Snow process modeling in the North American Land Data Assimilation System (NLDAS): 1. Evaluation of model-simulated snow cover extent

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Received 2 December 2002; revised 3 June 2003; accepted 30 July 2003; published 21 November 2003.

[1] This study evaluates the cold season process modeling in the North American Land Data Assimilation System (NLDAS) and consists of two parts: (1) assessment of land surface model simulations of snow cover extent and (2) evaluation of snow water equivalent. In this first part, simulations of snow cover extent from the four land surface models (Noah, MOSAIC, Sacramento land surface model (SAC), and Variable Infiltration Capacity land surface model (VIC)) in the NLDAS were compared with observational data from the Interactive Multisensor Snow and Ice Mapping System for a 3 year retrospective period over the conterminous United States. In general, all models simulate reasonably well the regional-scale spatial and seasonal dynamics of snow cover. Systematic biases are seen in the model simulations, with consistent underestimation of snow cover extent by MOSAIC (−19.8% average bias) and Noah (−22.5%), and overestimation by VIC (22.3%), with SAC being essentially unbiased on average. However, the level of bias at the regional scale varies with geographic location and elevation variability. Larger discrepancies are seen over higher elevation regions of the northwest of the United States that may be due, in part, to errors in the meteorological forcings and also at the snow line boundary, where most temporal and spatial variability in snow cover extent is likely to occur. The spread between model simulations is fairly low and generally envelopes the observed data at the mean regional scale, indicating that the models are quite capable of simulating the general behavior of snow processes at these scales. Intermodel differences can be explained to some extent by differences in the model representations of subgrid variability and parameterizations of snow cover extent. *INDEX TERMS:* 1833 Hydrology: Hydroclimatology; 1863 Hydrology: Snow and ice (1827); 1878 Hydrology: Water/energy interactions; 3337 Meteorology and Atmospheric Dynamics: Numerical modeling and data assimilation; *KEYWORDS:* land surface models, NLDAS, snow cover extent

Citation: Sheffield, J., et al., Snow process modeling in the North American Land Data Assimilation System (NLDAS): 1. Evaluation of model-simulated snow cover extent, *J. Geophys. Res.*, *108*(D22), 8849, doi:10.1029/2002JD003274, 2003.

1. Introduction

[2] Cold season processes play an important role within the hydrological cycle through their influence on the dynamics of moisture storage and the partitioning of incident radiation [*Groisman et al.*, 1994]. The strength of this influence is due in part to the large spatial scales involved and quantity of equivalent water held in frozen storage. Snow cover extends over vast regions of the Northern Hemisphere during the winter and permanent snow cover exists over much of northern Eurasia, North America and

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0148-0227/03/2002JD003274$09.00

areas of high elevation [*Groisman et al.*, 1994; *Brown*, 2000]. Frozen moisture in the soil and overlying snowpack form large reservoirs that may store water for many months before being released during the spring melt. This has great implications for the environment and water resources, which rely on the regularity of the melting process and subsequent flooding. In turn, the high albedo of the snowpack reflects a large proportion of incoming radiation, altering the radiation balance with the atmosphere and instigating changes to circulation patterns that may be felt thousands of kilometers away [*Cohen and Entekhabi*, 2001; *Yang et al.*, 2001].

[3] Accurate prediction of cold season processes is therefore vital in determining the budgets of water and energy and the feedbacks to the atmosphere. Within the North American Land Data Assimilation System (NLDAS) [*Mitchell et al.*, 1999, 2000; K. Mitchell et al., The multi-institution North American Land Data Assimilation System (NLDAS) Project: Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, submitted to *Journal of Geophysical Research,* 2003, hereinafter referred to as Mitchell et al., submitted manuscript, 2003] simulations of snow cover, along with soil moisture, have a central role in improving forecasts from Numerical Weather Prediction models, which benefit from enhanced predictions of the water and energy fluxes and states at the lower boundary of Earth's surface (Mitchell et al., submitted manuscript, 2003). To this end, the NLDAS will assimilate predictions from land surface models (LSM) of cold season process variables to improve the accuracy of weather forecasts. This paper assesses the cold season process simulations from the four land surface models participating within the NLDAS. Assessment of the accuracy of model simulations and identification of the differences between models will enhance the understanding of cold season processes and help identify the applicability and limitations of LSM models in this area. Previous cold season modeling studies have looked at model intercomparisons and validation against observations but these have been limited in spatial scale (e.g., *Essery et al.* [1999], the Project for Intercomparison of Landsurface Parameterization Schemes (PILPS) Phase 2(d) catchment scale experiment in Russia [*Slater et al.*, 2001], the PILPS Phase 2(e) experiment in northern Scandinavia [*Bowling et al.*, 2003a, 2003b; *Nijssen et al.*, 2003] and the International Association of Hydrological Sciences/International Commission on Snow and Ice Snow Model Intercomparison Project (SnowMIP) [*Essery and Yang*, 2001; *Etchevers et al.*, 2002]), or have used coupled models that suffer from errors in the atmospheric forcings, e.g., *Foster et al.* [1996] and *Frei and Robinson* [1998]. The NLDAS modeling framework is implemented over the conterminous US at 1/8-degree grid resolution for multiple simulation years and at a subdaily time estep. As such, it provides the opportunity to evaluate cold season process modeling, using observation-based forcings, eat time and space scales not achieved in previous studies.

[4] Two of the most important cold season process variables are snow cover extent (SCE) and snow water equivalent (SWE). Snow cover extent is a measure of the spatial extent of snow and determines the spatial influence of snow on the atmosphere through the partitioning of incident radiation. Snow water equivalent quantifies the amount of frozen moisture storage and will in turn determine the amount and timing of runoff during subsequent spring melt. This study is split into two parts in which these two quantities are treated separately. This paper forms the first part of the study and concentrates on the assessment of model simulations of snow cover extent through intermodel and observational data comparisons. The second part of this study [*Pan et al.*, 2003] evaluates the simulations of snow water equivalent.

2. Cold Season Process Modeling

[5] The four land surface models that contribute to the NLDAS modeling effort (MOSAIC, Noah, SAC and VIC) simulate cold season processes with varying degrees of complexity. In general, all models simulate the physical processes of changes of moisture states and the related partitioning of energy fluxes (except the SAC model which does not simulate the land surface energy balance) but the parameterizations used may differ between models. In addition, each model handles subgrid variability of vegetation and elevation at different levels of complexity, which affects snow cover simulations through subgrid variations in precipitation, temperature and radiation budgets.

[6] The snow modules used in the different models are based on balances of mass and energy in the snowpack. The change in snowpack SWE is balanced by the input snowfall and output snowmelt and snow sublimation. The heat flux through the snowpack (sum of net radiation, sensible/latent heat, ground heat fluxes) is used to change the temperature, phase composition, and amount of snowpack. MOSAIC, Noah, and VIC run at full energy mode, which means that the snow energy process is coupled into the energy transfer processes of the entire LSM. Thus in one time step, temperatures of soil layers, soil surface, and snowpack layers (if any) will be solved from heat transfer/balance equations for the entire system (soil, snowpack, vegetation, and air) together with the corresponding water balance equations. Each individual model may have different simplifying assumptions, e.g., linearization of the heat transfer equation (MOSAIC) or constant temperature boundary conditions in the deep layer (VIC). Noah, uniquely, addresses the change of snow density due to compaction in time, and assumes the maximum liquid water storage capacity in the snowpack to be 13%, above which it is removed from the snowpack [*Koren et al.*, 1999]. Noah also accounts for effects from frozen soil, e.g., the reduction of soil infiltration capacity. Noah and VIC account for snow aging by decreasing the albedo, and model the retention of liquid water in the pack [*Wigmosta et al.*, 1994; *Koren et al.*, 1999]. SAC differs from the other three models by simulating only the snowpack water balance, using the SNOW17 snowpack model of *Anderson* [1973], which is run separately. SNOW17 does not simulate sublimation and calculates snowmelt as a function of air temperature. Different models also apply slightly different approaches to convert SWE to snow cover extent as described below.

[7] Figure 1 illustrates how each model represents subgrid processes and the parameterizations used for deriving snow cover extent. All models parameterize SCE as a

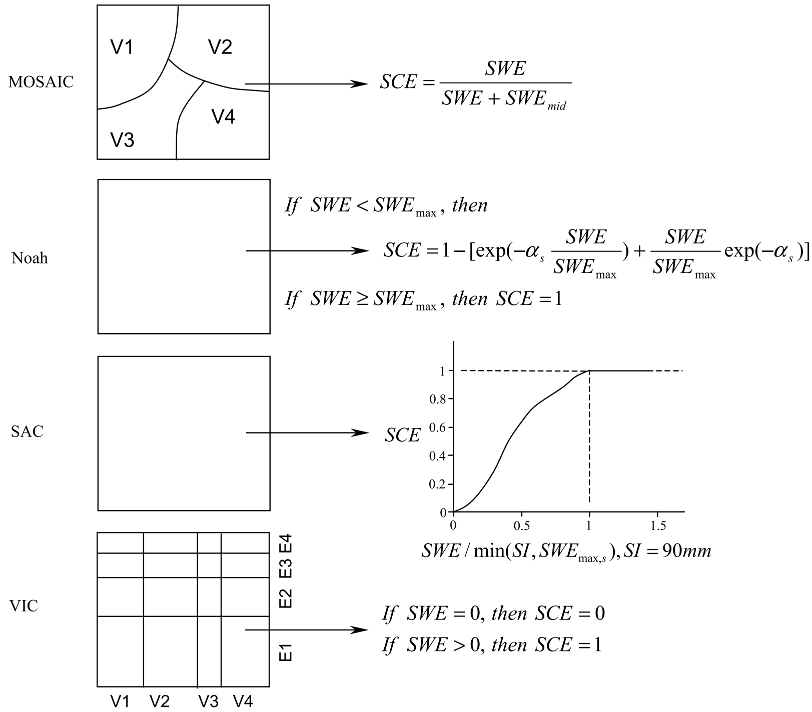

Figure 1. Representation of subgrid processes and parameterizations of snow cover extent in the NLDAS land surface models. Subgrid tiling is denoted by V1, V2, etc., for vegetation and by E1, E2, etc., for elevation.

function of SWE. The MOSAIC model [*Koster and Suarez*, 1996] uses the following formulation:

$$SCE = \frac{SWE}{SWE + SWE_{mid}}, \tag{1}$$

where SWE_{mid} is a vegetation-dependent parameter (0.05 m for forest and tall shrubs, 0.002 m otherwise). Each computational grid is divided into vegetation tiles and *SCE* is calculated independently over each vegetation type within a grid. The final grid cell mean SCE is the weighted average of the tile values. The Noah model [*Betts et al.*, 1997; *Chen et al.*, 1996, 1997; *Koren et al.*, 1999] has no subgrid vegetation tiling but uses the following vegetation-dependent formulas to calculate fractional snow covered area:

$$\begin{aligned} &\mathit{If}\ SWE < SWE_{\max},\ \mathit{then}\ SCE = 1 - \left[\exp\left(-\alpha_s \frac{SWE}{SWE_{\max}}\right) + \frac{SWE}{SWE_{\max}} \exp(-\alpha_s)\right] \\ &\mathit{If}\ SWE \geq SWE_{\max},\ \mathit{then}\ SCE = 1 \end{aligned} \tag{2}$$

SWE_{max} is the value of SWE at which the snow cover reaches full coverage (0.08 m for forest, 0.025 m for bare soil, 0.04 m otherwise) and α_s = 2.6 is a curve shape parameter. This formula is equivalent to an empirical areal snow depletion curve [*Anderson*, 1973; *Koren et al.*, 1999]. The SAC model [*Burnash et al.*, 1973; *Burnash*, 1995] has no subgrid variability, but also uses the empirical areal snow depletion curve [*Anderson*, 1973] which relates SCE to a normalized value of SWE:

$$SWE = \frac{SWE}{\min(SI, SWE_{\max})}, \tag{3}$$

where $SWE_{\max}$ is the maximum SWE for the grid over the simulation period and *SI* is the lower limit of SWE at which there is full snow coverage (set to 90mm here). The VIC model [*Liang et al.*, 1994, 1996, 1999; *Cherkauer and Lettenmaier*, 1999] uses both subgrid vegetation tiling and elevation banding and simply assumes that any snow fully covers the tile:

$$\begin{aligned} &\mathit{If}\ SWE = 0,\ \mathit{then}\ SCE = 0 \\ &\mathit{If}\ SWE > 0,\ \mathit{then}\ SCE = 1 \end{aligned}. \tag{4}$$

Note that VIC handles the water/energy budgets and tracks all the states separately for each tile depicting a specific vegetation cover and for each elevation band. Precipitation input is uniformly distributed (weighted only by area) to each tile, and temperature forcing is adjusted according to an elevation lapse rate. As with MOSAIC, the weighted average of the tile SCE values gives the final grid cell mean value.

3. Data

3.1. Land Surface Model Simulations

[8] The land surface models participating in the NLDAS operate within a framework that consists of a common

Figure 2. Example of IMS snow/ice cover map for the Northern Hemisphere (white color is snow, black color is ice).

1/8-degree geographic grid over the conterminous United States, using common soil and vegetation parameters and distributions, and common meteorological forcings. Simulations were run retrospectively for the period October 1996 to September 1999. Model outputs include predictions of grid average snow cover extent as well as standard water and energy states and fluxes. Details of the NLDAS modeling framework and the retrospective simulations are given in the NLDAS overview paper of Mitchell et al. (submitted manuscript, 2003).

3.2. Observed Snow Cover Extent

[9] In this study the snow cover product from the Multi-Sensor Snow and Ice Mapping System (IMS) [*Ramsay*, 1998] is used to compare with model-simulated snow cover extent. The IMS product was designed to replace and improve upon the older National Environmental Satellite, Data and Information Service (NESDIS) Northern Hemisphere snow analysis and is currently operated by the Satellite Analysis Branch (SAB) of the National Oceanic and Atmospheric Administration/Satellite Services Branch (NOAA/SSB). The IMS product is a spatially complete data set of snow cover extent from 1997 to the present and is derived from a number of data sources. Snow and ice maps are produced each day by human snow analysts using the IMS to incorporate a series of snow observations, including remote-sensing from geostationary satellites (NOAA Geostationary Operational Environmental Satellites (GOES), European Space Agency (ESA) Meteosat, National Space Development Agency of Japan (NASDA) Geostationary Meteorological Satellite (GMS)), and polar orbiting satellites (NOAA Polar Operational Environmental Satellites (POES) carrying the Advanced Very High Resolution Radiometer (AVHRR) and Advanced Microwave Sounding Unit (AMSU); United States Air Force (USAF) Defense Meteorological Satellite Program (DMSP) carrying the Special Sensor Microwave/Imager (SSM/I)), station data and some other ancillary data sources for cloud obscured areas. IMS products cover the Northern Hemisphere and are

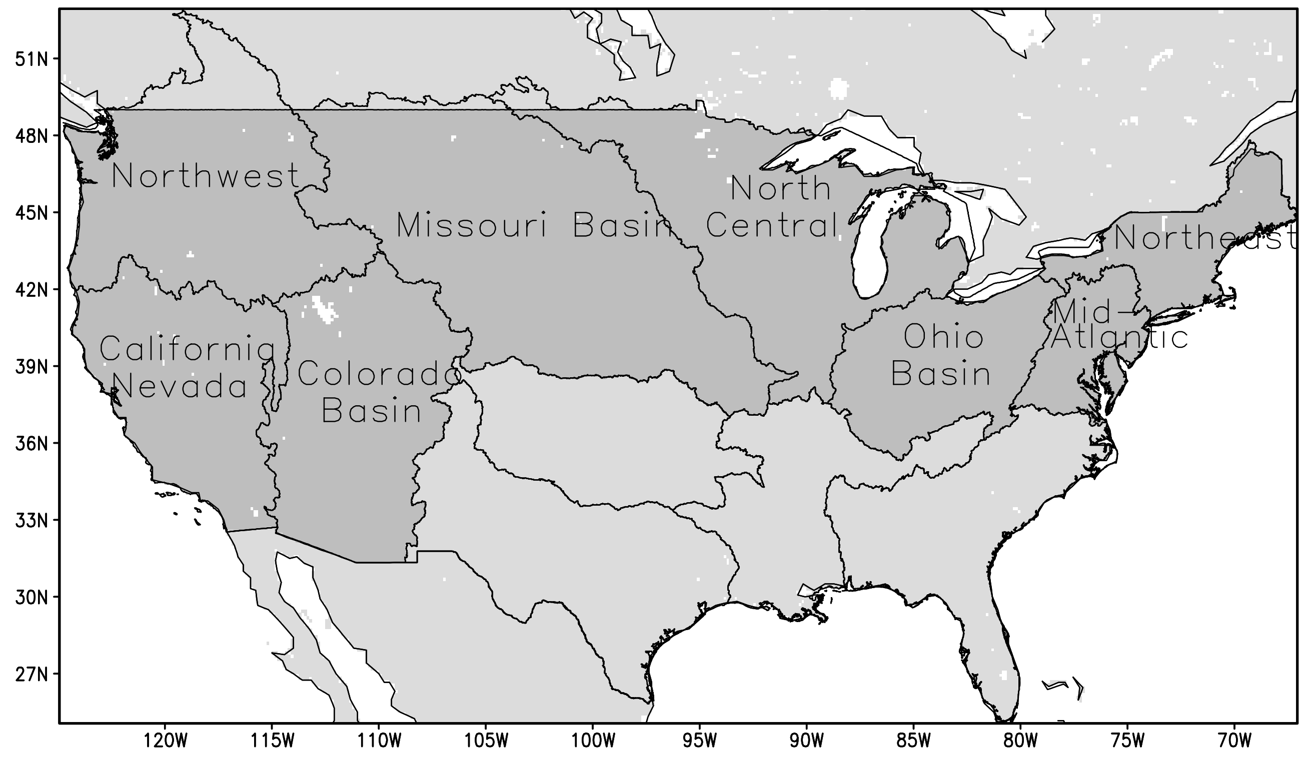

Figure 3. Map of the eight Regional Forecast Center (RFC) regions used in this study.

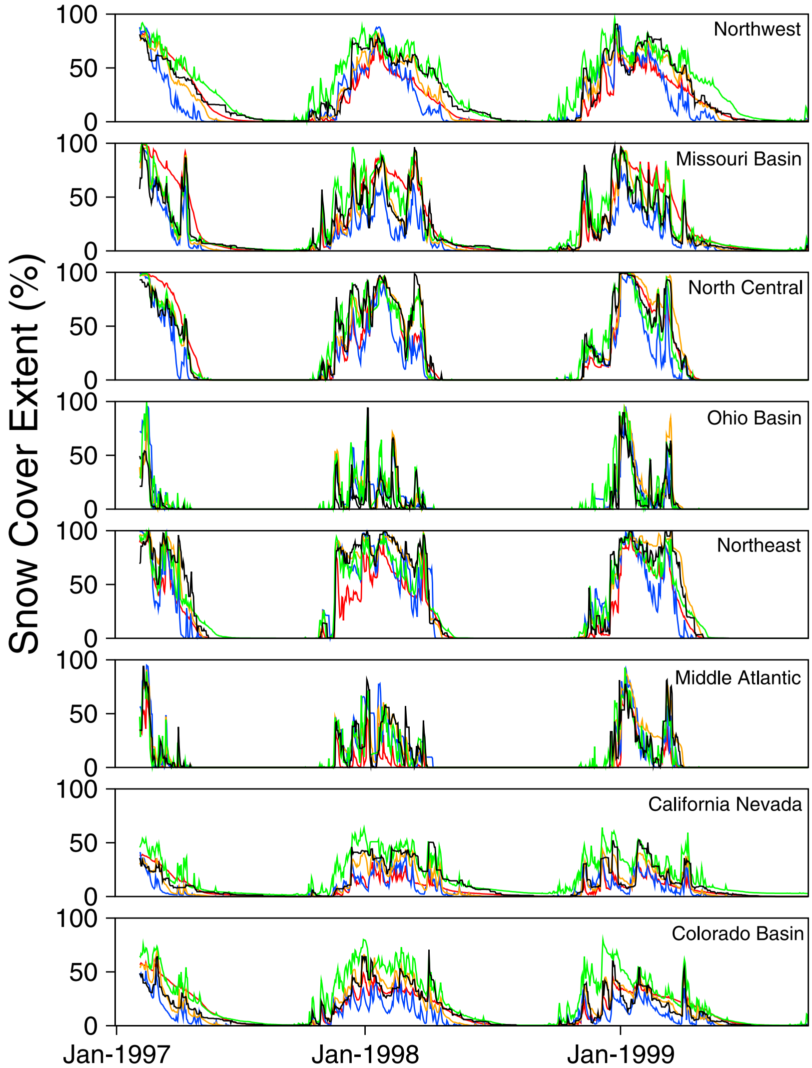

Figure 4. Time series of percentage snow cover extent (SCE) over the eight RFC regions for the IMS observed data and the NLDAS model simulations for the period February 1997–September 1999. IMS (black), MOSAIC (red), Noah (blue), SAC (gold), VIC (green).

projected to a polar stereographic grid with spatial resolution of about 25 km, and classify each land grid to have presence or absence of snow. Figure 2 shows an example of an IMS image. For comparison with the higher spatial resolution NLDAS model data, the IMS product was resampled to the NLDAS grid (~12 km) using the nearest neighbor algorithm. This may introduce errors at the snow line boundary but as the occurrence of snow is primarily controlled by meteorological processes that behave at a much larger scale these errors should be relatively small. Validation of the IMS product was carried out under a joint effort by NESDIS, the National Weather Service (NWS) and Rutgers University [*Ramsay*, 1998].

4. Analysis

[10] To compare with the observed IMS data, the model-simulated data were converted to presence/absence values using a threshold of 0.1 fractional cover, i.e., if a pixel has at least 0.1 fractional coverage, then it is considered as snow covered and snow free if the fractional cover is less than 0.1. Through their parameterizations of snow cover extent and subgrid variability in vegetation cover and elevation, the model simulations may have quite variable total fractional snow cover at the full pixel scale. Thus the threshold value of model predicted fractional snow cover used in classifying pixels as snow covered or not snow covered has an important effect on the comparisons. Setting the threshold value too high may lead to the number of model predicted snow covered pixels being set too low and conversely, biased too high when a low threshold is used. In addition, given the differences in parameterizations of snow cover extent between models, a specific threshold value may give better results for some models and not for others and this may vary according to the region of comparison. The threshold value was chosen after sensitivity tests were carried out (not shown) on the affect of the threshold on model performance when compared with the observation data. It was found that the VIC model is relatively insensitive to the threshold value, given its binary parameteriza-

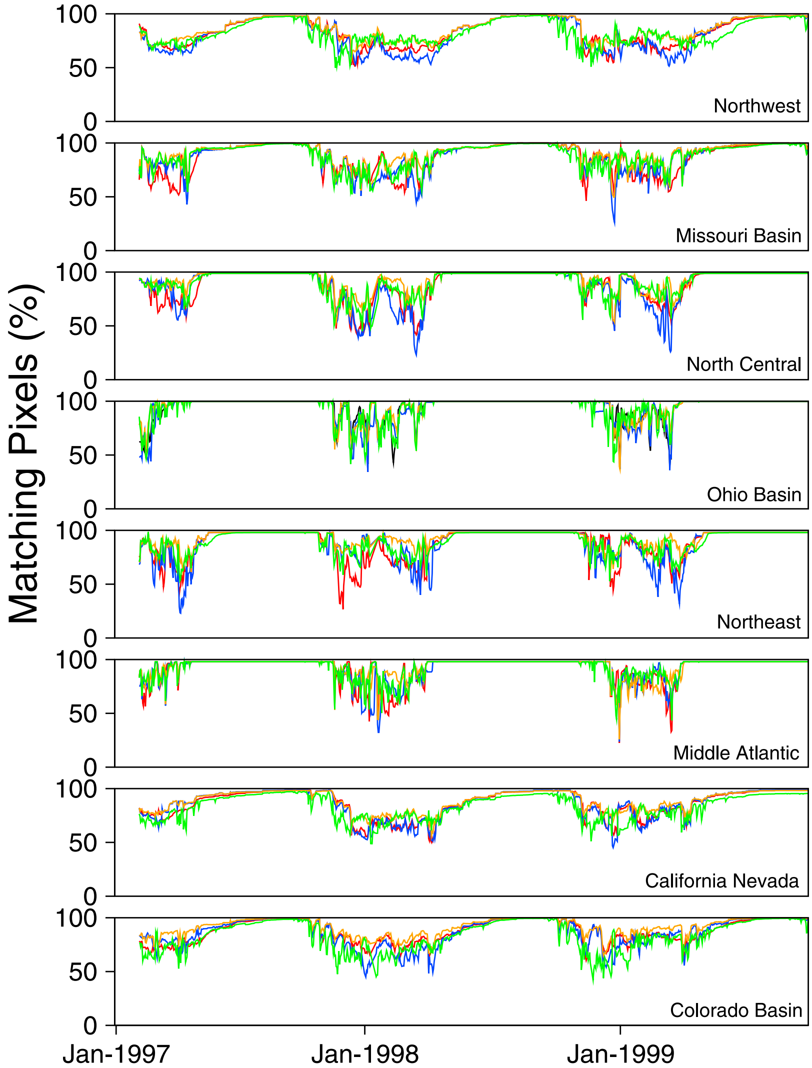

Figure 5. Time series of the percentage of matching snow covered pixels between the IMS observed data and the NLDAS model simulations for the period February 1997–September 1999. MOSAIC (red), Noah (blue), SAC (gold), VIC (green).

tion of SCE at the subgrid level. The MOSAIC model showed more sensitivity, especially in the snow accumulation phase of the winter months. SAC and especially Noah are very sensitive to the threshold value. For example, a threshold value of 0.3 resulted in a significant under estimation of SCE by both models. In the end, the threshold value chosen in this study (0.1) was set low so as to encompass the majority of pixels that were predicted to have snow coverage. In this way a model is not penalized for modeling the subgrid variability of snow processes that may result in small concentrated areas of snow cover within the whole grid.

4.1. Snow Cover Extent at Regional Scales

[11] Comparison of the observed and modeled snow cover extent was carried out over eight River Forecast Center (RFC) regions chosen to encompass higher elevations and the winter time snow cover extent of the United States (see Figure 3). The mean SCE value for the observed IMS product and the model simulations was calculated over each RFC region for each day and the time series is shown in Figure 4.

[12] In general, the results indicate a good agreement between the modeled and observed mean regional SCE although there are systematic biases for all models and regionally dependent differences in how well the models perform. For all regions, the SAC and VIC models predict the highest agreement, and Noah the lowest, while MOSAIC falls somewhere in between. On average, VIC tends to over estimate SCE (average bias over all regions = 22.3%), MOSAIC and Noah tend to under estimate (−19.8%, −22.5%, respectively) and SAC is essentially unbiased (−0.02%). The more mountainous regions (Colorado, California/Nevada and northwest) appear to show the largest differences. This is especially the case in the northwest region during the spring melt period where the VIC model overestimates the snow cover extent (spring bias = 26.1%) and the other models tend to make underestimates (MOSAIC = −20.2%, Noah = −65.6%, SAC = −22.0%).

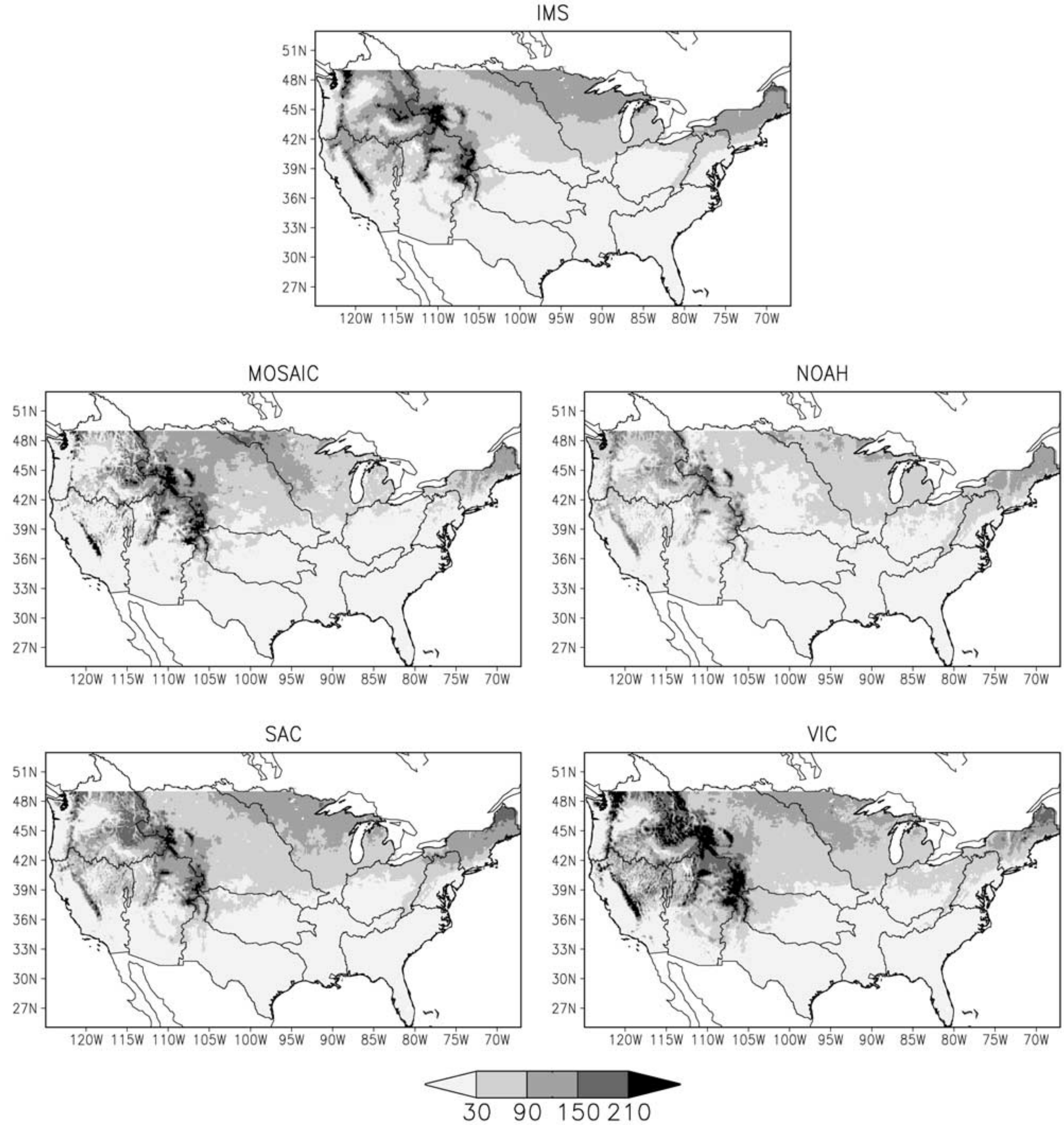

Figure 6. Maps of mean annual cumulative snow covered days for the IMS observed data and NLDAS model simulations for the period October 1997–September 1999.

[13] Although comparison of the regional mean SCE provides valuable information about the general performance of the models in terms of the simulated total cover of snow in a region, it does not necessarily indicate whether the models are predicting snow to be in the correct place. To address this, a pixel-by-pixel comparison of snow cover was undertaken to determine how well the models simulate the spatial pattern of snow through the year. Again, comparisons were carried out for the eight RFC regions and the time series of the percentage of matching pixels are shown in Figure 5.

[14] Overall, all models match at least 50% of the observed data throughout most of the comparison period and on average predict about 75–80% of the pixels correctly during the winter months (MOSAIC = 75.4%, Noah = 73.3%, SAC = 81.3%, VIC = 77.6%) and about 85–90% correctly in the spring (MOSAIC = 85.1%, Noah = 85.1%, SAC = 90.0%, VIC = 86.6%). The exceptions to this are in the flatter regions such as the north central and northeast where the models periodically predict less than 50% of the pixels correctly. During the summer when there is usually no snow over each region, the match between modeled and

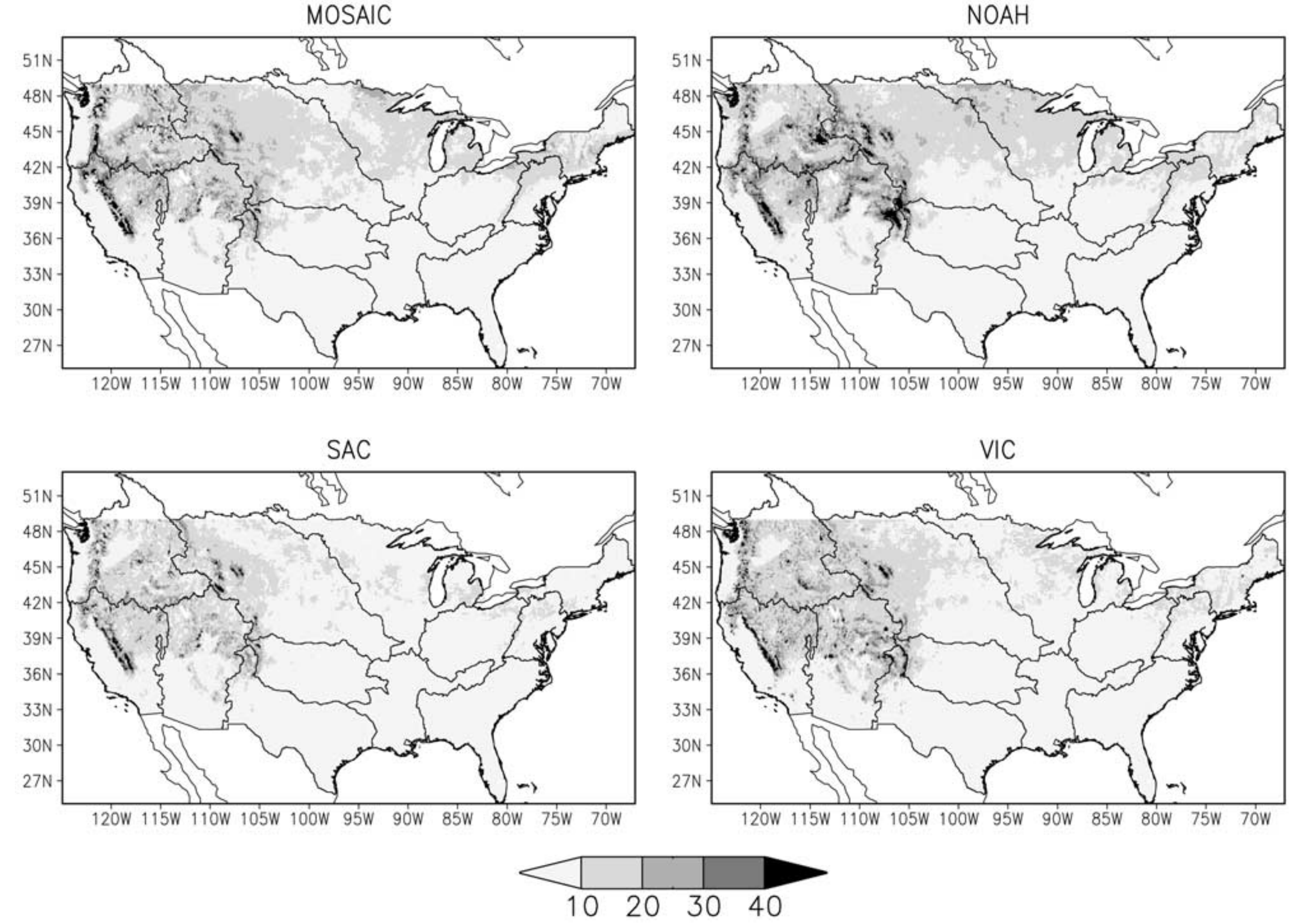

Figure 7. Percentage of incorrect snow covered days in the NLDAS model simulations compared to IMS observed data for the period October 1997–September 1999.

observed data is 100%, which is to be expected. In general, the SAC model appears to perform well over mountainous regions and less well over flatter areas such as the mid-Atlantic region. The VIC model tends to do better in the midwinter months (except in the Colorado basin) and the MOSAIC and Noah models predict snow cover more accurately during the late winter and spring melt periods.

4.2. Temporal Analysis of Snow Cover Extent

[15] To assess model performance at the pixel level rather than just at the regional mean level, maps of annual cumulative snow covered days were plotted for October 1997 to September 1999, for the observed data and model simulations (see Figure 6). In this way, it can be seen whether the models overestimate or underestimate the snow cover for any one pixel over the year. The cumulative snow day maps indicate that the models simulate the general spatial pattern of snow over the USA well, although each model may differ somewhat at smaller scales in individual regions. Overall, the following general relationship holds: $SCE_{VIC} > SCE_{SAC} > SCE_{MOSAIC} > SCE_{Noah}$ while the observed data lie somewhere in between. This is consistent with the mean SCE time series shown in Figure 4.

[16] Figure 7 shows maps of the percentage of days that were incorrectly simulated by the models. An incorrect day is defined as one on which the measured record indicated the presence of snow but the model simulation indicated otherwise or vice versa. This shows how well the models perform in predicting the timing of the occurrence of snow. There is reasonable agreement between the observations and the models with the percentage of incorrect days being generally less than 20% for the majority of the domain. The exception is in the regions of higher elevation and most notably over the Cascades and the Sierra Nevada mountains and in north and central Wyoming for all models. In general, the Noah model tends to have the most incorrect days and the SAC model the least.

4.3. Distribution of Snow Cover Extent With Elevation

[17] Elevation is one of the key factors in governing cold season processes in midlatitude regions due to its relationship with temperature. This controls the partitioning of precipitation into snowfall and rainfall and is a limiting factor in the melting of the snowpack in the spring. Figure 8 shows the histograms of elevation distribution for each RFC region using 200 m elevation intervals. The four western RFC regions (Northwest, Missouri, California/Nevada and Colorado) have a wide elevation range, indicating that topography may play an important role in cold season processes.

[18] Figure 9a shows the mean and Figure 9b the standard deviation of snow cover extent as a fraction of the total area

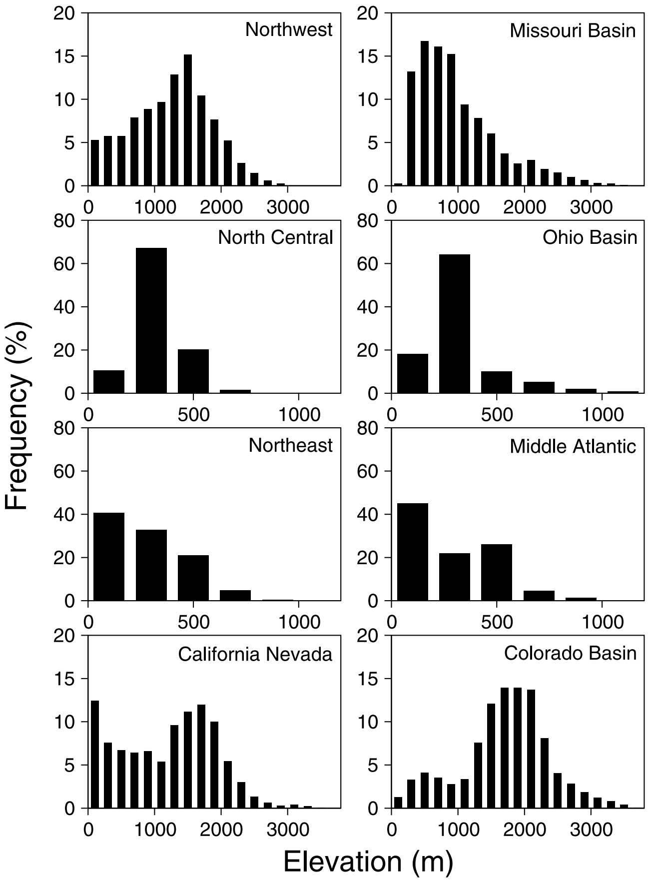

Figure 8. Histograms of elevation distribution for the eight RFC regions (elevation interval = 200 m).

over each elevation interval for the RFC regions during the winter/spring period (Dec–May). All model simulations show reasonable agreement with the mean observed data in terms of the shape of the histograms. Again it can be seen that the VIC model tends to overestimate snow cover, especially in mountainous regions. The Noah model tends to underestimate snow cover extent at all elevations except in the eastern regions (northeast, mid-Atlantic and Ohio) where it does reasonably well. The opposite is true for the MOSAIC model which tends to match the observed data less well in eastern regions and better in the western regions, although here it tends to underestimate the lower elevation snow cover extent and overestimate at higher elevations. Most noticeable is the good agreement with observations for the SAC model with the sole exception of the California/Nevada region where there is a somewhat spurious drop in the observed snow cover percentage at very high elevations. This may be due to the lower spatial resolution of the IMS observations which may limit the accuracy to which it can represent the small number of high elevation pixels that exist in this region (see elevation distribution, Figure 8).

[19] The plots of standard deviation indicate the variability of snow cover at different elevations. For flatter regions (north central, Ohio Basin, northeast and mid-Atlantic) observed variability increases with elevation and all models reproduce this well, although the MOSAIC model tends to underestimate the variability in the mid-Atlantic and Ohio regions. All models do less well in representing the variability in the mountainous regions of the western USA, especially at higher elevations.

5. Discussion

5.1. General Discussion

[20] All models do reasonably well in simulating the seasonal cycle of mean snow cover extent over the 8 RFC regions. The spread between model simulations is fairly low and generally encompasses the observed data. The differences between model simulations may be attributed, to some extent, to model specific parameterizations of snow cover extent. A comparison of the threshold values of SWE required to give large values of SCE in each of the models (section 2) reveals that SAC and Noah require a relatively deep snowpack, while MOSAIC requires substantially less and VIC requires very little. Therefore, for a given nontrivial but nondeep SWE value, VIC will generally yield the highest snow cover, followed by MOSAIC, then Noah, and finally SAC. VIC tends to over predict snow cover extent and this may be due to its parameterization of snow cover as only fully covered or snow free within a subgrid tile. Although the subgrid tiling in the VIC model translates

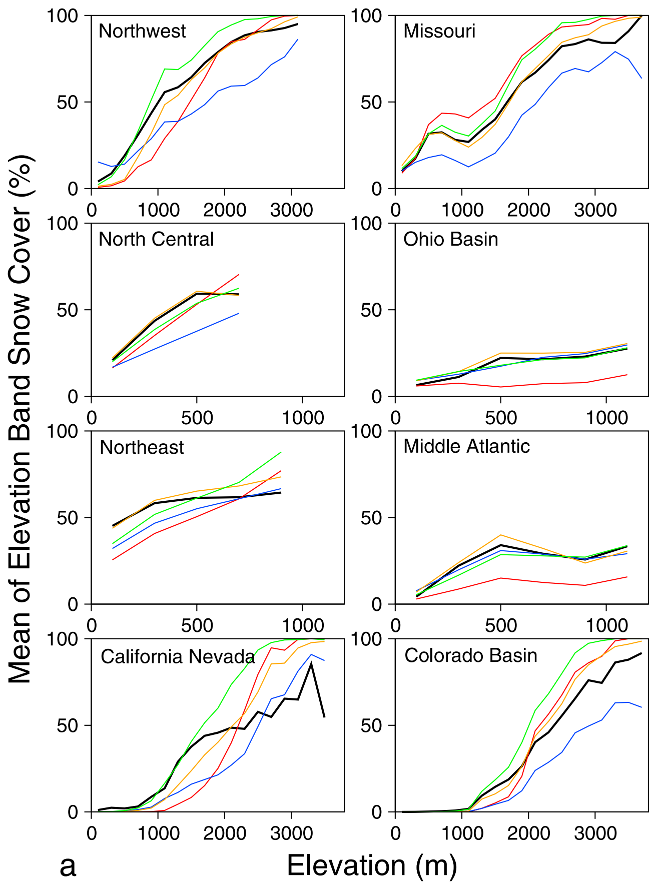

Figure 9. Histograms of (a) mean and (b) standard deviation of RFC region snow cover as a function of elevation. MOSAIC (red), Noah (blue), SAC (gold), VIC (green).

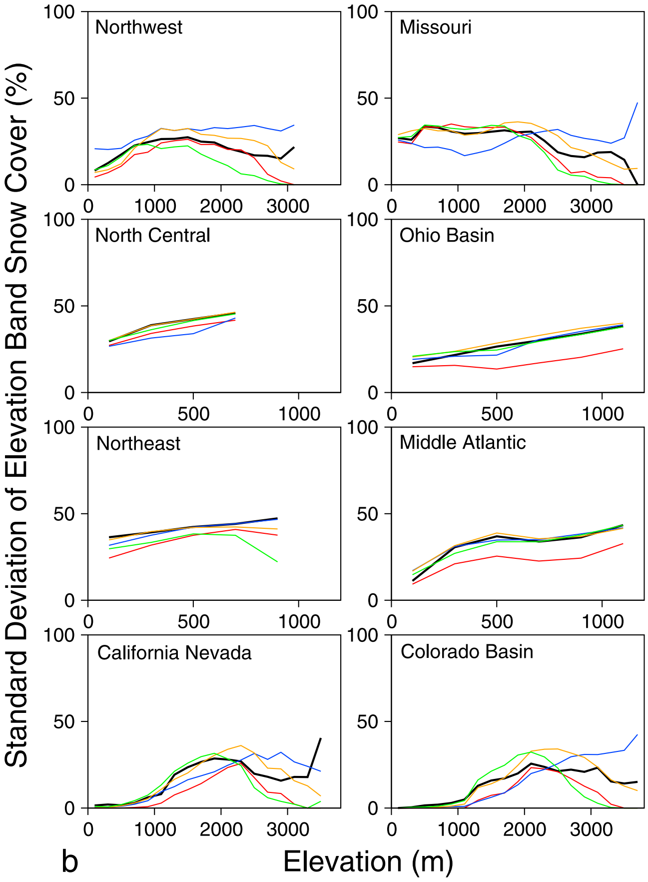

Figure 9. (continued)

into a fractional coverage at the grid scale, the coverage within each tile is biased toward full coverage. This will in turn bias the full pixel scale value toward presence of snow. In addition, the VIC model uses subgrid elevation banding, which through temperature lapsing and lower temperatures at the higher elevation bands, increases the probability of the existence of snow cover within the grid as a whole. The tendency of the Noah model to under predict SCE may be attributable, in part, to its relatively higher SWE threshold for large SCE values. With all other things equal, this will bias the Noah SCE values low in relation to the other models for moderate to low SWE values. Despite the relative simplicity of the representation of snow processes in the SAC model, it appears to perform just as well, if not better, than the other models when compared at these large regional scales. By forcing a simple snow model with only the primary controlling factors on snowpack development (e.g., air temperature), the SAC model may actually be able to capture the major dynamics of the snowpack while avoiding the propagation of errors that may occur in a fully coupled energy and water balance scheme.

[21] It appears that all models do less well over the mountainous regions to the northwest of the United States. This is to be expected due to the inherent difficulties in modeling snow processes over variable topography where meteorological variables such as precipitation, air temperature and downward solar radiation are more variable and any errors in these input forcings may be higher due to the scarcity of observational data over these regions. A comparison of NLDAS forcing data with station measurements in high elevation western regions of the United States is presented in the second part of this paper [*Pan et al.*, 2003]. The results of this show a reasonable agreement for air temperature but large differences in precipitation. Furthermore, a high bias in the NLDAS insolation forcing is reported by *Pinker et al.* [2003], although the effects of this has not yet been quantified. Such biases in the precipitation and insolation forcing data may account for some of the differences seen between the observed data and the model simulations.

[22] The pixel-by-pixel comparison of model-simulated snow cover extent and observation data indicate reasonable skill by the models to reproduce the spatial pattern of snow over large regions. Although there are periods when the number of matching pixels drops below 50% for any model, the average wintertime value is in the region of 75%. The cumulative snow maps are consistent with the mean regional time series and pixel-by-pixel comparisons, reflecting the general underestimation of the Noah model and the overestimation of the VIC model, with the other two models falling somewhere in between.

5.2. Observation Data Characteristics

[23] For meaningful conclusions to be drawn about the validity of the model simulations, the reliability of the observational data with which it is compared must be sufficient in terms of the length of record, the spatial and temporal resolution and the level of error in the data. The IMS data set provides daily observations of snow cover extent which have sufficiently high temporal resolution to evaluate model simulations given the relatively low variability of snow cover over daily scales.

[24] The IMS data set is essentially binary data, i.e., snow is either present or absent at the pixel scale. Satellite sensors can only report the pixel-averaged surface radiative emissions, which means that the value for snow cover (fully covered or snow free) obtained from the retrieval algorithms will be a compromise. For example, a pixel may in reality have only 20% snow cover but may be classified as fully snow covered in the final product. In addition to a number of satellite and ancillary data sources, the IMS also includes the use of human operators, which may result in a certain level of subjectiveness in the classification process. Therefore it is difficult to ascertain what the threshold value for categorizing the simulated SCE data should be in relation to the observational data. The threshold value of 0.1 was chosen low to allow for this.

[25] The spatial resolution of the IMS data set (~25 km) is lower than the model data (~12 km) but the low spatial variability of snow cover means that the effect of disaggregating the observed data to the modeled resolution will be small over large regions of continuous snow cover. Any detrimental effects are likely to be seen at the snow line and in regions of high topographic variability where the snow line may be more dynamic and spatially variable.

5.3. Effect of Elevation

[26] The analysis of snow cover extent with respect to elevation, as described in section 4.3, indicates differences

in how well the models perform between the western and eastern regions. This may be due in part to regional differences in which cold season processes are dominant and the varying ability of models to simulate these processes. For example, in mountainous regions where the cold season weather may be dominated by low temperatures and heavy snowfalls and thus large snowpacks, some models may fair better than others at simulating the long-term development and decay of deep snowpacks. Conversely, the parameterizations used in other models may be more suitable over the flatter areas of the midwest and east, where pack depths may be lower and the freeze/melt process is more dynamic. Further analysis is required to determine the exact nature of the differences exhibited by the models and whether these differences depend on the type of cold season process that is dominant in a particular region.

[27] All models generally perform worse at higher elevations and this is likely due in part to the difficulties in specifying the meteorological forcings correctly at high elevations and over complex terrain. The large differences in precipitation between the NLDAS forcing and station measurements as described in the second part of this paper [*Pan et al.*, 2003] may account for some of the differences seen at these higher elevations but the number of pixels at these elevations is relatively small and so the effect on the regional mean may not be significant.

5.4. Detailed Analysis of Intermodel Differences

[28] The differences between model simulations are clearly apparent and are consistent in all the analysis presented so far. Although the systematic biases may be due to model specific parameterizations of SCE and representations of subgrid variability of vegetation and elevation, more detailed analysis of the modeled cold season processes is required to gain insight into the reasons for these differences. To this end, Figure 10 shows mean monthly time series of snowmelt, snow sublimation and surface albedo averaged over the northwest RFC for the four models (SAC does not calculate sublimation and does not use albedo in its snow model). This region showed some of the largest differences between model simulations. The recent PILPS Phase 2 high latitude modeling experiments [*Slater et al.*, 2001; *Bowling et al.*, 2003a, 2003b; *Nijssen et al.*, 2003] found large differences in snow ablation and snowmelt among 21 LSMs and concluded that the differences in model parameterizations of albedo and snow cover had a large effect on available energy to the snowpack.

[29] Figure 10 clearly illustrates that the Noah model simulates significantly higher wintertime snowmelt and sublimation than the other models. During the late spring, the snowmelt and sublimation reduce to almost zero as much of the snowpack has already melted. This reflects the behavior seen in the regionally averaged time series in Figure 4 where the Noah predicted snow cover extent tends to disappear early. SAC and MOSAIC tend to have higher melt in the spring than the winter months while VIC melts at a more constant rate throughout the winter and spring and has virtually zero sublimation in the second year.

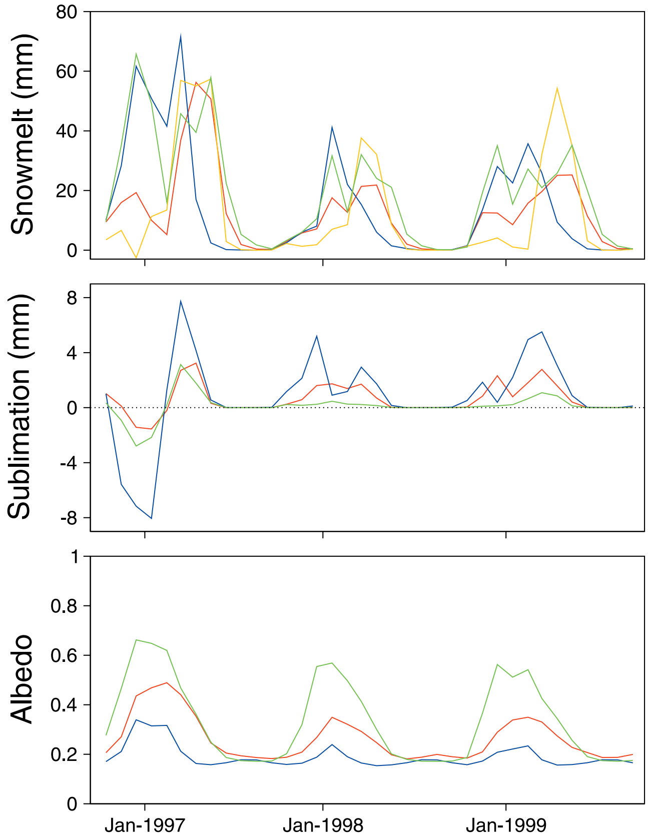

Figure 10. Time series of regional mean monthly i) snowmelt, ii) snow sublimation and iii) surface albedo for three NLDAS models for the northwest RFC. MOSAIC (red), Noah (blue), SAC (gold), VIC (green).

[30] The Noah model-simulated albedo values (0.2–0.3) shown in Figure 10 are lower than the other two models (0.3–0.5 for MOSAIC and 0.5–0.65 for VIC). This is consistent with the aforementioned general ordering of Noah, MOSAIC and VIC having low, moderate and high snow cover extent. The calculated albedo for the Noah model may be low because it represents a grid mean value and not just a value for the snow-covered fraction. Therefore, when the snow covered fraction within a grid is less than 100%, the albedo used may be unrepresentative of the snowpack, as it also represents vegetation and bare soil which generally have lower albedo values. Lower albedo values will lead to greater absorption of downward solar radiation by the snowpack and thus more available energy for snowmelt. This is demonstrated for the Noah model in Figure 10 with high snowmelt and sublimation during the winter. Conversely, the VIC model tends to have relatively higher albedo values and this is reflected in the overestimates of snow cover extent seen previously. The effect of lower albedo on the energy balance of the snowpack may be reinforced as reduced snow cover within a grid may lead to further reductions in the albedo value and thus further melting. This feedback may be accelerated by the reported high bias in the NLDAS incoming solar radiation [*Pinker et al.*, 2003]. Interestingly, the relatively good performance of the SAC model in simulating SCE

over large scales, may be due, in part, to the use of a simple temperature index method that avoids these feedback loops.

6. Conclusions

[31] Simulations of snow cover extent from the four land surface models within the NLDAS were compared with observational data from the IMS over a 3 year retrospective period over the continental United States. In general, all models do reasonably well in simulating the regional-scale spatial and seasonal dynamics of snow cover. However, the model simulations show systematic biases, with consistent underestimation of snow cover extent by the MOSAIC and Noah models, and overestimation by the VIC model, with the SAC model being essentially unbiased. The level of bias at regional scales is dependent on geographic location and elevation variability. Larger discrepancies are seen over higher elevation regions that may be due in part to errors in the meteorological forcings. Know biases in the NLDAS precipitation and incoming solar radiation may have a significant effect on the performance of the models and further validation of these data is needed. Other discrepancies are apparent at the snow line boundary where most temporal and spatial variability in snow cover extent is likely to occur. However, the spread amongst model simulations is fairly low and generally envelopes the observed data at the mean regional scale, indicating that the models are quite capable of simulating the general behavior of snow processes at these scales. Although intermodel differences can be explained to some extent by differences in the model representations of subgrid variability and parameterizations of snow cover extent, further analysis is required to understand where and why the differences between models are occurring and why some models perform better than others under different conditions. For example, detailed analysis of model simulation output over the northwest region revealed that the way in which the models calculate albedo may be a key factor in explaining the differences in the predicted snow cover extent.

[32] **Acknowledgments.** This work was supported by NOAA grant NA86GP0258 "Development of a Hydrologically Based Land Data Assimilation System for the U.S." (Eric F. Wood, PI). The work on this project by NCEP/EMC, NWS/OHD, and NESDIS/ORA was supported by the NOAA OGP grant for the NOAA Core Project for GCIP/GAPP (co-PIs K. Mitchell, J. Schaake, D. Tarpley). The work by NASA/GSFC/HSB was supported by NASA's Terrestrial Hydrology Program (P. Houser, PI). The work by Rutgers University was supported by NOAA OGP GAPP grant GC99-443b (A. Robock, PI), the Cook College Center for Environmental Prediction, and the New Jersey Agricultural Experiment Station, and additionally, figures were drawn with GrADS, created by Brian Doty. The work by NCEP/CPC was supported by NOAA/NASA GAPP Project 8R1DA114 (R. W. Higgins, PI). The work by University of Maryland was supported by grants NA56GPO233, NA86GPO202 and NA06GPO404 from NOAA/OGP and by NOAA grant NA57WC0340 to University of Maryland's Cooperative Institute for Climate Studies (R. Pinker, PI). IMS data were obtained from Bruce H. Ramsay, NOAA/NESDIS, NOAA Science Center.

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