Incorporating radiation inputs into an operational snowmelt model

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Incorporating radiation inputs into an operational snowmelt model

by

Phillip John Butcher

A thesis submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Meteorology

Program of Study Committee:
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Ames, Iowa
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# TABLE OF CONTENTS

LIST OF FIGURES iv

LIST OF TABLES vi

ABSTRACT vii

CHAPTER 1: INTRODUCTION 1

1.1 Motivation and Overview 1

1.2 Snow Energy Balance 4

1.3 Snow Modeling Approaches 6

1.4 SNOW17 Model 8

CHAPTER 2: MODEL DEVELOPMENT 14

2.1 SNOW17 Energy Balance Model (SNOW17-EB) 14

2.1.1 Melt Function 14

2.1.2 Heat Function 16

2.1.3 Snow Albedo Function 16

2.1.4 Incoming Longwave Function 17

2.1.5 Clear Sky Solar Irradiance Function 19

2.2 Study Site – Reynold’s Creek Experimental Watershed 21

2.3 Model Calibration 22

2.4 Results 24

2.4.1 Validation of Calibration Period 25

2.4.2 Comparison of Heat Methods 27

2.4.3 SNOW17 Versus SNOW17-EB 28

2.4.4 Sensitivity to Inputs 31

2.4.5 Analysis of Cloud Cover 34
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5 Summary</td>
<td>36</td>
</tr>
<tr>
<td>CHAPTER 3: ADDRESSING SNOW MODEL UNCERTAINTY FOR HYDROLOGIC PREDICTION</td>
<td>38</td>
</tr>
<tr>
<td>3.1 Introduction</td>
<td>38</td>
</tr>
<tr>
<td>3.2 Methods</td>
<td>42</td>
</tr>
<tr>
<td>3.2.1 Study Sites and Data</td>
<td>42</td>
</tr>
<tr>
<td>3.2.2 Multi-model Approach</td>
<td>44</td>
</tr>
<tr>
<td>3.2.2.1 Albedo Methods</td>
<td>45</td>
</tr>
<tr>
<td>3.2.2.2 Calibration</td>
<td>47</td>
</tr>
<tr>
<td>3.2.3 Bayesian Model Averaging</td>
<td>48</td>
</tr>
<tr>
<td>3.2.4 Model Evaluation</td>
<td>51</td>
</tr>
<tr>
<td>3.3 Results and Discussion</td>
<td>52</td>
</tr>
<tr>
<td>CHAPTER 4: CONCLUSIONS</td>
<td>64</td>
</tr>
<tr>
<td>4.1 Major Findings</td>
<td>64</td>
</tr>
<tr>
<td>4.2 Future Work</td>
<td>67</td>
</tr>
<tr>
<td>APPENDIX A: CALIBRATED PARAMETERS AND WEIGHTS FOR ALL SNOTEL SITES</td>
<td>68</td>
</tr>
<tr>
<td>APPENDIX B: SNOW MODEL RESULTS BY YEAR</td>
<td>71</td>
</tr>
<tr>
<td>APPENDIX C: RCEW FORCING TIME SERIES</td>
<td>76</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>81</td>
</tr>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>88</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure 1.1: Snow accumulation trends over the past 50 years. Open circles represent negative trends and filled circles represent positive trends. Source: Service (2004). 2

Figure 1.2: The SNOW17 flow chart. Source: Franz (2006) 9

Figure 2.1: Modified flow chart of the SNOW17-EB. 15

Figure 2.2: Mean annual statistics for precipitation (mm), temperature (°C), mean daily shortwave (W/m2), relative humidity (%), and the maximum annual SWE (mm). The horizontal black line is the mean value over WY1984-WY1993. 23

Figure 2.3: Calibration (WY1984-1988) versus verification period (WY1989-1993) MAE (mm), NSE, Pbias (%) statistics of modeled versus observed SWE. 26

Figure 2.4: The SNOW17-EB simulated snow water equivalent (SWE) using the old heat method (Equation 1.7) and the new heat method (Equation 2.3) are plotted against the observed SWE for water years 1984-1993. 28

Figure 2.5: The SNOW17 and the SNOW17-EB simulated snow water equivalent (SWE) plotted against the observed snow water equivalent for water years 1984-1993. 29

Figure 2.6: The SNOW17 snow water equivalent simulations with 0%, ±5%, and ±15% error added to the inputs for water year 1984. 32

Figure 2.7: The SNOW17-EB snow water equivalent simulations with 0%, ±5%, and ±15% error added to the inputs for water year 1984. 33

Figure 2.8: Cloud cover fraction and incoming longwave plotted during a one week period from May 14 – May 21 (during melt season) for WY1984. 35

Figure 2.9: The SNOW17-EB simulated snow water equivalent (SWE) under the effects of no clouds (N = 0) and under Equation 2.17 are plotted against the observed SWE for water years 1984-1993. 37

Figure 3.1: Location of the six SNOTEL sites in the Western U.S. 43

Figure 3.2: Normal probability plots of observed snow water equivalent (SWE) for six study sites. 50
Figure 3.3: Bayesian Model Average (BMA) weights for each study site computed from water years 1995 to 1999. The model numbers refer to models presented in Table 3.2.

Figure 3.4: Correlation (R) between normalized root mean squared error (nRMSE) of the model simulations and (a, e, i, m) precipitation, (b, f, j, n) temperature, (c, g, k, o) incoming shortwave, and (d, h, l, p) relative humidity. Models 1-3 are the SNOW17-EB with Sun and Chern (2005) albedo, Models 4-6 are the SNOW17-EB with Stasser et al. (2002) albedo, Models 7-9 are the SNOW17-EB with Verseghy (1991) albedo, and Models 10-11 are the SNOW17.

Figure 3.5: (a) Average Nash Sutcliffe efficiency score (NSE), (b) normalized mean absolute error (nRMSE), and (c) percent bias (Pbias) for the snow season from water years 1995 to 2005 for each study site. Results are from the highest weighted SNOW17 and the SNOW17-EB models at each site and Bayesian Model Average predictive mean (BMA).

Figure 3.6: Time series plots of observed (obs) snow water equivalent (SWE), Bayesian Model Average predictive mean SWE (BMA), simulated SWE from the highest weighted SNOW17 model at each site, and the 95% confidence interval (95% CI) of the BMA variance (shaded region). The best and worst performing water years (WY) are based on the highest and lowest containing ratios (CR), respectively.

Figure 3.7: Scatter plots of snow water equivalent (SWE) from the Bayesian Model Average (BMA) predictive mean, all SNOW17 models, and all SNOW17-EB models versus observed SWE from water years 1995 to 2004. The correlation coefficients (R) are provided on each plot.
LIST OF TABLES

Table 2.1: Calibrated parameters at RCEW for both the SNOW17 and the SNOW17-EB

Table 2.2: Evaluation statistics (MAE, NSE, and Pbias) calculated from WY1984-WY1993 for the SNOW17-EB using the new heat method and the old heat method.

Table 2.3: Model evaluation statistics (mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE), and Percent Bias (Pbias)) calculated for each water year from 1984-1993 for the SNOW17 and the SNOW17-EB.

Table 3.1: Elevation and climate averages for October to June from 1995 to 2004 for six SNOTEL sites.

Table 3.2: Number assigned to each model ensemble member and the approach taken to develop individual model formulations. The objective functions referred to are mean error (ME), root mean squared error (RMSE), and the mean error applied to transformed SWE values (ME-TRAN).

Table 3.3: Model parameters and ranges. X’s indicate calibrated parameters. Shaded regions indicate parameters that are not used by the model listed.
ABSTRACT

The primary snow accumulation and ablation model in the US National Weather Service streamflow prediction system is the temperature-based SNOW17 model. In this study, the SNOW17 snowpack heat exchange and melt subroutines are altered using a simplified energy balance approach, while the snow accumulation, water movement, and ground surface heat exchange processes of the SNOW17 are retained. The new model is referred to as the SNOW17 Energy Balance model (SNOW17-EB). Initial model development and testing was conducted with data from Reynold’s Creek Experimental Watershed (RCEW). The SNOW17-EB performed comparably to the SNOW17 in six years, but showed a tendency to over predict melt in at least 3 years. An ensemble of models were then created from the SNOW17 and the SNOW17-EB and combined within the Bayesian Model Averaging (BMA) framework. The BMA predictive mean and predictive variance were evaluated for six SNOTEL sites in the western U.S. The models performed best at the colder sites with high winter precipitation and little mid-winter melt. Model weights range from 0-58%, and at most sites all models received some weighting. Although, a single version of the SNOW17 often outperformed the BMA predictive mean, the ability to capture observed SWE within the 95% confidence intervals of the BMA variance was best at sites that gave more or equal weight to versions of the SNOW17-EB.
1.1 Motivation and Overview

Snow is an important source of water around the world, particularly in the Western U.S. At least one-third of the water used worldwide for irrigation and growth of crops is provided by snowmelt (Steppuhn, 1981). In the alpine basins of the Rocky Mountains as much as 75% of precipitation falls as snow (Storr, 1967) and 90% of the annual runoff is from snowmelt (Goodell, 1966). Recent analyses have shown declines in the winter snowpack of the western United States (Figure 1.1) associated with a warming climate. Decreasing winter snowpacks are of concern because they may lead to reductions in the annual available water for a region highly dependent upon this resource. Accurate forecasting of snowmelt runoff and the associated uncertainty will be essential under changing climatic conditions to allow for proper management strategies of this limited resource. Pagano et al. (2004) found that empirical runoff forecast models, such as those used by the National Weather Service River Forecasting Centers (NWSRFC) perform poorly during extreme climatic conditions underrepresented in the historical record. A modeling system that includes a physically-based energy balance snowmelt model may improve estimates of likely snowpack evolution scenarios during times of extreme climate variability since snowmelt physics are explicitly represented rather than based on empirical relationships.
In this study, the National Weather Service (NWS) empirically based snowmelt model, the SNOW17 (Anderson, 1973), is modified to be more physically based following methods to calculate melt based on net radiation presented in Brubaker (1996).

Figure 1.1: Snow accumulation trends over the past 50 years. Open circles represent negative trends and filled circles represent positive trends. Source: Service (2004).
The heat storage calculations in the SNOW17 are calculated from temperature inputs. They were replaced with basic energy balance equations to explicitly include the effects of net radiation and turbulent heat transfer. To minimize input requirements, the wind adjustment parameter from the SNOW17 is used in the heat calculation in lieu of observed wind. The modified model is called the SNOW17 Energy Balance (SNOW17-EB) model.

An overview of the snow energy balance is provided in this chapter, along with a discussion on the differences between the two common snowmelt modeling approaches; the temperature-index approach and the energy balance approach. An in-depth discussion of the SNOW17 model is presented in this chapter to provide basic knowledge of the model structure and processes. In Chapter 2, model development and testing at Reynolds Creek Experimental Watershed (RCEW) is presented. Reynolds Creek is used for model development because high quality and high resolution data was available at this location. In Chapter 3, the model test sites are expanded to include 6 SNow TELemetry (SNOTEL) sites. This part of the study provides the opportunity to assess the model across different climates. To supplement the skill of the SNOW17 with the SNOW17-EB an ensemble modeling system is created using the SNOW17 and SNOW17-EB models and the Bayesian Model Averaging (BMA) method that quantifies the uncertainty in the combined snow simulations. Finally, a summary of findings, conclusions, and future work are discussed in Chapter 4.
1.2 Snow Energy Balance

The energy balance of a snowpack governs the rate of snowpack water loss due to melting and sublimation/evaporation. The energy balance is expressed as the sum of energy gains and losses:

\[ Q_i = Q_{ns} + Q_{nl} + Q_h + Q_e + Q_r + Q_g + Q_m \]  

(1.1)

where \( Q_i \) is the change in snowpack internal heat storage, \( Q_{ns} \) is the net shortwave energy exchange, \( Q_{nl} \) is the net longwave energy exchange, \( Q_h \) is the convective exchange of sensible heat with the atmosphere, \( Q_e \) is the convective exchange of latent heat with the atmosphere, \( Q_r \) is the heat gained from rainfall, \( Q_g \) is ground heat conduction, and \( Q_m \) is the loss of heat due to melt water leaving the snowpack (DeWalle and Rango, 2008).

The net flux of shortwave radiation is the major source of energy for snowmelt. Once in earth’s atmosphere this energy can be transmitted, absorbed, scattered. The shortwave radiation that reaches earth’s surface is called global radiation and varies with latitude, season, time of day, topography, vegetation, cloud cover and turbidity of the atmosphere (Singh and Singh, 2001). The amount of global radiation absorbed by the snowpack is strongly affected by the snow surface albedo and thus albedo is one of the more important parameters in snowmelt studies (Singh and Singh, 2001). Snow surface albedo ranges from around 0.95 for fresh snow to below 0.40 for shallow, dirty snow.

The snowpack absorbs longwave radiation (2-100 µm) emitted by atmospheric gases, clouds, and forest vegetation. Unlike shortwave energy exchange which is driven by the sun, longwave energy exchange is able to occur day and night and is therefore an important contributor to the overall energy balance. The snowpack also emits longwave
energy (DeWalle and Rango, 2008). The net longwave radiation of the snowpack over a snow season is typically negative, but it can be positive in certain situations (Anderson, 1976; Kuusisto, 1986). Due to challenges in observing longwave radiation, it is usually estimated computationally (Singh and Singh, 2001).

Transfer of sensible heat to or from the snowpack occurs when a temperature difference exists between the atmosphere and the snow surface. The rate and direction of transfer (to or from the snowpack) is determined by the sign of the temperature gradient, wind speed, surface roughness, and stability of the air. Snow lasting late into the melt season can occur in conditions where the air temperature is over 20°C warmer than the snow temperature causing large gains of sensible heat to the snowpack. In contrast, during the accumulation season or at night the snow temperature can be warmer than the air temperature causing sensible heat loss from the snowpack (DeWalle and Rango, 2008).

Similar to sensible heat transfer, latent heat transfer is dependent upon wind speed, surface roughness, stability of the atmosphere, and, in addition, vapor pressure. When evaporation or sublimation occurs from the snowpack to the atmosphere, there is a loss of heat from the snowpack. Conversely, when condensation or deposition from the atmosphere to the snowpack occurs, energy is gained. Generally, latent heat is lost through evaporation and sublimation during the cold winter months, and, latent heat is absorbed through condensation or during rainfall (DeWalle and Rango, 2008).

Rain-on-snow adds heat to the snowpack in two main ways. First, sensible heat is added by the relatively warm volume of rain, and second, latent heat of fusion is added if
the rainfall freezes within the snowpack (DeWalle and Rango, 2008). A positive flux of heat into the snowpack also occurs from the underlying ground. The temperature of the underlying surface is reduced by the snowpack and thus the amount of heat added is negligible and often assumed to be a constant value (Singh and Singh, 2001).

1.3 Snow Modeling Approaches

There are two primary approaches to snowmelt modeling. One uses an explicit representation of the energy balance presented in section 1.2 and is called the energy-balance approach. This method is preferred because it makes direct use of physical principles (conservation of energy). However, the large number of required input variables, including air temperature, humidity, wind speed, cloud cover, precipitation, snow-surface temperature, and incoming and outgoing shortwave and longwave radiation, often limits use of this approach (Dingman, 2002).

The empirically based temperature index method, which requires only temperature and precipitation as inputs, is often used to predict snowmelt runoff due to the accessibility of these measurements. In this approach, snowmelt is a function of the air temperature (Dingman, 2002):

\[ M = mf \times (Ta - Tm), \quad Ta \geq Tm \quad (1.2) \]

\[ M = 0, \quad Ta < Tm \quad (1.3) \]

where \( M \) is melt, \( mf \) is a melt factor, melt coefficient, or degree-day factor, \( Ta \) is the air temperature, and \( Tm \) is the base temperature at which melt occurs. The melt factor varies by time of year and latitude and is determined empirically for each watershed (Dingman,
2002). $T_m$ is typically set to 0°C so that when the air temperature is above freezing melt is allowed to occur, however this too can be varied to account for instances when melt may occur when the air temperature is above or below freezing. Despite the simplifications made in the temperature-index method, Quick and Pipes (1988) found that an energy budget method and temperature index method gave similar results when tested against snow pillow and snow course data. Similar results between the two methods are likely due to uncertainties and sensitivity to the greater input data requirements of the energy balance method (Franz et al., 2008a).

A hybrid method has also been developed that combines both the temperature index method with the energy balance method while at the same time maintaining practical data requirements (Kustas et al., 1994; Brubaker et al., 1996). Snowmelt ($M$) using the hybrid approach is defined as:

$$M = a_r (T_a - T_m) + m_q R_n$$ (1.4)

where $a_r$ is a restricted melt factor, $m_q$ is the conversion factor for energy flux density to snowmelt depth, and $R_n$ is net radiation. To alleviate the data requirements to satisfy the net radiation balance, the shortwave and longwave components can be estimated from air temperature following the methods described in Kustas et al. (1994). It should be noted that the restricted melt factor is different than the melt factor described in Equation 1.2. The restricted melt factor is meant to parameterize just those components of melt that relate to the turbulent exchange processes so that the hybrid melt equation accounts for turbulent heat exchange as well as net radiation. This method was found to generally
perform better than a temperature-index method alone and performed more in line with a full energy balance model (Kustas et al., 1994).

### 1.4 SNOW17 Model

The SNOW17 model is a snow accumulation and ablation model used by the National Weather Service (NWS) as part of the river forecasting system. It falls into the category of temperature-index snowmelt models because temperature and precipitation are the only required inputs. However, the SNOW17 is more complex than most temperature-index methods. Air temperature is used as an index to energy exchange to track the heat content of the snowpack over time, which allows the model to explicitly account for the freezing of melt water due to a heat deficit and the retention and transmission of liquid water. Other temperature-index snowmelt models do not explicitly account for those processes (NWS, 2004).

An overview of the routines and methods in the SNOW17 are presented in Figure 1.2. The two most important processes in the model are the accumulation of snow cover and the computation of snowmelt. These two factors affect the amount of water available for runoff to streams. To determine whether new precipitation is in the form of rain or snow, the model compares the air temperature to the model parameter PXTEMP. When the air temperature is greater than PXTEMP, the form of precipitation is determined to be rain, and when the air temperature is less than or equal to PXTEMP, it is assumed to be snow.

Snowmelt is calculated differently during rain-on-snow periods than during non-rain periods. During rain-on-snow periods a modified energy balance approach is used
because several reasonable assumptions can be made (NWS, 2004; Anderson, 1968; Anderson 1976):

- incoming solar radiation is negligible because overcast conditions prevail
- incoming longwave radiation is equal to blackbody radiation at the temperature of the bottom of the cloud cover which should be close to the air temperature

Figure 1.2: The SNOW17 flow chart. Source: Franz (2006)
• the relative humidity is assumed to be 90%

These assumptions allow the energy balance to be estimated from just the air temperature to a reasonable degree.

During non-rain periods the energy balance cannot be estimated from air temperature due to variability in the meteorological conditions that can occur. The generalized equation to estimate snowmelt during non-rain periods is based on empirical relationships and is similar to those in other temperature index models. Snowmelt is proportional to the difference between the air temperature and a base temperature and is expressed as:

\[ M = M_f \cdot (T_a - MBASE) \]  \hspace{1cm} (1.5)

where \( M_f \) is the same melt factor defined before, \( T_a \) is the air temperature, and \( MBASE \) is a model parameter that defines the temperature at which melt occurs. The melt factor used in the SNOW17 has a sinusoidal variation with time and has been found to work well in the contiguous United States (NWS, 2004). It is defined as:

\[ M_f = \frac{MFMAX + MFMIN}{2} + \sin \left( \frac{n \cdot 2\pi}{366} \right) \cdot \frac{MFMAX - MFMIN}{2} \]  \hspace{1cm} (1.6)

where \( n \) is the day number beginning with March 21, \( MFMAX \) and \( MFMIN \) are model parameters of the maximum and minimum melt rates that are assumed to occur on June 21 and December 21, respectively.

Energy exchange between the air and the snowpack also occurs during non-melt periods. This exchange is proportional to the temperature gradient in the upper portions of the snowpack. The snow surface temperature is approximated by the air temperature
and the temperature within the pack is calculated as a function of the previous time periods snow surface temperatures. A model parameter, $TIPM$, is used to determine how much weight is applied to the previous time step’s air temperature. The gain or loss of heat is then calculated as:

$$\Delta D = NMF \cdot (ATI_1 + TIPM \cdot (T_a - ATI_1) - T_a)$$

(1.7)

where $\Delta D$ is the change in snow cover heat deficit, $ATI_1$ is the previous time step air temperature, and $NMF$ is a model parameter that determines the rate of heat transfer.

The heat storage of the snowpack is represented in the model as the heat deficit. The heat deficit is the amount of heat that must be added to the snowpack to return it to an isothermal state at 0°C. Once the heat deficit is zero, surface melt water or rainwater can contribute to snow cover outflow (NWS, 2004). If the heat deficit is greater than zero any melt or rainwater occurring is able to be refrozen within the snowpack.

Similar to soil, the snowpack is able to hold liquid water against gravity. The model parameter $PLWHC$ is a constant value that represents the amount of water the snowpack is capable of holding. Once this value is exceeded water is free to leave the snowpack as outflow.

Finally, the last major process accounted for within SNOW17 is the heat exchange at the snow-soil interface. The amount of melt caused by this process is typically very small on a daily time scale, but it can be significant over an entire snow season. The model parameter $DAYGM$ sets a constant rate of melt for this process.
Other processes such as water vapor transfer, interception of snow by vegetation, and redistribution of snow by the wind are implicitly accounted for in the model parameters (NWS, 2004).

In SNOW17 there are a total of 10 parameters that must be defined when modeling snowmelt at a point. These parameters are broken down into 4 major parameters that have the greatest effect on snowpack evolution and melt, and 6 minor parameters of lesser importance (NWS, 2004). The major parameters are:

1. SCF A multiplying factor that adjusts the precipitation data and corrects for gage catch deficiencies. SCF also implicitly accounts for processes not included in the model that affects SWE, such as vapor transfer, interception, and drifting.

2. MFMAX Maximum melt factor during non-rain periods. (mm °C^{-1} 6hr^{-1})

3. MFMIN Minimum melt factor during non-rain periods. (mm °C^{-1} 6hr^{-1})

4. UADJ The average wind function during rain on snow events. (mm mb^{-1})

The minor parameters are:

1. NMF Maximum negative melt factor. (mm °C^{-1} 6hr^{-1})

2. TIPM Antecedent temperature index.

3. PXTEMP Temperature that determines whether precipitation is rain/snow. (°C)

4. MBASE Base temperature for snowmelt computations. (°C)

5. PLWHC The maximum amount of liquid water that can be held in the snowpack.
6. DAYGM  Constant melt rate caused by the snow/soil interface. (mm)
CHAPTER 2: MODEL DEVELOPMENT

2.1 SNOW17 Energy Balance Model (SNOW17-EB)

Changes were made to the functions in the SNOW17 that calculate the melt during non-rain periods and the heat storage to create the SNOW17 energy balance model (SNOW17-EB) that uses the net radiation index approach of Brubaker et al. (1996) to determine melt amount, and a simplified energy balance algorithm to track the heat content of the snowpack. In order to determine the energy balance, functions to estimate snow albedo and incoming longwave radiation were added since observations of these forcings are generally not available. Figure 2.1 highlights where the new functions are added within the framework of the SNOW17. The following subsections detail these alterations.

2.1.1 Melt Function

Equation 1.5 is used to calculate melt in the SNOW17. In the SNOW17-EB this equation is replaced with a new melt equation that is a function of net radiation and is defined as:

\[ M = m_q \times R_{net} \]  

where \( m_q \) is an energy to water depth conversion (0.01 mm/W/m\(^2\)), and \( R_{net} \) is the net radiation absorbed by the snowpack and is defined as:

\[ R_{net} = (1 - \alpha)SW_{in} + LW_{in} + LW_{out} \]  

(2.2)
where $\alpha$ is the snow albedo, $SW_{in}$ is the incoming solar radiation at the surface, $LW_{in}$ is the incoming longwave radiation absorbed by the pack and $LW_{out}$ is the longwave radiation emitted by the pack.

Figure 2.1: Modified flow chart of the SNOW17-EB.
2.1.2 Heat Function

Equation 1.7 represents the old heat equation where the change in heat of the snowpack is a function of the difference between the air temperature at the previous time step \( p \) and the current time step \( c \). The new heat function is calculated as:

\[
\Delta D = e_w (Q_e + Q_h + R_{net})_c - e_w (Q_e + Q_h + R_{net})_p
\]

(2.3)

where \( e_w \) (0.000179 mmE/W/m²) converts W/m² to mmE (units of energy defined by the SNOW17), \( Q_e \) is latent heat transfer, and \( Q_h \) is sensible heat transfer. Latent and sensible heat were calculated from equations presented in NWS (2004):

\[
Q_e = 8.5 \times UADJ \times (e_a - e_s)
\]

(2.4)

\[
Q_h = 8.5 \times \gamma \times UADJ \times (T_a - T_s)
\]

(2.5)

where UADJ is the model parameter of the mean wind speed, \( e_a \) is the vapor pressure of the air, \( e_s \) is the vapor pressure at the snow surface (assumed equal to saturation vapor pressure at the snow surface temperature), \( T_a \) is the air temperature, and \( T_s \) is the snow surface temperature. Vapor pressures were estimated from relative humidity and temperature using the Clausius-Clapeyron equation. Equation 2.3 works similar to the old method except that the change in heat is now a function of all the energy inputs rather than just temperature.

2.1.3 Snow Albedo Function

A common method to estimate snow albedo is to assume it decays as a function of time. The method used by Strasser et al. (2002) was found to be a simple yet effective way to estimate the snow albedo. The snow albedo is estimated as:
\[ \alpha = \alpha_{\text{min}} + \alpha_{\text{add}} \cdot e^{-kn} \]  

(2.6)

where \( \alpha_{\text{min}} \) is the minimum snow albedo, \( \alpha_{\text{add}} \) is the difference between the maximum and minimum snow albedo, \( k \) is a recession factor, and \( n \) is the number of days since the last snowfall. When a fresh snowfall occurs the snow albedo is set to the maximum value of 0.84, otherwise the snow albedo is reduced from the maximum albedo by the recession factor (0.05 day\(^{-1}\)) and the number of days since the last snowfall. The minimum albedo is set to 0.4.

### 2.1.4 Incoming Longwave Function

Because observations of the incoming longwave radiation were not available, an empirical approach given by Steiner (2001) was used. Longwave radiation, using this method, requires knowledge of the air temperature, relative humidity, and percent cloud cover. The longwave radiation is then calculated as two parts; that originating from clouds, and that originating from atmospheric gases.

The atmospheric longwave radiation component is based on a modified version of the Stefan-Boltzmann law:

\[ l_{\text{atm}} = \varepsilon_{a} \sigma T_{a}^4 \]  

(2.7)

where \( \varepsilon_{a} \) is the emissivity of the atmosphere, \( \sigma \) is the Stefan-Boltzmann constant, and \( T_{a} \) is the atmospheric temperature. The atmospheric emissivity is based on the atmospheric vapor pressure, \( e \), and the air temperature:

\[ \varepsilon_{a} = 0.70 + 5.95 \times 10^{-4} e \exp(1500/T_{a}) \]  

(2.8)
The atmospheric vapor pressure can be obtained from the saturation vapor pressure and
the relative humidity:

\[ e = e_s \frac{RH}{100} \] (2.9)

where \( e_s \) is the saturation vapor pressure defined by the Clausius-Clapeyron equation:

\[ e_s = 6.11 \exp\left[ \frac{17.3}{T_a - 273.15} \right] \frac{T_a - 273.15}{T_a - 273.15 + 237.3} \] (2.10)

The component of downward longwave radiation produced by clouds is assumed to
transmit only in the 8-14 µm region (Idso, 1981). The transmissivity in this region is
defined as:

\[ \tau_8 = 1 - \varepsilon_8 \] (2.11)

where \( \varepsilon_8 \) is the hemispherical emissivity of the atmosphere in the 8-14 µm window. It is
represented as:

\[ \varepsilon_8 = \varepsilon_{8z} (1.4 - 0.4 \varepsilon_{8z}) \] (2.12)

where \( \varepsilon_{8z} \) is the zenith emittance defined by Idso (1981):

\[ \varepsilon_{8z} = 0.24 + 2.98 \times 10^{-6} e^2 \exp(3000/T_a) \] (2.13)

The fraction of the blackbody radiation emitted at a specific cloud temperature, \( T_c \) is
determined by:

\[ f_s = -0.6732 + 0.6240 \times 10^{-2} T_c - 0.9140 \times 10^{-5} T_c^2 \] (2.14)

Assuming a temperature lapse rate of 0.01 K m\(^{-1}\) (Steiner, 2001), the cloud temperature
can be calculated as:

\[ T_c = T_a - 1.23(T_a - T_d) \] (2.15)
where $T_d$ is the dew point temperature. The total cloud contribution towards the downwelling longwave radiation is then:

$$l_{\text{cld}} = \tau_v N e_c f_s \sigma T_c^4$$

(2.16)

where $N$ is the cloud cover fraction. Observations of cloud cover fractions were not available so a simple equation was used:

$$N = 1 - s$$

(2.17)

where $s$ is the ratio of observed solar radiation to computed clear sky solar radiation (discussed later). The nighttime cloud cover fraction was set to the value observed right before nightfall when observed solar radiation is still available. The total downwelling longwave radiation is then equal to the sum of the cloud and atmospheric components:

$$r_{ld} = l_{\text{atm}} + l_{\text{cld}}$$

(2.18)

### 2.1.5 Clear Sky Solar Irradiance Function

Also presented in Steiner (2001) is the method to computer clear sky solar irradiance which is used in the cloud cover estimation. Shortwave radiation reaching the top of the atmosphere arrives at the earth’s surface as a combination of diffuse, direct, and backscattered radiation. The amount of solar radiation reaching the top of the atmosphere is:

$$r_{\text{toa}} = SE_o \cos \theta$$

(2.19)

The solar constant, $S$, is assumed to be 1367 W m$^{-2}$. The eccentricity correction, $E_o$, corrects for the changing distance between the Earth and Sun and is a function of the time of year. The latitudinal position, $\theta$, describes the location on the earth’s surface.
The direct component reaching the surface is the amount of radiation that is transmitted through the atmosphere. It is defined as:

\[ r_{\text{dir}} = r_{\text{toa}} \tau \]  

(2.20)

where \( \tau \) is the atmospheric transmissivity. It is the amount of energy that reaches the surface after scattering and absorption by water vapor and other gases and is a function of the water content of the atmosphere and the path length of the radiation (Steiner, 2001): 

\[ \tau = \exp(a + bM_{\text{opt}}) \]  

(2.21)

where \( a \) and \( b \) describe the effects of water vapor and \( M_{\text{opt}} \) is the optical path length. The effects of water vapor are a function of the precipitable water, \( W_p \), and are empirically described as:

\[ a = -0.124 - 0.0207W_p \]  

(2.22)

\[ b = -0.0682 - 0.0248W_p \]  

(2.23)

The precipitable water is a function of the dewpoint temperature:

\[ W_p = 1.12 \exp(0.0614T_d) \]  

(2.24)

The optical path length is empirically described as a function of the solar zenith angle:

\[ M_{\text{opt}} = \frac{1}{(\cos \theta + 0.50572(96.07995 - \theta))^{-1.6364}} \]  

(2.25)

The diffuse component of radiation is the result of solar energy scattered by the atmosphere comprises anywhere from 20% to 80% of the solar energy received at the surface (DeWalle and Rango, 2008). It is parameterized as:

\[ r_{\text{diff}} = 0.5\gamma_s r_{\text{toa}} \]  

(2.26)

where \( \gamma_s \) accounts for the radiation scattered by atmospheric gases:
\[ \gamma_s = 1 - \tau_s \]  

(2.27)

where \( \tau_s \) is computed similar to \( \tau \), except \( a \) and \( b \) are now defined as:

\[ a = -0.0363 - 0.0084W_p \]  

(2.28)

\[ b = -0.0572 - 0.0173W_p \]  

(2.29)

The backscattered component is the radiation that is reflected by the surface and then backscattered towards the surface. It is a function of the direct and diffuse components, the surface albedo, and the attenuation term, \( \gamma_s \):

\[ r_{bs} = 0.5a\gamma_s (r_{dir} + r_{dif}) \]  

(2.30)

The total solar radiation received at the surface under clear sky conditions is the sum of the 3 individual components:

\[ r_{cs} = r_{dir} + r_{dif} + r_{bs} \]  

(2.31)

2.2 Study Site – Reynold’s Creek Experimental Watershed

Comparison of model results were conducted using data from Reynold’s Creek Experimental Watershed (RCEW) located in the Owyhee Mountains of southwestern Idaho approximately 80 km from Boise (Slaughter et al., 2001). The site was authorized by Congress in 1959 to develop a comprehensive climate database for research use because the watershed is typical of the watersheds in the intermountain region of the western United States (Seyfried et al., 2001). A 10 year dataset spanning water year’s (WY’s) 1984-1993 of 1-hour observations of precipitation, temperature, relative humidity, and solar radiation (Hanson et al., 2001) were used as input forcings and 1-
hour observations of snow water equivalent (SWE) (Marks et al., 2001) were used for comparison with model output.

Maximum annual SWE can be quite variable from year to year (Figure 2.2) ranging from a maximum of 1087 mm in WY1984 to a minimum of 186 mm in WY1992. Precipitation and temperature are the two main factors that affect the maximum SWE which tends to occur in the middle of the snow season. The low SWE observed in WY1992 is the result of the warm temperatures (6.5°C) and the low precipitation (584 mm). Annual daily mean relative humidity and incoming shortwave show little variability from year to year, however the 3 warmest years (WY87,88,92) all recorded mean annual relative humidity less than the 10 year mean relative humidity, indicating the effect atmospheric moisture has on the partitioning of solar energy.

2.3 Model Calibration

The Shuffled Complex Evolution Algorithm (SCE-UA) was used to automatically calibrate the parameters for both the SNOW17 and the energy balance SNOW17 (SNOW17-EB) at Reynolds Creek Experimental Watershed. SCE-UA is an automatic calibration method that was developed by Duan et al. (1993) at the University of Arizona in response to the limitations of previous automatic calibration methods which often found local optimum parameter sets rather than the global optimum parameter set. The first five years of the RCEW dataset were used to calibrate the model parameters and the remaining 5 years were used to validate the calibration. The mean absolute error statistic was used as the objective function to assess parameter set performance.
Figure 2.2: Mean annual statistics for precipitation (mm), temperature (°C), mean daily shortwave (W/m²), relative humidity (%), and the maximum annual SWE (mm). The horizontal black line is the mean value over WY1984-WY1993.
Model parameters are ideally representative of the modeled region, therefore it is promising that four of the six parameters (SCF, UADJ, PLWHC, DAYGM) shared between the two models are similar (Table 2.1). Only PXTEMP and TIPM showed significant change between the two models. These differences are likely the result of the parameters attempting to correct for mass differences. It should be noted that the SNOW17-EB no longer needs the parameters MFMAX, MFMIN, NFM, and MBASE with the addition of the energy balance equations.

Table 2.1: Calibrated parameters at RCEW for both the SNOW17 and the SNOW17-EB

<table>
<thead>
<tr>
<th></th>
<th>SNOW17</th>
<th>SNOW17-EB</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCF</td>
<td>0.92</td>
<td>0.99</td>
</tr>
<tr>
<td>MFMAX</td>
<td>0.92</td>
<td>-</td>
</tr>
<tr>
<td>MFMIN</td>
<td>0.05</td>
<td>-</td>
</tr>
<tr>
<td>UADJ</td>
<td>0.2</td>
<td>0.19</td>
</tr>
<tr>
<td>NMF</td>
<td>0.1</td>
<td>-</td>
</tr>
<tr>
<td>TIPM</td>
<td>0.6</td>
<td>0.27</td>
</tr>
<tr>
<td>PXTEMP</td>
<td>1</td>
<td>-0.29</td>
</tr>
<tr>
<td>MBASE</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>PLWHC</td>
<td>0.18</td>
<td>0.17</td>
</tr>
<tr>
<td>DAYGM</td>
<td>0.26</td>
<td>0.14</td>
</tr>
</tbody>
</table>

2.4 Results

Three common model evaluation statistics were used to assess modeled SWE versus observed SWE at RCEW.

Mean absolute error assesses the average discrepancy between simulated and observed values. It is calculated as:

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |x_i - y_i|
\]  

(2.32)
where $N$ is the total number of time steps, $t$ is the current time step, $x_t$ is the simulated variable, and $y_t$ is the observed variable.

The Nash Sutcliffe efficiency is a common statistical tool used to evaluate hydrological models. It is defined as:

$$NSE = 1 - \left( \frac{\sum_{t=1}^{N} (x_t - y_t)^2}{\sum_{t=1}^{N} (x_t - \overline{y_t})^2} \right)$$

(2.33)

It indicates how well the simulation captures the observed variance with a value of 1 indicating a perfect score.

Percent bias measures the average percentage that the simulated variable differs from the observed variable:

$$Pbias = \left[ \frac{\sum_{t=1}^{N} (x_t - y_t)}{\sum_{t=1}^{N} (y_t)} \right] \times 100$$

(2.34)

A percent bias of zero is ideal.

### 2.4.1 Validation of Calibration Period

To validate that the parameters found during the calibration period apply to other periods, model evaluation statistics were compared during the first 5 years (calibration period) and final 5 years (validation period) of the available dataset for both the SNOW17 and the SNOW17-EB (Figure 2.3). MAE increased from 13.6 mm during calibration to 20.5 mm during verification for the SNOW17 and increased from 31.0 mm to 40.5 mm for the SNOW17-EB. NSE decreased from 0.98 to 0.96 and from 0.86 to 0.75 for the SNOW17 and SNOW17-EB respectively. The magnitude of Pbias for the
SNOW17 increased from 0.59% during calibration to 6.71% whereas for the SNOW17-EB Pbias decreased from 2.92% to 2.26%. Overall, verification period statistics were slightly worse than the calibration period statistics, however, a slight decrease is expected in the validation period as climatic conditions not represented in the calibration period are likely to occur. Based upon these results it was determined that the calibration period chosen was appropriate.

Figure 2.3: Calibration (WY1984-1988) versus verification period (WY1989-1993) MAE (mm), NSE, Pbias (%) statistics of modeled versus observed SWE.
2.4.2 Comparison of Heat Methods

The heat calculation in the SNOW17 (Equation 1.7) was replaced with Equation 2.3 in the SNOW17-EB, but the SNOW17 heat calculation could be maintained in the SNOW17-EB if the parameters NMF, MFMAX, and MFMIN were also retained. The SNOW17-EB was tested using both Equation 1.7 and Equation 2.3 to determine the impact of retaining the original SNOW17 heat tracking routines.

In many of the years the two heat methods perform very similarly, but in WY’s 1986, 1992, 1991, the new heat method reduced the number of melt events during the spring and brought the simulated SWE closer to the observed SWE (Figure 2.4). It also slightly delays the onset of major melting. Evaluation statistics between the two methods gave more favorable results for the new method (Table 2.2). NSE is shown to improve from 0.73 to 0.8, Pbias improves from -8.18% to -0.33% and MAE improves from 36.6 mm to 35.8mm for the new heat method. Simply using temperature as an index for heat transfer within the SNOW17-EB resulted in quicker melting (Figure 2.4) suggesting that accounting for the full energy balance is important to this process in some years. Based on the improved model performance and the benefit of removing 3 model parameters, the new heat method represented by Equation 2.3 was deemed more suitable for the SNOW17-EB model.

Table 2.2: Evaluation statistics (MAE, NSE, and Pbias) calculated from WY1984-WY1993 for the SNOW17-EB using the new heat method and the old heat method.

<table>
<thead>
<tr>
<th></th>
<th>new heat</th>
<th>old heat</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>35.8</td>
<td>36.6</td>
</tr>
<tr>
<td>NSE</td>
<td>0.8</td>
<td>0.73</td>
</tr>
<tr>
<td>Pbias</td>
<td>-0.33</td>
<td>-8.18</td>
</tr>
</tbody>
</table>
Figure 2.4: The SNOW17-EB simulated snow water equivalent (SWE) using the old heat method (Equation 1.7) and the new heat method (Equation 2.3) are plotted against the observed SWE for water years 1984-1993.

2.4.3 SNOW17 Versus SNOW17-EB

SWE time series of the SNOW17 and SNOW17-EB versus the observed SWE was found to perform consistently well on a year to year basis over the 10 year data set (Figure 2.5). The SNOW17-EB also performed reasonably well in most years (Figure
2.5), however a consistent tendency to over-melt was observed, especially in WY’s 1985, 1990, and 1991. In WY1993 both models over-predicted SWE throughout the entire season suggesting an input bias in precipitation or temperature.

Figure 2.5: The SNOW17 and the SNOW17-EB simulated snow water equivalent (SWE) plotted against the observed snow water equivalent for water years 1984-1993.

MAE, NSE, and Pbias for the SNOW17 over the 10 year dataset were quite favorable with values of 17.1 mm, 0.97, and 3.1%, respectively, versus values for the
SNOW17-EB of 35.8 mm, 0.81, and -0.4% (Table 2.3). Although the SNOW17-EB Pbias was improved over the SNOW17 it was due to the large positive Pbias in WY1993. If WY1993 is removed, Pbias for the SNOW17 is -0.3% and -5.7% for the SNOW17-EB. It is interesting to note that the sign of the Pbias error for each year (Table 2.3) in the SNOW17-EB mimics that of the SNOW17 except the magnitude is increased. There is error introduced due to model uncertainties, but perhaps the increased error in the SNOW17-EB is the result of increased sensitivity to input errors. Conceptually, this should be true as the SNOW17-EB is more physically based than the SNOW17 and physically based models are inherently more sensitive to input forcings (DeWalle and Rango, 2008). This is likely because they generally require more inputs with more possibility to introduce data errors, and because they contain fewer parameters to account for these errors. Sensitivity to inputs is addressed in the following section.

The results found here are similar to several studies that have compared temperature index and energy balance snowmelt melt models (Kustas, 1994; Brubaker, 1996; Franz et al., 2008a). In these studies it was found that the energy balance method performed better than the temperature index method in only a couple years and typically performed slightly worse. The tendency for the SNOW17-EB to under predict SWE at RCEW contradicts the findings of Franz et al. (2008a). They compared the Snow-Atmosphere-Soil Transfer (SAST) model (an energy balance snowmelt model) with the SNOW17 at RCEW and found that the energy balance model tended to over predict SWE due to a lack of mid-winter melt. However, similar to our findings, excessive melt rates were noted during the spring.
Franz (2006) tested the longwave estimation scheme used here against observed longwave radiation at the Mammoth Mountain snow study site in California and found that estimates were, on average, 11% higher than the observed. Longwave radiation is a significant contributor to melt so a positive bias in its estimation could explain the under predicted SWE observed during the melt season.

Table 2.3: Model evaluation statistics (mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE), and Percent Bias (Pbias)) calculated for each water year from 1984-1993 for the SNOW17 and the SNOW17-EB.

<table>
<thead>
<tr>
<th>Year</th>
<th>MAE SNOW17</th>
<th>MAE SNOW17-EB</th>
<th>NSE SNOW17</th>
<th>NSE SNOW17-EB</th>
<th>Pbias SNOW17</th>
<th>Pbias SNOW17-EB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>18.3</td>
<td>33.8</td>
<td>0.99</td>
<td>0.98</td>
<td>-1.1</td>
<td>6.7</td>
</tr>
<tr>
<td>1985</td>
<td>17.9</td>
<td>57.2</td>
<td>0.97</td>
<td>0.64</td>
<td>-4.8</td>
<td>-15.7</td>
</tr>
<tr>
<td>1986</td>
<td>14.6</td>
<td>20</td>
<td>0.99</td>
<td>0.98</td>
<td>4</td>
<td>1.6</td>
</tr>
<tr>
<td>1987</td>
<td>5.7</td>
<td>16.8</td>
<td>0.99</td>
<td>0.91</td>
<td>5.6</td>
<td>4.7</td>
</tr>
<tr>
<td>1988</td>
<td>11.3</td>
<td>27.4</td>
<td>0.97</td>
<td>0.79</td>
<td>-6.7</td>
<td>-12</td>
</tr>
<tr>
<td>1989</td>
<td>14.4</td>
<td>32.4</td>
<td>0.99</td>
<td>0.97</td>
<td>3.6</td>
<td>7.7</td>
</tr>
<tr>
<td>1990</td>
<td>12.3</td>
<td>35.3</td>
<td>0.96</td>
<td>0.59</td>
<td>-12.2</td>
<td>-36.6</td>
</tr>
<tr>
<td>1991</td>
<td>7.9</td>
<td>28.9</td>
<td>0.99</td>
<td>0.52</td>
<td>7.7</td>
<td>-23.1</td>
</tr>
<tr>
<td>1992</td>
<td>6</td>
<td>15.8</td>
<td>0.96</td>
<td>0.86</td>
<td>1.4</td>
<td>15.1</td>
</tr>
<tr>
<td>1993</td>
<td>62.1</td>
<td>89.9</td>
<td>0.88</td>
<td>0.81</td>
<td>33.2</td>
<td>48.1</td>
</tr>
<tr>
<td>Mean</td>
<td>17.1</td>
<td>35.8</td>
<td>0.97</td>
<td>0.81</td>
<td>3.1</td>
<td>-0.4</td>
</tr>
</tbody>
</table>

2.4.4 Sensitivity to Inputs

An error of ±5% and ±15% was added to each input forcing for both the SNOW17 and the SNOW17-EB to test each model’s sensitivity to input uncertainty. The Pbias between the 0% error and the +15% error is reported to indicate how sensitive the modeled SWE is to each input forcing. The SNOW17 is quite sensitive to precipitation throughout the whole snow season with a Pbias increase of 26.4% (Figure 2.6). The input
uncertainty introduced in temperature had no effect until mid-April, the beginning of the melt season, suggesting temperatures were cold enough during the accumulation period to not be affected by a 15% error. A 15% increase in the temperature resulted in a Pbias of -6.7% from the 0% error.

Figure 2.6: The SNOW17 snow water equivalent simulations with 0%, ±5%, and ±15% error added to the inputs for water year 1984.
Figure 2.7: The SNOW17-EB snow water equivalent simulations with 0%, ±5%, and ±15% error added to the inputs for water year 1984.
The SNOW17-EB showed a similar sensitivity to precipitation as the SNOW17 with a 25.7% Pbias increase from the 0% error, however it was less sensitive to temperature (Pbias: -2.7%) because temperature is no longer the dominate variable affecting snowmelt as it is only used in the heat component to determine when melt occurs (Figure 2.7). A strong sensitivity to incoming shortwave radiation (Pbias: -16.8%) was observed beginning in mid-February. The SNOW17-EB is strongly affected by the amount of solar radiation received and the SNOW17-EB is more sensitive to this input than the SNOW17 is to temperature by 10.1%. A relatively small sensitivity is observed for relative humidity (-0.8%) which affects the amount of longwave energy emitted by the atmosphere as well as the latent heat transfer between the snowpack and atmosphere.

Not only does the SNOW17-EB have more input variables, but it is 10.1% more sensitive than the SNOW17 to the variable that most influences the amount of melt calculated within the model. Accurate input forcings are important for both models, but proper representation of data errors is even more essential for the SNOW17-EB. This is supported by Franz et al. (2008a) and Lei et al. (2007) who found that better estimates of input data are required for an operational energy balance snow melt model.

2.4.5 Analysis of Cloud Cover

It was observed in section 2.4.3 that the SNOW17-EB had a tendency to under-predict SWE during the melt season. Due to the simplifications made in the cloud cover fraction estimation, further analysis was done to test if clouds were providing an additional source of energy.
The cloud cover fraction was observed to jump to 1 every morning with a corresponding increase in calculated incoming longwave energy (Figure 2.8). Similar findings were observed by Franz (2006) using the same cloud cover estimation equation. In that study, adjustments were made to early morning and evening cloud cover estimates. Because clouds add to the amount of incoming longwave radiation the increase in early morning cloud cover could be a significant source of excess energy available for melt.

Figure 2.8: Cloud cover fraction and incoming longwave plotted during a one week period from May 14 – May 21 (during melt season) for WY1984.
To test if this additional energy significantly affected the SNOW17-EB predicted SWE, the cloud cover fraction was set to 0. A small increase in modeled SWE was observed with the cloud cover fraction set to 0 as compared to the current cloud cover estimation scheme (Figure 2.9). Errors introduced by the cloud cover scheme have relatively minor impacts on average. However, on a daily to weekly basis and during the melt season in particular, error in the longwave may be of concern. This issue will need to be addressed in future versions of the SNOW17-EB to limit any erroneous changes in the snowpack heat content due to errors in estimated longwave from clouds.

2.5 Summary

The melt and heat equations of the NWS SNOW17 model were altered to allow the calculation of snowmelt based on a modified energy balance. The new model was called the SNOW17 energy balance model (SNOW17-EB). Initial model results were tested at RCEW where a high quality, high resolution database of climatic forcings were available. Initial results show that the SNOW17-EB tends to perform slightly worse than the SNOW17 similar to results found in previous studies that compared energy balance and temperature index models (Kustas, 1994; Brubaker, 1996; Franz, 2008a). Despite the weaker performance of the SNOW17-EB, there is still value in developing such a model as remotely sensed albedo and other remotely sensed variables that are being developed can be applied as input forcings. Also, as climate becomes more variable the model will be better equipped to handle situations not currently in the climate record. Due to the remaining questions about input data quality and the lack of consideration of latent and sensible heat in the melt component of the SNOW17-EB, a multi-modeling application in
which information from both models is considered is a sensible approach to snow modeling. In part 3, model uncertainty is addressed utilizing an ensemble of snowmelt models developed from the SNOW17 and the SNOW17-EB.

Figure 2.9: The SNOW17-EB simulated snow water equivalent (SWE) under the effects of no clouds (N = 0) and under Equation 2.17 are plotted against the observed SWE for water years 1984-1993

Figure 2.9: The SNOW17-EB simulated snow water equivalent (SWE) under the effects of no clouds (N = 0) and under Equation 2.17 are plotted against the observed SWE for water years 1984-1993
CHAPTER 3: ADDRESSING SNOW MODEL UNCERTAINTY FOR HYDROLOGIC PREDICTION

This chapter contains the contents of a manuscript that is in preparation for submission for publication: Addressing snow model uncertainty for hydrologic predictions, by Kristie J. Franz, Phillip Butcher, and Newhsa K. Ajami. In this part of the study, the SNOW17-EB is combined with the SNOW17 model in a Bayesian multi-modeling framework to address the uncertainty in snow model simulations.

3.1 Introduction

Recently, hydrologic prediction methods that produce a probabilistic outlook have come into favor over the traditional deterministic methods. Probabilistic predictions provide a range of likely outcomes by accounting for one or several sources of uncertainty in the forecasting process. There are several approaches to producing a probabilistic forecast, including the generation of ensembles. The ensemble streamflow prediction (ESP) approach of the U.S. National Weather Service (NWS) (Day et al., 1985), for example, uses an ensemble of historical meteorological time series as input to a single hydrologic modeling system that is initialized to the current conditions of the basin. By running the forecast system with these meteorological sequences, multiple streamflow scenarios are produced. Although common, reliance on a single model in hydrologic analyses often leads to predictions that represent some phenomenon well at the expense of others (Duan et al., 2007). The varying strengths and weaknesses of individual models in capturing physical processes in the catchment prevent the ability to convincingly declare any one model to be the “best” model (WMO, 1975; Smith et al.,
Therefore, another approach to probabilistic prediction is to combine outputs from an ensemble of models to account for the uncertainty introduced by structural errors inherent in any model (Georgakakos et al., 2004; Ajami et al., 2006; Beven, 2006).

In this paper we present an ensemble snow modeling approach that addresses the uncertainty associated with the snowpack heat and melt computations. The multi-modeling system includes the temperature-based NWS SNOW17 model (Anderson, 1973) and a simple energy balance model developed from the SNOW17 framework that we call the SNOW17 Energy Balance model (SNOW17-EB). We focus on the SNOW17 model primarily because it is used as part of the operational streamflow prediction system in the United States.

There are several motivations for this work. Firstly, there is a need to explore snow model combinations for potential improvement of ensemble streamflow predictions. Snow melt is the dominant influence on seasonal water supply predictions in the Western U.S. Various studies have shown that the multi-model ensemble averages produced by model weighting methodologies have consistently performed better than any single model predictions from their pool of ensemble members (Shamseldin et al., 1997; Shamseldin and O’Conner, 1999; Krishnamurti et al., 1999; Xiong et al., 2001; Georgakakos et al., 2004; Ajami et al., 2006; Duan et al., 2007). Furthermore, current water supply outlooks do not include model structural uncertainty. Probability estimates are derived based on climatology (the NWS ESP method), and the calibration errors of
the National Resources Conservation Service water supply forecast regression equations (Pagano et al., 2004).

Secondly, model combination is a way to introduce new models into forecasting systems without removing the skill of existing models through complete model replacement. Studies have shown that temperature-based snowmelt models and energy balance snowmelt models perform equally well under most conditions (recent studies include Ohmura et al, 2001; Zappa et al., 2003; Franz et al., 2008a). A recent retrospective forecast analysis showed that hindcasts from an energy balance model were as skillful as the SNOW17 on average during a 13 year study period (Franz et al., 2008b). The Distributed Model Intercomparison Project (DMIP) results indicated that the lumped model application used by the NWS forecasting system had better overall performance than distributed models for the basins studied (Reed et al., 2004), but in some basins the distributed models out-performed the lumped model. While it is proving difficult to beat current operational standards, advancements in probabilistic prediction and forecasting at finer scales (such as for flood inundation) will require inclusion of additional modeling methodologies into operations.

Finally, spatially distributed data of remotely sensed variables such as albedo and insolation can be used to support snow modeling applications. Surface albedo has a large impact on the energy balance equations in the spring when large solar radiation variations considerably influence the energy balance (Jin et al., 1999). Changes in albedo due to aging of the snow can also cause drastic changes in the accuracy of temperature as an index to melt (Lang and Braun, 1990). Advances in remote sensing have established the
ability to estimate snow-surface albedo at sub-pixel resolution (Painter et al., 2003; Dozier et al., 2008). Incorporation of remotely-sensed albedo was shown to improve the timing and magnitude of snow melt from a spatially-distributed snowmelt model as compared to using an empirical albedo in the same model (Molotch et al., 2004). Therefore, remotely sensed albedo has the potential to improve streamflow predictions in a forecasting system that includes a snow energy balance approach. The SNOW17-EB was created, in part, to support future studies that will explore the use of remotely sensed data for streamflow prediction.

The SNOW17 model uses an empirical temperature-based approach to model heat exchange and melt within the snowpack, and requires only temperature and precipitation as inputs. Energy balance equations are only used during rain on snow events when assumptions about the value of climate variables other than temperature and precipitation can reasonably be made. In the SNOW17-EB, the SNOW17 heat and melt computations were replaced with simple snow energy balance algorithms that uses explicit energy exchange equations, an albedo estimation algorithm, and requires multiple climate inputs. The SNOW17 model components that simulate accumulation, movement of water in the snowpack, and heat exchange at the ground surface remain unchanged in the SNOW17-EB.

Multiple realizations of the SNOW17 and SNOW17-EB were applied within the Bayesian Model Averaging (BMA) framework to create a probabilistic modeling system for snow water equivalent (SWE) estimation. BMA is a probabilistic multi-model averaging technique which is a principled statistical scheme to infer from an ensemble of
competing predictions the probabilistic prediction that possesses more skill and reliability than the original ensemble members (Madigan et al. 1996, Raftery et al., 2003). A total of twelve different versions of the snow models, each using different parameter sets and albedo algorithms (SNOW17-EB only), were generated and the ensemble of models were combined using BMA. BMA has gained popularity in diverse fields such as statistics, management science, medicine and meteorology (Hoeting et al., 1999; Viallefont, et al., 2001; Fernandez, et al., 2001; Raftery et al., 2003, 2005; Tebaldi et al., 2005). BMA provides a realistic description of the predictive uncertainty that accounts for both between-model variances and in-model variances.

3.2 Methods

We first developed a modified version of the SNOW17 model that uses explicit snow energy balance equations, but retains several features of the original model. Multiple realizations of both snow models were applied and tested at six locations in the Western US. The models were applied at the point scale and run on a 24-hour time step. The Bayesian Model Averaging method was used to combine these multiple models to generate probabilistic simulations of SWE.

3.2.1 Study Sites and Data

The study sites include six SNOw TELemetry (SNOTEL) sites (Figure 3.1), which are operated by the National Resources Conservation Service (NRCS) throughout the Western US. The study sites represent four different climate zones as identified by Serreze et al., (1999). The data spans water years (WY) 1995 to 2004. Climatic averages
for each site are presented in Table 3.1. The two sites with the largest October to June precipitation are Independence Lake and Leavitt Lake, which are located in the Sierra Nevada Mountains of California. The driest location is White Horse Lake, AZ.

Figure 3.1: Location of the six SNOTEL sites in the Western U.S.

Table 3.1: Elevation and climate averages for October to June from 1995 to 2004 for six SNOTEL sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Elevation (m)</th>
<th>Daily Temperature (°C)</th>
<th>Annual Precipitation (mm)</th>
<th>Maximum Annual SWE (mm)</th>
<th>Daily Incoming Shortwave (W/m²)</th>
<th>Daily Relative Humidity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brumley, CO</td>
<td>3231</td>
<td>-3.5</td>
<td>490</td>
<td>293</td>
<td>243</td>
<td>0.62</td>
</tr>
<tr>
<td>Vallecito, CO</td>
<td>3316</td>
<td>-0.3</td>
<td>561</td>
<td>480</td>
<td>237</td>
<td>0.57</td>
</tr>
<tr>
<td>Independence Lake, CA</td>
<td>2546</td>
<td>0.9</td>
<td>1262</td>
<td>1351</td>
<td>221</td>
<td>0.62</td>
</tr>
<tr>
<td>Leavitt Lake, CA</td>
<td>2931</td>
<td>-0.4</td>
<td>1471</td>
<td>1874</td>
<td>225</td>
<td>0.56</td>
</tr>
<tr>
<td>Silver Creek, OR</td>
<td>1750</td>
<td>2.4</td>
<td>648</td>
<td>312</td>
<td>245</td>
<td>0.67</td>
</tr>
<tr>
<td>White Horse Lake, AZ</td>
<td>2188</td>
<td>5.4</td>
<td>378</td>
<td>112</td>
<td>248</td>
<td>0.46</td>
</tr>
</tbody>
</table>
SNOTEL temperature and precipitation observations were used as model inputs, and SNOTEL SWE observations were used for model calibration and verification. Incoming short-wave radiation and relative humidity inputs, which are required for the SNOW17-EB, were obtained from the National Center for Environmental Prediction’s (NCEP) North American Regional Reanalysis (NARR) data set (Mesinger et al., 2006). NARR is a long-term atmospheric and land-surface hydrology dataset for North America spanning 1979-present. The data was generated using the NCEP-DOE Global Reanalysis, NCEP Eta Model, and NCEP Data Assimilation System. The NARR spatial and temporal resolutions are 32-km and 3-hours, respectively. Model-derived data (such as NARR) has been used in other hydrologic modeling studies (Nijssen et al., 1997; Christensen et al., 2004; Stewart et al., 2004; Vanrheenen et al., 2004) when ground based alternatives were not available. Because the spatial resolution of the NARR data is quite course relative to our point-scale model applications, we chose to use the ground based temperature and precipitation from the SNOTEL rather than the NARR to improve the mass balance in our simulations relative to observed SWE.

3.2.2 Multi-model Approach

We generated 12 model realizations (ensembles) for this study. First we developed three different versions of SNOW17-EB by the inclusion of three different albedo methods in this model. We then automatically calibrated the three versions of SNOW17-EB model and the SNOW17 model three times with different objective functions. This yielded 9 realizations of the SNOW17-EB model and 3 realizations of the SNOW17 model (Table 3.2).
3.2.2.1 Albedo Methods

The three albedo estimation methods, based on two common approaches, were used to estimate snow albedo dynamically in the SNOW17-EB. One approach assumes that snow albedo decays as a function of time. The other approach relates snow albedo to snow density such that as the snow density increases, the snow albedo decreases.

1. Strasser et al. (2002) uses an ageing curve approach:

\[
\alpha = \alpha_{\text{min}} + \alpha_{\text{add}} \times e^{-kn}
\]  

where \( \alpha_{\text{min}} \) is the minimum snow albedo, \( \alpha_{\text{add}} \) is the difference between the maximum and minimum snow albedo, \( k \) is a recession factor, and \( n \) is the number of days since the last snowfall. When a fresh snowfall occurs the snow albedo is set to the maximum value of 0.84, otherwise the snow albedo
is reduced from the maximum albedo by the recession factor \((0.05 \text{ day}^{-1})\) and the number of days since the last snowfall. The minimum albedo is set to 0.4.

2. Verseghy (1991) uses a time decay method to model snow albedo under the assumption that the lower limit albedo is reduced during melt periods. During non-melt periods snow albedo is expressed as:

\[
\alpha(t + 1) = [\alpha(t) - 0.70] \cdot \exp \left[ \frac{-0.01 \Delta t}{3600} \right] + 0.70
\]  

(3.2)

and during melt periods albedo is expressed as:

\[
\alpha(t + 1) = [\alpha(t) - 0.50] \cdot \exp \left[ \frac{-0.01 \Delta t}{3600} \right] + 0.50 .
\]  

(3.3)

When a fresh snowfall occurs the albedo is reset to the maximum of 0.84.

3. Sun and Chern (2005) calculates snow albedo as a function of the snow grain diameter:

\[
\alpha = 1.0 - 0.206 \cdot C_s \cdot d_s^{0.5}
\]  

(3.4)

where the snow grain diameter \((d_s)\) is calculated as:

\[
d_s = a + b \cdot \rho_s^4
\]  

(3.5)

where \(a = 1.6 \times 10^{-4} \text{ m}\), \(b = 1.1 \times 10^{-13} \text{ m}^3\text{kg}^{-4}\), and \(\rho_s\) is the snow density. Snow density is an internal state variable in the SNOW17 that was added in recent years. Snow density is estimated based on density changes due to compaction, destructive metamorphism, the presence of liquid water, and new snowfall (Koren et al., 1999; Anderson, 2006).
3.2.2.2 Calibration

Automatic model calibration was conducted using the Shuffle Complex Evolution (SCE-UA) (Duan et al., 1992). Three calibrations were conducted for each model in an attempt to obtain parameter sets that highlighted various features in the snow time series. The root mean square error (RMSE) was used to optimize the peak SWE values and the mean error (ME) was used to optimize the range of SWE values equally:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2}
\]  

(3.6)

\[
ME = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)
\]  

(3.7)

where \(x\) is the simulated output at time \(t\), \(y\) is the observed output at time \(t\), and \(N\) is the number of simulation timesteps. Equation 3.7 was used twice, once to unaltered SWE values and once to SWE values altered by the following transformation (TRAN) to achieve a better match to the lower SWE values:

\[
TRAN = \left(\frac{SWE_i + 1}{\lambda}\right)^{\frac{1}{\lambda}} - 1
\]

(3.8)

where \(SWE_i\) is the data to be transformed at time \(t\), and \(\lambda\) determines the type of transformation (e.g. \(\lambda = 0\) is a log transformation, \(\lambda = 1\) yields no transformation). A value of \(\lambda = 0.05\) was chosen to achieve a near log transformation in order to optimize the lower SWE values that occur during melting. A true log transformation was not possible due to periods when observed or simulated SWE equaled zero, but not both.

There are 4 major parameters and 6 minor parameters in the SNOW17 (Table 3.3). Parameter ranges are based on values given in Anderson (2002). DAYGM and,
MBASE are minor parameters and were set to typical values used for the western U.S. (Anderson, 2002). The SNOW17-EB retains only four of the original SNOW17 parameters: SCF, UADJ, TIPM, and PLWHC (Table 3.3). The temperature below which precipitation falls as snow (PXTEMP) was set to 1°C for both models.

Table 3.3: Model parameters and ranges. X’s indicate calibrated parameters. Shaded regions indicate parameters that are not used by the model listed.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>SNOW17</th>
<th>SNOW17-EB</th>
<th>Range</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCF</td>
<td>X</td>
<td>X</td>
<td>0.5-1.5</td>
<td>Snow correction factor (dimensionless)</td>
</tr>
<tr>
<td>MFMAX</td>
<td>X</td>
<td></td>
<td>0.5-2.2</td>
<td>Maximum melt factor (non rain events) (mm/°C/6h)</td>
</tr>
<tr>
<td>MFMIN</td>
<td>X</td>
<td></td>
<td>0.05-0.6</td>
<td>Minimum melt factor (non rain events) (mm/°C/6h)</td>
</tr>
<tr>
<td>UADJ</td>
<td>X</td>
<td>X</td>
<td>0.05-0.2</td>
<td>Wind function (rain events) (mm/mb)</td>
</tr>
<tr>
<td>NMF</td>
<td>X</td>
<td></td>
<td>0.05-0.3</td>
<td>Maximum negative melt factor (mm/°C/6h)</td>
</tr>
<tr>
<td>TIPM</td>
<td>X</td>
<td>X</td>
<td>0.05-0.2</td>
<td>Antecedent snow temperature index</td>
</tr>
<tr>
<td>MBASE</td>
<td>0</td>
<td></td>
<td>0-1.0</td>
<td>Base temperature for snowmelt (°C)</td>
</tr>
<tr>
<td>PLWHC</td>
<td>X</td>
<td>X</td>
<td>0.01-0.1</td>
<td>Maximum liquid water holding capacity (%)</td>
</tr>
<tr>
<td>DAYGM</td>
<td>0.3</td>
<td>0.3</td>
<td>0.0-0.3</td>
<td>Average daily ground melt (mm/day)</td>
</tr>
</tbody>
</table>

3.2.3 Bayesian Model Averaging

The 12 ensembles generated by our multi-model approach were combined using Bayesian Modeling Averaging (BMA). BMA is a statistical method used to derive a probabilistic prediction from an ensemble of models (Madigan et al., 1996; Raftery et al., 2003, 2005). Each member model is assigned a weight that corresponds to the probability that the model’s prediction explains the observation. BMA is more advantageous than using a simple model average because better performing models receive higher weights. Also the method yields a BMA variance which gives a measure of the uncertainty for the BMA prediction.
By using BMA, structural deficiencies in a single model are reduced through multimodel combination. Models are combined based on the assumption that at each particular time step, there is only one best ensemble member (or model), which is unknown. Consider a quantity $y$ to be the forecasted variable (or predictand) and $f=(f_1, f_2, \ldots, f_k)$ the ensemble of all considered model predictions. $P_k(y|f_k, D)$ is the posterior distribution of $y$ given a model prediction $f_k$ and observational data set $D$. The posterior distribution of the BMA prediction is therefore given as:

$$p(y \mid f_1, f_2, \ldots, f_K, D) = \sum_{k=1}^{K} p(f_k \mid D) \cdot p_k(y \mid f_k, D)$$

(3.9)

where $p(f_k|D)$ is the posterior probability of $f_k$, and is the likelihood of a model prediction $f_k$ being the correct prediction given the observational data $D$. This term reflects how well this particular ensemble member matches the observations. If each model weight ($w_k$) is determined by $w_k = p(f_k|D)$, then $\sum_{k=1}^{K} w_k = 1$. The posterior mean and variance of the BMA prediction can be expressed as (Raftery et al., 2003, 2005):

$$E[y \mid f_1, \ldots, f_K, D] = \sum_{k=1}^{K} w_k f_k$$

(3.10)

$$\text{Var}[y \mid f_1, \ldots, f_K, D] = \sum_{k=1}^{K} w_k \left( f_k - \sum_{i=1}^{K} w_i f_i \right)^2 + \sigma^2$$

(3.11)

where $\sigma^2$ is the variance of the BMA prediction with respect to observations $y$. In essence, the expected BMA prediction is the average of individual predictions, weighted by the likelihood that an individual model is correct given the observations.
Figure 3.2: Normal probability plots of observed snow water equivalent (SWE) for six study sites.

The BMA prediction receives higher weights from better performing models because the likelihood measure assigned to each model is a measure of the agreement between the model predictions and the observations. The BMA variance is essentially an uncertainty measure of the BMA prediction, which contains two components: the between-model-variance and the within-model-variance (Equation 3.11). This measure is a better description of predictive uncertainty than in a non-BMA schemes that estimate uncertainty based only on the ensemble spread (i.e., only the between-model variance is considered), and consequently results in under-dispersive predictions (Raftery et al.,
The combination weights and BMA variance are estimated using Expectation-Maximization Algorithm (EM; Dempster et al., 1977) which maximizes the log-likelihood function.

In driving the abovementioned BMA equations, an assumption is made that the data being modeled \( pk(y|fk, D) \) is nearly Gaussian (Duan et al., 2007). Despite some long tails that deviate from the normal line, the SWE observations from the six sites are mostly Gaussian and thus the use of the BMA method is justified (Figure 3.2).

### 3.2.4 Model Evaluation

The models and BMA weights were calibrated using water years 1995 to 1999 and verified on water years 2000 to 2004. All ten years are combined in the analysis. Model performance was evaluated using the Nash Sutcliffe model efficiency score (NSE), root mean square error normalized by the peak SWE for the snow season (nRMSE) (to allow comparison among sites), percent bias (PBIAS), correlation coefficient (R), and containing ratio (CR) (Xiong and O’Connor, 2008):

\[
NSE = 1 - \left( \frac{\sum_{r=1}^{N} (\bar{x}_r - \bar{y}_r)^2}{\sum_{r=1}^{N} (x_r - \bar{y}_r)^2} \right),
\]

\[
nRMSE = \frac{1}{\sqrt{N}} \left( \frac{\sum_{r=1}^{N} (x_r - \bar{y}_r)^2}{\text{SWE}_{\text{max}}} \right),
\]

\[
Pbias = \left[ \frac{\sum_{r=1}^{N} (x_r - y_r)}{\sum_{r=1}^{N} y_r} \right] \times 100,
\]
\[ R = \frac{n \sum_{i=1}^{N} x_i \cdot x_i - \left( \sum_{i=1}^{N} y_i \right) \times \left( \sum_{i=1}^{N} x_i \right)}{\sqrt{n \sum_{i=1}^{N} y_i^2 - \left( \sum_{i=1}^{N} y_i \right)^2} \times \sqrt{n \sum_{i=1}^{N} x_i^2 - \left( \sum_{i=1}^{N} x_i \right)^2}} \] 

and

\[ CR = \frac{\sum_{i=1}^{N} I[y_i]}{N} \]  

with

\[ I[y_i] = \begin{cases} 
1, & L_t < y_i < U_t \\
0, & \text{otherwise}
\end{cases} \]

\[ L_t \text{ and } U_t \text{ are the lower and upper bounds, respectively, of the 95\% confidence interval from the BMA prediction.} \]

NSE, R, and CR are positive measures with values closer to 1 indicating higher skill, higher positive correlation, and higher containment, respectively. nRMSE is a negative score with lower values indicating higher accuracy.

### 3.3 Results and Discussion

The BMA analysis resulted in individual model weights that varied from site to site (Figure 3.3). No individual model was always the best at all sites, reinforcing the motivation for using ensemble modeling approaches. The average model weights across all six sites ranged from a low of 3\% for Model 1 (SNOW17-EB with Sun and Chern (2004) albedo estimation and objective function ME) to a high of 18\% for model 8 (SNOW17-EB with Verseghy (1991) albedo estimation and objective function RMSE).

At Independence Lake, all SNOW17-EB models that applied the Sun and Chern (2005) albedo scheme (models 1, 2 and 3) received zero weighting, and the SNOW17 models calibrated with the RMSE and TRAN-ME (models 11 and 12) were weighted
significantly higher than other models (Figure 3.3). At Vallecito and Brumley, the SNOW17-EB models using the Verseghy et al. (1991) time decay albedo scheme (models 7, 8 or 9) were among the best performing models, and were weighted higher than the SNOW17 models (models 10-12) (Figure 3.3). These two sites are located in Colorado above 3000 meters in elevation, and receive approximately 500 mm of winter precipitation on average (Table 1). The model weights were close to uniform across models at White Horse Lake, Silver Creek, and Leavitt Lake (Figure 3.3).

Figure 3.3: Bayesian Model Average (BMA) weights for each study site computed from water years 1995 to 1999. The model numbers refer to models presented in Table 3.2.
nRMSE values for individual models using the Sun and Chern (2005) method were most highly correlated with precipitation, shortwave radiation, and relative humidity (Figure 3.4a, c, and d, respectively). Simulation errors for models using the Strasser et al. (2002) (Figure 3.4 e and f) and the Verseghy (1991) (Figure 3.4 i and j) albedo schemes were most highly correlated with temperature and precipitation. All of the SNOW17-EB models performed best at the coldest sites with the highest winter precipitation. Additionally, at Brumley and Vallecito the SNOW17-EB models received higher weights compared to the SNOW17 (Figure 3.3). Mean daily solar radiation were higher at these sites compared to Leavitt Lake and Independence Lake, where the SNOW17 received the highest weights (Table 1, Figure 3.3). This weighting presumably reflects the fact that the SNOW17 cannot account for the relatively larger influence of solar radiation on the snowpack at Brumley and Vallecito. Although Independence Lake had high winter precipitation, it also had relatively warm winter temperatures and low daily solar radiation which resulted in the lower weighting of the SNOW17-EB models at this site. Silver Creek and White Horse Lake are the two warmest sites with relatively low winter precipitation, which explains the nearly equal model weighting as the performance of all the models was poorest under these conditions (Figure 3.4).

The SNOW17-EB did not account for the influence of a shallow snowpack on the snow albedo, and could partially explain the lower weighting and poorer performance of the SNOW17-EB at sites with low winter precipitation and periodic melt throughout the winter (Silver Creek and White Horse Lake). Radiation will penetrate snow to different depths depending upon the transparency of the snowpack (which is a function of density).
Figure 3.4: Correlation (R) between normalized root mean squared error (nRMSE) of the model simulations and (a, e, i, m) precipitation, (b, f, j, n) temperature, (c, g, k, o) incoming shortwave, and (d, h, l, p) relative humidity. Models 1-3 are the SNOW17-EB with Sun and Chern (2005) albedo, Models 4-6 are the SNOW17-EB with Stasser et al. (2002) albedo, Models 7-9 are the SNOW17-EB with Verseghy (1991) albedo, and Models 10-11 are the SNOW17.
A major portion of the radiation is absorbed by the upper 10cm of the pack, and the energy gained is typically confined to the upper 50cm. Albedo for shallow snow decreases rapidly as solar radiation is able to penetrate the snow cover and be absorbed by the underlying soil (Singh and Singh, 2001). However, the SNOW17 did not consider albedo and it also performed the best at sites with the most precipitation and coldest temperatures (Figure 3.4 m-p). This behavior may indicate a limitation in both snow modeling approaches or it may be a reflection of errors in snow pillow measurements.

Model performance of the BMA predictive mean (hereafter referred to as the BMA) and the highest weighted SNOW17 and SNOW17-EB models were compared at each site (Figure 3.5). The models with the highest weights could be considered to be, on average, the most accurate model at any given site. In all cases, the SNOW17 outperformed the BMA and the SNOW17-EB. At Brumley, Vallecito, and Independence Lake the three methods performed similarly. Although the SNOW17-EB was not given a high weight at Independence Lake, the performance of this model was not much different than the SNOW17. At Leavitt Lake, Silver Creek, and White Horse Lake the SNOW17-EB had considerably larger Pbias (Figure 3.5c) and lower NSE (Figure 3.5a), while the SNOW17 performance was relatively consistent across sites. Our results compare similarly to Brubaker et al. (1996) who found that a radiation index method performed better than a temperature index method in only 2 of 6 years. They suggested that assuming melt occurs when $R_{\text{net}} > 0$ would lead to a positive melt bias (under-estimation of SWE) when negative turbulent fluxes may negate a positive $R_{\text{net}}$. Because only $R_{\text{net}}$ is considered in the SNOW17-EB for calculating melt, melt would erroneously occur in
these situations. This explains the slight increase in error with higher mean solar radiation (Figure 3.4 c, g, k).

Figure 3.5: (a) Average Nash Sutcliffe efficiency score (NSE), (b) normalized mean absolute error (nRMSE), and (c) percent bias (Pbias) for the snow season from water years 1995 to 2005 for each study site. Results are from the highest weighted SNOW17 and the SNOW17-EB models at each site and Bayesian Model Average predictive mean (BMA).

The SNOW17 models tend to simulate SWE more accurately than the SNOW17-EB models based on all statistics shown (Figure 3.5). This tendency was known (Franz et al., 2008a,b). While it is interesting to note once again that the SNOW17 outperformed the energy balance approach, this finding is somewhat irrelevant for
prediction purposes as the best model cannot be known a priori. Therefore, the fact that the BMA performs almost as well as the individual best SNOW17 model is significant and shows the benefit of the multi-model approach over a single model which may or may not be the best in any given situation. The primary benefit of the BMA method over the individual model approach is the ability to quantify model uncertainty (Raftery et al., 2005; Duan et al. 2007; Vrugt and Robinson, 2007). As we will show, the variability in modeled SWE was much greater for the SNOW17-EB models than the SNOW17 models and this variability can be related to the range and accuracy of the BMA variance.

The 95% confidence intervals of the BMA variance and the associated containing ratios (CR) are plotted in Figure 3.6. For brevity and to illustrate the range in performance that was observed at each site, only the years with the highest and lowest CR values are shown. The BMA and highest weighted SNOW17 model at each site are also plotted as reference. We observed that sites with high snow accumulation and least mid-winter melt (Brumley, Vallecito, Independence Lake, and Leavitt Lake) had little difference between simulated and observed SWE during the accumulation period for all methods. The largest differences between model behaviors arise during melting periods, which begin near March at these sites (Figure 3.6). The two warmest sites, Silver Creek and White Horse Lake, showed discrepancies between the BMA and observed SWE at various times throughout the winter (Figure 3.6).

The variability of output from the different versions of the SNOW17-EB was relatively large at all sites compared to the SNOW17, particularly for smaller SWE values (Figure 3.7). As the variability in the SNOW17-EB models increased relative to
Figure 3.6: Time series plots of observed (obs) snow water equivalent (SWE), Bayesian Model Average predictive mean SWE (BMA), simulated SWE from the highest weighted SNOW17 model at each site, and the 95% confidence interval (95% CI) of the BMA variance (shaded region). The best and worst performing water years (WY) are based on the highest and lowest containing ratios (CR), respectively.
the SNOW17, the range of the 95% confidence intervals from the BMA variance increased (Figure 3.6). The SNOW17-EB at Leavitt Lake and Vallecito, for example, showed relatively large scatter about the 1:1 line as compared to the SNOW17 (Figure 3.7). At these sites, the SNOW17-EB models received either more or equal weights as the SNOW17 models. As a result, the confidence intervals of the BMA were wider and the observations were captured well even in the worst years (Figure 3.6). By contrast, the SNOW17 model received the highest weights at Independence Lake (Figure 3.3), and the BMA behaved very similarly to the SNOW17 simulations (Figure 3.6 and 3.7). The SNOW17-EB models showed significant variability, but received very low weights at this site and contributed little to the BMA variance. Consequently, the range of BMA variance was very small and there was poor containment of the observation in some years (Figure 3.6).

White Horse Lake and Silver Creek had the worst model performance and lowest containing ratios for individual years (Figure 3.6). However, models were given almost equal weights at these sites and as a result the confidence intervals were quite large and improved the ability of the BMA variance to capture the observations. CR values averaged across all 10 years ranged between 0.74 at White Horse Lake and 0.85 at Silver Creek. All model simulations at Brumley were very similar (Figure 3.7) and highly accurate (Figure 3.5), and the effect of the model combination was less apparent. The average containing ratio at this location was 0.89 despite the low range of uncertainty represented by the BMA variance (Figure 3.6).
Consideration of the BMA variance in a probabilistic system was clearly more informative about snow conditions than either the SNOW17 model or the BMA prediction alone. Furthermore, although the SNOW17-EB model was seldom the best performing model, the variability and uncertainty introduced by using this method improved the ability to capture the observations within the confidence intervals.

However, explicit estimation of various sources of uncertainty in the modeling process, such as input and parameter uncertainty (Ajami et al, 2007), is highly recommended in order to have more accurate measure of predictive uncertainty. The width of the
confidence intervals decreased during the melting period, and as a result this time period showed the lowest frequency of capturing the observations. Snow pillow estimates have higher error and may become uncertain during the melting period (when compared to snow core measurements) (Sorteberg et al., 2001). The addition of the uncertainty associated with observed SWE may also improve our results and provide a more realistic measure of uncertainty in simulated SWE.

The skill of the BMA was dependent on the skill of all the combined models included in the ensemble set, and the poorer performance of some of the models caused the BMA to perform more poorly than the best individual snow model. Additionally, when all of the models/ensemble members failed to capture an event, the BMA predictive mean also failed to capture that event. For example, the BMA over-predicted large SWE values at Leavitt Lake and under-predicted large SWE values at White Horse Lake (Figure 3.7). Both the SNOW17 models and the SNOW17-EB models showed the same tendencies for over- or under-predicting at these sites. In some cases individual model biases influence the BMA results. Underestimation of high SWE values by the BMA at Silver Creek were primarily due to the SNOW17-EB models, which received almost equal weighting as the SNOW17 at this site (Figure 3.7).

We observed that model weights at individual sites did not necessarily correspond with the best performing model when analyzed with the model performance statistics in Figure 3.5. The BMA weights are based only on the lowest mean error at individual time steps and were dominated by the models’ behaviors during the accumulation periods, which are generally longer than the melt periods. During accumulation, differences
between the models were very insignificant at most sites. Weights derived based in part on accumulation errors may be irrelevant during the melt period when the largest model errors and variations occurred. Future studies will be conducted to explore the effect of generating BMA weights from the melt periods only for those sites with clearly identifiable melt periods in the spring. Furthermore, results from the SNOWMIP study showed that albedo parameterizations that are based on the snow age are more accurate during melting periods than winter non-melt periods (Etchevers et al., 2004). Therefore, focusing only on the melt period may impact the weights given to the SNOW17-EB models using the Sun and Chern (2005) and Strasser et al. (2002) methods.

Finally, we also observed that our estimated long-wave values tended to increase during dawn and dusk due to estimations in cloud cover which were based on the ratio of NARR solar radiation to computed clear sky solar radiation. The inputs to the SNOW17-EB most likely included excess long-wave energy contributed by the over-estimated cloud cover, and would explain the tendency of the SNOW17-EB models to underestimate SWE. Additionally, the SNOW17-EB does not account for vegetation cover or turbulent energy exchange. The underestimated SWE by the SNOW17-EB contradicted Franz et al (2008a) who found that the energy balance method tended to over predict SWE accumulation, and warrants further investigation. Despite the potential errors in the available data and the processes represented in the model, the SNOW17-EB applied within the BMA framework significantly improved the representation of model uncertainty in the SWE simulations at 5 of our 6 study sites.
CHAPTER 4: CONCLUSIONS

4.1 Major Findings

We have created the SNOW17-EB energy-based snow model based on the framework of the SNOW17. The new model uses simplified energy balance estimations to compute the heat exchange and melt within the snowpack. Initial model development and testing was done at RCEW. Next, through the use of various albedo functions and parameterizations an ensemble of 12 models was created from the SNOW17-EB and the SNOW17. The 12 models were combined in a BMA multi-model application and tested at 6 SNOTEL sites in the Western U.S. The findings of this study are as follows:

(1) Initial testing at RCEW showed that the SNOW17-EB performed similar to the SNOW17 in 6 years but showed a tendency to over melt in at least 3 years. The longwave estimation scheme used has been found to overestimate incoming longwave by 11% (Franz, 2006), and is suspected to be one possible source of extra energy during the years the melt is overdone. A tendency in the cloud cover estimation method to jump to 1 during the morning hours was also suspected of being a source of too much longwave energy. However, it was found that the model was not sensitive to cloud cover.

(2) A modified heat storage equation was implemented in SNOW17-EB that allowed 3 parameters to be removed from the model. In addition to the removal of parameters, the new heat method was found to increase NSE by 7% over the 10 year data set.
The SNOW17-EB requires more input forcings than the SNOW17 and is also more sensitive to its inputs. As a result it is crucial to have an accurate representation of these forcings to get good results from the SNOW17-EB.

The SNOW17-EB performed comparably to the SNOW17 at most sites, particularly the coldest sites. A benefit of the SNOW17-EB application is that it has 4 fewer parameters than the SNOW17 that require regional identification compared to the SNOW17. Additionally, the model provides an alternative modeling method that retains many of the original features of the SNOW17, but can account for the influence of radiation and albedo on the snowpack.

The SNOW17 and SNOW17-EB models performed best at sites that had cold winter temperatures and deep snowpacks. Model errors increased at sites with the highest temperatures and shallow snowpacks, and those that experienced mid-winter melt periods. Additionally, the BMA efficiency was lowest at the warmer, drier sites (Silver Creek and White Horse Lake). These results may be due to a small positive melt bias that occurs at each time step that is more pronounced at the warm sites where melt is occurring during most of the season. At the cold sites melt occurs in a period of 2 weeks to 1 month and is likely too short to cause noticeable effects.

The model weights assigned by the BMA technique to each member model varied from site to site. The SNOW17 received lower weights at locations with higher mean daily solar radiation. In the warmer sites, BMA tended to
assign weights equally among models, and the colder, high elevation sites weighed the SNOW17-EB model with the Versegehy (1991) method most highly. Further work is needed to verify these relationships between site or climate characteristics and model weights. Further analysis may lead to guidelines for choosing a subset of models appropriate for specific sites or preliminary model weights.

(7) Based on our results, we recommend that multiple model structures be used for snow modeling in probabilistic streamflow prediction. Although a single model often outperformed the BMA prediction, the best model cannot be identified a priori. Furthermore, a single model gives no information about model uncertainty. The best model varied from year to year and time step to time step at any given place (i.e. not one single model was found to be most accurate at all times at one site). With further understanding of model performance under varying situations, it may be possible to alter weights for specific conditions, such as low accumulation years.

(8) The SNOW17 model alone was insufficient to account for uncertainty in the SWE simulations, even with consideration of multiple parameter sets. At sites that weighed the SNOW17-EB equally or higher than the SNOW17, the range of uncertainty in the BMA variance was larger and more accurate. The SNOW17-EB, which considered the influence of radiation on the snowpack, provided valuable information for the probabilistic model application and would be useful for probabilistic predictions.
4.2 Future Work

Future work will explore how BMA weights and the uncertainty represented in the BMA variance change when the snow models are applied at the watershed scale. We plan to assess the SNOW17-EB driven with remotely sensed albedo and within a data assimilation framework for improved streamflow predictions. Additionally, continued investigation of the positive melt bias in the SNOW17-EB and the biases in longwave radiation is required. Along with this, the inclusion of latent and sensible heat in the SNOW17-EB melt equation will be explored to more fully account for the energy balance in that model. Vegetation effects on the energy budget of the snowpack also need to be addressed. Finally, a thorough analysis of parameter sensitivity in the SNOW17-EB model is required to better understand how to calibrate the model at the watershed scale and for distributed model applications.
## APPENDIX A: CALIBRATED PARAMETERS AND WEIGHTS FOR ALL SNOTEL SITES

Table A-1: List of calibrated parameters for each model number (M#) at the six SNOTEL sites. The model numbers are defined in Table 3.2.

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Table A-2: Model weights assigned by BMA technique at each SNOTEL site

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<th>Independence Lake, CA</th>
<th>Leavitt Lake, CA</th>
<th>Silver Creek, OR</th>
<th>White Horse Lake, AZ</th>
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</table>
APPENDIX B: SNOW MODEL RESULTS BY YEAR

WY1995
CR=0.96

WY1996
CR=0.75
Brumley, CO

CR=0.97
Vallecito, CO

CR=0.96
Independence Lake, CA

CR=0.74
Leavitt Lake, CA

CR=0.95
Silver Creek, OR

CR=0.86
White Horse Lake, AZ

SWE (mm)

month

95% CI
BMA
obs
SNOW17
APPENDIX C: RCEW FORCING TIME SERIES
REFERENCES


Fernandez, C., E. Ley, , and M. Steel (2001), Benchmark Priors for Bayesian model averaging, J. Econometrics, 100, 381-427.


Kuusisto, E. (1986), The energy balance of a melting snow cover in different environments. *International Association of Hydrological Sciences IAHS Publication 155*.


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