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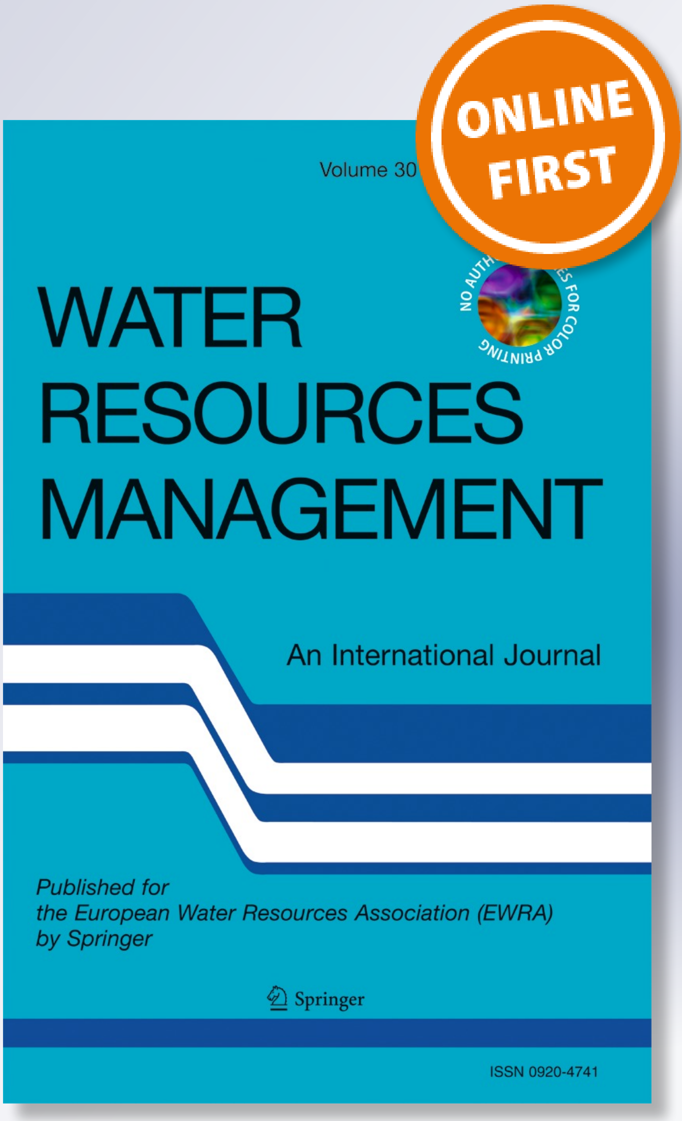

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Developing a Snowmelt Forecast Model in the Absence of Field Data

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Abstract In data poor regions predicting water availability is a considerable challenge for water resource managers. In snow-dominated watersheds with minimal in situ measurements, satellite imagery can supplement sparse data networks to predict future water availability. This technical note presents the first phase of an operational forecast model in the data poor Elqui River watershed located in northern Central Chile (30°S). The approach applies remotely-sensed snow cover products from the Moderate Resolution Imaging Spectrometer (MODIS) instrument as the first order hydrologic input for a modified Snowmelt Runoff Model. In the semi-arid Elqui River, snow and glacier melt are the dominant hydrologic inputs but precipitation is limited to up to six winter events annually. Unfortunately winter access to the Andean Cordillera where snow accumulates is incredibly challenging, and thus measurements of snowpack are extremely sparse. While a high elevation snow monitoring network is under development, management decisions regarding water resources cannot wait as the region is in its eighth consecutive year of drought. Our model applies a Monte Carlo approach on monthly data to determine relationships between lagged changes in snow covered area and previous streamflow to predict subsequent streamflow. Despite the limited data inputs the model performs well with a Nash-Sutcliffe Efficiency and R^2 of 0.830 and 0.833 respectively. This model is not watershed specific and is applicable in other regions where snow dominates hydrologic inputs, but measurements are minimal.

Keywords Snowmelt runoff · Hydrological model · Remote sensing · Hydrological prediction

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1 Introduction

In the semi-arid Elqui River basin (ERB, 30° S, Fig. 1) of northern central Chile snow and glacier melt dominate the annual hydrological budget (Favier et al. 2009; Young et al. 2010). This watershed is steep, rising from sea level to over 6000 m in 150 km, and elevation has a pronounced effect on the precipitation gradient (Fig. 1). The lower valleys and coastal areas receive less than 90 mm of annual precipitation, where regions above 4000 m receive almost

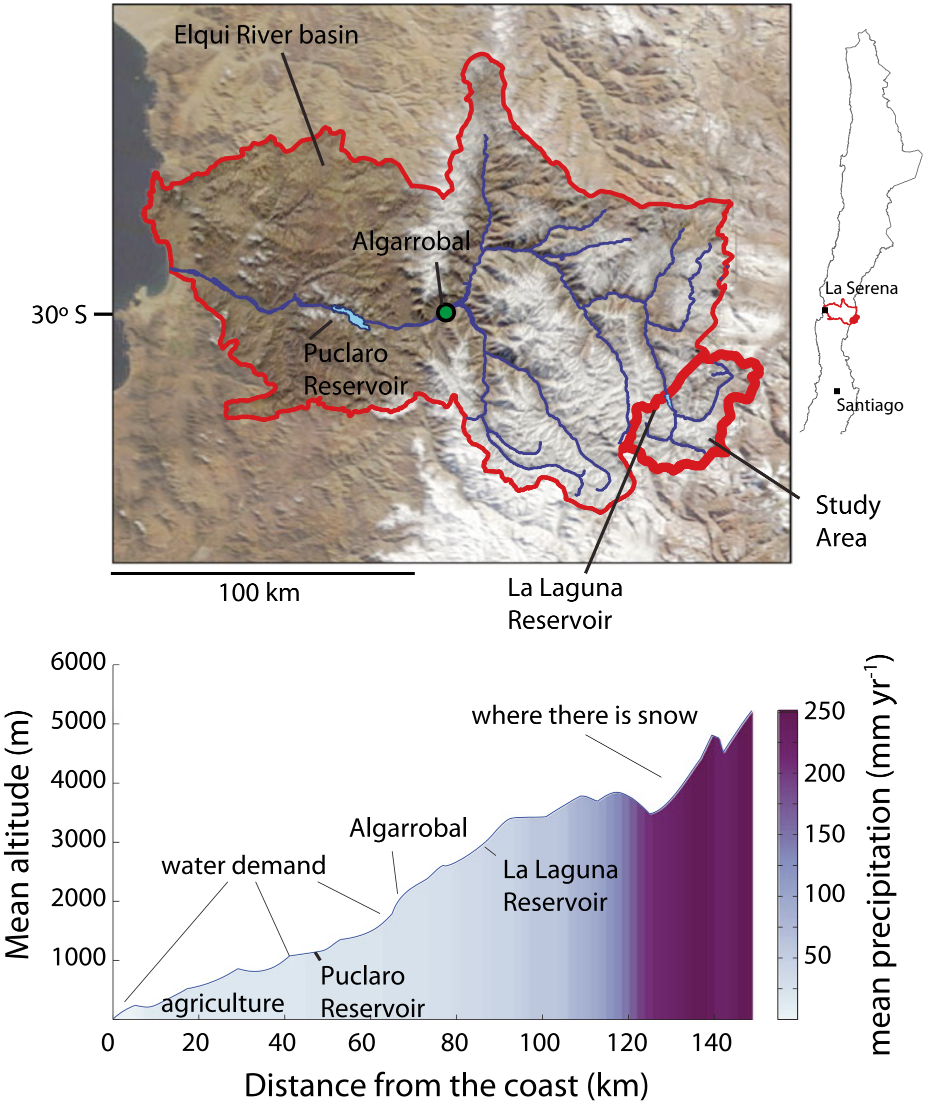

Fig. 1 Context map for the Elqui River Basin in northern central Chile. The *lower figure* illustrates how precipitation varies with elevation in the Elqui River, with over 10 times as much precipitation falling above 3500 m than in the valley bottoms. Water demand for irrigated agriculture and domestic use exists predominantly in the lower elevation, central portions of the watershed

250 mm of average annual precipitation (Favier et al. 2009). Most of this precipitation at upper elevations falls as snow that is generally isolated to up to six events per year (Falvey and Garreaud 2007). This makes snowpack in the Andean Cordillera extremely important for water resources downstream (Favier et al. 2009). In the lower elevation agricultural valleys and populated coastal areas there is a distinct disconnect between supply and demand (Young et al. 2010). Despite its importance there is one automated measurement of snow water equivalence (SWE, the amount of water contained in snow) in the ERB at 3000 m, an elevation where snowpack generally does not accumulate. The rugged terrain and altitude restricts winter access for field measurements at high elevation sites above 4000 m where seasonal snow pack accumulates. The only longer term snow data are infrequent measurements from snow courses (0–2 times per year) at approximately 3500 m that began in 2001 (Dirección General de Aguas 2015).

A regional snow-monitoring network in the upper elevations is under development, which will augment a nascent meteorological network. However, in its current state the limited hydrological data in the ERB leads to large uncertainties in quantifying the dominant hydrological processes (Souvignet et al. 2008; Hublart et al. 2015). Model simulations have led to encouraging results for SWE (Gascoin et al. 2013) and streamflow (Ruelland et al. 2011; Hublart et al. 2013, 2015) but forecasting of these quantities remains elusive. The limited point-scale in situ measurements of snow are augmented by remote sensing data, which have enabled spatial assessments of the snow cover in the region (CEAZAMET 2015).

Seven consecutive years of below average precipitation in the region (Dirección General de Aguas 2015) compound the absence of in situ snow data in the Cordillera. This drought overlaps with a 32 % population increase from 2002 to 2012, a rapidly growing tourist economy, and an expanding agricultural sector (Salinas et al. 2015). This has resulted in a 14.5 % increase in the demand for water from 2009 to 2013 (Salinas et al. 2015). The combination of decreased supply and the subsequent withdrawals due to increased demand have reduced annual median streamflow at Algarrobal (Fig. 1) for April 2014 – March 2015 to 36 % of the long-term median (1980 – present). These shifts in supply and demand are also present in lowered groundwater levels (Ribeiro et al. 2014), as 60–90 % of groundwater in the region originates as streamflow (Squeo et al. 2006; Valdés-Pineda et al. 2014).

During this prolonged drought, reservoir storage from previous years has sustained streamflow and helped address water demand in the ERB, but this has greatly reduced the amount of water stored in the basin's two reservoirs. The larger, downstream Puclaro Reservoir (Fig. 1) has dropped from 100 % of capacity (200 M m^3) at the onset of the drought in 2008 to 15 % of capacity in August 2015. The dramatically reduced storage downstream has increased reliance on the smaller upstream La Laguna Reservoir (40 M m^3, Fig. 1). During the summer months when demand from irrigators and tourists peak, up to 80 % of steamflow in the middle reaches of the ERB near Algarrobal are sustained by outflows from La Laguna Reservoir (Junta de Vigilancia del Rio Elqui y sus Alfuentes 2015; Dirección General de Aguas 2015). In turn, storage in this headwater reservoir has been reduced from 84 % of capacity in March 2012 to 42 % of capacity in March 2015 (CEAZAMET 2015; Dirección General de Aguas 2015).

Despite the importance of inflows into La Laguna Reservoir for the entire ERB, estimates of future inflows do not exist. There is an immediate need for a predictive model to estimate La Laguna inflows especially during prolonged droughts. This modeling framework was developed in partnership with Junta de Vigelancia del Rio Elqui y sus Afluentes (the water management agency in the watershed) as the initial component of an integrated modeling system. Even with a one-month lead-time this model provides an important tool for water resource managers to improve the management and planning of water resources downstream.

2 Model Development

We hypothesized that snow covered area (SCA) could serve as a proxy for snowmelt based upon the offset between streamflow and SCA observed from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) satellite. Figure 2 visually demonstrates a six-month offset between maximum SCA and subsequent streamflow above La Laguna Reservoir. Additionally satellite data represents snow cover for the entire watershed, where as point-based data only represents specific locations, and the only automated station (3000 m) does not have seasonal snow accumulation. MODIS provides daily spatial resolution and has good accuracy (Parajka and Blöschl 2008). Our approach leverages the availability of daily MODIS data at 500 m resolution, the clear skies and absence of vegetation in the ERB, and removes the need for a model to be reliant on multiple data inputs.

Our initial model assumed future discharge is a function of past discharge, precipitation, sublimation, and evaporation. These inputs are organized in a simplified Snowmelt Runoff Model (SRM) (Martinec 1975; Martinec and Rango 1986):

$$Q_{current} = P + kQ_{previous} - C \tag{1}$$

Where Q is streamflow, P is precipitation contributing to runoff (headwater snowmelt in this model), k is a recession coefficient during periods of no melt, and C represents losses from snowpack due to sublimation and evaporation.

We modify this model to address our limited data by applying SCA as a proxy for P, as most precipitation falls as snow. We also assume C is implicit in the SCA signal. This assumption is based on the climate of the arid, vegetation free headwaters of the ERB where transpiration is essentially zero, and that when snow sublimates or evaporates its spatial extent will decrease proportionately. This provides the following model structure:

$$Q_{current} = SCA + kQ_{previous} \tag{2}$$

The ERB above La Laguna Reservoir has sustained year round base flow, which is attributed to contributions from glacier melt and groundwater (Strauch et al. 2006; Ruelland et al. 2011). To separate streamflow into seasonal and longer-term baseflow components we

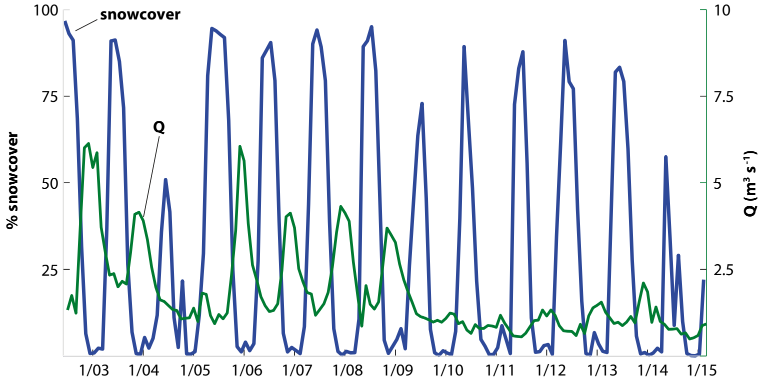

Fig. 2 Monthly time series of inflows into La Laguna Reservoir (*green line*), and upstream snow covered area (*blue line*) derived from MODIS data. The annual peaks of two data sets are offset by around six months, which describes the seasonal accumulation and melt cycle of snowpack

partition $Q_{previous}$ into near (Q_{near}; recent seasonal changes) and long-term (Q_{long}; longer-term baseflow) contributions to develop a modified SRM based upon the equation:

$$Q_{current} = aSCA^{b} + cQ_{near} + dQ_{long} \tag{3}$$

Where *a*, b, *c*, and *d* are scaling coefficients specific to each model forcing. *a* scales the influence changes in snow-covered area and *b* is an exponential scaling parameter representing the tapering effect of snowpack contributions to streamflow as it melts (Leibowitz et al. 2012). *c* weights the influence of recent seasonal changes to streamflow. The *d* parameter conceptually represents the contributions of baseflow from glacier melt and groundwater, which are estimated to be approximately 6–12 %.

In order to incorporate antecedent conditions and minimize the influence of an individual runoff or melt event, we calculated a moving average of *SCA,* Q_{near}, Q_{long} with the averaging period matching the term they represent. For instance because of the six–month offset between *SCA* and *Q*, we applied a six-month running average of snow cover ($\overline{SCA}$), which encapsulates annual accumulation and melt cycles and allows winters with more extensive and prolonged snowpack to provide greater melt contributions. The two-month moving average was used for Q_{near} ($\overline{Q}$) in order to represent previous conditions and also include rain events that are not captured in the MODIS images. For base-flow and longer-term conditions a twelve-month moving average was used for Q_{long} ($\overline{Q}'$). Incorporating these parameters into Eq. 3 gives the following estimation for *Q* at La Laguna in month *m*:

$$Q_{m} = a\overline{SCA}^{b}{}_{m-1} + c\overline{Q}^{*}{}_{m-1} + d\overline{Q}'{}_{m-1} \tag{4}$$

3 Methods

Model inputs for *SCA* were based upon MODIS-10 daily data product to calculate the mean monthly percentage of snow cover of the ERB upstream of La Laguna Reservoir (567 km^2). Model inputs for mean monthly *Q* were calculated from daily flows into La Laguna Reservoir for Apr 2003 – Mar 2015 (Junta de Vigilancia del Rio Elqui y sus Alfuentes 2015).

These data were divided into three sub-sets because *SCA* and *Q* have decreased substantially over the study period due to drought conditions (Fig. 2). The first set represents Calibration data (Dec 2004–Nov 2007). This middle portion of the dataset (Fig. 2) captures SCA and Q both above and below median values, and provides a dataset that is representative of hydrological conditions prior and during the drought. The second data set, Validation A (Apr 2003–Nov 2004), represents a relatively wetter period prior to the onset of drought when SCA and Q are above median values. Validation B (Dec 2007–Mar 2015) represents drier conditions where SCA and Q are commonly below median values and is in a prolonged state of drought.

To ensure that the selection of a single Calibration period did not bias parameterization, we also calibrated and validated the model using staggered two-year windows of data (Table 1). For the remainder of the paper the two Calibration approaches will be referred to as Single Window and Staggered Window. Additionally the model starts in April 2003 reflecting the start of the water year and the first low-flow month in the MODIS data record.

Table 1 Calibration and validation periods applied in the Staggered Window approach

Calibration	Validation
April 2003–March 2005	April 2005–March 2007
April 2007–March 2009	April 2009–March 2011
April 2011–March 2013	April 2013–March 2015

The calibration of the four model parameters was conducted using Monte Carlo simulations over multiple iterations for both the Single Window and Staggered Window approach. In each iteration 5000 simulations were conducted and a single parameter varied randomly within a defined range while the other three parameters remained fixed. Initial parameter ranges were 0.1 to 20 for *a* and *b,* −20 to 20 for *c* and *d.* These ranges were selected to provide simulations that would test the data across a broad parameter space, and avoid any initial bias that could potentially accompany narrowly focused parameter bounds.

Nash-Sutcliffe Efficiency (NSE; Legates and McCabe 1999; Nash and Sutcliffe 1970) of Q_{m} served as the objective function to evaluate model performance (Patil and Stieglitz 2014). Dotty plots (Beven and Binley 1992) were used to refine and further constrain each parameter individually and systematically through visual inspection and computational metrics (i.e. maximum NSE). Dotty plots graphically represent model skill for the 5000 simulations across the parameter space. This dotty plot calibration continued for an individual parameter until model performance was optimized. Once the graphical apex (optimization) was reached for an individual parameter the calibration focused on the subsequent parameter, and subsequently model skill would also improve. The calibration process first focused on the *SCA* (*a* and *b*), and once model performance was optimized the *Q* parameters (*c* and *d*) were calibrated. For a more detailed description of this calibration approach please refer to Patil and Stieglitz (2014).

The data sub-sets representing the validation and calibration periods were assessed separately and as a continuous time series with optimized model parameters using NSE, Root Mean Squared Error (RMSE), Correlation of Determination (R^2), NSE of log(Q) (emphasis on low flows) and NSE of $\sqrt{Q}$ (emphasis on overall hydrograph match) (Patil and Stieglitz 2014). We also tested whether our model could be simplified but retain the same level of skill by reducing the number of parameters (b to 1; or *a*, *c*, or *d* to zero) and using the same methods.

4 Results

The Single Window approach provided a high level of skill predicting streamflow one month in advance (Fig. 3) using the simplified SRM with an NSE of 0.830 using the final calibrated formula of:

$$Q_m = 5.458\overline{SCA}_{m-1}^{3.981} + 0.7458\overline{Q}^{*}{}_{m-1} + 0.092\overline{Q}'_{m-1} \tag{5}$$

The NSE of log(Q) (0.831, emphasis on low-flows) and $\sqrt{Q}$ (0.843, emphasis on overall hydrograph match) provide similar model metrics across the transformed objective functions. The RMSE (0.44 m^3s^{-1}) for the full model was higher than desired. However estimating low flows is the primary objective of this model-based study, and when calculated for the lower flow periods ($Q<2$ m^3s^{-1}), RMSE was reduced by 34 % (0.28 m^3s^{-1}). Confidence intervals

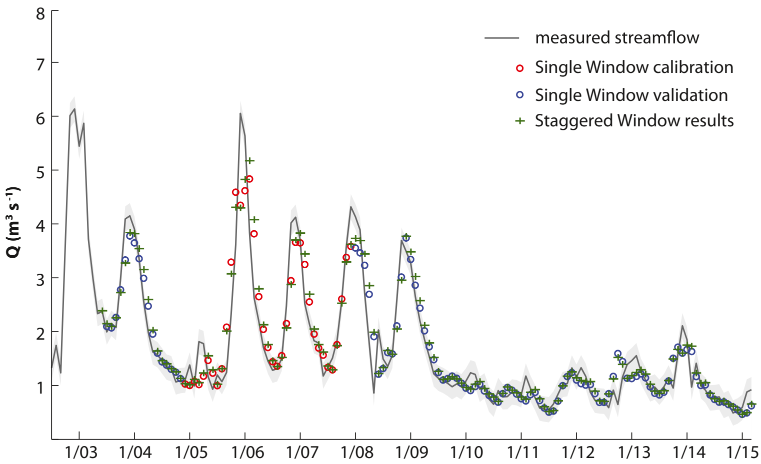

Fig. 3 Model results for the simplified Snowmelt Runoff Model for both the Single and Staggered Window calibration approaches. The *grey shading* represents the 95 % confidence intervals. For visual clarity, the three calibration and three validation periods for the Staggered Window approach are not included. Please refer to Table 1 for exact dates

for the observed and modeled data show a similar relationship. For the entire study period, roughly 50 % of simulations are within the 95 % confidence intervals. Where for lower flow months, 64 % of simulations are within the 95 % confidence intervals (Fig. 3). Complete model metrics including calibration and validation sub-sets are provided in Table 2.

The optimized parameters for the simulations using the Staggered Window calibration were quite similar to the Single Window calibration (Table 2) using the final calibrated formula of:

$$Q_m = 4.807\overline{SCA}_{m-1}^{3.925} + 0.825\overline{Q}_{m-1}^{*} + 0.057\overline{Q}_{m-1}^{\prime} \tag{6}$$

and provided a similar level of skill (NSE of 0.824). The NSE of log(Q) (0.8136, emphasis on low-flows) and $\sqrt{Q}$ (0.829, emphasis on overall hydrograph match) provide similar model

Table 2 Model parameters (a, b, c, d), Nash-Sutcliffe Efficiency (NSE), Root Mean Squared Error (RMSE) and Correlation of Determination (R^2) performance metrics from the validation and calibration phases of the model and the full model run for both the Single Window and Staggered Window time periods

Single window				
	a = 5.458	b = 3.918	c = 0.754	d = 0.092
	Calibration	Validation A	Validation B	Full Period
NSE	0.771	0.888	0.838	0.830
RMSE	0.571	0.295	0.419	0.431
R^2	0.774	0.888	0.839	0.833
Staggered window				
	a = 4.807	b = 3.925	c = 0.825	d = 0.057
	Calibration periods	Validation periods	Full period	
NSE	0.810	0.842	0.824	
RMSE	0.414	0.416	0.420	
R^2	0.813	0.860	0.832	

metrics across the transformed objective functions. Overall the NSE values for the Staggered Window approach indicated slightly less skill as compared to the Single Window approach, however the differences were negligible. The RMSE and R^2 using the staggered datasets reflected a similar level of skill as the single dataset (RMSE = 0.42 m^3s^{-1}, R^2 = 0.832, Table 2). The percentage of simulations that fall within the 95 % confidence interval for the Staggered Window approach are slightly less (48 % entire simulation; 62 % low flow periods) as compared to the Single Window approach, and visually they are virtually identical (Fig. 3). The results from the two calibration approaches showed no discernable difference in performance, but the Single Window approach performed slightly better.

We evaluated changing the individual scaling parameters (b to 1; or a, c, or d to zero) and repeating the same Monte Carlo analysis for the Single Window approach, as performance between the two models was nearly identical. Negating the influence of any of the individual scaling parameters provided inferior simulations of Q. For model iterations where b was set to 1, and the tapering effect of SCA was removed, predictions overestimated Q with an NSE of 0.73. This was particularly pronounced in years of low streamflow, when predictions are most important. The exclusion of SCA (a = 0) provided inferior model results (NSE = 0.64), and the model simulations lagged modeled outputs by three months. Removing Q_{long} (parameter d) underestimated streamflow across the time series but still provided a high level of skill (NSE = 0.79), however RMSE was 0.49 m^3s^{-1} for the full data series and 0.31 m^3s^{-1} during lower flow periods. Removing Q_{near} resulted in negative NSE values, signifying the model provided less skill than simply applying mean Q of the data record. Using only Q_{near} as a predictor provided a forecast that was late in predicting increases and decreases in streamflow, with an NSE of 0.23.

5 Discussion and Conclusion

We successfully predict streamflow in the semi-arid ERB one month in advance (NSE = 0.83) using only SCA and previous streamflow measurements. In this snow data poor region, we demonstrate how SCA from the MODIS instrument can be applied as a proxy for snowmelt inputs for a simplified SRM. These model results address the immediate need to estimate monthly inflows to the La Laguna Reservoir one month in advance. The region is experiencing continued drought and outflows from the reservoir provide up to 80 % of streamflow in the lower portions of the basin. The model performs well across years and captures the seasonal variability of streamflow in the study area, which is represented in the similar NSE values of $\log(Q)$ and $\sqrt{Q}$.

By implementing the Single and the Staggered Widows for model calibration and validation, we demonstrate that the model effectively predicts streamflow across the dataset, and does not rely on one time period to provide working parameters. The optimized parameters for the two calibration datasets are similar, but not identical. This similarity infers model equifinality, or that the solution can be reached by several parameter sets (Beven 1999).

Simplification of the model reduced its predictive skill, indicating that the inclusion of the three model components (SCA, Q_{near}, and Q_{long}) and the four parameters provides the best predictions for this modeling framework. The exclusion of SCA and Q_{near} reduced model performance considerably (NSE = 0.64 and 0.23 respectively), where eliminating Q_{long}, which conceptually represents baseflow, resulted in a more modest loss of model performance

(NSE = 0.79), and increased the RMSE during periods of low flow where accurate predictions are most pertinent.

The Single Window parameter values for *a*, *c*, and *d* (5.457, 0.7454, and 0.091 respectively) also provide insights into hydrological processes. For example the Dotty Plots indicated that optimal range of values of *d* (glacial contributions to baseflow) were between 0.08 and 0.10, which suggests conceptually that 8-10 % of baseflow is from glacier melt. The Staggered Window for *d* was 0.57, which while slightly, lower supports field-based estimates of base flow contributions from glacier melt.

The modeling framework that we present is a simplified version of an SRM and represents an important first step in predicting streamflow for the semi-arid ERB in the absence of in situ snow data and a process-based model. It does not represent a fully-informed model. Subsequent work is building upon this SRM framework that includes precipitation, solar radiation, field measurements of snowpack, groundwater, and data from stable isotopes to provide a better physical representation of the hydrological processes.

While this model would have to be calibrated for an individual watershed or region, the process is straightforward and easily adaptable. This modified SRM framework shows promise as a forecast model for similar climates that are data poor, but highly reliant on snowmelt such as the other regions of the Andean Cordillera, as well as the Atlas, Elburz, Caucasus, Hindu Kush, and Zagros mountain range.

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