Journal of Hydrology 564 (2018) 1008–1021

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Targeting high robustness in snowpack modeling for Nordic hydrological applications in limited data conditions

Alexandre Mas, Michel Baraer*, Richard Arsenault, Annie Poulin, Jonathan Préfontaine

Department of Construction Engineering, École de technologie supérieure, University of Quebec, 1100 Notre-Dame Street West, Montreal, QC H3C 1K3, Canada

ARTICLE INFO

This manuscript was handled by marco borga, Editor-in-Chief, with the assistance of Massimiliano Zappa, Associate Editor

Keywords:
Snowpack modeling
Hydrological model
Snow
Energy balance
Robustness

ABSTRACT

Most hydrological models simulate snowmelt using a degree day or simplified energy balance method, which usually requires a calibration of snow-related parameters using discharge data. Despite its apparent efficiency, this method leads to empirical relations which are not proven to remain valid in a changing climate. The direct application of robust physically-based snow models in hydrological modeling is difficult due to the high number of not easily available input variables this model type requires. The objective of this study is to test the robustness of a physically-based snowpack model that requires only a limited number of common meteorological parameters. The MASiN model computes the energy and mass balance of multiple layers of the snowpack using hourly air temperature, relative humidity and wind speeds, as well as daily precipitations. MASiN was tested at 23 sites across Canada and Sweden, using a unique set of parameters fixed at a single site. At each site, the snow depth simulated by MASiN was compared against measurements. Robustness was challenged by comparing MASiN's performance to that of three other models on three different criteria. MASiN showed the highest robustness among the tested models. With a unique set of parameters, it showed better results than the three reference models when used in similar conditions and matched their performances when reference models were calibrated at each site. The results prove non-data intensive physically based models to be promising tools for hydrological and other snow cover-related studies.

1. Introduction

In Nordic regions, most precipitation occurs as snow during winter. Snow accumulation for these regions represents a major portion of the watershed water storage (Ferguson, 1999). The release of melt water at the end of the winter period drives the hydrology of snow-covered catchments as well as downstream areas with little or no snow (Thompson et al., 2000). In snow-dominated regions, both surface runoff and groundwater flow are strongly influenced by the amount of melt water released and its temporal distribution (Dingman, 2002; Lundberg et al., 2016). In a context where Nordic regions exhibit deep vulnerability to climate change (Minder, 2010; Stone et al., 2002), it is necessary to properly simulate the evolution of snow cover in hydrological models, to be able to anticipate changes in water resources, flood risks and ecosystems (Ferguson, 1999; Shamir and Georgakakos, 2006; Troin et al., 2016).

The phenomena occurring inside a snowpack, the interaction between a snowpack and its environment, as well as general snow physics, have been extensively studied in order to address specific snow hydrology problems (DeWalle and Rango, 2008). The current state of the art is that we can adequately, often even expertly, model snowmelt when we have the requisite input data (Sturm, 2015).

Traditionally, models simulating the evolution of a snowpack can be classified into two categories: conceptual models (CO) and energy balance (EB) models, also called physically-based models (Ohara and Kavvas, 2006). EB models developed over the last decades have proven to be highly accurate in snowpack characteristics modeling (Langlois et al., 2009). Different physically-based models, such as the "point energy and mass balance model of a snow cover" (Anderson, 1976), CROCUS (Brun et al., 1989), SNOWPACK (Bartelt and Lehning, 2002) or SNTHERM (Jordan, 1991), among others, have been developed to simulate the evolution of a snow cover for demanding applications such as avalanche prediction.

Despite their recognized performances, full EB approaches are demanding in terms of data collection and computations. For many applications in hydrology, detailed methods are simply not feasible, and simpler methods are required (Bavera et al., 2014; Franz et al., 2008; Meeks et al., 2017; Morin, 2014; Raleigh et al., 2016; Tobin et al., 2013).

CO models rely mainly on empirical relationships to estimate the

* Corresponding author.
E-mail address: Michel.baraer@etsmtl.ca (M. Baraer).

https://doi.org/10.1016/j.jhydrol.2018.07.071
Received 13 February 2018; Received in revised form 20 July 2018; Accepted 26 July 2018
Available online 31 July 2018
0022-1694/

amount of accumulated and melted snow at a given time step (Hock, 2003). They require a calibration of their parameters against measurements in order to provide good simulated values. They can be subdivided into empirical (EM), temperature index (TI) and enhanced TI (ETI) models. EM models simply compute a unique snow characteristic like the depth of the snowpack (SD) or the snow water equivalent (SWE) based on a single equation, not specifically conveying any physical meaning (e.g. Baraer et al., 2010; Scott et al., 2003). TI models are based on simple or enhanced degree day methods, as in CEMANEIGE (Valéry, 2010), HBV (Bergström, 1976) and SRM (Martinec and Rango, 1986). TI models associate linear relationships between ablation and air temperature, usually expressed in the form of positive temperature sums (Hock, 2003). ETI models are often adaptations of the traditional TI models that aim to overcome the model's simplicity and consequent limitations (Meeks et al., 2017). Model enhancements are achieved by incorporating additional input variables into melt equations (Brubaker et al., 1996; Machguth et al., 2006; Pellicciotti et al., 2005; Singh et al., 2009) and/or adding temperature-based equations for simulating processes involved in snowpack conditions (Hock, 2003; Hood and Hayashi, 2015; Mosier et al., 2016; Rutter et al., 2009; Tobin et al., 2013; Turcotte et al., 2007). The use of CO models presents two principal advantages. They usually require simple meteorological data, such as the daily precipitation and the air temperature (daily mean or daily maximum). Using CO models also makes for short and simple formulations, meaning that the model is usually not demanding in terms of computation time (Hock, 2003). Different studies have shown that, despite their simplicity, CO models are efficient in simulating SWE evolution in time (Debele et al., 2010; Troin et al., 2016; Watson and Putz, 2014; Williams and Tarboton, 1999). Despite the obvious advantages CO models propose, concerns have been expressed relating to the fact that quantities known to influence the energy balance and snowmelt processes, such as vapor pressure, wind and reflected radiation, are neglected (Tobin et al., 2013). Moreover, recourse to extensive calibration often makes CO models less robust and raises the question of their transferability in space and time (Mauser and Bach, 2009), and their ability to provide good predictions in a changing climate has been questioned (Bougamont et al., 2007; Ludwig et al., 2009). Snow accumulation, duration of snow cover period and snowmelt processes are expected to be strongly affected by the projected global warming trend during the 21st century (Adam et al., 2009; Barnett et al., 2005; Pohl et al., 2006). Empirical relationships that are currently used in CO models are derived from calibration using past and present conditions, and may no longer be valid in the context of future climate conditions (Warscher et al., 2013). In hydrological models, key parameters, including those describing snow, are generally calibrated against discharge measurements (Saelthun et al., 1998), and calibration of snow parameters solely at the basin outlet does not necessarily lead to optimal performances (Franz and Karsten, 2013). The snow parameters are thus sensitive to equifinalities, and can lead to unreasonable snow cover evolution estimations (Finger et al., 2015; Konz et al., 2010). Even the use of ETI models in such conditions does not necessarily improve the overall performance of hydrological models. In general, including too many parameters requiring calibration against stream discharge causes an increase in the number of undefined parameters, which can lead to over-fitting and poor predictive capabilities of the hydrological models (Magnusson et al., 2014).

Recently, increasing attention has been paid to multi snowpack models and ensemble modeling approaches in the literature (Essery et al., 2013; Franz et al., 2010; Magnusson et al., 2014). These methods allow the inter-comparison of different model types and an estimation of the modeling uncertainties associated with the various sources of error in the forecasting process (Franz et al., 2010). However, the direct applicability of such ensemble modeling approaches to hydrology appears uncertain as they increase the computational demand while still requiring difficult-to-access meteorological parameters. To date, the datasets required to run multiple concurrent model types have limited such approaches to a restricted number of sites and to limited periods (Essery et al., 2016). Also, useful insights have been gained; snowpack model comparisons have generally failed to find clear relationships between model complexity and performance and have not succeeded in finding an overall best model (Essery, 2015).

Despite all efforts and recent advances in snowpack modeling, the choice for hydrological modelers remains mainly between CO models of different complexities and data intensive EB models. Moving ahead from this dilemma requires integrating a more process-based approach into the development of snowpack models for hydrology (Mendoza et al., 2014; Sturm, 2015). After testing 1701 different model combinations, Essery et al. (2013) concluded that models including prognostic equations for changes in snow density and albedo, and that take some account of storage and refreezing of liquid water, perform better than simpler models. Meeks et al. (2017) claim that snowmelt modeling uncertainty may be reduced by the inclusion of more data that allow the use of more complex approaches such as the energy balance method. Lundberg et al. (2016) conclude a literature review on snow and frost by underlining that process-based models are more suited than CO models for different applications such as modeling rain-on-snow events or heat advection from bare soils.

Introducing empirical relationships into EB models to compensate for the lack of input data availability offers the possibility of moving toward more process-based modeling in snowpack hydrology (Förster et al., 2014; Raleigh et al., 2016). While not designed for feeding common hydrological models, snowpack models proposed by Jacobi et al. (2010) and Strasser and Marke (2010) have demonstrated that this approach might represent an interesting solution.

Another method for developing more process-based snowpack models involves keeping EB snowpack models as simple as possible by designing them based on their intended application (Magnusson et al., 2014). EB models dedicated to avalanche forecasting, for example, describe snow grain size and type, characteristics that have not been reported as critical for hydrological applications (e.g. Essery et al., 2013).

In the present study, we target non-mountainous Nordic hydrological applications in designing a process-based snowpack model named MASiN (Modèle Autonome de Simulation de la Neige). The objective is to move toward the high robustness associated with pure EB models (Hood and Hayashi, 2015) with a model applicable to sites where only simple metrological variables are available. Using a survey presented by Raleigh et al. (2016) on Automatic Weather Stations across over the western United States, we selected the air temperature, precipitation, wind speed and relative humidity as model input variables. According to the survey, 35% of the 1318 studied stations that measure SWE also provide those variables, whereas only 24% also measure incoming solar radiation.

Targeting hydrological applications limits the requirement for output variables to SWE, snow depth and melt water outflow volumes. Finally, targeting non-mountainous environments allows keeping coverage processes reasonable by, for example, not accounting for slope effects. Because model robustness cannot be tested on the very limited number of sites where long SWE time series exist, the model performance was assessed by evaluating its ability to estimate the more commonly measured snow depth, the close second most fundamental metric used to characterize the hydrological role of snow (Sturm et al., 2010).

Ultimately, the MASiN model's robustness was assessed by setting a unique set of parameters on a single site and comparing its performance to other models (1) calibrated following the same protocol and (2) specifically calibrated on each test site.