A negative snow water equivalent (SWE) bias in the snow model of the Noah land surface scheme used in the NCEP suite of numerical weather and climate prediction models has been noted by several investigators. This bias motivated a series of offline tests of model extensions and improvements intended to reduce or eliminate the bias. These improvements consist of changes to the model’s albedo formulation that include a parameterization for snowpack aging, changes to how pack temperature is computed, and inclusion of a provision for refreeze of liquid water in the pack. Less extensive testing was done on the performance of model extensions with alternate areal depletion parameterizations. Model improvements were evaluated through comparisons of point simulations with National Resources Conservation Service (NRCS) Snowpack Telemetry (SNOTEL) SWE data for deep-mountain snowpacks at selected stations in the western United States, as well as simulations of snow areal extent over the conterminous United States (CONUS) domain, compared with observational data from the NOAA Interactive Multisensor Snow and Ice Mapping System (IMS). The combination of snow-albedo decay and liquid-water refreeze results in substantial improvements in the magnitude and timing of peak SWE, as well as increased snow-covered extent at large scales. Modifications to areal snow depletion thresholds yielded more realistic snow-covered albedos at large scales.

1. Introduction

The Noah land surface model (LSM; Mitchell et al. 2001) is the land surface scheme in the numerical weather and climate prediction models of the National Centers for Environmental Prediction (NCEP) of the National Weather Service (NWS). Several investigators (e.g., Sheffield et al. 2003; Ek et al. 2003; Pan et al. 2003; Mitchell et al. 2004; Jin and Miller 2007) have noted that the Noah LSM exhibits a negative bias in snow water equivalent (SWE), especially in early spring. This SWE bias impacts model performance in partitioning of atmospheric radiative inputs (largely because of the strong contrast in albedo of snow-covered and snow-free areas) and in turn heat fluxes and surface temperature. It also affects model performance in offline mode, particularly estimates of soil moisture and runoff, which are used for drought diagnosis, among other purposes (Shukla and Wood 2008). Figure 1 shows an example of the bias in the predicted number of snow-covered days over the conterminous United States (CONUS) as compared with satellite observations. The panels on the right in Fig. 1 show that the model’s SWE bias is particularly acute in deep mountain snowpacks.

Snow cover extent (SCE) has an appreciable impact on large-scale surface water and energy budget for many parts of the Northern Hemisphere. Robinson and Frei (2000) found, using 18 yr of satellite data (1978–95), that more than 50% of the land area of the extratropical Northern Hemisphere is covered by snow during winter months. Empirical evidence suggests that snow cover can influence temperature and precipitation patterns at various scales through its alteration of the surface radiative
Seasonal snow cover also affects the ground thermal regime, insulating the soil from the atmosphere and creating a sink for latent heat during snowmelt (Zhang 2005).

Besides affecting surface heat fluxes, snow cover strongly influences land surface hydrologic state variables such as soil moisture and SWE that exert strong controls on the timing and magnitude of streamflow. Coupled model studies have shown that SCE plays a major role in atmospheric feedbacks (Cess and Potter 1988; Randall et al. 1994; Qu and Hall 2006; Jin and Miller 2007).

Jin and Miller (2007) examined the control exhibited by a snow model on weather variability in a regional climate model (RCM). They considered several snow scenarios: the Noah LSM snow model (similar to the control version herein), a more sophisticated snow model, and direct observations of SWE. They found that the Noah LSM produced a negative SWE bias, which led to an overestimation of model precipitation and near-surface air temperature compared to both SWE assimilation and direct observations of temperature and precipitation. Excessive near-surface temperature stemmed from a shorter duration of snow cover in the model relative to observations. Overestimates of precipitation were due to (i) a less stable lower atmosphere with increased upward air motion and (ii) elevated surface evaporation rates. The Noah LSM SWE bias was attributed to anomalously high snowmelt rates, of which a large part was due to surface albedos that were deemed too low.

The current version of the Noah LSM (2.7; referred to here as the control or control model) uses a single-layer representation of snow processes. Relevant snow model parameters are provided in Table 1. A schematic of the control model is shown in Fig. 2.

Fig. 1. (left) Maps of mean annual cumulative snow-covered days for the IMS observed data and Noah model simulation for the period October 1999–September 2003. (right) Noah SWE simulation (solid line) vs SNOTEL observations (dashed line) for the same period from (top)–(bottom) Olallie Meadows, Washington; Schofield Pass, Colorado; and Leavitt Lake, California.
Koren et al. (1999) added important upgrades to the snow model that are included in the control version, including compaction and frozen soil physics. However, representations of other processes discussed herein, including snow albedo and liquid water within the snowpack, were not addressed. Jin et al. (1999) compared several snow models of varying complexity and concluded that considering liquid water processes within the snowpack are crucial for simulating diurnal variations in SWE correctly. These considerations underscore the significance of accurately estimating snow processes for skillful numerical weather and climate, as well as hydrologic prediction, and motivate our investigation of improving and reparameterizing the Noah snow model.

2. Approach

Our approach is to explore alternative parameterizations for the Noah snow model through comparisons of offline simulations with observations at both large (gridded forcing) and point (direct observed forcing) scales. Based on results of previous investigations and on a detailed inspection of model performance, we confine the focus of this study to two primary issues:

1) Evaluation of an alternative albedo parameterization that captures the seasonally varying characteristics of the snowpack better than the current parameterization and thus changes the net radiation and melt energy available to the pack;

2) Implementation of an algorithm that accounts for liquid water storage and refreeze within the pore space of the snowpack, a process not represented in the control model.

We also report on sensitivity testing of enhancements to the model’s treatment of fractional snow coverage and its interaction with the albedo-decay algorithm.

a. Snow-albedo representation

Snow albedo defines the fraction of incident radiation reflected by the snowpack, which is usually the dominant component of the surface-energy balance over snow during the melt season (Warren and Wiscombe 1980; Warren 1982). However, numerous complexities exist in obtaining representative values for snow albedo, depending on its scale of application and measurement method. In situ measurements have revealed considerable anisotropy in snow reflectance (Grenfell et al. 1994; Perovich 1994; Warren et al. 1998; Li and Zhou 2003; Wuttke et al. 2006), which has been attributed in large part to snow grain size and generally becomes more important with increasing solar zenith angle (Stroeve and Nolin 2002). Correction methods for anisotropy and viewing-angle dependence have been developed with some success to interpret large-scale satellite imagery (Jin and Simpson 2001; Green et al. 2002; Stroeve and Nolin 2002; Painter and Dozier 2004). However, values obtained with ground-based measurements of snow albedo are still not directly applicable to satellite scales, because measurements typically relate to relatively small homogeneous areas, whereas the footprint of a spaceborne instrument is much larger, inhomogeneous, and often only partly covered by snow (Arola et al. 2003). Length scales on the order of kilometers are typical to both satellite measurements and numerical weather prediction models; thus, the assimilation of point measurements requires careful consideration to scale-dependent features. The presence of objects of lower reflectance (vegetation, bare ground, or debris) complicates the measurement of snow albedo by blocking and shading of radiation, and it can create negative feedbacks in albedo because of anisotropic interaction with the higher absorption rates of non-snow-covered areas (Melloh et al. 2002b).

Variations in albedo with seasonally changing snow physical properties are generally acknowledged (U.S. Army Corps of Engineers 1956; Wiscombe 1980; Baker et al. 1990; Moody et al. 2007; among others). Furthermore, reflectance can vary considerably with wavelength (spectral dependence). For example, within the solar spectrum of radiation reaching the earth’s surface (0.3 µm ≤ λ ≤ 5 µm), physical properties such as grain size, shape, age, liquid water content, solar zenith angle, cloud cover, snowpack thickness, and snow density play a large role in albedo decay (Warren 1982). However, Grenfell et al. (1994), in a study of the reflection of solar radiation by the Antarctic snow surface, found that
across the UV and visible spectrum ($\lambda \leq 0.7 \mu m$) albedo was nearly independent of snow grain size and solar zenith angle. Thus, aside from measurement errors, estimation of the albedo of a snow-covered area may be complicated by its inherent angular and spectral dependence; variable rates of surface metamorphosis resulting from aging and wind; and proximity to vegetation, bare ground, or debris.

The parameterization of snow albedo in land surface schemes has a substantial influence on the accuracy of model-calculated snowpack-energy absorption (Molotch et al. 2004). Most LSMs use a wavelength-integrated (all-wave) albedo, which is a function of multiple factors including snow temperature, depth, age, solar latitude, cloud cover, or an index of daily temperatures (Baker et al. 1990; Pederson and Winther 2005). All-wave snow albedos are generally highest immediately following snowfall and they decay thereafter; seasonally, they are highest in late winter and early spring and decline during the snowmelt season (Warren 1982). Parameterizations should thus provide for a changing value of snow albedo to reflect the metamorphosis taking place at the snow surface between snowfall events, something that is typically achieved by decaying an initial maximum snow albedo ($0.75 \leq \alpha_{max} \leq 0.90$; Warren 1982) as a function of the time since last snowfall and/or other physical proxies.

The control model applies a spatially varying upper bound on snow albedo, based on a conversion of scene brightness imagery taken from Defense Meteorological Satellite Program imagery (Robinson and Kukla 1985). The alternative treatment tested here is an albedo-decay scheme adapted from the Distributed Hydrology Soil Vegetation Model (DHSVM; Wigmosta et al. 1994) and Variable Infiltration Capacity (VIC; Cherkauer et al. 2003) model treatments, which in turn are based on U.S. Army Corps of Engineers (1956). This scheme imposes a decay in albedo from the new snow value that varies seasonally; specifically, the decay is faster (slower) during the ablation (accumulation) season, with an initial, maximum snow-albedo value that is usually much higher than the maximum value from the Robinson and Kukla (1985) data. The prescribed snow albedo $\alpha_{snow}$ from these two albedo-decay rates is parameterized as

$$\alpha_{snow} = \alpha_{max} A^t B,$$  \hfill (1a)

where $\alpha_{max}$ is the albedo value of fresh fallen snow, $t$ is the number of days since the last snowfall, and $A$ and $B$ are equal to 0.94 and 0.58 (0.82 and 0.46), respectively, during accumulation (ablation) phase.

Although values of $A$ and $B$ are seasonally constant in this parameterization, spatial heterogeneity was accounted for in the maximum albedo of fresh fallen snow $\alpha_{max}$ by incorporating the Robinson and Kukla (1985) satellite snow-covered albedo values. These satellite conversions of scene brightness to snow albedo effectively capture the relative geographic variability of snow-covered albedo. To this effect, a second stage adjustment was imposed to assure that the nature of the decay is consistent with the U.S. Army Corps of Engineers (1956) values as shown in Fig. 2. The maximum snow albedo was therefore computed as

$$\alpha_{max} = \alpha_{max,sat} + C \times (\alpha_{max,C of E} - \alpha_{max,sat}),$$ \hfill (1b)

where $\alpha_{max,sat}$ is the satellite-based maximum snow albedo from Robinson and Kukla (1985), $\alpha_{max,C of E}$ is a maximum snow albedo based on Eq. (1) from U.S. Army Corp of Engineers (1956), and $C$ is a proportionality coefficient ($C = 0.5$).
During the melt phase, when albedo decays most rapidly, an issue arises with using a maximum snow albedo that is lower than the value reported by the U.S. Army Corps of Engineers (1956), because the asymptotic value of decaying albedo may fall below the minimum of roughly 0.4 shown in Fig. 3. To avoid this, we constrained the snow albedo to a physically realistic lower bound of 0.4.

We made a minor change to the U.S. Army Corps of Engineers (1956) curves by triggering the switch between the two decay curves in Fig. 3 based on the temperature of the snow surface, rather than using a fixed date. The criterion for seasonal decay is ripe conditions (i.e., temperature of 273.15 K), such that when it is below freezing, the albedo is computed using the accumulation (melt) decay rate.

Because the control model considers only a single snow layer, changes to snow-albedo treatment become more conceptualized for snow over canopy vegetation (e.g., forest vegetation classes). Melloh et al. (2002a) found open-area and subcanopy snow albedos to be quite similar, both decaying throughout the season. However, only slightly less than half of the incident radiation reached the albedo surface because of the presence of the overlying canopy. This disparity was indirectly represented in Eq. (1b), which uses a weighted maximum snow-albedo value that is intermediate between the satellite-based value (which effectually “sees” the canopy) and the higher value for fresh snow. To this effect, when snow cover is incomplete over a grid cell (depth thresholds described in section 2c), the model computes a composite albedo as a weighted average of the albedos of the snow and locally dominant vegetation type. These criteria were applied over the continental U.S. domain, as well as at the test National Resources Conservation Service (NRCS) Snowpack Telemetry (SNOTEL) observation sites.

b. Refreeze and cold content

The amount of liquid water in the snowpack exerts an important control on snowmelt and in turn on runoff production, particularly in areas with deep snowpacks. It is also important for avalanche generation (Stein et al. 1997). Throughout the diurnal cycle, substantial amounts of snow can melt and refreeze in snowpacks, and this phase change can have an appreciable impact on surface-energy and moisture fluxes (Jin et al. 1999).

Similar to the field capacity of a soil, the amount of liquid water in the pack just prior to runoff is called the irreducible water content, or irreducible saturation, beyond which the pack will transmit liquid water. So, as the pack warms and becomes isothermal, the meltwater is first used to satisfy the irreducible water content of the pack, and the remainder leaves the bottom of the snowpack (Melloh 1999).

The onset of snow metamorphism near the freezing point complicates the measurement of snow liquid water content. Techniques for measuring snow wetness include centrifugal separation, melting/freezing calorimetry, alcohol dissolution, microwave emissions, and methods based on snow dielectric properties such as time domain reflectrometry. Various studies using microwave emissions, dielectric snow properties, and calorimetry have found maximum snow liquid water contents (percent volume) of 8% (Denoth et al. 1984), 7.5% (Stein et al. 1997), 4.5% (Macelloni et al. 2005), and 9% (Kendra et al. 1994). Considerable variability exists in these instantaneous measurements, depending on whether the snow is supersaturated or below its irreducible water content (e.g., during melt or refreeze cycles). However, Denoth (2003) showed experimentally that the long-term irreducible water content (for an alpine snowpack) consistently asymptotes to 4% of total pore volume (pv) for a range in initial moisture conditions. Therefore, although instantaneous values much higher than 4% are possible (generally after several hours of melt), liquid water in excess of the irreducible saturation is assumed to exit the pack.

Depending on their complexity, snow models provide for varying levels of detail in their representations of liquid water processes within the pack. The irreducible water content is typically a user-specified quantity, which essentially acts as a storage term for meltwater prior to runoff or refreeze. In some models, irreducible water saturation is parameterized as a function of SWE depth (the VIC model uses 3.5% of SWE depth), snow density [the Snow Thermal Model (SNTHERM; Jordan 1991) uses 4% of pore volume], and total snow volume [the Snowmelt Numerical-Analytical Package (SNAP) model (Albert and Krajeski 1998) uses 3% of total volume].

FIG. 3. Snow-albedo decay as a function of days since last snowfall (from U.S. Army Corps of Engineers 1956).
Rather than directing all meltwater to runoff, as is done in the control version, an irreducible liquid water content approach was implemented to store a defined quantity of liquid water in the pack. To monitor heat exchange, which may result from melt and refreeze, the thermal inertia of the pack is also computed using an energy balance approach. The proposed snowpack-energy balance is represented as

\[ Q_{\text{net}} = Q_{SW} + Q_{LW} + Q_h + Q_l + Q_g + Q_a + \Delta CC/\Delta t, \]

where \( Q_{\text{net}} \) is the net energy available to heat or cool (melt or refreeze) the pack; \( Q_{SW} \) is the net shortwave radiation at the surface of the pack, considering emission absorption and reflection; \( Q_{LW} \) is the net longwave radiation at the surface; \( Q_h \) is the surface sensible heat flux; \( Q_l \) is the surface latent heat flux; \( Q_g \) is the ground heat flux; \( Q_a \) is the energy advected to the pack from external sources (e.g., rain); and \( \Delta CC/\Delta t \) is the change in internal energy within the pack, where CC denotes cold content, or negative heat storage.

The major addition to the energy balance relative to the control model is the cold content term, which accounts for changes in pack temperature and accompanied heat exchange between successive time steps. Additionally, this new approach uses an iterative scheme to solve for the pack temperature and heat exchange that balance Eq. (2). This approach also allows for separate temperatures to be computed for an upper thin snow “skin” layer and a deeper snow layer. This addition overcomes some of the shortcomings of the control model’s single-layer snowpack, particularly for deep snowpacks, for which differences in snow boundary temperatures (ground and snow surface) cannot be accurately resolved by a single snow temperature.

The solution procedure for Eq. (2) involves assuming a pack temperature of 0°C and computing the resulting net energy \( Q_{\text{net}} \). If the net energy at 0°C is positive, the pack is assumed to be ripe (isothermal at 0°C) and the surplus energy is used to convert the appropriate amount of snow into meltwater. This meltwater is first used to satisfy the irreducible water content, after which it runs off. When \( Q_{\text{net}} \) is negative, the energy deficit is first applied to refreeze any liquid water within the pack at 0°C. Should an energy deficit remain after the refreeze of all liquid water, an iterative solver is employed to balance Eq. (2) and assign the correct temperature to the snowpack.

In terms of mass balance, Eq. (2) is invoked after new moisture terms (precipitation, condensation, and sublimation) have been computed for the current model time step. Based on the resulting value of \( Q_{\text{net}} \), pack temperature may be changed, and mass may be converted to or from solid and liquid phases. If ample mass is converted to the liquid phase (positive \( Q_{\text{net}} \)) so as to exceed a specified porosity (\( S_{wi} \) in this case), liquid water will exit the pack, hence reducing the total mass. The snowpack can be conceptualized as a mixture of water (in solid and liquid forms only) and air, in which water flow is not explicitly modeled. The irreducible saturation of the pack \( S_{wi} \) is computed dynamically as a function of snow porosity (a function of density and SWE). Similar to Denoith (2003) and Jordan (1991), the maximum allowable liquid water content within the pack is parameterized as a fraction of the total pore volume of the pack \( pv_{\text{pack}} \) (in this case set to 4%), which can be converted to a fraction of SWE depth, such that

\[ S_{wi} = 4\% \text{ of } pv_{\text{pack}} = 0.04 \times d_{\text{snow}} \times \phi_{\text{snow}} \]

\[ = 0.04 \times \frac{\text{SWE}}{\rho_{\text{pack}}} \times \left( 1 - \frac{\rho_{\text{pack}}}{\rho_{\text{ice}}} \right), \]

where \( \rho_{\text{pack}} \) is the bulk density of the pack (computed internally); \( \rho_{\text{ice}} \) is the density of ice (=917 kg m\(^{-3}\) at 0°C); \( \phi_{\text{snow}} \) is the porosity of the snowpack; and \( d_{\text{snow}} \) is the depth of the snowpack.

In effect, 4% \( pv_{\text{pack}} \) can range from approximately 2.5% of SWE depth for dense snow to approximately 10% of SWE depth for fresh snow. Ice density \( \rho_{\text{ice}} \) increases with decreasing temperature, varying between 917 kg m\(^{-3}\) at 0°C to approximately 934 kg m\(^{-3}\) at −180°C (Eisenberg and Kauzmann 1969). However, the impact of \( \rho_{\text{ice}} \) variability on pore volume is practically negligible, resulting in less than a 0.5% difference in computed \( S_{wi} \) over a reasonable range of temperatures. Other parameterizations of the irreducible saturation \( S_{wi} \) (listed earlier) were considered, however these fixed-ratio approaches do not account for the observed change in liquid water storage with snowpack density. For this reason, we preferred the parameterization given in Eq. (3).

\( c. \) Fractional snow cover

Periods when partial snow coverage exists are particularly important to accumulation and ablation processes, which tend to evolve in a nonlinear way. Koren et al. (1999) implemented a relationship in the Noah model, based on Anderson’s (1973) areal snow depletion curves, that indexes snow coverage by a SWE threshold value \( W_{\text{max}} \) above which complete coverage always exists. This nonlinear relationship is shown graphically in Fig. 4.

Within the Noah model, \( W_{\text{max}} \) is assigned a greater value for forest than for nonforest (0.04 m and 0.02 m, respectively) to reflect the irregular geometry of forest cover. The assigned value of \( W_{\text{max}} \) has a strong impact.
on snowpack evolution, particularly at the end of the snow season, because, during periods of partial snow coverage (i.e., $\text{SWE} < W_{\text{max}}$), albedos are lower and skin temperatures are increased. These conditions cause more rapid ablation as SWE diminishes.

Until recently, little attention was given to the parameterization of $W_{\text{max}}$. Using both modeling and measurements, Hedstrom and Pomeroy (1998) emphasized the importance of considering alternative treatments for snow accumulation processes in forested areas. A recent study by Wang and Zeng (2010) examined the way partial snow cover is represented in several models (including Noah) and attempted to reproduce ground-based albedo measurements using varying thresholds of $W_{\text{max}}$ for both forest and nonforested land cover. The study found that ground-based albedo measurements could be more closely matched by reducing $W_{\text{max}}$ for nonforest to 0.01 m and increasing $W_{\text{max}}$ for forest to 0.20 m.

To evaluate the model-scale impact of these SWE thresholds on snow cover fraction, we report in section 4c a sensitivity analysis of $W_{\text{max}}$ using modeled and satellite-based snow-covered albedo values. The modeled values use the albedo-decay algorithm (section 2a) in combination with alternate $W_{\text{max}}$ values.

3. Methods

Model performance was evaluated through comparisons of offline model simulations with observations. Precipitation and temperature, required for offline forcing of the Noah model, were obtained from three SNOTEL sites, where time series of observed SWE were also available. The three SNOTEL sites were selected so as to provide a reasonable cross section of snow types (continental, maritime, and intermediate) across the mountainous West (Table 2).

Parameters in SNOTEL site simulations were selected based on the available site characteristic data. For instance, site photographs confirmed that sensors were located in clearings, for which the “bare soil” land cover class was selected, rather than the local dominant vegetation type. Soil characteristics were assigned using the 1-km Natural Resources Conservation Service State Soil Geographic (STATSGO) database. Thermal qualities of the sensor (rather than those of soil) as well as potential shading and wind perturbation from surrounding vegetation may skew direct comparisons with observations. Within a plausible range of parameter values, sensitivity testing of these biases was performed (not shown), which indicated that vegetation effects (bare soil versus forest cover) generally had the greatest effect on SWE, such that considering bare soil in the place of forest cover resulted in increased SWE by amounts that were mostly less than 20%.

Over larger areas, modeled patterns of SCE were compared with satellite observations. Spatial plots of SCE were made for model runs with modifications to various physics components. Cumulative snow-covered days are the primary metric used in the SCE evaluations.

a. Model forcing data

Model simulations were performed offline using observation-based forcings. These were based on point observations at SNOTEL stations, and gridded data from the North American Land Data Assimilation System (NLDAS; Mitchell et al. 2004) for spatial comparisons. SNOTEL stations measure minimum and maximum daily temperature, total daily precipitation, and SWE. Serreze et al. (1999) identified the potential for erroneous SWE measurements at SNOTEL sites resulting from instrumentation sensitivity issues, as well as problems such as ice bridging across snow pillows and environmental factors such as snow drifting, wind scour, or falling debris. At the two southernmost SNOTEL stations (in Colorado and California), we observed that the accumulated total precipitation for some years was less than the observed SWE for those years. We suspect this was most likely the result of precipitation gauge undercatch, so we rescaled precipitation uniformly in these cases to equal SWE at its peak value for that year (close to 1 April in 2001 and 2003). A uniform rescaling method was selected based on the assumption that a consistent fraction of precipitation was not captured by the rain gauge, in amounts ranging between approximately 10% and 20%. This procedure may still yield a slight negative bias, because it does not account for sublimation. Disparities of this nature were most frequent at the Colorado site, for which high sublimation rates are regionally common (Hood et al. 1999).
The daily SNOTEL maximum and minimum temperature data were disaggregated to a finer temporal resolution and used to derive several other essential quantities for model forcing. Details of these procedures are described by Maurer et al. (2002). In summary, subdaily temperatures were interpolated by fitting an asymmetric spline through daily minima and maxima; dewpoint temperature was calculated using the method of Kimball et al. (1997) relating dewpoint to daily minimum temperature and precipitation; downward shortwave radiation was calculated based on daily temperature range and dewpoint temperature (Thornton and Running 1999); and longwave radiation was estimated based on vapor pressure of the air and skin temperature (Bras 1990). Algorithm performance is dependent on the quality of daily data, topographic complexity, and the degree of algorithm dependence on model-derived quantities such as skin temperature.

For large-scale simulations, the gridded NLDAS data (Mitchell et al. 2004) were used to force the model. Pan et al. (2003) found that NLDAS precipitation had a substantial negative bias relative to SNOTEL stations across the western United States. The NLDAS precipitation was consequently rescaled with Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al. 1994) data using an inverse distance algorithm (Schaake et al. 2006). The rescaling process described by Schaake et al. (2006) involved adjusting monthly station-gauge precipitation values to match PRISM precipitation and weighting the adjusted station-gauge precipitation values based on distance from the grid center. All simulations were performed for the period of water years (October–September), 2000–03. The gridded NLDAS data are continuous throughout this period.

b. Satellite observations

To evaluate model-simulated SCE, we used the National Oceanic and Atmospheric Administration (NOAA) Interactive Multisensor Snow and Ice Mapping System (IMS; Ramsay 1998). This product produces daily maps of snow and ice coverage over the Northern Hemisphere using several satellite and ancillary sources, most notably NOAA Geostationary Operational Environmental Satellites (GOES) and the NOAA Polar Operational Satellites carrying the Advanced Very High Resolution Radiometer (AVHRR) and Advanced Microwave Sounding Unit (AMSU). IMS daily snow maps are available at a gridded spatial resolution of approximately 25 km, with a polar stereographic projection. The IMS data were converted to the NLDAS 1/8° latitude–longitude grid resolution using the nearest neighbor algorithm employed by Sheffield et al. (2003) with the assistance of Dr. Ming Pan at Princeton University. This regridding process may introduce errors at the snow line boundary; however, because the occurrence of snow is primarily controlled by meteorological processes that act at much larger spatial scales, these errors should be relatively small. To compare the modeled and regridded IMS-based SCE, a threshold value of 50% fractional coverage was employed, as is used by IMS at its native spatial grid.

4. Results

The two metrics used to evaluate snow model performance were annual peak SWE (which affects the land surface water balance through streamflow volume and timing, as well as evapotranspiration through soil moisture evolution) and duration of SCE, which affects albedo and hence the surface-energy budget as discussed in section 1. We therefore followed a general strategy of evaluating the time series of model-predicted SWE as compared with SNOTEL observations, as well as spatial plots of cumulative snow-covered days as predicted by the model and observed by IMS. For the purpose of combining multiple years of SNOTEL data, both observations and simulations were normalized by the peak SWE value of the given water year to avoid biasing results toward years with large snowpacks.

a. Albedo-decay scheme

The effect of a seasonally decaying albedo [Eq. (1)] on simulated SWE is compared in Fig. 5 with the Noah control model at the three SNOTEL sites, as well as spatially over the CONUS. The effect of the albedo-decay parameterization is likely related to latitude, initial albedo, background-satellite albedo, and vegetation type. The time series analysis (Fig. 5a) shows varying improvements in SWE for the specific albedo-decay scheme applied: Site 1 (Olallie Meadows, Washington)

<table>
<thead>
<tr>
<th>Site</th>
<th>Lat</th>
<th>Lon</th>
<th>Elevation (m MSL)</th>
<th>Precipitation (mm)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Olallie Meadows</td>
<td>47.37°N</td>
<td>121.44°W</td>
<td>1137</td>
<td>2730</td>
<td>Sensor in a clearing</td>
</tr>
<tr>
<td>Schofield Pass</td>
<td>39.00°N</td>
<td>107.03°W</td>
<td>3261</td>
<td>1335</td>
<td>Sensor in a clearing</td>
</tr>
<tr>
<td>Leavitt Lake</td>
<td>38.26°N</td>
<td>119.60°W</td>
<td>2931</td>
<td>1745</td>
<td>Sensor in a clearing</td>
</tr>
</tbody>
</table>
shows proportionally increasing improvements in peak SWE timing and magnitude under both albedo adjustments ($C = 0.5$ and $C = 1.0$, respectively), whereas the southern sites (Schofield Pass and Leavitt Lake) only show a substantial response to a coefficient of $C = 1.0$ compared with the control case.

The largest relative improvement for any of the three sites was Schofield Pass for the $C = 1.0$ case. The impact of solar radiation and its associated melt energy is likely of increasing (decreasing) importance with decreasing (increasing) latitude, given the greater abundance of radiation moving equatorially. However, latitude alone does not reconcile differences in model performance at the three sites, for which a higher albedo [from Eq. (1)] should result in the most significant increase in SWE at the southernmost sites (Colorado and California). Rather, it indicates that the extent of SWE improvement is also related to the increase in maximum snow albedo represented by Eq. (1) relative to the satellite-based values used in the control version of Noah, because the value from Eq. (1) will decay between snowfall events and may asymptote to a value lower than the control case. For example, the relatively low-latitude SNOTEL site in California (Leavitt Lake) receives more radiation than
the higher-latitude site in Washington (Olallie Meadows); however, because it has a much higher satellite-based maximum snow albedo ($a_{\text{max,sat}} = 0.53$ and $a_{\text{max,sat}} = 0.38$, respectively), its albedo for the $C = 0.5$ case quickly decays below the satellite value. This example is depicted in Fig. 6. So, for locations with relatively high control snow albedo such as Leavitt Lake ($a_{\text{max,sat}} = 0.53$), the application of a substantially higher initial albedo is required to improve SWE performance [e.g., Eq. (1): $C = 1.0$, $a_{\text{max}} = 0.85$], where a lesser increase in albedo [e.g., Eq. (1): $C = 0.5$, $a_{\text{max}} = 0.69$] results in the albedo value decaying to less than the satellite value in approximately 2 days for the melt-season decay rate.

At the larger scale, the difference in performance when including the albedo-decay scheme follows a relatively coherent spatial pattern (Fig. 5b) that is highly correlated with the satellite-based maximum snow albedo of the control model. More explicitly, including the albedo-decay scheme increases (decreases) cumulative snow-covered days over areas with low (high) satellite-based maximum snow albedo. This occurs via the same mechanism as for the SNOTEL comparisons and is most evident for the Great Plains region, which is characterized by high snow-covered albedo (Fig. 7a: $0.65 < a_{\text{max,sat}} < 0.80$).

The satellite-based maximum snow-albedo value is strongly related to vegetation type, specifically whether the area is forested or nonforested. Under the same snow cover, forests are generally much darker (lower albedo) than grasslands (Barlage et al. 2005; Roesch et al. 1999). This is confirmed by Fig. 7, which shows the spatial correlation between low satellite-based maximum snow albedo (Fig. 7a) and forest vegetation classes (Fig. 7b). Thus, the impact of the albedo-decay algorithm on the negative SWE bias of the control model is closely related to both latitude and land cover. Further analysis of land cover influence on snow model performance is presented in section 4c.

b. Refreeze and cold content

One of the most important aspects of the proposed melt–refreeze algorithm is its enhanced snowpack-energy
balance computation, which simulates snowpack temperature, liquid water content, and refreeze-energy exchange based on cold content (all variables not explicitly simulated in the Noah control version). Capturing melt–refreeze cycles is particularly important for deep, alpine snowpacks in which thermal inertia is of consequence for the majority of the melt season. Additionally, during melt season, when temperatures fluctuate around freezing levels (e.g., diurnally), warm period (daytime) meltwater is frequently frozen during colder periods (nighttime).

The value of including the new snowpack features described earlier is illustrated in Fig. 8a, which compares time series of the control model, two liquid water capacity (WC) schemes, and observations, where the liquid water capacity schemes include the control albedo parameterization. At each site, the proposed liquid water storage volume of 4% of pore volume tends to capture observed SWE behavior substantially better than the control, delaying the timing of simulated peak SWE and increasing its magnitude. At the Washington and Colorado sites, utilizing a liquid water storage volume of 3.5% of SWE produces less improvement in SWE behavior; at the California site SWE performance under this assigned liquid water is much poorer than the 4% pv case [Eq. (3)]. This is likely the result of the California site having the highest variability of daily maximum temperatures during winter months over the study period, with maximum temperatures frequently reaching several degrees Celsius (0°C to +11°C) for multiple consecutive days. During these warm periods, the fixed 3.5% SWE liquid water capacity is exceeded, yielding significant runoff, whereas the comparatively larger refreeze capacity of the 4% pore volume (translates to more than 3.5% SWE, especially for fresh snow) retains and refreezes larger quantities of meltwater, because the daily minimum temperatures during these events were mostly below 0°C. A departure between the two time series is evident in early winter and becomes critical by late winter when what can be described as a feedback develops: (i) for a given energy input (e.g., warm day, large radiative forcing), the larger pack (4% pore volume case) will melt less snow than the smaller pack (3.5% SWE case), because, if the packs are cooler than 0°C, more energy will be needed to ripen a pack with greater cold content; (ii) for a given energy deficit (e.g., \( T_{air} < 0°C \), radiative deficit), the larger pack is able to retain greater mass through its more voluminous refreeze capacity.

An artifact of the enhanced snowpack-energy balance is a slightly altered skin temperature computation and energy balance response to atmospheric inputs, especially radiative. Figure 8b illustrates the spatial performance of the refreeze-cold-content approach versus the control, which generally shows an increase in duration of SCE. Both simulations use the same snow-albedo scheme as in the control, so Fig. 8b bears some semblance to Fig. 7b in its correlation between refreeze-cold-content performance and the signature of low satellite-based snow albedo. In effect, over certain regions of low snow albedo, the enhanced energy balance of the melt–refreeze version ablates snow faster than the linearized energy balance of the control version, because the melt–refreeze computed skin temperatures tend to be slightly warmer in these cases. This is the result of the fundamental difference between the two energy balance computations.

The control snowpack-energy balance utilizes a two-step decision process for snowmelt in which (i) an “effective” snow-ground temperature is computed. This
temperature is governed by a surface-energy balance that includes heat transfer from below (because of soil–snow skin temperature differences) and from above (by skin temperature and atmospheric inputs), but it does not include an explicit independent snow temperature. (ii) Melt is computed in a secondary step only if this effective temperature is greater than freezing.

The refreeze-cold-content method directly computes snowpack temperature for every time step in which snow is present and uses it to dictate whether melt will occur. The skin temperature disparity between the two versions occurs for low snow-albedo conditions when the pack is ripe (at 0°C) or nearly ripe and when the ground temperature is slightly lower than the pack temperature. In these cases, the control energy balance frequently yields an effective snow-ground temperature at or slightly below 0°C (i.e., does not reach second step in melt decision process; no melt computation occurs), whereas the refreeze-cold-content energy balance yields a ripe pack, allowing melt to occur. Figure 9 shows the spatial distribution of differences in skin temperatures between the control and refreeze-cold-content simulations, which has strong spatial correlation to Fig. 8b. It is under these somewhat infrequent circumstances that the control
snowpack can persist longer than the refreeze-cold-content pack. This suggests that the refreeze-cold-content energy balance may be well supplemented by the previously described albedo-decay scheme and the ability to consider separate snow/no-snow albedos during partial snow coverage rather than a mixed satellite-based value, a scenario that is discussed in section 4d.

c. Fractional snow coverage

Our objective in this section is to test the physically based model changes (albedo decay, refreeze cold content) together with alternate $W_{\text{max}}$ values to determine whether a reasonable match with satellite snow-albedo values could be obtained. This was done by computing an average snow-covered albedo for each grid cell over the study period (i.e., averaging albedo values when greater than 1 mm of SWE is present) and comparing them with the Robinson and Kukla (1985) satellite imagery, as is shown in Fig. 10.

There are certain caveats with this comparison; namely, the satellite data were obtained more than two decades prior to the study period and thus the underlying assumption of stationarity must be made (i.e., that snow patterns have remained relatively unchanged over this period). This assumption, although perhaps subject to question, is also implicit in the control model. Additionally, the dynamics of changing snow cover fractions (and ensuing bulk albedos) simulated by the model are not completely represented in the single satellite “snapshot” used for validation.

As expected, the time-integrated simulations of modeled snow-covered albedo are generally less spatially continuous than the satellite values (Fig. 10). The control model reveals albedo values that are consistently lower than the satellite maximum values because of the effect of partial snow cover during the study period. Simple albedo decay (bottom two plots) does not effectively capture the spatial variability of snow-covered albedo, because albedo in forested/mountainous regions is generally overpredicted, whereas the nonforested/plains are underpredicted. The most representative snow albedo as compared with satellite-based values was ultimately obtained by adjusting $W_{\text{max}}$ (sensitivity plots not shown) to the thresholds suggested by Wang and Zeng (2010; middle plots of Fig. 10) and by considering refreeze and a weighted decaying albedo ($C = 0.5$) and refreeze. The negative correlation between $W_{\text{max}}$ and snow cover is clearly depicted in Fig. 11, confirming our previous assertion that partial snow coverage leads to more rapid snow ablation. Although a decaying albedo was not used by Wang and Zeng (2010), they suggested that a decaying, initially higher albedo (than the satellite value) would improve snow-albedo predictions over nonforested areas.

d. Interpretation and optimal model performance

To obtain the most realistic simulations for operational use, each of the parameterizations described here was tested in combination. In addition, an issue related to turbulent heat exchange, first noted by Slater et al. (2007), was examined: namely, whether excessive sublimation was occurring during stable atmospheric conditions. The stability correction they proposed for heat exchange during stable conditions was extended at NCEP to encompass momentum exchange as well, because their computation is coupled (this extension is included in the control model). However, our testing of stability corrections (not shown) indicated that this was not as important a determinant of model performance (either with respect to SWE simulations in deep mountain snow-packs or SCE performance over larger areas) as albedo decay, liquid water refreeze, and areal depletion adjustments were.

Sections 4a and 4b demonstrate the importance of incorporating a decaying albedo and liquid water content in snow simulations; substantial improvements resulted relative to the control model at both low and high elevations. Of additional importance for coupled modeling are the large-scale albedo considerations described in section 4c, which involve adjustments to the SWE threshold $W_{\text{max}}$ associated with fractional snow coverage.

Thus, the combination of refreeze cold content, albedo decay ($C = 0.5$), and adjusted snow coverage thresholds were applied in combination for the simulation in Fig. 12. The point simulations (SNOTEL) including both refreeze cold content and albedo decay demonstrate ubiquitous improvement in the timing and quantity
of peak SWE (Fig. 12a), most dramatically at the California site (panel 2). As described earlier, the combination of a relatively low satellite-based snow albedo and high variability of maximum daily temperatures (i.e., frequent diurnal freeze–thaw) made the respective albedo decay and refreeze provisions critical for model performance relative to observations. The sensitivity of the refreeze-cold-content energy balance to low albedo (and ensuing warmer skin temperatures noted in section 4b) was amended by the increased initial albedo from Eq. (1). The adjustments to $W_{\text{max}}$ are not relevant at the point scale, because, for a single point, the value of $W_{\text{max}}$ approaches zero, as described by Anderson (1973).

At large spatial scales, adjustments to $W_{\text{max}}$ are essential for obtaining representative snow-albedo values and for assigning melt energy to the snowpack. Through the energy balance enhancements described in section 3b, we were able to use separate albedo values during periods of fractional cover for energy balance computations of snow-covered and snow-free areas within a grid cell, rather than using a bulk value. This adds an additional physical improvement to model physics and performance, as illustrated in Fig. 12b.

The spatial estimates of SCE duration (Fig. 12b) are quite realistic, with few exceptions. Two areas which do not compare favorably with satellite snow cover are
(i) the area immediately southwest of Lake Superior and (ii) the state of Maine. An examination of land cover and annual snow depths suggests that reduced SWE in these areas may be attributed to auxiliary influences. These regions are covered by forest, which has lower snow albedos (both satellite based and decaying value; Fig. 10), with peak snowpack depths typically close to the higher (forested) $W_{\text{max}}$ threshold that may act together in a second-order (feedback) manner, keeping snow cover partial in these areas for extended periods throughout the cold season and producing a low bias in the number of snow cover days.

5. Conclusions

Several important physical aspects of the Noah snow model were addressed with an emphasis on improved hydrologic modeling through comparisons with in situ and satellite-based observations. Although modifications to model physics were implemented with the intent of improving physical realism, model simulations are still inherently idealized with uncertainties in the quality of forcing data and model parameters, given the scale of simulations and relative disparity of data points. To be computationally efficient, numerous model simplifications of physical phenomena are inevitable, though this study has attempted to reduce the number of such simplifications. The most important conclusions are as follows:

1) Utilizing an elevated fresh snow-albedo value that decays with snow surface age in place of a fixed spatially varying maximum value is physically consistent with numerous observations and serves to generally improve SWE performance with respect to hydrologic predictions as shown at point simulations (SNOTEL) in mountainous deep-snow conditions. Including this extension alone did not ubiquitously improve performance when compared to the control model over the entire CONUS, particularly for nonforested regions with high satellite-based albedo values, because the decayed albedo often falls below satellite values in these regions. The inclusion of a realistic and physical lower bound on decaying albedo was invoked to this effect and provided limited benefit.

2) Providing a liquid water holding capacity within the snowpack effectively reduced negative SWE bias between the control model and observations. Ultimately, an observational-based value of liquid water capacity was chosen as a function of the total pore space of the pack, inversely proportional to snow density. By including a pack temperature computation, an effective “memory,” or thermal inertia term, was made possible. This modification was better suited to the albedo-decay scheme as compared with the control albedo scheme, because the energy balance is sensitive to very low, fixed snow-albedo values, which are somewhat unrealistic nonetheless.

3) Incorporating changes to the model areal snow depletion thresholds in combination with albedo decay and refreeze provides a good match with satellite observations of maximum snow albedo. Using an increased (decreased) SWE depth threshold for forest (nonforest) to achieve complete snow coverage improves snow-albedo behavior at the large scale. For energy balance computations during periods of partial snow coverage, considering a separate snow and non-snow albedo performs well with the $W_{\text{max}}$ thresholds and is more physically plausible than a bulk albedo.

Utilizing these modifications in concert yields substantial improvements in SWE and duration of SCE, as described in section 4d. The recommended model improvements effectively capture changes related to the age of the snow surface (albedo decay), the age of the snowpack (variable liquid water content with density), and physical aspects associated with partial snow cover. Disparities between model performance and observations at both large and small spatial scales still exist, however, which may be related to second-order interactions of areal depletion thresholds and snow albedo. We believe that future model improvements should be directed toward the application of a combination of better exploitation of field observations along with more rigorous methods of model parameter estimation focusing on albedo-decay.

FIG. 11. Difference in number of snow-covered days (water years 2000-03) between proposed (0.20 m) and original (0.04 m) $W_{\text{max}}$ thresholds, for forested pixels only. The increase in $W_{\text{max}}$ results in a decrease in snow-covered days, whereas the opposite occurs for nonforested pixels (proposed decrease in $W_{\text{max}}$ not shown).
parameters, snowpack density, irreducible saturation, and areal depletion thresholds over continental domains. Additionally, developing a multilayer snow model to capture metamorphism and intrasnow heat exchange, as well as the addition of a canopy layer, could provide immediate improvements in simulations.

REFERENCES


