcanic influence and is composed of various types of lava flows that were formed by different volcanic processes that have occurred in the last 650 thousand years (Dixon *et al.* 1999, Naranjo *et al.* 2008). The mean annual precipitation in the area is around 2300 mm, the mean annual air temperature is 9.2°C and the annual average potential evapotranspiration is around 630 mm. The basin is mostly covered by evergreen and semi-deciduous forests (~65%) and to a lesser extent (~30%) by forest-shrubland-grassland (Muñoz *et al.* 2016). The watershed presents a predominant rain flow regime during the winter with a slight snowmelt influence during the spring and early summer (Zúñiga *et al.* 2012).

Quino at Longitudinal (Fig. 1(b)) presents a temperate cold rainy climate with a mediterranean influence, which is characterized by mean annual temperatures of 8.4°C and annual precipitation of around 3000 mm, with the greatest streamflows in the winter months (as a result of rainfall) and the lowest in summer. In wet years, the greatest streamflows occur between May and August as a result of the significant winter rain, whereas the lowest streamflows are observed between January and April (Dirección General de Aguas 2004). The annual average potential evapotranspiration is around 550 mm. The Quino River is widely used for irrigation and the land in the basin is used for agriculture. The watershed was formed during the Pleistocene and has pyroclastic deposits, mainly rhyolitic associated with caldera collapse (Dirección General de Aguas 1986). The basin is mostly covered by broadleaved evergreen or semi-deciduous forest (~55%), vegetation or cropland (~34%) and to a lesser extent (~11%) by forest-shrubland-grassland.

Both models (HBV and HYMOD) have been applied in basins with characteristics, such as climate and size, similar to those of the basins in this study (e.g. Kollat *et al.* 2012 applied both models in several basins with a Mediterranean climate on the west coast of the USA).

For the study, a 10-year span (from April 2000 to March 2010) of hydro-meteorological records was used. Precipitation data (daily and monthly) were recorded at seven rain gauge stations and were obtained from the General Water Directorate (DGA) (see location in Fig. 1). Since there are no continuous temperature time series from

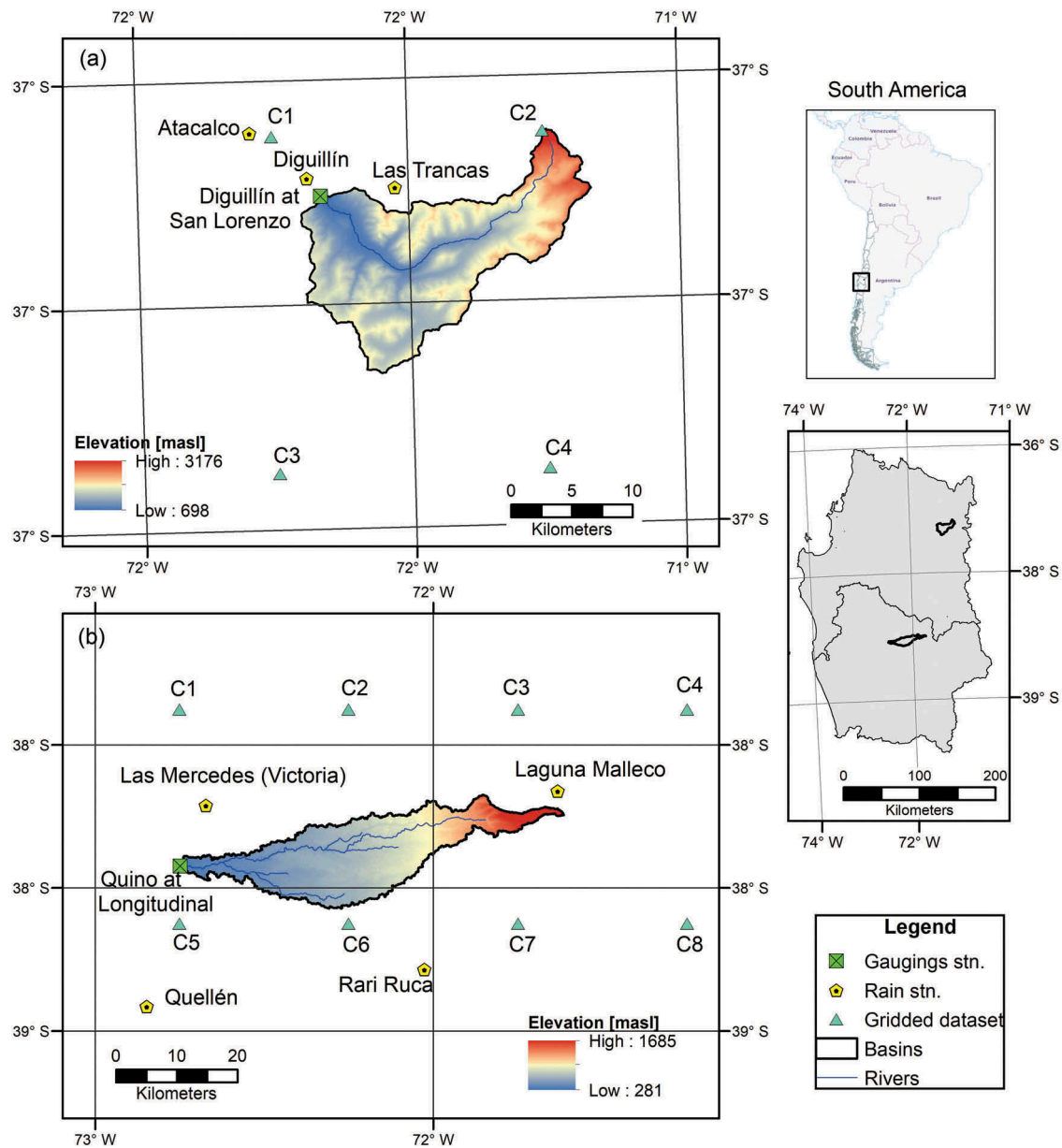


Figure 1. Location of the (a) Diguillín and (b) Quino river basins.

nearby stations, (daily) temperature time series were obtained from the AgMERRA database (Ruane *et al.* 2015) (see points in Fig. 1). AgMERRA is an open-access 0.25°-resolution (~25 km) dataset. To estimate potential evapotranspiration, the Thornthwaite method (Thornthwaite 1948) and AgMERRA temperature datasets were used.

To estimate representative and distributed precipitation, temperature and potential evapotranspiration in each watershed, the inverse-distance weighting method (IDW) (Lu and Wong 2008) was used. In addition, streamflow records were obtained from the Diguillín at San Lorenzo and Quino at Longitudinal gauging stations.

3 Methods

The HBV and HYMOD models were designed to function on a daily time step; however, in this study, both models were adapted to run on a monthly time step.

3.1 HBV model

The HBV model is a semi-distributed conceptual snow-rain water balance model. In this study, the simplified version of this model developed by Aghakouchak and Habib (2010) and based on Bergström (1992) was used. The model simulates daily discharge based on daily

precipitation, temperature and potential evapotranspiration time series (Bergström 1992) and includes a snow routine, a soil routine and a response routine (see conceptual diagram in Fig. 2).

Precipitation is deemed to be snow or rain depending on the temperature on the corresponding day above or below a threshold temperature (TT). All precipitation is snow when the temperature is below TT, and is multiplied by a snow accumulation correction factor (S_f). All the snow contributes directly to the snow storage (SS). If the actual temperature is greater than TT, there will be snowmelt. Snowmelt water is controlled by a degree-day factor (C_{melt}), which determines the daily amount of melted snow depending on the difference between the actual and threshold temperatures. Subsequently, the sum of precipitation and snowmelt (ΔP) passes to the soil routine, which includes two modules. The first module calculates the actual evapotranspiration (E_a), which is equal to potential evapotranspiration (PET) if the relationship between soil moisture (SM) and field capacity (FC) (SM/FC) is above a threshold value for potential evapotranspiration (LP). However, for soil moisture values below LP the actual evapotranspiration will be linearly reduced, as shown in Fig. 2 (upper left corner).

To calculate evapotranspiration, Bergström (1992) introduced a routine that incorporates a correction factor (C) to obtain daily potential evapotranspiration from daily mean air temperature and the long-term PET and monthly temperature averages. For simulations on a monthly time step, this routine was not

considered because it is not necessary to estimate daily evapotranspiration values.

Subsequently, the model calculates runoff (ΔQ), which depends on precipitation (ΔP), the actual water content of the soil (SM), the maximum soil moisture (FC) and an empirical coefficient (β), which determines the relative contribution of rain or snowmelt to runoff (see upper left corner of Fig. 2). Finally, the runoff response routine estimates the runoff at the watershed outlet. The system consists of two storage compartments, one above the other, which are directly connected to each other through a constant infiltration rate (Q_{perc}).

The upper deposit has two outlets (Q_0 and Q_1), while the lower deposit has one (Q_2). When the water level in the upper deposit exceeds a threshold value (L), runoff is produced quickly in its upper part (Q_0). The response of the other outlets is relatively slow. The streamflows are controlled by recession coefficients k_0 , k_1 and k_2 , which represent the response functions of the upper and lower deposits. The constant infiltration rate (Q_{perc}) is controlled by a coefficient k_p .

In order to ensure that the surface runoff process is quicker than the subsurface and groundwater runoff, the initial value of k_0 must always be greater than k_1 . In addition, the response of the third outlet (groundwater runoff) (Q_2) must be slower than that of the second one (Q_1); therefore, k_2 must be lower than k_1 (Aghakouchak and Habib 2010). For a better understanding of the model, see Bergström (1992), Lindström *et al.* (1997) and Seibert (2000).

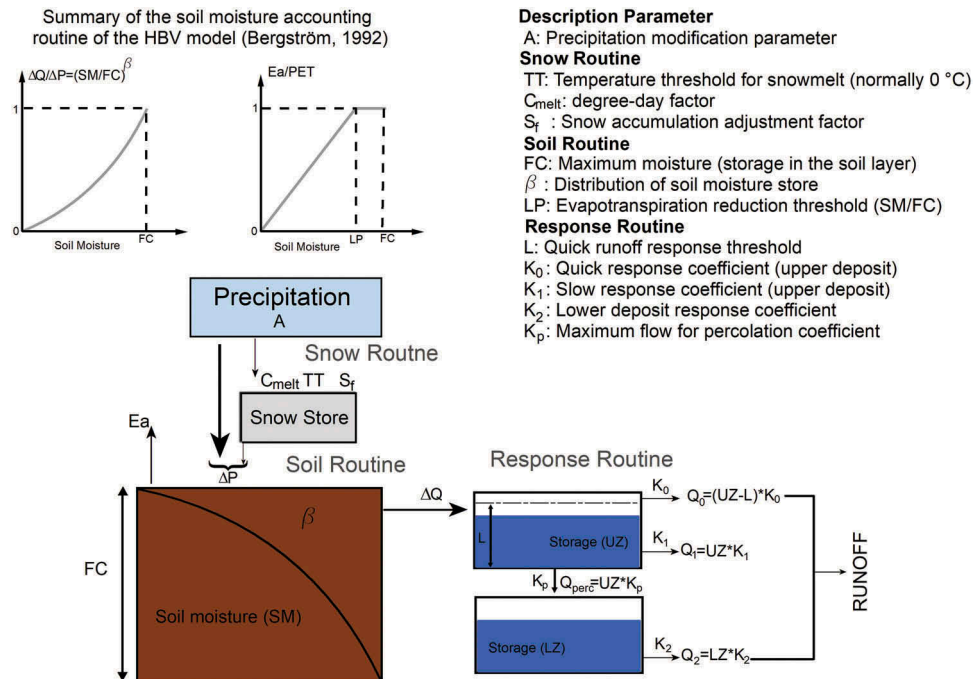


Figure 2. Conceptual diagram of the simplified HBV model, including description of its parameters and main equations.

3.2 HYMOD model

HYMOD is a simple conceptual hydrological model. It was originally created as a parsimonious 5-parameter model designed to function on a daily scale (Boyle 2001). The model consists of a variety of different excess generation (interception, storage tension storage, free storage), percolation and streamflow routing functions that can be put together in different combinations to describe the different hydrological behaviors of the watershed system (Boyle 2001). The input data necessary to carry out simulations are precipitation (mm) and potential evapotranspiration (mm).

The HYMOD model has been extensively used in studies on streamflow, forecasting and model calibration (Wagener *et al.* 2004, Vrugt *et al.* 2008, Kollat *et al.* 2012, Gharari *et al.* 2013, Remesan *et al.* 2013). It uses an excess precipitation model with two parameters: maximum soil moisture capacity (FC) and the degree of spatial variability of the soil moisture capacity (β) (Moore 1985). This allows the effective precipitation to be calculated, with potential evapotranspiration (PET) and soil moisture capacity (SM) considered. A portion of excess precipitation (α) is then directed to the quick flow reservoirs (with residence time K_q) in order to generate quick runoff (Q_f). The quick flow is represented by three quick-flow tanks that describe the surface flow (Sun *et al.* 2015), as shown in Fig. 3. The rest of the excess precipitation ($1 - \alpha$) is directed to the slow reservoir (with residence time K_s) to generate slow runoff (Q_s). The flow of each reservoir is controlled by the quick flow residence time (K_q) and the slow

residence time (K_s) (Kollat *et al.* 2012). The sum of the slow and quick runoff totals is the streamflow of the watershed (see Fig. 3). For more information about the model, see Boyle (2001).

In the present study, to account for snowmelt processes, the model was modified by incorporating the simple degree-day method (Bergström 1972). In Fig. 3, the model is shown with the snowmelt routine included; the parameters of this routine are the same as described in Section 3.1.

Table 1 shows the calibration parameter ranges used for each model. The valid range of model parameters is based on the conceptual representation of hydrological processes and the equations that allow such processes to be simulated. Parameter ranges of the HBV model were defined following the values presented in Kollat *et al.* (2012), who defined the maximum range of the parameters to be used with the purpose of capturing a large range of geographic and climatic conditions present in 392 catchments that they examined. For HYMOD, meanwhile, the selected parameter ranges were those published by Sun *et al.* (2015). For both models, 0°C was considered the threshold temperature (TT) for the initiation of snowmelt.

In order to adequately represent the spatial variability of precipitation and include the orographic effects in the study basins, a precipitation adjustment factor (A) was considered in both models. This factor allows the model to obtain a long-term mass balance (Muñoz *et al.* 2014) and thereby correct the underestimation of precipitation resulting from the absence of records in the highest parts of each basin.

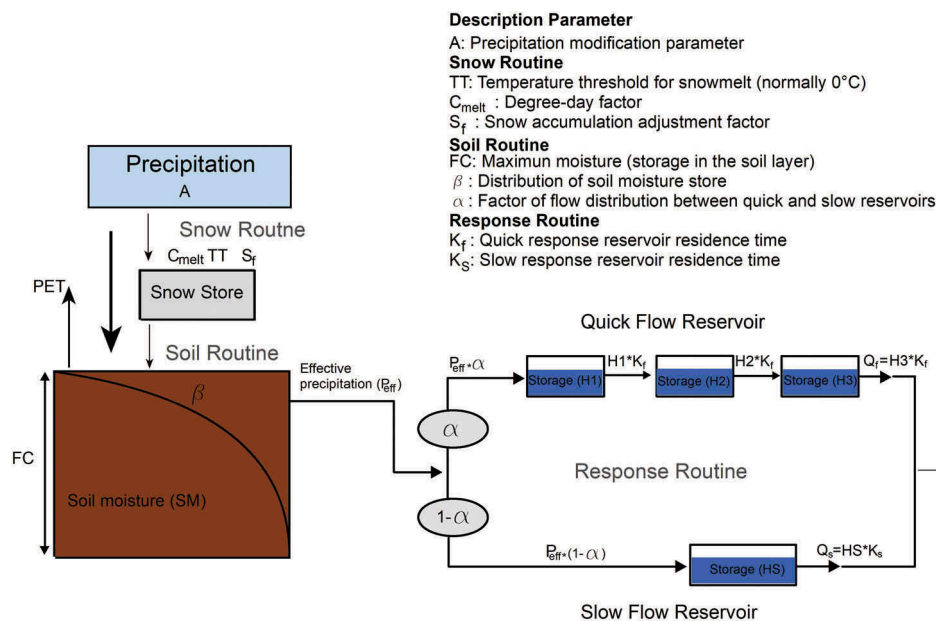


Figure 3. Conceptual diagram of the HYMOD model, including description of its parameters and main equations.

Table 1. Calibration parameter ranges for HBV and HYMOD models.

Parameter (Units)	HBV	HYMOD
<i>Mass balance</i>		
A	0.8–2.5	0.8–2.5
<i>Snow routine</i>		
TT (°C)	0	0
C_{melt} (mm°C ⁻¹ d ⁻¹)	0.5–7	0.5–7
S_f	0.5–1.2	0.5–1.2
<i>Soil routine</i>		
FC (mm)	0–2000	1–500
β	0–7	0–2
α	-	0–1
LP	0.3–1	-
C(°C – 1)	0.01–0.3	-
<i>Response routine</i>		
L (mm)	0–100	-
k_0 (d ⁻¹)	0.3–0.6	-
k_1 (d ⁻¹)	0.1–0.2	-
k_2 (d ⁻¹)	0.01–0.1	-
k_p (d ⁻¹)	0.01–0.1	-
K_f (d ⁻¹)	-	0.5–1.2
K_s (d ⁻¹)	-	0.001–0.5

3.3 Process sensitivity analyses and model calibration

In order to ascertain the dependence between the parameters and response of each model, an RSA was carried out. To this end, the Matlab toolbox *Sensitivity Analysis For Everybody* (SAFE) was used. This toolbox was conceived for the application of multiple sensitivity analysis (SA) methods in order to complement and validate individual results, evaluate and review user decisions in the application of each SA model and provide effective visualization tools (Pianosi *et al.* 2015).

For the simulation and analyses, a calibration period of six years (April 2000–March 2006) was used. The first year of simulation was used to warm up the model, and the results for that year were not included in the subsequent analyses. In order to complement the analyses, a validation was carried out for the April 2005–March 2010 period. As with the calibration, the first hydrological year (April 2005–March 2006) was used to warm up the model and the results were not used for further analyses. According to Seibert and Vis (2012), one year of warm-up is sufficient to accommodate the initial values of hydrological models.

Although 5 years of calibration (plus one of warm-up) may be viewed as a short time window, acceptable or satisfactory results have been obtained using the same or a smaller span of data (e.g. Gupta *et al.* 2009, Cui *et al.* 2015). Most of the natural variability and seasonality in the study area is well recorded in a 5-year timespan; therefore, the main results should be representative of such variability. For example, Harlin (1991) found that a calibration period between two and six years was

sufficient to find optimal parameters for the HBV model. Perrin *et al.* (2007) mentioned that good model results can be obtained with approximately 350 days of data chosen randomly within a longer period of time. In the same line, Brigode *et al.* (2013) found that validation efficiencies are generally similar to those obtained with a 3-year calibration period, indicating that wider calibration periods do not necessarily lead to more robust parameter sets. However, one disadvantage that must be addressed is that extreme scenarios (extreme wet and dry years) would probably not be well represented by the obtained results. Therefore, if such analyses are pursued, a longer time period might be necessary to perform them.

A total of eight scenarios were implemented. Each comprises a combination of two watersheds, two models and two time scales of analysis. A total of 100,000 simulations of each of the scenarios were run, with parameters in the ranges indicated in Table 1. The results and parameters of each simulation were then stored for subsequent analysis.

Behavioral/non-behavioral models can be defined as models with an equally acceptable/non-acceptable representation of the system under simulation, and can be classified as models with a performance measure better/worse than a threshold of eligibility (acceptability) (Yilmaz *et al.* 2010). The sensitivity analysis was carried out on the behavioral models, which were defined as those with a Nash-Sutcliffe Efficiency (NSE) index (Nash and Sutcliffe 1970) (Equation (1)) greater than 0.6.

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{sim} - Q_0)^2}{\sum_{i=1}^n (Q_0 - \bar{Q}_0)^2} \quad (1)$$

NSE quantifies the differences between the simulated (Q_{sim}) and observed streamflows (Q_0) along with the deviation of Q_0 with respect to the mean of the observed streamflows ($\bar{Q}_0$). In a perfect model, there are no differences between Q_{sim} and Q_0 ; therefore, NSE will equal 1. Meanwhile, as Q_{sim} differs more from Q_0 , NSE tends toward values less than 1.

A sensitivity index was calculated, which was defined as the maximum vertical difference (MVD) between the cumulative distribution functions (cdf) of the behavioral and non-behavioral models for each parameter. The MVD statistic uses the Kolmogorov-Smirnov two-sample test and both its asymptotic and small sample distributions are known for any continuous cumulative distribution function (Spear 1980). The MVD index is calculated according to Equation (2):

$$MVD = \max |(S_{bi} - S_{nbi})| \quad (2)$$

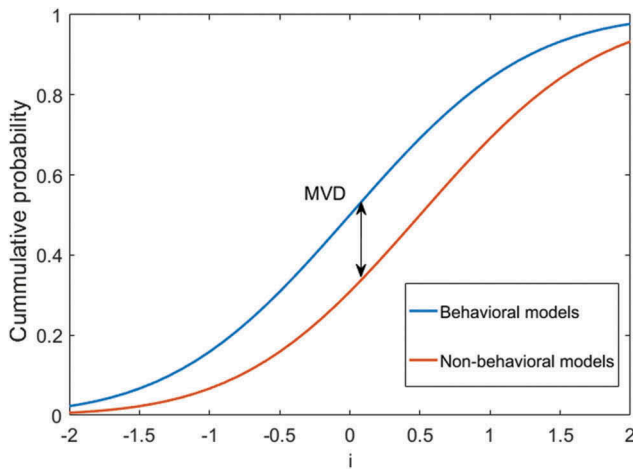


Figure 4. Example of the maximum vertical difference between two cdf for a parameter i .

where S_{bi} and S_{nbi} are the sample distribution functions for behavioral and non-behavioral models, respectively. The subscript i represents each parameter range. Figure 4 shows an example of the MVD between two cumulative distribution functions for a parameter i , which has a range between -2 and 2 . As the maximum vertical difference increases, so does the sensitivity of that parameter. Conversely, if MVD is equal to 0, both cumulative distribution functions are equal, which suggests insensitivity of the parameter, while if it is equal to 1, the cdf will be mutually exclusive; thus, the parameter highly influences the quality of the results (Pianosi *et al.* 2015) (i.e. the model is highly sensitive to that parameter). Finally, for the model calibration, the parameter values of the 50th percentile of the behavioral models were used.

4 Results and discussion

For the eight implemented scenarios, Fig. 5 shows the MVD values and Fig. 6 shows box plots of the MVD for low streamflows (streamflows below the 33rd percentile, Q_{33}), medium streamflows (streamflows between the 33rd and 66th percentiles, Q_{66}) and high streamflows (streamflows over the 66th percentile, Q_{100}). In addition, Table 2 presents the calibration parameters obtained for each model, along with the associated NSE value.

In Fig. 5, it can be seen that the HBV model presents greater sensitivity to parameter β on a daily time scale than on a monthly time scale. In addition, this parameter presents greater sensitivity in the HBV model in comparison to HYMOD (Fig. 5(a) and (c)). This suggests that the HBV model tends to identify, and, therefore, more adequately represent, quick precipitation–runoff processes

such as flooding, with these processes being dominant in obtaining behavioral models (parameter β). This sensitivity is more apparent when simulating on a daily time scale in the HBV model (Fig. 5(a)). Because β also exhibits sensitivity on a monthly time step, the slower, time-aggregated response processes take on greater importance (e.g. FC).

In addition, in the HYMOD model, the parameter related to water distribution between quick and slow reservoirs (α) is that which exhibits the greatest sensitivity, followed by the parameter associated with slow runoff (K_s) and then surface runoff (K_f). The foregoing shows that independent of the time scale in the HYMOD model, the slow response processes take on greater importance than the quick streamflow generation processes. However, on a shorter time scale, the relative importance (MVD) of parameter K_f increases, which is associated with a quick watershed response.

Thus, it is deduced that the differentiation of surface runoff and baseflow is a key process for obtaining behavioral models. This is observed on monthly and daily time steps in both models.

Regarding the optimum parameters found for each watershed and time scale, parameter β in the daily Diguillín/Quino watershed model showed an optimum value of 0.546/1.138, versus 1.972/5.687 in the monthly model (Table 2). That β is greater in the monthly model implies that there is greater water retention in the soil. Therefore, on a greater time scale (i.e. monthly), the model responses become more lumped. Greater values of β were obtained in HYMOD than in the HBV model. This is in agreement with the results obtained in the sensitivity analysis and shows that the HBV model is more adequate for simulation of fast rainfall–runoff processes than HYMOD. Therefore, the HBV model exhibits comparative advantages over HYMOD for simulating high streamflows (quick precipitation–runoff processes).

The quick runoff response structures of both HBV and HYMOD prove to be different from each other. The HBV model consists of one upper non-linear reservoir that better captures different responses (Stoelzle *et al.* 2015). The response structure and the greater sensitivity to quick runoff processes of the HBV model result in a better approximation of high streamflows (at daily time scale) in comparison to the HYMOD model (see Q_{100} in Fig. 6 (a), (c), (e) and (g)). Conversely, the HYMOD model consists of one linear reservoir with three sub-reservoirs. This structure represents a damped runoff response. Therefore, this structure and the greater sensitivity to damped processes than that of HBV results in a better approximation of low streamflows (see Q_{33} in Fig. 6(a), (c), (e) and (g)). These results are in line with that which is observed based on the MVD in Fig. 5.

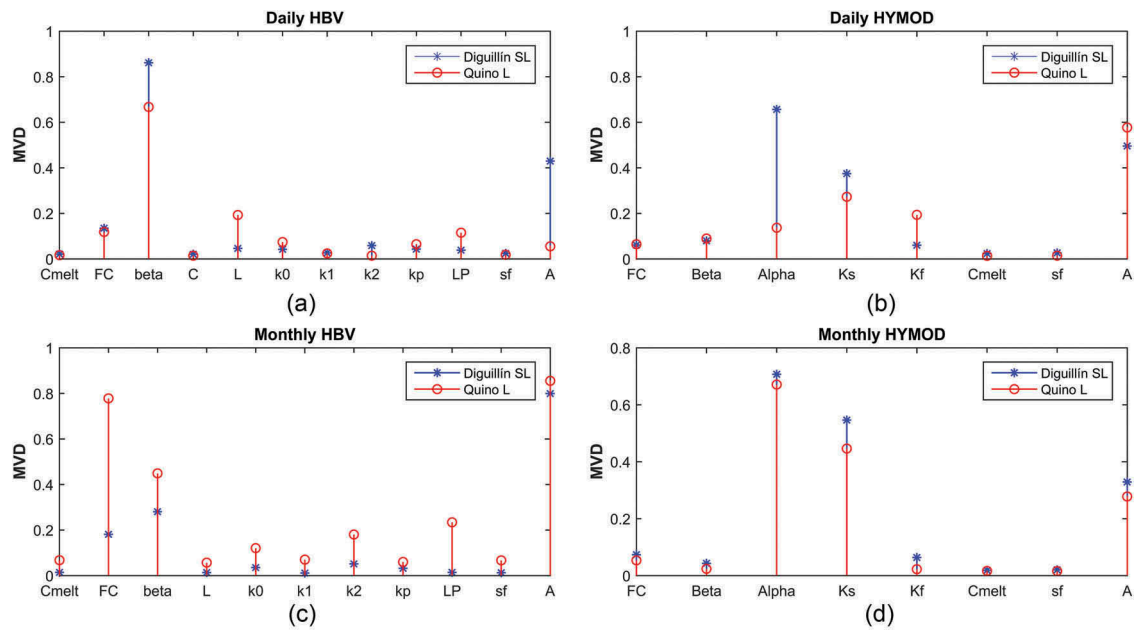


Figure 5. Mean maximum vertical difference (MVD) values between the cumulative distribution functions (cdf) for each parameter.

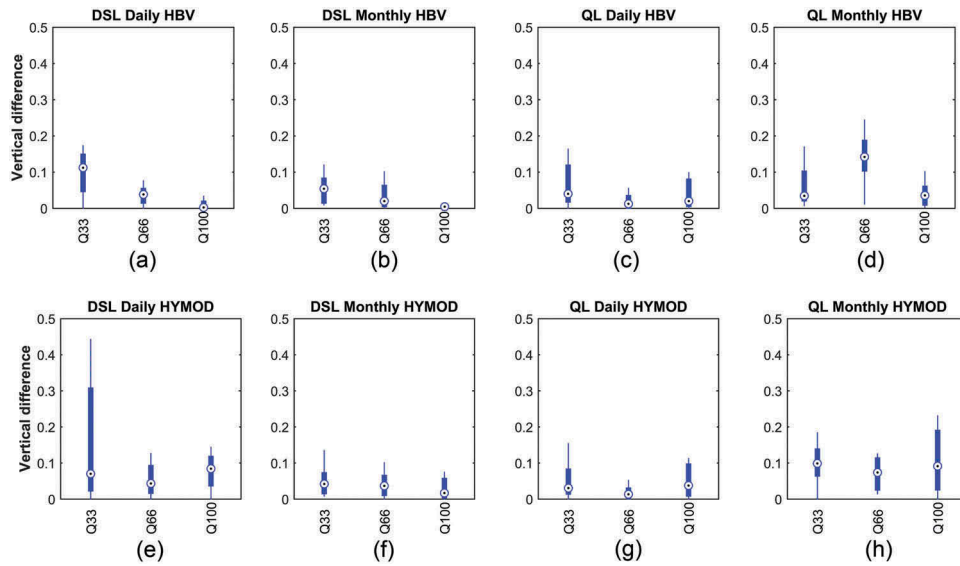


Figure 6. Box plots of the MVD between the simulated and observed cumulative distribution functions for low (streamflows below the 33rd percentile, Q_{33}), medium (streamflows between the 33rd and 66th percentile, Q_{66}) and high streamflows (streamflows above the 66th percentile, Q_{100}).

With respect to parameter A , almost all of the developed scenarios (seven of eight) showed sensitivity (MVD over 0.25 in Fig. 5) to this factor. This demonstrates the need to correctly represent the precipitation input to the watershed. In addition, it proved necessary in all of the scenarios to enlarge the precipitation records by 3 to 54%, which shows that the orographic effect was not correctly represented in both watersheds with these characteristics (mountain watersheds with hard-to-access high areas). Zúñiga *et al.* (2012) obtained similar results in the Diguillín River watershed.

In both models and watersheds, the parameters associated with slow runoff take on greater importance (sensitivity) on larger time scales (e.g. FC and K_2 in the HBV model and K_f in HYMOD). This suggests that at greater time aggregation, better representativeness of storage-release processes is necessary, and, therefore, greater emphasis on adequate representation of these processes is required. The foregoing is confirmed with the calibration values obtained for different time scales (see Table 2).

Table 2. Optimal parameters and objective function for the HBV and HYMOD (daily and monthly) models.

Parameter	HBV model				HYMOD model			
	Diguillín		Quino		Diguillín		Quino	
	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
<i>Mass balance</i>								
A	1.239	1.086	1.542	1.032	1.237	1.250	1.255	1.320
<i>Snow routine</i>								
TT	0	0	0	0	0	0	0	0
C_{melt}	3.665	3.723	3.662	3.661	3.708	3.238	3.767	3.288
S_f	0.863	0.852	0.855	0.798	0.839	0.850	0.856	0.852
<i>Soil routine</i>								
FC	1172	763	1114	225	248	249	254	228
β	0.546	1.972	1.138	5.687	0.988	0.986	1.003	0.971
α	-	-	-	-	0.515	0.510	0.499	0.122
LP	0.667	0.644	0.716	0.549	-	-	-	-
C	0.157	-	0.154	-	-	-	-	-
<i>Response routine</i>								
L	47.3	49.5	64.7	52.8	-	-	-	-
k_0	0.457	0.445	0.430	0.417	-	-	-	-
k_1	0.151	0.150	0.148	0.149	-	-	-	-
k_2	0.051	0.052	0.054	0.044	-	-	-	-
k_p	0.057	0.057	0.059	0.052	-	-	-	-
K_f	-	-	-	-	0.748	0.749	0.750	0.751
K_s	-	-	-	-	0.274	0.272	0.271	0.399
<i>Objective function</i>								
NSE Calibration	0.76	0.81	0.87	0.81	0.67	0.86	0.87	0.89
NSE Validation	0.68	0.72	0.76	0.81	0.49	0.51	0.70	0.76

In Fig. 5 it can be seen that the model outputs do not exhibit sensitivity to parameters S_f and C_{melt} ($\text{MVD} < 0.1$) in either watershed or time scale, which suggests that the effect of snowmelt on the magnitude and variability of the streamflows in both watersheds is small. This is probably because the both watersheds have a small portion above the mean snow line (Casassa 1995, Arumí *et al.* 2012).

In relation to medium streamflows (Q_{66}), no clear advantages in one model over another are observed (Fig. 6) with regard to the daily and monthly time scales. On a monthly time scale, smaller differences are observed for the HBV model and the Diguillín at San Lorenzo watershed in comparison to HYMOD, while the HYMOD model presents smaller differences in Q_{66} in the Quino at Longitudinal watershed.

In comparing the performance of the HYMOD and HBV models, we note that HBV presents negligible differences (greater NSE) for maximum streamflows, whereas HYMOD exhibits smaller differences for minimum streamflows. It is likely that the lower capacity of HYMOD to represent extreme events is due to its simplicity, as mentioned in Quan *et al.* (2015). In addition, the NSE values show that HYMOD tends to simulate time-aggregated (i.e. monthly) variables with greater accuracy, whereas HBV proves more suitable for simulations on a daily scale.

Figure 7 presents the simulated streamflows for both watersheds. It is seen that in general, both models adequately simulate the observed streamflows; however, better performance of the HBV model in high

streamflows on a daily time scale is observed (Fig. 7(a) and (c)), confirming the results obtained from the sensitivity analysis.

Based on the calibration results, both models provided satisfactory simulation results (see Table 2). With both models, better results are obtained on a monthly time scale than on a daily time scale, with NSE values over 0.8 (Table 2). In other studies, similar results have been obtained with a better fit in monthly than in daily models according to the objective functions (Behrendts *et al.* 2011, Griffen 2014, Ytoui 2014). Meanwhile, Griffen (2014) mentioned that with large streamflow variations, models cannot simulate streamflows well; however, aggregating them over time reduces the temporal streamflow variability, which results in a better simulation of them. Additionally, better NSE values are achieved at monthly time steps with HYMOD, while better simulation results are obtained at daily time-step simulations with HBV. The simplicity of HYMOD results in a disadvantage when representation of temporally variable hydrological processes is expected. However, the increased complexity of models is accompanied by an over-parametrization, transforming the hydrological model into a black box, where it may become more complex to understand physical processes. According to Orth *et al.* (2015), it is important that a model has the appropriate complexity; if models are overly complex, they suffer from over-parametrization, but if they are too simple, they can miss relevant processes. Added complexity does not necessarily lead to improved performance of hydrological models, and

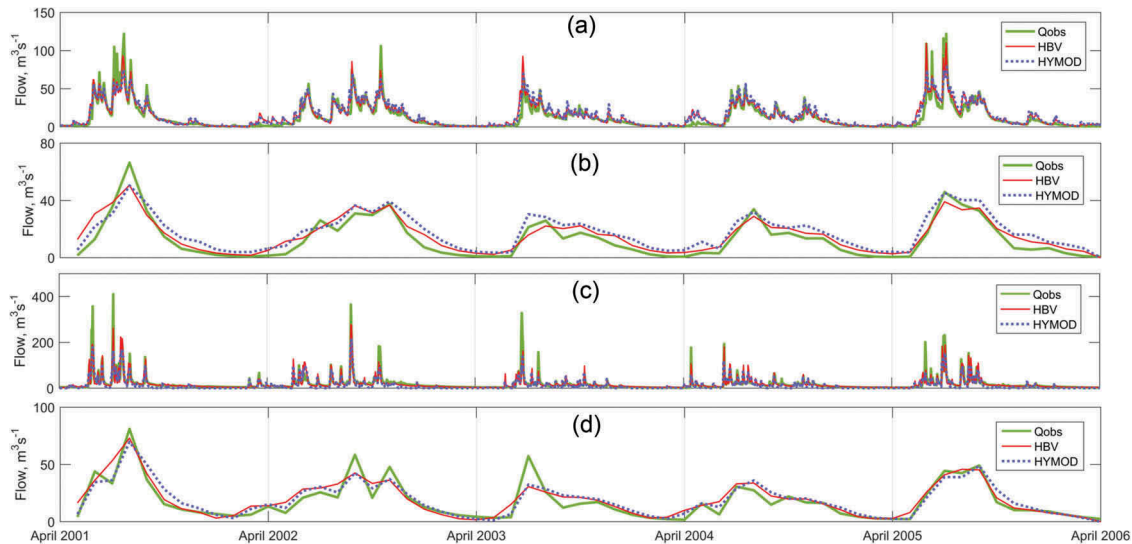


Figure 7. Comparison of observed and simulated streamflows for (a) the Quino River at Longitudinal watershed on a daily time scale; (b) the Quino River at Longitudinal watershed on a monthly time scale; (c) the Diguillín River at San Lorenzo on a daily time scale; and (d) the Diguillín River at San Lorenzo on a monthly time scale.

performance can vary greatly depending on the considered hydrological variable or hydrological conditions.

Both models proved to be insensitive to parameters associated with snowmelt. Therefore, both models are suitable for rain-dominated basins, such as those of this study. Orth *et al.* (2015) used three models (including HBV) and noted that they consistently have difficulties capturing snow- and ice-related processes.

Model robustness can be defined as the insensitivity of model parameters to calibration data (Dakhlaoui *et al.* 2017) and refers to the reliability of the model under conditions other than those considered for calibration. Regarding the validation results, better results (NSE values) are obtained for the HBV model than for the HYMOD model in all the cases analysed (Table 2), suggesting that the HBV model is more robust than HYMOD. This may be because the structure of the soil moisture routine of the HBV model is more physically-based (and therefore more adaptable to different watershed conditions) than HYMOD. Bergström (2006) mentioned that the most robust part of the HBV model is probably its soil moisture accounting, which has proved very versatile in applications all over the world. Similarly, Kollat *et al.* (2012) concluded that in several cases the additional complexity of HBV was sufficient to produce a well-identified single solution, whereas the simple HYMOD was unable to achieve a similar level of performance. In many catchments, the additional HBV model parameters allow it to outperform the more empirical HYMOD model. They also concluded that HBV performs better in terms of NSE.

The average difference between calibration and validation is -0.07 for HBV, while for HYMOD it is $-$

0.21 , suggesting that, although HYMOD is a simpler model and could be more efficient for monthly time-step simulations, it tends to be less robust in comparison to HBV. Therefore, for medium- or long-term studies the HBV model may be more accurate.

5 Conclusions

The HBV and HYMOD models were implemented in the watersheds of the Diguillín and Quino rivers on daily and monthly time scales. The results allowed differences and comparative drawbacks of each model to be identified. The processes associated with a quick runoff response (high streamflows) proved to be more sensitive in the HBV model than in the HYMOD model, facilitating a better representation of these processes and therefore greater accuracy in the simulation of high streamflows. Similarly, HYMOD presented high sensitivity to slow-response or storage-release processes in both watersheds, with a consequent advantage over the HBV model in the simulation and representation of low streamflows. This latter aspect, along with the high sensitivity of K_s , associated with the slow response of the watershed, indicates that the HYMOD model is more suitable for time-aggregated variables in comparison to the HBV model.

In both models, groundwater release processes appeared to be more sensitive at monthly than daily time scale. This suggests that on a monthly time scale, streamflows in the study watersheds are more stable (time aggregated) and these must be correctly represented to qualify as behavioral models.

The HBV model proved to be more suitable for modelling on a daily time scale since it is very sensitive to quick precipitation–runoff processes in comparison to HYMOD. In addition, HYMOD better simulates the slow responses of a watershed, making it more suitable for analysis on a monthly time-scale. HBV is a more complex model with a greater number of parameters than HYMOD; therefore, it requires more computational resources for the calibration stage.

The NSE values obtained for the validation stage, together with the model analysis, suggest that the HBV is a more robust model than HYMOD. The HYMOD performance measurements tend to move away (to worse values) from the values obtained for calibration; therefore, caution is necessary when HYMOD is to be used for medium- and long-term analyses where climatic conditions differ too much from those considered for calibration because the model could tend to behave as an unsatisfactory or non-representative model of the basin and the simulated processes.

It is recommended that HBV be used for simulations on a daily time scale and HYMOD on a monthly time scale. The latter presents an advantage in being a parsimonious model that is easier to calibrate. However, caution is necessary when HYMOD is to be used for medium- and long-term predictions because it did not prove to be a very robust model and therefore may not be adequate for such simulations.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

- Aghakouchak, A. and Habib, E., 2010. Application of a conceptual hydrologic model in teaching hydrologic processes. *International Journal of Engineering Education*, 26 (4), 963–973.
- Arumí, J.L., et al., 2012. Interacciones entre el agua superficial y subterránea en la región del Bío Bío de Chile. *Obras y Proyectos*, 12, 4–13.
- Behrends, F., et al., 2011. Aplicación del modelo hidrológico-swat-en una microcuenca agrícola de la Pampa ondulada. *Ciencia del Suelo*, 29 (1), 75–82.
- Bergström, S., 1972. *Utvechling och tillämpning av en digital avrinningsmodell*. Stockholm: Swedish Meteorological and Hydrological Institute. Swedish.
- Bergström, S., 1992. *The HBV model: its structure and applications*. Norrköping: Swedish Meteorological and Hydrological Institute.
- Bergström, S., 2006. *Experience from applications of the HBV hydrological model from the perspective of prediction in ungauged basins*. Norrköping: Swedish Meteorological and Hydrological Institute. Swedish.
- Boyle, D., 2001. *Multicriteria calibration of hydrologic models*. Thesis (PhD). University of Arizona, USA.
- Brigode, P., et al., 2013. Hydrological model parameter instability: A source of additional uncertainty in estimating the hydrological impacts of climate change? *Journal of Hydrology*, 476, 410–425.
- Casassa, G., 1995. Glacier inventory in Chile: current status and recent glacier variations. *Annals of Glaciology*, 21, 317–322.
- Chilkoti, V., Bolisetti, T., and Balachandar, R., 2017. Climate change impact assessment on hydropower generation using multi-model climate ensemble. *Renewable Energy*, 109, 510–517.
- Cui, X., et al., 2015. Effect of length of the observed dataset on the calibration of a distributed hydrological model. *Proceedings of the International Association of Hydrological Sciences*, 368, 305–311.
- Dakhlaoui, H., et al., 2017. Evaluating the robustness of conceptual rainfall–runoff models under climate variability in northern Tunisia. *Journal of Hydrology*, 550, 201–217.
- Devia, G., Ganasri, B., and Dwarakish, G., 2015. A review of hydrological models. *Aquatic Procedia*, 4, 1001–1007.
- Dirección General de Aguas, 1986. *Mapa hidrogeológico de Chile: texto explicativo, escala 1:2:500.000*. Santiago: Ministerio de Obras Públicas.
- Dirección General de Aguas, 2004. *Diagnóstico y clasificación de los cursos y los cuerpos de agua según objetivos de calidad: cuenca del río Imperial*. Santiago: Ministerio de Obras Públicas.
- Dixon, H., et al., 1999. The geology of Nevados de Chillán volcano, Chile. *Revista Geológica De Chile*, 26 (2), 227–253.
- Gharari, S., et al., 2013. An approach to identify time consistent model parameters: sub-period calibration. *Hydrology and Earth System Sciences*, 17 (1), 149–161.
- Griffen, J., 2014. *A Continuous hydrologic model structure for applications at multiple time scales*. Masters. University of Central Florida, USA.
- Gupta, H.V., et al., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. *Journal of Hydrology*, 377 (1–2), 80–91.
- Harlin, J., 1991. Development of a process oriented calibration scheme for the HBV hydrological model. *Nordic Hydrology*, 22 (1), 15–36.
- Ibrahim, B., et al., 2015. Hydrological predictions for small ungauged watersheds in the Sudanian zone of the Volta basin in West Africa. *Journal of Hydrology: Regional Studies*, 4, 386–397.
- Jiang, T., et al., 2007. Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China. *Journal of Hydrology*, 336 (3–4), 316–333.
- Kollat, J., Reed, P., and Wagener, T., 2012. When are multi-objective calibration trade-offs in hydrologic models meaningful? *Water Resources Research*, 48, 3.
- Li, Q., et al., 2009. Intercomparison of hydrological modeling performance with multi-objective optimization algorithm in different climates. *Annual Journal of Hydraulic Engineering*, 53, 19–24.

- Lindström, G., *et al.*, 1997. Development and test of the distributed HBV-96 hydrological model. *Journal of Hydrology*, 201 (1–4), 272–288.
- Lu, G. and Wong, D., 2008. An adaptive inverse-distance weighting spatial interpolation technique. *Computers & Geosciences*, 34 (9), 1044–1055.
- Martina, M., Todini, E., and Liu, Z., 2011. Preserving the dominant physical processes in a lumped hydrological model. *Journal of Hydrology*, 399 (1–2), 121–131.
- Moore, R., 1985. The probability-distributed principle and runoff production at point and basin scales. *Hydrological Sciences Journal*, 30 (2), 273–297.
- Moussoulis, E., *et al.*, 2015. Modelling surface runoff to evaluate the effects of wildfires in multiple semi-arid, shrubland-dominated catchments. *Hydrological Processes*, 29 (20), 4427–4441.
- Muñoz, E., *et al.*, 2014. Identifiability analysis: towards constrained equifinality and reduced uncertainty in a conceptual model. *Hydrological Sciences Journal*, 59 (9), 1690–1703.
- Muñoz, E., *et al.*, 2016. Unraveling complex hydrogeological processes in Andean basins in south-central Chile: an integrated assessment to understand hydrological dissimilarity. *Hydrological Processes*, 30 (26), 4934–4943.
- Naranjo, J., Gilbert, J., and Sparks, R., 2008. *Geología del complejo volcánico Nevados de Chillán, Región del Biobío*. Santiago: Carta Geológica de Chile, Serie Geología Básica. Servicio Nacional de Geología y Minería.
- Nash, J. and Sutcliffe, J., 1970. River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, 10 (3), 282–290.
- Nicolle, P., *et al.*, 2013. Benchmarking hydrological models for low-flow simulation and forecasting on French catchments. *Hydrology and Earth System Sciences Discussions*, 10 (11), 13979–14040.
- Orth, R., *et al.*, 2015. Does model performance improve with complexity? A case study with three hydrological models. *Journal of Hydrology*, 523, 147–159.
- Pellicer-Martínez, F., González-Soto, I., and Martínez-Paz, J., 2015. Analysis of incorporating groundwater exchanges in hydrological models. *Hydrological Processes*, 29 (19), 4361–4366.
- Perrin, C., *et al.*, 2007. Impact of limited streamflow data on the efficiency and the parameters of rainfall-runoff models. *Hydrology Sciences Journal*, 52 (1), 131–151.
- Pianosi, F., Sarrazin, F., and Wagener, T., 2015. A Matlab toolbox for Global Sensitivity Analysis. *Environmental Modelling & Software*, 70, 80–85.
- Przeczek, K., *et al.*, 2009. Field testing and comparison of four snowmelt model approaches in the Quesnel Highlands, Interior British Columbia. In: Bruce McGurk, ed. *77th Annual Western Snow Conference*. Canmore, AB.
- Quan, Z., *et al.*, 2015. Evaluation of the HYMOD model for rainfall-runoff simulation using the GLUE method. *Proceedings of the International Association of Hydrological Sciences*, 368, 180–185.
- Remesan, R., Bellerby, T., and Frostick, L., 2013. Hydrological modelling using data from monthly GCMs in a regional catchment. *Hydrological Processes*, 28 (8), 3241–3263.
- Ruane, A., Goldberg, R., and Chrysanthacopoulos, J., 2015. Climate forcing datasets for agricultural modeling: merged products for gap-filling and historical climate series estimation. *Agricultural and Forest Meteorology*, 200, 233–248.
- Rusli, S., Yudianto, D., and Liu, J., 2015. Effects of temporal variability on HBV model calibration. *Water Science and Engineering*, 8 (4), 291–300.
- Seibert, J., 1997. Estimation of parameter uncertainty in the HBV model. *Nordic Hydrology*, 28 (4–5), 247–262.
- Seibert, J., 2000. Multi-criteria calibration of a conceptual runoff model using a genetic algorithm. *Hydrology and Earth System Sciences*, 4 (2), 215–224.
- Seibert, J. and Vis, M., 2012. Teaching hydrological modeling with a user-friendly catchment-runoff-model software package. *Hydrology and Earth System Sciences Discussions*, 9 (5), 5905–5930.
- Solomon, S., 2007. *The physical science basis*. Cambridge: Cambridge University Press.
- Spear, R., 1980. Eutrophication in peel inlet—II. Identification of critical uncertainties via generalized sensitivity analysis. *Water Research*, 14 (1), 43–49.
- Staudinger, M., *et al.*, 2011. Comparison of hydrological model structures based on recession and low flow simulations. *Hydrology and Earth System Sciences*, 15 (11), 3447–3459.
- Stoelzle, M., *et al.*, 2015. Is there a superior conceptual groundwater model structure for baseflow simulation? *Hydrological Processes*, 29 (6), 1301–1313.
- Sun, W., *et al.*, 2015. Estimating daily time series of streamflow using hydrological model calibrated based on satellite observations of river water surface width: toward real world applications. *Environmental Research*, 139, 36–45.
- te Linde, A., *et al.*, 2007. Comparing model performance of two rainfall-runoff models in the Rhine basin using different atmospheric forcing data sets. *Hydrology and Earth System Sciences Discussions*, 4 (6), 4325–4360.
- Thorntwaite, C., 1948. An approach toward a rational classification of climate. *Geographical Review*, 38 (1), 55.
- Vrugt, J., *et al.*, 2008. Response to comment by Keith Beven on “Equifinality of formal (DREAM) and informal (GLUE) Bayesian approaches in hydrologic modeling?”. *Stochastic Environmental Research and Risk Assessment*, 23 (7), 1061–1062.
- Wagener, T., *et al.*, 2001. A framework for development and application of hydrological models. *Hydrology and Earth System Sciences*, 5 (1), 13–26.
- Wagener, T., *et al.*, 2004. *Rainfall-runoff modelling in gauged and ungauged catchments*. London: Imperial College Press.
- Yilmaz, K., *et al.*, 2010. Model calibration in watershed hydrology. In: B. Sivakumar and R. Berndtsson, eds. *Advances in databased approaches for hydrologic modeling and forecasting*. Hackensack: World Scientific, 53–105.

- Younis, S. and Ammar, A., 2017. Quantification of impact of changes in land use-land cover on hydrology in the upper Indus Basin, Pakistan. *The Egyptian Journal of Remote Sensing and Space Science*. doi:10.1016/j.ejrs.2017.11.001.
- Ytoui, Y., 2014. Rainfall-runoff modeling at monthly and daily scales using conceptual models and neuro-fuzzy inference system. In: P. Găstescu, W. Marszelewski and P. Bretcan, eds. *2nd International Conference-Water resources and wetlands*, 11–13 September 2014, Tulcea. Romania: Romanian Limnogeographical Association, 263–270.
- Zúñiga, R., Muñoz, E., and Arumi, J., 2012. Estudio de los procesos hidrológicos de la cuenca del Río Diguillín. *Obras y Proyectos*, 11, 69–78.