# Description of SRM

The snowmelt runoff model (SRM) is a conceptually based, temperature index model designed to simulate snowmelt in mountainous areas (Martinec et al., 1994; Mitchell and Dewalle, 1998). Like most temperature index models, SRM is run in a semi-distributed manner. Model Input variables are distributed among several elevation zones (each with approximately 500m of relief), and include daily estimates of air temperature, precipitation, and snow-covered area (SCA) (refer to section 2 for a full description of SCA). SRM also operates on a daily time step (common among temperature index models), which eliminates the need to simulate snow pack processes that operate on sub-daily timescales. The following equation is used in SRM to simulate daily streamflow discharge Q (m<sup>3</sup> s<sup>-1</sup>):

$$Q_{n+1} = Q_n k_{n+1} + (1 - k_{n+1}) f \sum \left[ (c_{\text{S}i,n} * a_{i,n} (T_{i,n} + \Delta T_{i,n}) S_{i,n} + c_{\text{R}i,n} * P_{i,n}) A_i \right]$$
(1)

where *n* is the day number, *i* is the index for each elevation zone, and *f* is a conversion factor (cm km<sup>2</sup> day<sup>-1</sup> to m<sup>3</sup> s<sup>-1</sup>). The recession coefficient, *k*, is the proportion of daily melt water production that immediately appears as runoff (Martinec et al., 1994), and corresponds to the ratio of runoff on consecutive days without snowmelt and rainfall. Snowmelt and rainfall contributions are calculated separately for each elevation zone (area of *A*), and require the following input variables and parameters: T (°C day<sup>-1</sup>), the number of degree-days, the temperature-lapse-rate adjustment  $\Delta T$  (°C), the precipitation *P* contributing to runoff (cm), the fraction of snow-covered area *S* (SCA), the degree-day factor *a* (cm °C<sup>-1</sup> day<sup>-1</sup>), and the runoff coefficients for snow and rain ( $c_S$  and  $c_R$ ), which represent the difference between the available water volume and the outflow from the basin.

To aid in the operational implementation of SRM, two enhancements were made to model (by the University of Idaho): 1) the use of an antecedent temperature index (ATI) method to track snowpack cold-content and determine when the snowpack is ripe, and 2) the use of both maximum and minimum critical temperatures to partition precipitation into rain, snow, or a mixture of rain and snow. The snowpack is considered to be "ripe" if it is isothermal (temperature equal to 0 °C) and is saturated. The inclusion of the ATI method into SRM is significant since the base version of the model does not track the heat deficit of the snowpack, and the user must estimate when the snowpack is ripe. Thus the addition of the ATI method will reduce the amount of expertise in snowpack-dynamics required by the user. The use of both maximum and minimum critical temperatures to partition precipitation is designed to increase the physical basis of the model. At any given time of the year, the base version of SRM uses a single critical temperature to divide precipitation into either rain or snow, however, this does not take into account times where there are mixed rain/snow conditions, which typically occur when the air temperature is near 0 °C.

# Literature Review

SRM has been successfully tested in numerous mountainous watersheds around the world (e.g., Rango and Martinec, 1979; Shafer *et al.*, 1982; Martinec, 1985; Hall and Martinec, 1985; Dey *et al.*, 1989; Rango and Katwijk, 1990; Martinec *et al.*, 1994; Rango and Martinec, 1997; Mitchell and Dewalle, 1998; Ferguson 1999; Nagler *et al.*, 2000; Wang and Li, 2001; Gomez-Landesa and Rango, 2002; Hong and Guodong, 2003), however it has only been used on a limited basis to create short-term streamflow forecasts. Rango and Martinec (1994) used SRM, as part of a model intercomparison project conducted by the World Meteorological Organization (WMO, 1992), to forecast streamflow in the Illecillewaet Basin in the Canadian Rocky

Mountains. The streamflow forecasts extended out from 1 to 20 days (for 1983, 1985, and 1986). The results indicated that SRM performed well in the simulations with the accuracy of the forecasts decreasing as time increases. Nagler *et al.* (2000) used SRM to generate real-time runoff forecasts up to six days in advance for four basins in the Alps of the Zillertal, Austria. The results indicated that the model performed fairly well out to 6 days (average  $R^2$  value of 0.6), with the major limitation being the accuracy of the meteorological forecasts.

Nagler *et al.* (2008) used SRM to generate real-time ensemble runoff forecasts for the Otztal drainage basin (Austrian Alps) for the years of 2005 and 2006. The ensemble forecasts extended out from 1 to 6 days. Meteorological ensemble predictions, obtained from the European Centre for Medium Range Weather Forecast Model (ECMWF), were used to force the model (51 ensembles were used). The ensemble forecasting results showed that the model performed favorably, but they identified significant errors, which were attributed to the large uncertainty in the precipitation forecasts. In addition errors in the temperature forecasts were found to have a significant influence on the streamflow forecast results. Thus, they concluded that downscaling processes needed to be applied to remove bias and error in the meteorological forecasts.

The main advantage of temperature index models (i.e. SRM), over other model types, is that they only require air temperature data to obtain estimates of melt. The wide availability of these data (mainly in mountainous areas) has led to the popularity of temperature index models, especially in operational streamflow forecasting. Also, since temperature index models are mainly run in a semi-distributed manner, they often require less parameterization than do fullydistributed physically-based models. One disadvantage, however, is that melt factors obtained using point surface measurements may not be representative of the entire basin or zone (as in the semi-distributed approach). This is due to the fact that the melt factor may vary significantly over short distances (Hock, 1999). Another limitation of temperature index models is that, although temperature and solar radiation are generally correlated, they cannot account explicitly for the spatial and temporal variation exhibited by solar radiation (Ferguson, 1999). Also, other factors that control melt, including latent and sensible heat exchange, wind speed and surface roughness are not included in the melt factor. Consequently there are at least three cases in which the temperature index method fails to accurately predict snowmelt: (i) warm temperatures with little wind (overestimation due to small amounts of sensible heat exchange), (ii) high dew point temperatures with high wind (underestimation due to large amounts of condensation melt, and (iii) low temperatures with clear sky conditions (underestimation due to the dominance of solar radiation).

#### Model Enhancements

## Antecedent Temperature Index Method

To account for rain-on-snow events, SRM uses a parameter called the rain contributing area (RCA) to determine whether rain falling on the snowpack is retained by the snowpack or added to snowmelt. Rain falling on the snowpack early in the melt season is retained by the snow, which is usually dry and deep (option 0). After the snowpack becomes ripe, rain falling on the snow is added to melt (option 1). The antecedent temperature index (ATI) method is used in the enhanced version of SRM to determine when the snowpack is ripe and to automatically alter the rain contributing area (RCA). This method works on the premise that the amount of heat required to warm the snowpack to the ripe phase (the heat deficit) is proportional to the difference between the average daily air temperature ( $T_a$ ) and the ATI, as well as the addition of

any snowfall (Anderson, 1973). The ATI is used in the model as a surrogate for the temperature of the surface layer of the snowpack and is calculated using the following equation:

$$ATI_{n} = ATI_{n-1} + TIPM(Ta_{n} - ATI_{n-1})$$

$$(2)$$

where  $ATI_n$  and  $ATI_{n-1}$  are the antecedent temperature index values (°C) for day n and day n-1, Ta<sub>n</sub> is the average daily air temperature (°C) on day n, and TIPM is the antecedent temperature index parameter. The TIPM is a parameter used to estimate the effectiveness of the air temperature in altering the temperature of the surface layer of the snowpack (ATI). The TIPM ranges from zero to one and changes in response to the thickness of the snowpack. TIPM values less than 0.1 are indicative of a deep snowpack and suggest that differences between the air temperature and the previous day's ATI will have little impact in altering the ATI. In other words, the temperature of the surface layer of the snowpack would be expected to change slowly over time. On the other hand, TIPM values greater than 0.5 suggest that differences between the air temperature and the previous day's ATI will have a significant impact in altering the ATI. This is indicative of a shallow snowpack. Anderson (1973) found that a TIPM value of 0.5 provides reasonable results for mountainous watersheds. A value of 0.5 is also used in this study.

The heat deficit (represented as cm of water equivalent) provides a cumulative account of the heat required to warm the snowpack to the ripe phase and must be reduced to zero for the rain contributing area to be switched to 1. The change in the heat deficit is based on the difference between the previous day's ATI (snowpack surface temperature) and the average daily air temperature as well as the addition of any snowfall. The following equation is used to calculate the change in the heat storage ( $\Delta H_s$ ) when the average daily air temperature is less than or equal to 0 °C:

$$\Delta H_s = NMF(ATI_{n-1} - Ta_n) - \frac{P_s * Ta_n}{160}$$
(3)

where NMF is the negative melt factor (cm  ${}^{\circ}C^{-1} day^{-1}$ ) and P<sub>s</sub> is the amount of snowfall (cm) falling on day n. Equation (3) makes the assumption that the temperature of the new snow is equal to the average daily air temperature.  $\Delta H_s$  is greater (less) than zero when the air temperature is colder (warmer) than the previous day's ATI.

The NMF is used in equation (3) to represent the rate of change in the heat deficit based on the air temperature per unit time. Although, the NMF has the same units as the degree-day factor, it is only used in the model to estimate the change in the heat deficit. With the TIPM value set at 0.5, values for the NMF were initially set using values suggested by Anderson (1973) then were adjusted slightly to minimize the absolute error in the forecasts. Values of the NMF, used in this study, increased from 0.3 cm  $^{\circ}C^{-1}$  day<sup>-1</sup> at the beginning of the snowmelt season (March 1) to 1.2 cm  $^{\circ}C^{-1}$  day<sup>-1</sup> at the end of the snowmelt season. These values are expected to increase throughout the snowmelt season in response to changes in the snow depth (Anderson, 1973). If the average daily air temperature is greater than 0  $^{\circ}C$ , the change in heat deficit is assumed to be equal to zero, and the heat deficit is reduced by the melt (M) calculated in the following equation:

$$\mathbf{M} = a \left( \mathbf{T} \mathbf{a}_{\mathbf{n}} - \mathbf{0}^{\circ} \mathbf{C} \right) \tag{4}$$

where M is the daily snowmelt depth (cm), *a* is the degree-day factor (cm  ${}^{\circ}C^{-1}$  day<sup>-1</sup>), and Ta<sub>n</sub> is the daily average air temperature ( ${}^{\circ}C$ ).

### Maximum and Minimum Critical Temperatures

The enhanced version of SRM uses both maximum and minimum critical temperatures to partition precipitation into rain, snow, and mixed conditions with rain and snow. This partitioning is accomplished using the following equations:

$$\begin{array}{ll} P_{s}=P & T_{a} <= Tcrit_{min} & (5) \\ P_{s}=(Tcrit_{max}-T_{a})/(Tcrit_{max}-Tcrit_{min}) \times P & Tcrit_{min} < T_{a} <= Tcrit_{max} & \\ P_{s}=0 & T_{a} <= Tcrit_{max} & \\ P_{r}=P-P_{s} & \end{array}$$

where P is the total amount of precipitation (cm),  $P_s$  is the total amount of snowfall,  $P_r$  is the total amount of rainfall,  $Tcrit_{max}$  is the maximum critical temperature (°C),  $Tcrit_{min}$  is the minimum critical temperature (°C), and  $T_a$  is the average daily air temperature (°C).

# Model Inputs

#### Temperature and Precipitation

Ensemble forecasts of temperature and precipitation are obtained from the Global Forecasting System (GFS) model (2.5 degree grid cells) produced by the National Center for Environmental Prediction (NCEP). Due to the coarse spatial resolution of the GFS forecast data, the forecasted values are downscaled to the locations of Snow Telemetry (SNOTEL) stations, located within or surrounding the study basin. SNOTEL data are provided by the Natural Resources Conservation Service (NRCS). The downscaling process uses historical forecast data from the GFS to assess the statistical relationship between weather forecast variables and observed temperature and precipitation values from the SNOTEL stations (Clark *et al.*, 2004; Moore, 2005). GFS forecasts are generated every 12 hours and extend out 1 to 15 days in advance (Hamill *et al.*, 2004). Each forecast initialization uses 15 different initial conditions from which 15 meteorological forecast ensembles are derived, however only the control (best guess) forecast is used to determine the regression coefficients used in the downscaling process. Seven forecast variables are used, including, 2m air temperature, precipitation, 700mb RH, sea level pressure, 10m meridional and zonal wind components, and total column precipitable water. These variables have been previously found to be important predictor variables for downscaling temperature and precipitation in the contiguous USA (Clark and Hay, 2004) and verified for the intermountain West region by Moore (2005).

Multiple-linear regression with forward selection is used to downscale the temperature and precipitation forecasts to the location of SNOTEL sites located within or surrounding each basin. Unique regression equations are generated for each SNOTEL site, variable (temperature and precipitation), month (March-July), and forecast leadtime (30 leadtimes extending out 15 days), using the technique outlined by Clark and Hay (2004). These equations are based on the seven GFS variables from the three nearest consecutive 12-hour time steps. This results in 21 predictors (7 variables at 3 time steps) each for both temperature and precipitation. In addition to the multiple linear regression method described above, logistic regression with forward selection is used to estimate the probability of precipitation occurrence (Clark and Hay, 2004). The coefficients are determined by training the regression equations (multiple linear regression and logistic regression) on a subset of the data (i.e. 1995-2001); the remainder of the data are then used for validation.

Once the regression coefficients have been determined, they can be applied to real-time GFS ensemble forecasts to obtain ensemble forecasts of temperature and precipitation. The coefficients are applied to each of the 15 forecast ensembles and all 30 forecast leadtimes. This results in 15 ensemble forecasts of temperature and precipitation amount (QPF) that extend out

15 days (30 leadtimes, each with a length of 12 hours). Once the precipitation forecasts have been computed, the logistic regression coefficients obtained during the downscaling process are applied to estimate the probability of precipitation occurrence. Random numbers are then generated from a uniform distribution for each ensemble and forecast leadtime. If the probability of precipitation occurrence is less than the random number, we assume that there is no precipitation. However, if the probability of precipitation occurrence is greater than the random number, we assume that precipitation will occur and the amount determined from the multiple regression is used in the forecast.

Since SRM runs on a daily time step, the 15 temperature and precipitation ensemble forecasts (30 leadtimes, extending out 15 days), are converted to daily forecast values. This is accomplished by temporally matching the forecasts with the SNOTEL observations. GFS forecasts are generated at both 1200 UTC (5am Mountain Standard Time; MST) and 0000 UTC (5pm MST) and are valid for the previous 12 hour period. Analysis of hourly SNOTEL data records indicates that the minimum daily temperature  $(T_{min})$  typically occurs between 5pm and 5am, and the maximum temperature  $(T_{max})$  typically occurs between 5am and 5pm. Therefore, the downscaled T<sub>min</sub> ensemble forecasts are calculated using forecast leadtimes 1, 3, 5...29, and the downscaled  $T_{max}$  ensemble forecasts are derived from forecast leadtimes 2, 4, 6...30. As a result, daily T<sub>min</sub> and T<sub>max</sub> ensemble forecasts are computed out to 15 days. The forecasted ensemble values T<sub>max</sub> and T<sub>min</sub> are then converted to forecasted values of daily average temperature (15 ensembles) by simply averaging them. The ensemble precipitation forecasts are converted to daily values by taking the sum of the precipitation forecasts obtained for each of the two time steps for a given day. For example, the precipitation forecast for time step 1 is added to the forecast for time step 2.

Coherence between the temperature and precipitation forecasts is achieved through the use of the 'Schaake Shuffle' as described by Clark et al. (2004). The Shuffle essentially integrates the coherence in the historical record into the forecast ensembles. Time-series historical daily-average temperature values (extending out 15 days) from the SNOTEL sites used in the downscaling process are collected so as to lie within 7 days before and 7 days after the forecast date; dates can be selected from all years in the historical record except from the year that is being forecasted. This process is completed separately for each of the 15 forecast ensembles; however, the same historical dates are used for each station. The historical dailyaverage temperature values are then sorted from lowest to highest. In addition, the daily-average temperature forecast ensemble members are also sorted from lowest to highest. The sorted historical data is replaced with the sorted ensemble forecasts, and then resorted by (historical) year. For example, if the first year in the historical time series (say 1979) had the 20<sup>th</sup> highest temperature, then the first temperature ensemble member would be the ensemble with the 20<sup>th</sup> highest temperature. The corresponding precipitation forecast ensemble would then be used for ensemble #1. This preserves the observed correlation between temperature and precipitation for the ensemble members (Clark et al., 2004). The downscaling process results in 15 forecast ensembles of daily-average temperature and precipitation for each SNOTEL station and each of the 15 forecast leadtimes (days). A sixteenth ensemble member (for temperature and precipitation) is then created by taking the average of the 15 ensemble members described above. This ensemble member is now referred to as the "mean" ensemble.

Finally, the daily-average temperature ensemble forecasts for each station and leadtime are averaged to create a synthetic station and are extrapolated to the hypsometric mean elevation of each elevation zone using monthly mean lapse rates from Blandford *et al.* (2007). This

process is completed separately for each ensemble member. For example, temperature ensemble #1 from station #1 is averaged with temperature ensemble #1 from the remaining stations. The elevation of the synthetic station is the mean elevation of all of the SNOTEL stations used to model each basin (Richard and Gratton, 2001). The precipitation ensemble forecasts are also averaged to create a synthetic station; however, the average values are applied across the entire basin. No adjustment is made to account for changes in precipitation with elevation.

# Snow Covered Area (SCA)

SCA data are obtained from the MODIS 8-day composite snow cover data product (MOD10A2). This data product was provided to us by the National Snow and Ice Data Center (NSIDC). Eight-day composite data are used to minimize the effect of cloud cover and maximize the amount of useable SCA images. Since the SCA data are only available every 8 days, modified snow depletion curves (MDCs) are generated from the raw SCA data. MDCs relate the daily reduction in SCA to the cumulative melted depth. The melted depth is determined by multiplying the degree-day factor by the average daily temperature. Because there is often a considerable amount of scatter in the raw SCA data, a Gaussian distribution is used to fit a curve to the data. Separate depletion curves are generated for each elevation zone and year. Using the equation obtained from the Gaussian fit, forecasted values of snow-covered area (extending out 1 to 15 days in advance) can be obtained using the forecasted melted depth. *Model Updating* 

Real-time model updating is used to avoid the propagation of errors in the streamflow forecasts. This is important since the accuracy of the streamflow forecasts is dependent on the accurate representation of conditions over the basin at the start of each forecast period (Martinec *et al.*, 1994). Since a new 15-day streamflow forecast is generated every day, the model is

updated with observed temperature and precipitation values from the previous day, obtained from the SNOTEL sites used to model each basin. The actual measured data are handled in the same manner as the forecast data (e.g., synthetic station). The replacement of forecasted model inputs with actual temperature and precipitation values is important since SRM temporarily stores new snow in areas deemed non-snow covered from the SCA imagery. This temporary snowpack is then melted off and contributes to runoff when a sufficient number of degree-days are accumulated. Thus, updating the model with actual temperature and precipitation data is important to make sure that the amount of new snow accumulated in the model is as accurate as possible.

In addition to updating the model with observed SNOTEL data, the model is also updated with actual streamflow values from the previous day. These data are obtained from the United States Geological Survey (USGS) [http://water.usgs.gov]. The observed streamflow data are also used to evaluate the accuracy of the streamflow forecasts.

# Model Parameters

### Degree-day Factor

As stated in the model description section, the degree-day factor is used in SRM to simulate the amount of melt occurring within each elevation zone. The degree-day factor is not a constant, and changes in response to changing snow properties and atmospheric conditions. Most studies indicate that the degree-day factor typically increases during the snowmelt season (e.g., Semadeni-Davies, 1997; Singh *et al.*, 2000; Hock, 2003). This may be due to several factors, such as increasing snow density, increasing solar radiation, decreasing snow albedo, and other changes to the surface energy balance (Arendt and Sharp, 1999; Dunn and Colohan, 1999; Hock 2003). Martinec (1975) developed the following relationship for the computation of the degree-day factor (*a*), which takes into account the positive correlation between snow density and the degree-day factor:

$$a = 1.1 \frac{\rho_s}{\rho_w} \tag{6}$$

where  $\rho_s$  (g cm<sup>-3</sup>) and  $\rho_w$  (1 g m<sup>-3</sup>) are the densities of snow and water. Daily snow water equivalency (SWE) and snow depth data, obtained from SNOTEL sites, are used to estimate the density of the snowpack. The density of the snowpack is calculated using the following equation:

$$\rho_s = (SWE * \rho_w) / d_s \tag{7}$$

where  $d_s$  is the depth of the snowpack (cm). Since there is more than one SNOTEL station in each of the test basins, basin-wide average values (time-series) are obtained and applied to each elevation zone.

#### Runoff Coefficients

The runoff coefficients ( $c_s$  and  $c_R$ ) represent the difference between the available water volume and the outflow from the basin. Separate coefficients are used for snowmelt and rainfall to account for differences between these two processes (Martinec *et al.*, 1994). Adjustment of the runoff coefficient is typically required when the runoff simulations are not initially successful (Martinec *et al.*, 1994), but only after the input data have been checked for errors. Many times, changes to the runoff coefficients can be avoided by correcting errors detected in the data *Recession Coefficients* 

The recession coefficient (k), used in SRM to govern the decline of discharge during periods with no snowmelt or rainfall, can be determined using historical daily streamflow (timeseries) data. This is accomplished by dividing the actual stream discharge on day n+1 by the actual discharge on day n ( $k = Q_{n+1}/Q_n$ ). Since we are interested in the streamflow recession, we are only concerned with k values that are less than 1 (when the discharge on day n+1 is less

than the discharge on day n). The k value is not constant and tends to increase as the magnitude of the stream discharge decreases, thus SRM uses x and y coefficients to estimate the recession coefficient on day n+1 ( $k_{n+1}$ ) using the magnitude of the simulated discharge on day n ( $Q_n$ ):

$$k_{n+1} = x * Q_n^{-y}$$
 (8)

The x and y coefficients can be estimated taking the log of the k and actual stream discharge values on day n and plotting them against one another. A regression line can then be fit to the data. An alternative would be to fit a lower envelope line to the data, since the regression fit may not always provide the best estimate for the k values. The value  $(k_1)$  when the actual stream discharge value on day n is equal to 1 cms  $(Q_1)$  and the value  $(k_2)$  when the actual stream discharge value reaches its maximum  $(Q_2)$  are then obtained from the plot. The x and y coefficients are then calculated using the following equations:

$$\log k_1 = \log x - y \log Q_1 \tag{9}$$

$$\log k_2 = \log x - y \log Q_2 \tag{10}$$

Since the log of  $Q_1$  (1 cms) is equal to 0, the value for x is equal to the value for  $k_1$ . The value for x can then be inserted into equation (10) to obtain the y value

### Temperature Lapse Rates

Temperature lapse rates (°C / 100m) are used in SRM to distribute point-based observations of daily average air temperature to the hypsometric mean elevation of each elevation zone. For the purpose of simplification, an average value of 0.65 °C per 100 meters is typically used in hydrologic modeling studies (Barry and Chorley, 1987). The results, however, may be inadequate since the lapse rate changes continually (e.g., daily, seasonally, etc.) with varying conditions (Roland, 2003; Blandford *et al.*, 2007). To avoid the need for estimating daily forecasted lapse rates, mean monthly lapse rates are used in this study. Mean monthly

lapse rates are estimated by obtaining daily average temperature (average of maximum and minimum temperatures) data for each SNOTEL station in (or surrounding) the basin of interest and plotting them versus their respective elevations (Blandford *et al.*, 2007). A regression line is then fit to the data, and the daily lapse rate is equal to the slope of the line. The resulting lapse rates are then averaged on a monthly basis to obtain mean monthly values. If near-surface monthly average temperature data (e.g., SNOTEL data) are available, there is no need to estimate daily lapse rates. Monthly average lapse rates can then be obtained directly from the average temperature values.

## Maximum and Minimum Critical Temperatures

The maximum and minimum critical temperatures (Tcrit<sub>max</sub> and Tcrit<sub>min</sub>) were estimated using precipitation, SWE, and average daily temperature data measured at the SNOTEL sites. Precipitation was assumed to have fallen as snow if the SWE value (for the same station) showed a corresponding increase. If the SWE value decreased or remained constant, the precipitation is determined to have fallen as rain. The corresponding daily average air temperature values (for the days that the precipitation events occurred on) were binned into data classes with half degree increments. This process was completed to ensure that there was a sufficient amount of precipitation observations at each temperature value. The data were then sorted and used to calculate the probabilities (rain and snow) can be plotted against daily average air temperature to obtain estimates of the critical temperatures. The minimum critical temperature is the highest temperature at which the precipitation falls as snow 100% of the time. Likewise, the maximum critical temperature is the lowest temperature at which the precipitation falls as rain 100% of the time. In this study, maximum and minimum critical temperatures are estimated for each

SNOTEL station located within the basin of interest. Once the values are found, they are averaged and applied to the individual elevation zones.

This methodology is similar to the one applied by Auer (1974), which used approximately 1000 weather observations to determine of the probability of precipitation falling as snow or rain using two-meter air temperatures. Auer (1974) indicates that rain was never recorded when the two-meter air temperature was below 0  $^{\circ}$ C and snow was never observed when the temperature was above 6  $^{\circ}$ C.

#### Time Lag

The time lag is used in SRM to account for the amount of time that streamflow discharge lags behind the rise in temperature (Martinec *et al.*, 1994). The default value for the time lag in SRM is 18 hours, however, the time lag can be estimated using historical streamflow data. For example, if the air temperature begins to rise at 6 am and the discharge starts rising each day at noon, the streamflow lags behind the rise in temperature by 6 hours. The time lag may require adjustment if the timing of the forecasted and measured streamflow do not coincide.

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