1 Supplemental

1.1 MODIS Pre-processing

The MOD10A1 fractional SCE data are developed based on the normalized difference snow index (NDSI), which is calculated as a ratio of band 4 and band 6 on the Terra satellite:

$$\mathrm{NDSI}=\frac{b_4-b_6}{b_4+b_6} \qquad (1\text{-}1)$$

Snow is mapped when NDSI is greater than 0.4 (Hall et al., 2002) and where reflectance in MODIS band 2 is >11% and MODIS band 4 is >10%, although with a number of other spectral tests and screens (Riggs et al., 2006). The fractional product is then calculated developed from binary Landsat Thematic Mapper scenes processed using an empirical algorithm generated from a linear regression and applied to the MODIS NDSI (Salomonson and Appel, 2004).

MODSCAG is a spectral mixing model that utilizes end member analysis to identify the best fit of linear end members that has the strongest relationship to surface spectral reflectance in the Terra MOD09GA product (Painter et al., 2009). Operating under the assumption that spectral reflectance viewed by the MODIS sensor varies based on grain size of the snow, MODSCAG utilizes a radiative transfer model to calculate reflectance across different snow grain sizes. A look up table is used to store and retrieve the spectral reflectance end member formulations. From this look up table, all the end members are permuted to generate multiple models and the algorithm selects the minimized model solution (i.e. low error and minimum number of end members). When a pixel is identified as containing snow, then the fraction of the pixel containing snow is calculated in relation to other end members (soil, rock, ice, vegetation), normalized by the shading geometry (Rittger et al., 2013). Both MODIS products are initially screened to remove any values that are classified as cloud cover; only SCE data from 0-100% for October 1st to June 30th are ingested into CHPS.

Both MOD10A1 and MODSCAG fractional products require correction to adjust the values of SCE estimates (Raleigh et al., 2013; Rittger et al., 2013), which do not account for the snow that is blocked from the sensor view. For the MOD10A1 SCE product, this calculation is based on the viewable gap fraction, or the amount of snow covered ground between trees that the sensor can see (Liu et al., 2004). This technique, while widely applied, assumes that the viewable gap fraction remains constant through the snowmelt season, which is incorrect as the viewable gap fraction can vary based on a complex number of factors, including forest canopy density, age and class, zenith angle of the sensor, solar zenith angles, topography and snow loading (Kane et al., 2008; Liu et al., 2008; Molotch and Margulis, 2008; Raleigh et al., 2013; Rittger et al., 2013). To account for some of these issues, rather than applying a forest cover product to correct the product itself, the MOD10A1 data are used (Durand et al., 2008). All 2000-2013 March 1-March 15th MOD10A1 pixels across Interior Alaska are differenced from 100 and then a composite average of all days (n=207) is calculated. While in southeast Alaska some melt may have occurred during this time, the Interior SCE should still be at 100% across most of the region. To account for bare ground regions such as open, wind-blown rocky faces, values less than 20% SCE are removed from the correction. The standard division by viewable gap fraction,

$$\mathrm{SCE}_{\mathrm{fadj}}=\frac{\mathrm{SCE}_{\mathrm{f}}}{1-F_{\mathrm{veg}}} \qquad (1\text{-}2)$$

where F_{veg} is the tree cover percentage, $\mathrm{SCE}_{\mathrm{fadj}}$ (henceforth referred to simply as SCE) is the fractional SCE adjusted for canopy cover, and $\mathrm{SCE}_{\mathrm{f}}$ is the unadjusted SCE data. This formulation is applied as a static adjustment to each SCE pixel in all days and years. For MODSCAG, the daily vegetation fractional product provided with the data product is utilized, resulting in a dynamic adjustment for each SCE pixel in all days and years. In both cases the results are constrained to 100% SCE when exceeded.

1.2 Community Hydrologic Prediction Framework (CHPS)

The Community Hydrologic Prediction System (CHPS) was implemented at River Forecast Centers across the United States in 2012 and builds on the Delft-Flood Early Warning System (Delft-FEWS) model framework, developed by Deltares. The system allows for integration and ensemble forecasting of multiple models under a single synchronous system. The framework can be run in live mode for forecasting purposes or in an offline standalone mode for testing and development purposes (Werner et al., 2013). The offline model is implemented for this study at the University of Alaska Fairbanks using the calibration capabilities introduced to the NWS with the FEWS 2013.01 build in November, 2013.

The CHPS framework is modified to allow for the ingestion of the MODIS SCE data to replace the SNOW17 snow cover areal depletion curve, or to update the curve in the case of SCTOL > 0. The MODIS SCE grids are read in using an import function, and then clipped and averaged over each sub-watershed area using a preprocessing module. The SCE grids are imported as special forms of ArcInfo ASCII files in a Stereographic projection (this projection, which is generally inappropriate for Alaska, is used due to the limitations of CHPS projection parameters). Calibration modules are configured for peakflow, discharge statistics and water balance for each sub-watershed. We developed a parallel configuration to allow simultaneous display of MODIS and non-MODIS-forced model output. Statistics are generated for calibration, validation and for the entire time period by altering the initial conditions appropriately for each run using the input MOD10A1 data.

The framework is set up to run on semi-lumped upper and lower sub-basins with additional designations (referred to as units) for north and south facing slopes in the Chena, Chatanika, Salcha and Goodpaster basins. The model runs at a six-hourly timestep, and is run continuously from 2000 to September 2010, with initial conditions starting in October, 1999. Updates to the model framework included the basin area, and north/south facing slope delineation with new information from the 2012 NED digital elevation model (Gesch et al., 2002). This also formed the basis of updates to the model's area elevation curves and unit hydrographs.

1.3 SCE in SNOW17

A tolerance parameter is available in the SNOW17 model that can be used to alter the impact of the observed MODIS SCE data. The tolerance setting for snow cover (SCTOL) can be altered from 0 to 1 to incorporate observed data when there are differences in the simulated versus observed areal extents. When the areal extent of snow cover subtracted from the observed (in absolute terms) is greater than the tolerance multiplied by the observed, the snow cover is updated. Otherwise it is left the same. The effect of this parameter is to rely solely on the observed data value (SCTOL=0), rely partially on observed only when there are large differences (0.1-0.9), or to rely wholly on the simulated data (SCTOL=1).

Linear interpolation is used to estimate snow cover over periods when no MODIS SCE data are available. An optional element in CHPS, maxGapLength, can be configured to define the maximum length of gaps that should be filled. Gaps equal to or smaller than maxGapLength will be filled with interpolated values, while gaps larger than maxGapLength will not be filled. This ensures that periods with extensive cloud cover obscuring the MODIS SCE data are interpolated but long periods with no data, such as the summer period, are not interpolated. A maxGapLength of 11 days was selected after testing revealed that longer and shorter interpolation time steps resulted in lower streamflow simulation skill.

1.4 Calibration of SAC-SMA/SNOW17

The goal of the *physically realistic* calibration was one that focused only on the empirical parameters that have physically-based schemes associated with them. For example, the maximum melt factor for non-rain melt periods (MFMAX, specified for June 21st) represents the melt rate; increasing this parameter is indicative of increasing melt responses towards an earlier date in the season and changing melt timing. The MFMAX value incorporates slope, aspect, forest cover and meteorological conditions; it is generally considered to be higher for open regions with predominantly deciduous tree covers, higher wind speeds and mountainous terrain. The TAELEV parameter is used to warm or cool the mean areal temperature (MAT) without recompiling the historical data. The mean elevation of the catchment (ELEV) is the elevation at which the MAT is applied in the snow model. TAELEV is the elevation associated with the historical MAT time series. Using a standard lapse rate of 0.6ºC per km, if ELEV is 1000m and TAELEV is set to 1200m, then the MAT that is applied in the SNOW17 model is effectively warmed by 1.2ºC. Since MAT is generated for the entire upper zone, we used TAELEV to "warm" the temps for the southern basin units and "cool" the temps for the northern basin units. Slight adjustments to the NMF parameter were made across all basins and sub-basin units to correct a small over estimate of the values; this was anticipated to have little impact on the overall results but was undertaken to ensure representativeness of the north, south and lower basins.

2 References

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