Available online at www.sciencedirect.com
SCIENCE DIRECT®
Journal of Hydrology 300 (2005) 65–75
Journal of Hydrology
www.elsevier.com/locate/jhydrol

Process-based snowmelt modeling: does it require more input data than temperature-index modeling?

M. Todd Walter[a,*], Erin S. Brooks[b], Donald K. McCool[c], Larry G. King[d], Myron Molnau[b], Jan Boll[b]

[a]*Department of Biological and Environmental Engineering, Cornell University, Ithaca, NY 14853-5701, USA*
[b]*Department of Biological and Agricultural Engineering, University of Idaho, Moscow, ID, USA*
[c]*USDA-ARS, Department of Biological Systems Engineering, Washington State University, Pullman, WA, USA*
[d]*Department of Biological Systems Engineering, Washington State University, Pullman, WA, USA*

Received 6 March 2003; revised 30 April 2004; accepted 12 May 2004

Abstract

Modeling snow hydrology for cold regions remains a problematic aspect of many hydro-environmental models. Temperature-index methods are commonly used and are routinely justified under the auspices that process-based models require too many input data. To test this claim, we used a physical, process-based model to simulate snowmelt at four locations across the conterminous US using energy components estimated from measured daily maximum and minimum temperature, i.e. using only the same data required for temperature-index models. The results showed good agreement between observed and predicted snow water equivalents, average $R^2 > 0.9$. We duplicated the simulations using a simple temperature-index model best fitted to the data and results were poorer, $R^2 < 0.8$. At one site we applied the process-based model without substantial parameter estimation, and there were no significant ($\alpha = 0.05$) differences between these results and those obtained using temperature-estimated parameters, despite relatively poorly predicted specific energy budget components ($R^2 < 0.8$). These results encourage the use of mechanistic snowmelt modeling approaches in hydrological models, especially in distributed hydrological models for which landscape snow distribution may be controlled by spatially distributed components of the environmental energy budget.

Keywords: Snowmelt; Energy budget; Distributed hydrological model; Environmental energy; Process-based model; Temperature-index model

1. Introduction

Snow plays important roles in cold regions hydrology, enhancing melt-time runoff, absorbing rain during cold, deep pack periods, and insulating the soil, thus, inhibiting soil frost penetration and thawing (Male and Gray, 1981; Steppuhn, 1981). Flooding, contaminant transport, water supply recharge, and erosion are a few processes receiving public attention that are directly linked to snow processes. Modeling snowmelt in a hydrological model is especially problematic because an incorrectly simulated melt event not only incorrectly predicts flow

* Corresponding author. Tel.: +1-607-255-2488; fax: +1-607-255-4080.
E-mail address: mtw5@cornell.edu (M.T. Walter).

0022-1694/$ - see front matter
doi:10.1016/j.jhydrol.2004.05.002

on that day, but also on the day when the actual melt occurs. So, an incorrectly predicted snowmelt event results in at least two periods of incorrect streamflow simulation rather than just one period, as expected with an incorrectly simulated streamflow from a rainfall event. Thus it is not surprising that snowmelt-modeling problems are commonly acknowledged weaknesses in hydrological models (Fontaine et al., 2002; Frankenberger et al., 1999). Some improvement has been achieved by distributing temperature, usually by using an adiabatic lapse rate, and including solar radiation, for which spatial distributions are relatively straightforward (Cazorzi and Fontana, 1996). This short study investigates the utility of simply adopting a full energy balance approach to model snowmelt and estimating, by straightforward methods, the required parameters that are seldom available.

Despite the well-established accuracy of process-based, energy budget snowmelt models (Anderson, 1968, 1976; Flerchinger and Saxton, 1989; Barry et al., 1990; Blöschl et al., 1991; Morris, 1991; Marks and Dozier, 1992; Grant, 1992; Walter, 1995), there is a propensity towards using temperature-index or degree-day snowmelt relationships in hydrological models, e.g. TOPMODEL (Ambroise et al., 1996), especially those designed for water resource management purposes; e.g. SWAT (Fontaine et al., 2002), AGNPS (Young et al., 1989), GWLF (Haith and Shoemaker, 1987; Schneiderman et al., 1998). In models that estimate flow contributions from various hydrological reservoirs using lumped-parameter methods, like the popular *Curve-Number* approach (USDA-SCS, 1972), a more precise description of snowmelt may not be justifiable. However, these models are being used as distributed models, which require the developers to revisit the physical interpretation of the lumped-parameters being used to describe the hydrological systems. Distributed snowmelt modeling, which integrates several energy exchange processes, is dependent on how the relevant processes are spatially distributed and it is unlikely that a temperature-index model will meaningfully capture this heterogeneity. Oddly, many models employ energy balance approaches like the Penman equation (Penman, 1948), for estimating potential evapotranspiration (PET) and, thus, it is inconsistent that these models do not employ the same energy balance approaches for modeling snowmelt.

The most common justification for temperature-index snowmelt models is that energy budget calculations require too many input data (Rango and Martinec, 1995; Cazorzi and Fontana, 1996; Beven, 2000). Indeed, many hydrologic models that use energy budget approaches are published using large, and often complicated, input data sets (Flerchinger, 1987; Wigmosta et al., 1994), however, substantial information is also required to meaningfully calibrate the 'melt factor' used in temperature-index models. Similar large-data-input arguments are often made with respect to modeling PET. To which the well-known biophysicist, Gaylon Campbell, replied 'the data requirements are substantial, but one usually obtains better results using the Penman–Monteith equation and estimating missing data, than by using a simpler equation that does not use such a mechanistic approach' (Campbell and Norman, 1998). In this project, we tested the feasibility of 'estimating missing data' to facilitate mechanistic snowmelt modeling. Our objective was to see how well this type of modeling approach works using no more data than simple temperature-index approaches, i.e. daily maximum and minimum air temperatures. Thus, this paper also summarizes some simple approaches for approximating commonly unknown energy balance parameters such as snow albedo and atmospheric vapor density (or pressure).

2. Daily snow energy budget and simple parameter approximations

We used the following energy balance for a snowpack:

$$\lambda\Delta\mathrm{SWE} = S + L_a - L_t + H + E + G + P - \mathrm{SWE}(C\Delta T_s) \tag{1}$$

where λ is the latent heat of fusion (3.35×10^5 kJ m^{-3}), ΔSWE is the change in the snowpack's water equivalent (m), S is the net incident solar radiation (kJ m^{-2}), L_a is the atmospheric long wave radiation (kJ m^{-2}), L_t is the terrestrial long wave radiation (kJ m^{-2}), H is the sensible heat exchange (kJ m^{-2}), E is the energy flux associated with the latent heats of vaporization and condensation at the surface (kJ m^{-2}), G is ground heat conduction to the bottom of the snowpack (kJ m^{-2}), P is heat added by rainfall (kJ m^{-2}) and SWE($C\Delta T_s$) is the change of snowpack heat storage (kJ m^{-2}). None of these energy fluxes is routinely measured directly. The following are the methods adopted in this study to estimate these parameters using only the day of the year, daily maximum and minimum temperature, and geographic latitude, all of which are readily available throughout much of the world.

Solar radiation. The solar radiation incident on a local slope, S, can be calculated from:

$$S = (1 - A)T_t S_o \tag{2}$$

where A is the surface albedo, T_t is the atmospheric transmissivity, and S_o is the potential extraterrestrial solar radiation (kJ m^{-2}). Other terms can be included to simulate the effects of topography (Montieth, 1973; Swift, 1976; Cazorzi and Fontana, 1996) and vegetative cover (Link and Marks, 1999), but these will not be discussed in this short paper. The potential extraterrestial solar radiation on a horizontal plane is readily estimated from well established astronomical relationships and the common assumption of a solar constant, S' (117.5×10^3 kJ m^{-2} day^{-1}) (Garnier and Ohmura, 1968; Swift, 1976; Gates, 1980):

$$S_o = \frac{S'}{\pi}\{\cos^{-1}(-\tan\delta\tan\phi)\sin\phi\sin\delta + \cos\phi\cos\delta\sin[\cos^{-1}(-\tan\delta\tan\phi)]\} \tag{3}$$

where ϕ is the latitude of the location (radians) and δ is the solar declination (radians), which can be calculated by a variety of methods. For example (Rosenberg, 1974):

$$\delta = 0.4102\sin\left(\frac{2\pi}{365}(J - 80)\right) \tag{4}$$

where J is the day of the year (e.g. $J = 1$ on January 1, $J = 2$ on January 2, etc.).

The atmospheric transmissivity, T_t, can be calculated with an equation originally proposed by Bristow and Campbell (1984) and later modified by Campbell (Ndlovu, 1994):

$$T_t = 0.75\left[1 - \exp\left(-\frac{B}{S_{o30}}(T_x - T_n)^2\right)\right] \tag{5}$$

where B is an empirical coefficient, S_{o30} is the potential extraterrestrial solar radiation 30 days previous to the simulation day (MJ m^{-2}) (Eq. (3)), and T_x and T_n are the daily maximum and minimum temperatures, respectively (°C). Ndlovu (1994) showed that B is seasonally and geographically dependent and developed some general correlations between summer and winter B values and latitude; summer encompasses the 90 days proceeding and 90 days following the summer solstice and winter is the rest of the year:

$$B = 0.282\phi^{-0.431} \text{ for summer} \tag{6a}$$

$$B = 0.170\phi^{-0.979} \text{ for winter} \tag{6b}$$

Thornton and Running (1999) proposed a slightly improved form of the Bristow–Campbell equation (Bristow and Campbell, 1984) but its relative complexity was not warranted for this project's objective.

We approximated the temporal decay of snow albedo, A, with an empirical relationship developed using the information from the US Army Corps of Engineers report (1960):

$$A = 0.35 - (0.35 - A_x) \times \exp\left[-\left(0.177 + \ln\left(\frac{A_x - 0.35}{A' - 0.35}\right)^{2.16}\right)\right]^{0.46} \tag{7}$$

where A' is the albedo for the previous day, and A_x is the maximum albedo (~ 0.95). When new snow falls it covers darker, low albedo, surfaces. Kung et al. (1964) found that ~ 12 cm of snow will essentially mask an underlying surface (McKay and Gray, 1981). Based on these observations, we estimated an average albedo after snowfall with:

$$A = A_x - (A_x - A')\exp\left[-\left(\frac{4R_p\rho_{sn}}{0.12}\right)\right] \tag{8}$$

where R_p is the water equivalent depth of new snow (m) and ρ_{sn} is the density of the new snow (kg m^{-3}), which can be approximated as the maximum of 50 or $50 + 3.4(T_a + 15)$ (based on data from Goodison et al., 1981); T_a is the average daily air temperature (°C). For very shallow snowpacks (SWE $< \sim 0.3$ m), the underlying ground influences the snow albedo and we assumed that below this point the albedo decays linearly with snow water equivalent (SWE); when SWE $= 0$, the albedo is 0.25, a generic emissivity for snowless ground (Campbell, 1977).

Long wave radiation. Long wave radiation, L, is calculated with the Stefan–Boltzmann equation

$$L = \varepsilon \sigma T_K^4 \tag{9}$$

where ε is the surface emissivity, σ is the Stefan–Boltzmann constant (4.89×10^{-11} kJ m^{-2} K^{-4} day^{-1}), and T_K is the temperature of the radiating body (K). For atmospheric long wave radiation we used the average air temperature, T_a, directly. One estimate for atmospheric long wave emissivity, ε_a, is (Campbell and Norman, 1998):

$$\varepsilon_a = (0.72 + 0.005T_a)(1 - 0.84C) + 0.84C \tag{10}$$

where T_a is the average air temperature (°C) and C is the fraction of cloud cover. For simplicity, we grossly estimated C as 100% cloud cover on rainy days ($P > 0.5$ cm) and 0% on other days. One might also consider back-calculating cloud cover from atmospheric transmissivity, Eq. (5). For determining terrestrial long wave radiation, the long wave emissivity of snow was 0.97.

Sensible heat exchange. Sensible heat exchanged between a surface and the air, H, can be calculated with:

$$H = C_a\left(\frac{T_s - T_a}{r_h}\right) \tag{11}$$

where C_a is the heat capacity of air (~ 1.29 kJ m^{-3} °C^{-1}), T_s is the snow temperature (°C), T_a is the average air temperature (°C), and r_h is the resistance to heat transfer (day m^{-1}). Turbulent eddy mechanisms are usually assumed to govern the heat resistance term and can be calculated with (Campbell, 1977)

$$r_h = \frac{\ln\left(\frac{z_u - d + z_m}{z_m}\right)\ln\left(\frac{z_T - d + z_h}{z_h}\right)}{k^2 u}\frac{1}{86400} \tag{12}$$

where z_u is the height of the windspeed measurements (~ 2 m), z_T is the height of the air temperature measurements (~ 1 m), d is the height of the zero-plane displacement (for snow ~ 0 m), z_m is the momentum roughness parameter (for snow ~ 0.001 m), z_h is the heat and vapor roughness parameter (for snow ~ 0.0002 m), k is von Karman's constant (0.41), and u is the windspeed (m s^{-1}). Windspeed is often unavailable and is not easily predicted so we used a constant windspeed equal to the geometric mean of the nearest measurements.

Heat from convective vapor exchange (evaporation and condensation):

$$E = \lambda_v\left(\frac{\rho_s - \rho_a}{r_v}\right) \tag{13}$$

where E is the daily heat flux due to vaporization and condensation, (kJ m^2), λ_v is the latent heat of vaporization (2500 kJ kg), ρ_s is the vapor density at the surface (kg m^{-3}), ρ_a is the vapor density of air (kg m^{-3}), and r_v is the resistance to vapor exchange (day m^{-1}) which was assumed to be equal to r_h (Eq. (12)). We assumed the vapor density at the surface was the saturation vapor density at the snow temperature. Since minimum air temperature and vapor density are strongly correlated (Campbell and Norman, 1998), we approximated the dew point temperature as equal to the minimum daily temperature. Thus, the vapor density of the air is the saturation vapor density at the minimum daily air temperature. When relative humidity or measured dew point data are available this assumption is unnecessary, but herein we restricted our input data to air temperature. Saturation vapor density, ρ_o (kg m^{-3}), at a temperature, T (°C), can be calculated with (Allen, 1990):

$$\rho_o = \exp\left(\frac{16.78T - 116.8}{T + 273.3}\right)\left[\frac{1}{(273.15 + T)R}\right] \tag{14}$$

where R is the thermodynamic vapor constant (0.4615 kJ kg^{-1} °K^{-1}). Possibly improved approximations for vapor density by Kimball et al. (1997); Thornton et al. (2000) were not used here because the additional complexity was not warranted for this paper's objective.

Ground heat conduction. Heat conduction from the ground into a snowpack tends to be small. A constant value of 173 kJ m^{-2} day^{-1} was assumed based on US Army Corps of Engineers (1960) melt estimates.

Precipitation heat. If rain water is assumed to have the same temperature as the air, T_a (°C), and heat is added to the snow pack by lowering the rain's temperature to the freezing point, (0 °C), heat from precipitation can be estimated as:

$$P = C_w R_p T_a \tag{15}$$

where C_w is the heat capacity of water (4.2×10^9 kJ m^{-3} °C^{-1}) and R_p is the depth of rain (m).

Stored snowpack energy. During periods of net energy loss from the snow pack, the snow temperature will decrease proportionally and will rise during periods of net energy gain, but will not exceed the freezing point (0 °C). Eq. (1) was used to estimate snowpack temperature change and snow heat capacity was considered constant (0.0021 kJ m^{-3} °C^{-1}). We assumed the liquid water holding capacity as 5% of the SWE and during periods of net energy loss from the pack this water was refrozen before the snowpack temperature was modified. Snow was assumed to accumulate whenever precipitation coincided with an average daily air temperature below 0 °C.

3. Methods

We used four data sets from across the conterminous US to test the applicability of the simplified energy budget presented here to a wide range of environments. The sites were near the following towns, Danville, VT (~44°N), Bloomville, NY (latitude ~41°N), Easton, MN (latitude ~44°N), and Troy, ID (latitude ~47°N). All the sites were open and level. We predicted SWE at Danville, VT for the period March 9–31, 1973 and compared results to published data collected at the NOAA-ARS research station (Anderson et al., 1977). Windspeed was measured on site and the geometric mean for March 1973 was 1.7 m s^{-1} (range: 0.3–4.2). The other three sites were remote, relative to the Danville, VT site, and data were collected in conjunction with various other projects. Bloomville, NY, in the Catskill Mountains, was simulated for the Spring 1997 melt and used temperature and precipitation, from Walton, NY located ~40 km away and the geometric mean of the windspeed, 3.0 m s^{-1} (range: 0.4–8.4 m s^{-1}), from Sullivan County airport located ~60 km away. The Easton, MN, in south-central MN, was simulated for the December 1994–March 1995 snow season using meteorological data collected at the site (Brooks, 1997); geometric mean windspeed = 2.5 m s^{-1} (range 0.6–8.3 m s^{-1}). Snow density was not consistently measured at Easton, MN so some SWE were estimated from snow depth and average season snow density; these data are indicated in the results. Troy, ID, near Moscow, ID, was simulated for the 2000 melt season using on-site temperature data and geometric mean of on-site wind data, 1.4 m s^{-1} (range: 0.2–7.7 m s^{-1}).

4. Results and discussion

Fig. 1 shows the predicted and observed SWE for each site. All the simulations have low standard errors (Ste), generally <10% of range of observed SWE, and high R^2. There were no significant ($\alpha = 0.05$) differences between the regression slopes of observed vs. predicted SWE and the 1:1 relationship. These results indicate good agreement between predicted and observed SWE for all simulations. The Danville, VT results were the best, probably because this site was the most carefully monitored. Although none of the other simulation results agreed with observations as well as at Danville, VT, the correlations between observations and predictions were still good. Not surprisingly, the Bloomville, NY results were the worst, probably due to the large proximal distance between the measured SWE site and the meteorological stations from which input data were obtained. In fact, removing the 2/4/97 observation, for which no associated new snow was recorded in our meteorological record despite the obvious increase of snow at the site, the $R^2 = 0.98$ and Ste = 0.008 m. Although the indirectly estimated SWE data at Easton, MN (marked symbols in Fig. 1c) constituted the points of poorest agreement, it would be difficult to substantially improve the agreement with any meaningful adjustments to measured snow density because the range of measured snow densities was small. Thus it is probable that the errors in these results show real limitations to this model and, thus, suggest that improvements are still needed.

For comparison purposes, we repeated the simulations for all sites using a simple temperature index approach in which the melt, ΔSWE, was calculated by (Beven, 2000):

$$\Delta SWE = F \max(0, T_a - T_f) \tag{16}$$

where F is the daily melt factor (m °C^{-1}), T_a is the average daily air temperature (°C), and T_f is the freezing temperature (0 °C). Numerous variations, arguably improvements, on Eq. (16) have been

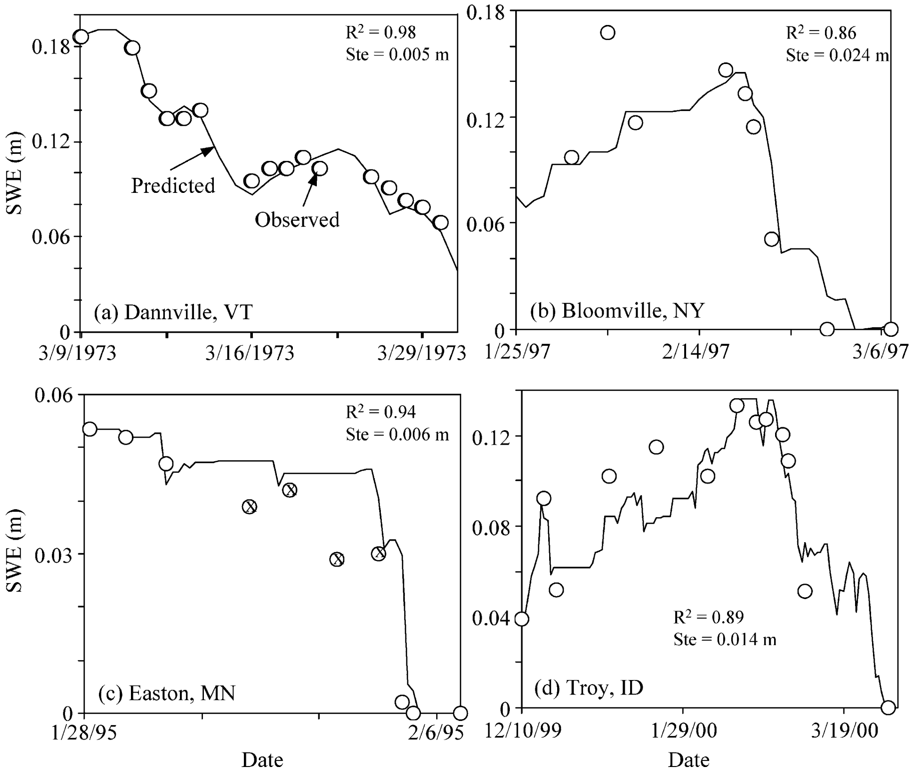

Fig. 1. Comparison between predicted and observed SWE for simulations at (a) Danneville, VT, (b) Bloomville, NY, (c) Easton, MN and (d) Troy, ID. Symbols, measured data; line, simulated results using the physically based model. Statistics are shown on each graph (ste, standard error). Marked symbols in (c) were estimated from direct snow depth measurements and average snow density measurements.

published but we chose not to address those here because most improved temperature-index methods require more input data, arguably defeating the purpose of using this simple type of model. Eq. (16) was best fitted to the data from each site using the daily melt factor, F, as a calibration constant. The melt factors were 0.006, 0.017, 0.027, and 0.0007 m °C^{-1} for Danville, VT, Bloomville, NY, Easton, MN, and Troy, ID, respectively. Published melt factors similarly range over more than an order of magnitude (van der Leeden et al., 1990). Fig. 2 shows the observed vs. predicted correlations for the process-based, or physical, model (Fig. 2a) and the temperature-index model (Fig. 2b) for the four sites study sites. The correlation and standard error were better for the process-based model than for the temperature-index model and the process-based results were generally as good as or better than published temperature-index results. Removal of the out-lying data point (Bloomville, NY 2/4/97) from the data improved the physically-based results ($R^2 = 0.95$, Ste $= 0.011$ m) but had no effect on the temperature-based results. The wide range of melt factors reinforces the fact that an accurate temperature-index modeling approach requires calibration data, which implies a large amount of input data is needed to use this approach.

The Dannville, VT data set included enough meteorlogical and snowpack data to apply a process-based modeling approach without the need to estimate virtually any parameters (Anderson et al., 1977). The data include specific measurements for solar radiation, surface albedo, atmospheric long wave radiation, snow surface temperature, air vapor pressure, windspeed, maximum and minimum air temperature, and precipitation and SWE. The only term that needed to be estimated was the surface vapor density, for which we used Eq. (13) with the measured snow

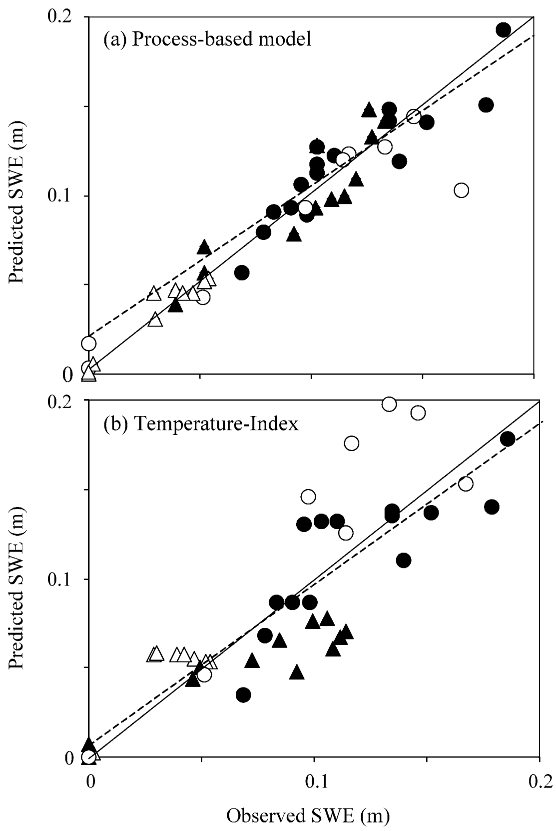

Fig. 2. Comparison of predicted and observed SWE from all the sites using the (a) process based model ($R^2 = 0.92$, Ste = 0.014 m, regression slope = 0.92) and (b) the temperature-index model ($R^2 = 0.76$, Ste = 0.025 m, regression slope = 0.95). Solid Circles, Danville, VT; open circles, Bloomeville, NY; solid triangles, Troy, ID; open triangles, Easton, MN.

temperature. There were no significant ($\alpha = 0.05$) differences between these SWE results and those obtained by estimating the parameters ($R^2 = 0.97$ and Ste = 0.006 m) for both simulations. However, predicted and observed components of the energy balance did not agree as well (Fig. 3), which suggests acceptable snowmelt modeling is possible without precise predictions of the individual energy budget terms or parameters. This may explain why acceptable results are often published for simple temperature-index approaches.

For solar radiation (Fig. 3a), 90% of the data lie within 2400 kJ m^{-2} of the 1:1 line and removing the two most substantial outliers improves the statistics noticeably, $R^2 = 0.83$, RD = 36%, although these are still substantially worse than for snowmelt. Atmospheric long wave radiation (Fig. 2b) is consistently underestimated however this systematic error did not appear to impact snowmelt predictions appreciably. This is probably because terrestrial long wave radiation (triangle in Fig. 2b), which is similar in magnitude to atmospheric long wave radiation, was consistently over estimated, although to a much smaller degree. Our estimated snow temperature varied by less than 0.5 °C, which is small compared to the measured snow temperature variations of ~4 °C. However, the range of observed terrestrial long wave radiation, based on measured surface temperatures (horizontal error bars in Fig. 3b), is much narrower than the range of atmospheric long wave radiation, which suggests that our poor estimates of snow temperature introduced relatively little error into net long wave radiation estimates. Sensible and evaporative heat exchanges were generally over predicted. We reran our simulation using estimated parameters, but used measured windspeeds instead of geometric mean windspeed to see if sensible and evaporative heat exchange predictions would improve. Very little difference was noted between predictions using measured windspeed (light symbols in Fig. 3c) and using a constant windspeed (dark symbols in Fig. 3c). Although windier locations might experience greater sensitivity to windspeed, our result is consistent with similar to energy budget observations made regarding PET (Priestly and Taylor, 1972). The total net energy (Fig. 3d) was predicted about as well as the individual components, although the relative difference is somewhat poorer. The worst absolute estimates were for atmospheric long wave radiation, which exhibited an RD associated with 2400 kJ m^{-2} d^{-1}; this seemingly large error corresponds to 0.007 m of snowmelt, which is similar to the standard errors of the SWE estimates shown in Fig. 1a. This supports our earlier suggestion that accurate snowmelt predictions may not be critically sensitive to errors in individual energy budget terms.

Fig. 4 compares predicted or estimated albedo and vapor density for Danville, VT and, not surprisingly, agreement is similar to that for the associated energy budget components (Fig. 3a and c). The surface albedo (Fig. 4a) disagreement is clearly systematic and might be improved by employing a more refined relationship, perhaps accounting for the season. Fig. 4b shows that

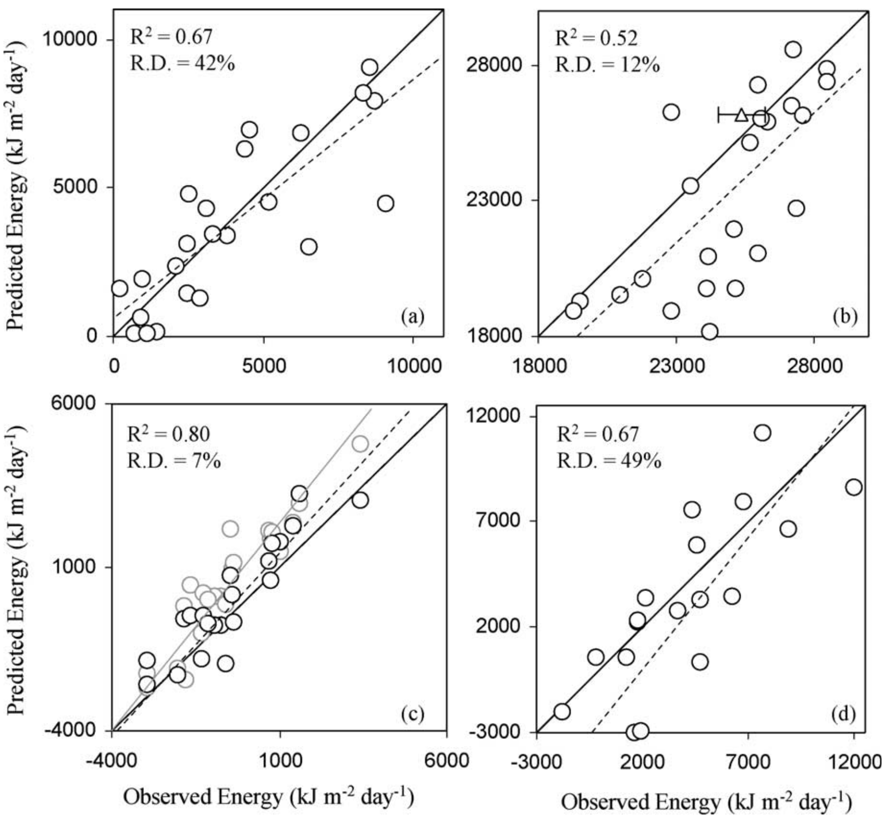

Fig. 3. Comparisons of predicted vs. observed components of the energy budget at Danville, VT; (a) solar radiation, (b) atmospheric long wave radiation (circles) and terrestrial long wave radiation (triangle shows median, error bars show extent of observed values; extent of estimated values is smaller than the triangle), (c) sensible + evaporative heat, and (d) total net energy. Symbols are data, dashed lines show linear regression, solid lines show 1:1 relationship, statistics are indicated on the graphs (RD, relative difference). The gray symbols and gray dashed line in (c), were for the model simulation using measured windspeed ($R^2 = 0.86$, RD = 9%).

atmospheric vapor density was almost always over estimated, implying that the minimum daily air temperature is generally higher than the dew point temperature. However, the impact of this error was probably somewhat lessened by the fact that surface vapor density (triangle in Fig. 4b) was also over estimated. Note that the range of surface vapor densities, based on observed surface temperatures (horizontal error bars in Fig. 4b), is narrower than the range of atmospheric vapor density and similar in magnitude to the errors in estimating atmospheric vapor density (Fig. 4b). Thus, as with terrestrial long wave radiation, the impact of poorly estimated snow temperature had only a small impact on vapor energy exchange.

The results from this study demonstrate that accurate snowmelt predictions from a process- or physically-based energy budget are attainable with simple estimates of a few controlling parameters and require no more data than more popular temperature-index methods. In fact, because published temperature-index 'melt factors' vary by as much as an order of magnitude (van der Leeden et al., 1990) substantial data are required to empirically calibrate these coefficients (Cazorzi and Fontana, 1996). It is arguable, then, that the processed-based approach presented here requires substantially less data input than temperature-index models. It is interesting and surprising (at least it was to the authors) that assuming constant windspeed introduced relatively little error into the snowmelt predictions. It is likely that in areas where windspeed fluctuates dramatically, the assumption of constant values might

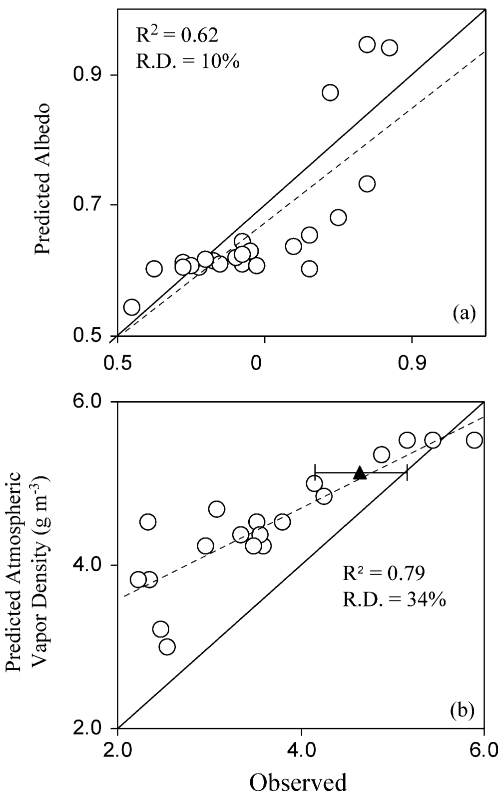

Fig. 4. Comparisons of predicted (estimated) vs. observed (a) surface albedo and (b) atmospheric vapor density (circles) and surface vapor density (triangle shows mean, error bars show extent of observed values; extent of estimated values is smaller than the triangle) for Danville, VT. Symbols are data, dashed lines show linear regression, solid lines show 1:1 relationship, statistics are indicated on the graphs (RD, relative difference).

introduce more error. Although the empirical estimates and various approximations used in this study apparently provided reasonable estimates for the purposes of snowmelt modeling, there is obviously substantial room for improvement. There are published approaches to estimating some of the model parameters that are better than those used here (Wachler and Wigmosta, 2003), although generally more complicated to use, which is why we did not use them. One advantage to a process-based approach, like the one used here, over a temperature-index method, is that sources of error can be meaningfully identified and improved upon. For example, this study used a very crude estimate of atmospheric emissivity that could use substantial improvement. Hopefully continued research on distributed snowmelt modeling will improve our understanding about how to estimate parameters and terms in the energy budget rather than developing better 'index' methods.

5. Conclusions

This short study demonstrates that snowmelt can be simply and reliably modeled with a physically based energy budget using no more data than required for most temperature-index methods, i.e. maximum and minimum daily air temperature. All parameters can be reasonably estimated from simple published relationships, like the albedo approximation used here, or simplifying assumptions, like setting the windspeed equal to the geometric mean windspeed. Snowmelt predictions were good despite substantial discrepancies in the estimates of individual energy components or parameters. Indeed, because specific sources of error, such as a particularly poorly estimated energy budget components, can be identified, improvements can be meaningfully addressed. Additionally, the physically based approach used in this paper was uncalibrated, which is rarely the case for temperature-index models. Physically-based snowmelt modeling is a logical addition to current distributed hydrological models and does not appear to require copious input data.

References

Allen, R.G. (Ed.), 1990. Evapotranspiration and Irrigation Water Requirements, American Society of Civil Engineering (ASCE), New York, NY, p. 332.

Ambroise, B., Freer, J., Beven, K.J., 1996. Application of a generalised TOPMODEL to the small Ringelbach catchment, Vosges, France. Water Resour. Res. 32, 2147–2159.

Anderson, E.A., 1968. Development and testing of snow pack energy balance equations. Water Resour. Res. 4(1), 19–37.

Anderson, E.A., 1976. A point energy and mass balance model of snow cover. US Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service. NOAA Technical Report NWS 19. 150pp.

Anderson, E.A., Whipkey, R.Z., Greenan, H.J., Machell, C.T., 1977. NOAA-ARS Cooperative Snow Research Project-Watershed hydro-climatology and data for water years 1960–1974, Report, US Department of Commerce Silver Spring, MD. Various pagings.

Barry, R.M., Prevost, M., Stein, J., Plamondon, A., 1990. Application of a snow cover energy and mass balance model in a balsam fir forest. Water Resour. Res. 26(5), 1079–1092.

Beven, K.J., 2000. Rainfall-Runoff Modelling, The Primer, Wiley, New York, p. 360.

Blöschl, G., Kirnbauer, R., Gutnecht, D., 1991. Distributed snowmelt simulations in an alpine catchment 1. Model evaluation on the basis of snow cover patterns. Water Resour. Res. 27, 3171–3179.

Bristow, K.L., Campbell, G.S., 1984. On the relationship between incoming solar radiation and daily maximum and minimum temperature. Agric. Forest Meteor. 31(2), 159–166.

Brooks, E.S., 1997. The Spatial and Temporal Variability of a Frozen Soil Layer in a Heterogeneous Landscape. MS Thesis, University of Minnesota, Minneapolis, MN.

Campbell, G.S., 1977. An Introduction to Environmental Biophysics, Springer, New York, p. 159.

Campbell, G.S., Norman, J.M., 1998. An Introduction to Environmental Biophysics, second ed., Springer, New York, p. 286.

Cazorzi, F., Fontana, G.D., 1996. Snowmelt modelling by combining air temperature and a distributed radiation index. J. Hydrol. 181, 169–187.

Flerchinger, G.N., 1987. Simultaneous Heat and Water Model of a Snow-Residue-Soil System. Doctorate Thesis. Department of Agricultural Engineering (Engineering Sci.). Washington State University. Pullman, WA. 138pp.

Flerchinger, G.N., Saxton, K.E., 1989. Simultaneous heat and water model of a freezing snow-residue-soil system I: theory and development. Trans. ASAE 32(2), 565–571.

Fontaine, T.A., Cruickshank, T.S., Arnold, J.G., Hotchkiss, R.H., 2002. Development of a snowfall-snowmelt routine for mountainous terrain for the soil water assessment tool (SWAT). J. Hydrol. 262, 209–223.

Frankenberger, J.R., Brooks, E.S., Walter, M.T., Walter, M.F., Steenhuis, T.S., 1999. A GIS-based variable source area model. Hydro. Proc. 13(6), 804–822.

Garnier, B.J., Ohmura, A., 1968. A method of calculating the direct shortwave radiation income of slopes. J. Appl. Meteorol. 7(5), 796–800.

Gates, D.M., 1980. Biophysical Ecology, Springer, New York.

Goodison, B.E., Ferguson, H.L., McKay, G.A., 1981. Measurement and data analysis. In: Gray, D.M., Male, D.H. (Eds.), Handbook of Snow, Pergamon Press, Toronto, ON, pp. 191–274.

Grant, R.F., 1992. Dynamic simulation of phase changes in snowpacks and soils. Soil Sci. Soc. Am. J. 56(4), 1051–1062.

Haith, D.A., Shoemaker, L.L., 1987. Generalized watershed loading functions for stream-flow nutrients. Water Resour. Bull. 23(3), 471–478.

Kimball, J.S., Running, S.W., Nemani, R., 1997. An improved method for estimating surface humidity from daily minimum temperature. Agric. Forest Meteorol. 58(1–2), 87–98.

Kung, E.C., Bryson, R.A., Lenschow, D.J., 1964. Study of a continental surface albedo on the basis of flight measurements and structure of the earth's surface cover over North America. Mon. Weather Rev. 92, 543–564.

Link, T., Marks, D., 1999. Distributed simulation of snowcover mass- and energy-balance in the boreal forest. Hydrol. Proc. 13(14–15), 2439.

Male, D.H., Gray, D.M., 1981. Snowcover ablation and runoff. In: Gray, D.M., Male, D.H. (Eds.), Handbook of Snow, Pergamon Press, Toronto, ON, pp. 360–436.

Marks, D., Dozier, J., 1992. Climate and energy exchange at the snow surface in the alpine region of the Sierra Nevada. 2. Snow cover energy balance. Water Resour. Res. 28(11), 3043–3054.

McKay, G.A., Gray, D.M., 1981. The distribution of snow. In: Gray, D.M., Male, D.H. (Eds.), Handbook of Snow, Pergamon Press, Toronto, ON, pp. 153–190.

Montieth, J.L., 1973. Principles of Environmental Physics, American Elsevier, New York.

Morris, E.M., 1991. Physics-based models of snow. In: Bowles, D.S., O'Connel, P.E. (Eds.), Recent Advances in Modeling of Hydrological Systems, Kluwer Academic, Dordrecht, pp. 85–112.

Ndlovu, L.S., 1994. Weather Data Generation and Its Use in Estimating Evapotranspiration. PhD Thesis. Department of Biosystems Engineering (Engineering Science). Washington State University. Pullman, WA. 143pp.

Penman, H.L., 1948. Natural evaporation from open water, bare soil, and grass. Proc. R. Soc. A194, 220.

Priestly, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux and evaporation using large-scale parameters. Mon. Weather. Rev. 100, 81–92.

Rango, A., Martinec, J., 1995. Revisting the degree-day method for snowmelt computations. Water Resour. Bull. 31(4), 657–669.

Rosenberg, N.J., 1974. Microclimate: The Biological Environment, Wiley, New York, p. 495.

Schneiderman, E.M., Lounsbury, D.G., Dibeler, B.J., Thongs, D.J., Tone, J.W., Danboise-Lohre, R., 1998. Application of GWLF non-point source loading model to the NYC Catskill and Delaware system watersheds. NYCDEP, 1998.

Steppuhn, H., 1981. Snow and agriculture. In: Gray, D.M., Male, D.H. (Eds.), Handbook of Snow, Pergamon Press, Toronto, ON, pp. 60–125.

Swift, L.W., 1976. Algorithm for solar radiation on mountain slopes. Water Resour. Res. 12, 108–112.

Thornton, P.E., Running, S.W., 1999. An improved algorithm for estimating incident daily solar radiation from measurements of temperature, humidity, and precipitation. Agric. Forest Meteorol. 93(4), 211–228.

Thornton, P.E., Hasenauer, H., White, M.A., 2000. Simultaneous estimation of daily solar radiation and humidity from observed temperature and precipitation: an application over complex terrain in Austria. Agric. Forest Meteorol. 104(4), 255–271.

US Army Corps of Engineers, 1960. Runoff from Snowmelt. (EM 1110-2-1406): 68. Washington, DC. US Govt Printing.

USDA-SCS, 1972. Hydrology, In National Engineering Handbook, Sec. 4, GPO, Washington, DC.

van der Leeden, F.F., Troise, D., Todd, K., 1990. The Water Encyclopedia, second ed., Lewis Publishers, Inc., Chelsea, MI, p. 808.

Waichler, S.R., Wigmosta, M.S., 2003. Development of hourly meteorological values from daily data and significance to hydrological modeling at H.J. Andrews experimental forest. J. Hydrometeorol. 4(2), 251–263.

Walter, M.T., 1995. Winter-Time Hydrological Modeling Over a Three Dimensional Landscape. PhD Dissertation, Engr Sci. Washington State Univ. Dept. of Biosystems Engr. pp. 97.

Wigmosta, M.S., Vail, L.W., Lettenmaier, D.P., 1994. A distributed hydrology-vegetation model for complex terrain. Water Resour. Res. 3(6), 1665–1679.

Young, R.A., Onstad, C.A., Bosch, D.D., Anderson, W.P., 1989. AGNPS: a nonpoint-source pollution model for evaluating agricultural watersheds. J. Soil Water Conserv. 44(2), 168–173.