USING SATELLITE IMAGERY AND THE DISTRIBUTED ISNOBAL ENERGY BALANCE MODEL TO DERIVE SWE HETEROGENEITY IN MOUNTAINOUS BASINS

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18.1 ABSTRACT

A novel reconstruction method that estimates the spatial distribution of snow water equivalent (SWE) in mountainous areas is presented. This model is based on remote sensing imagery and energy balance calculations only and allows us to compute the SWE distribution at sub-pixel resolution for any day during the melt season. No precipitation input is needed to drive this model; hence it could be a valuable addition to the existing tool boxes of hydrologic modelling researchers and practitioners.

18.2 RÉSUMÉ

Une nouvelle méthode de reconstruction permettant d’estimer la distribution spatiale de l’équivalent en eau de la neige (EEN) dans les régions montagneuses est présentée. Ce modèle est basé sur l’imagerie de télédétection et sur des calculs du bilan énergétique seulement et il nous permet de calculer la distribution EEN à une résolution sous-pixel pour n’importe quel jour pendant la saison de la fonte. Aucune donnée d’entrée sur les précipitations n’est nécessaire pour exécuter ce modèle. Par conséquent, il pourrait s’agir d’un ajout précieux à la boîte à outils existante des professionnels en exercice et des chercheurs du domaine de la modélisation hydrologique.
18.3 INTRODUCTION

Spatial variability in snow water equivalent (SWE) plays an important role in the prediction of a basin’s streamflow at both daily and seasonal times scales, because it affects the timing and magnitude of daily and annual melt; areas of heterogeneous SWE will cause patchy snow coverage during the melt season. This heterogeneity reduces the surface-to-volume ratio of the remaining snow, compared to homogeneous snowcover, because the same amount of snow has a smaller surface. Consequently, the snow will persist longer into the melt season and sustain stream discharge into the summer months. In addition to the effect on streamflow, SWE heterogeneity also affects soil moisture and vegetation; areas of high accumulation produce quasi-riparian zones of increased soil moisture that remain wet longer into the dry season.

Spatial patterns of snow heterogeneity are expected to be similar between years, since they are related to interannually invariant parameters like topography, vegetation, and prevailing wind direction. Capturing these patterns, even by a retrospective method, could improve predictive modelling. It is also important to evaluate just how similar these spatial patterns are.

Remote sensing can give us a good measurement of the areal extent of snowcover, but quantifying the depth of snow from remote sensing is very difficult. Snowmelt and energy balance models can estimate the daily melt, but capturing the progression of spatial heterogeneity of SWE throughout the water year exceeds most models’ capabilities. Combining the strengths of both methods will enable us to predict snowmelt runoff most effectively.

18.4 METHOD

SWE reconstruction from snowcover depletion was first proposed by Martinec and Rango (1981) and further developed by others (Cline et al., 1998a, 1998b; Molotch et al., 2004; Molotch and Bales, 2005). Martinec and Rango (1981) reconstructed basin SWE backward in time using estimates of snow covered area from Landsat and aerial photography combined with daily melt computed by a temperature-index model. The basic idea was both simple and clever: starting at peak snow accumulation, the potential melt is summed up daily for each pixel until the remote sensing imagery shows that this pixel is snow-free. The sum yields the total amount of SWE per pixel. The novelty of the model presented here is that it does not just sum up the
pixel SWE to a grand total, but instead determines the distribution of SWE within each pixel in order to study the degree of heterogeneity.

The temporal resolution of MODIS allows tracking of daily changes in fractional snowcover area ($f_{SCA}$). Using this record, the reconstruction model follows the pixel fractions and the time when each of them melts out. From this the snowpack is reconstructed day by day as shown in Figure 18.1.

![Daily potential melt](image1) ![f_{SCA}](image2) ![Reconstructed SWE](image3)

**Figure 18.1** Conceptual model to estimate heterogeneous snow water equivalent (SWE) in a MODIS grid cell.

The potential melt estimates snow in the vertical dimension and $f_{SCA}$ masks out the fraction of the pixel to which this snow is added. The product of these will give us a SWE volume for one day. This calculation is done each day until we reach the end of the melt season; the final product yields the distribution of SWE for one day within one pixel and can be plotted as a histogram of SWE values. Since visual inspection of histograms is impractical for the study of an entire watershed, statistical measures are used to represent the distributions instead. The median is chosen to represent pixel average and the percentile range from 25th to 75th percentile, referred to as C50, quantifies the spread. C50 scales with the pixel’s average SWE value, because precipitation increases towards higher elevations. To eliminate this dependence, C50 can be normalized by the median to represent SWE heterogeneity by the coefficient of variation of the pixels’ SWE distribution. For direct quantitative comparison with the heterogeneity from melt, however, C50 is better suited.

Fractional snow covered area is derived from spectral-mixture analysis of daily MODIS data at 500 m resolution (Painter et al., 2009). The daily $f_{SCA}$ estimates are modelled to interpolate and smooth across data gaps and errors, such that the final product is continuous in time and space (Dozier
et al., 2008). The potential daily melt is modelled with the snowmelt model Isnabal (Marks et al., 1999; Garen and Marks, 2005) at 30 m resolution. The model assumes a two-layer snowpack and computes the full mass and energy balance at hourly steps. To simulate a full water year, input of distributed radiation and meteorological data, as well as precipitation maps for each storm event are required. Alternatively the melt season can be modelled by itself, without the need for any precipitation input. In that case the snowpack is simply initialized with the appropriate amount of SWE, and subsequent melt can be computed from radiation, temperature, and humidity alone. For the reconstruction model, only the melt output of Isnabal is needed, and it is aggregated at the MODIS resolution to combine it with the previously described $f_{SCA}$ data.

Heterogeneity from melt is derived from modelled 30 m Isnabal melt. It is computed as the standard deviation of the cumulative melt within the larger region of the 500 m MODIS pixels. Since melt is a surface effect without strong dependence on the depth of the snowpack, normalization by average SWE values is not appropriate.

18.5 RESULTS

SWE reconstruction

Heterogeneity from accumulation:

- derived from reconstructed SWE at peak accumulation (the point in time when snow melt has not begun)
- inter-annually consistent
- highest above the timberline (effects of redistribution and sublimation)
- used C50 here (not coefficient of variation) to allow quantitative comparison with heterogeneity from melt in Figure 18.2 below

Vegetation cover plays an important role, because it provides shelter from wind, the main driver of sublimation and redistribution. Histograms of individual pixels around the transition zone from forest to open illustrate the resulting SWE distributions (Figure 18.3). The three example pixels are located in close spatial proximity at elevations between 2600 m and 3000 m (Table 18.1; Figure 18.3). Pixel 132 is in the forest, pixel 136 at the timberline and pixel 138 in the open. Forested and open pixels have similar
average SWE values, but their distributions are distinctly different, leading to an order of magnitude difference in coefficient of variation. The pixel with dense canopy is an example of a homogeneous snowpack, while the pixel in the open exhibits a heterogeneous snowpack.

Pixel 136 at the transition between forest and open is closer to the open pixel, both in terms of horizontal and vertical distance, but the shape of its SWE distribution resembles that of the forested pixel. Pixel average SWE

**Table 18.1** Statistics of SWE distribution from the three example pixels in Figure 18.3.

<table>
<thead>
<tr>
<th>pixel ID</th>
<th>elev (m)</th>
<th>fveg</th>
<th>Med (mm)</th>
<th>C50 (mm)</th>
<th>Cov</th>
</tr>
</thead>
<tbody>
<tr>
<td>132</td>
<td>2614</td>
<td>0.8</td>
<td>888</td>
<td>89</td>
<td>0.10</td>
</tr>
<tr>
<td>136</td>
<td>2800</td>
<td>0.4</td>
<td>1341</td>
<td>265</td>
<td>0.20</td>
</tr>
<tr>
<td>138</td>
<td>2957</td>
<td>0</td>
<td>949</td>
<td>903</td>
<td>0.95</td>
</tr>
</tbody>
</table>
values tend to increase toward the upper elevations since precipitation is higher there; however, this trend halts at the timberline, probably due to sublimation and scouring effects, which deplete the snowpack during the accumulation period. As a result pixel 138 has less SWE than pixel 136.

The spatial patterns of SWE heterogeneity from melt are similar in 2007-2009. During 2006 the relative distribution is distinctly different. Heterogeneity values are lower and more uniform throughout the basin. April 2006 had several storms, hence new snow accumulated and very little melted. Since April is the month with the highest spatial variability in melt, the 2006 snowpack does not pick up much of that and remains more homogeneous for the rest of the season.

The consistency of the spatial patterns in the remaining years suggests spatial correlation with other invariant basin characteristics. A comparison of a typical pattern of SWE heterogeneity with a map of fractional vegetation cover reveals a number of spatial similarities (Figure 18.4).
There are three zones of high heterogeneity. The first is a thin line of high heterogeneity along the southeastern edge of the basin, which coincides with the park road (depicted with black line in Figure 18.5). The road runs in a forest aisle representing an abrupt change in the vegetation cover, which causes a high change in melt and thus high heterogeneity. Another zone of high heterogeneity is outlined with dotted blue ovals across the northwest corner of the basin. In some years the heterogeneity is higher in the north, in others in the south. This zone lies along the timberline so again there is a relatively rapid change in vegetation cover. The southern end of this oval shows particularly high values of heterogeneity. It coincides with a narrow valley where south-facing and north-facing slopes meet, so topography accentuates the SWE heterogeneity. The third zone of high heterogeneity approximately forms a cross at mid-elevations. The 500 m map of fractional canopy cover derived from a binary map at 30 m resolution indicates values of around 0.5 for these pixels. By the nature of this derivation, 0.5 does not...
**Figure 18.5** left: Typical pattern of heterogeneity in SWE (mm) due to melt (June 1st, 2007); right: Vegetation cover fraction derived from binary vegetation cover based on NLCD at 30 m resolution. Black oval: high SWE heterogeneity around timberline, dashed line: National Park Road in a forest aisle, dotted circles: zones of low heterogeneity in pixels with vegetation cover fraction near 1.

**Figure 18.6** Spatial distribution of absolute values of total annual deviation between Melt$_{500\text{m}}$ and Melt$_{30\text{m}}$ (%). Inset: distribution of the deviation values.
refer to the density of evenly spaced trees, but to the fraction of 30 m pixels in the 500 m pixel that has trees in it. Thus, as for the previous two zones, this group of pixels represents a heterogeneity canopy cover. The zones of low SWE heterogeneity coincide with pixels of homogeneous vegetation cover. The four zones below the timberline (circled in Figure 18.5) include almost no open pixels, and the vegetation fraction is near 1.0. Above the timberline the SWE heterogeneity is also low, but here the homogeneous lack of vegetation cover is the reason.

Heterogeneity from melt:

- Comparison of the two patterns show high persistence between years, but heterogeneity from melt depends on timing of onset of melt.
- Location of high values in the two components do not coincide spatially, but both are correlated with vegetation cover: Accumulation = above timberline; Melt = transition zone between forested and open.
- Maximum heterogeneity caused by accumulation is higher than the one caused by melt.

Limitations

Currently the reconstruction model is still limited in the extent of heterogeneity that can be captured during the melt season. Potential melt is simulated at 30 m resolution, but $f_{SCA}$ only provides one scalar per 500 m MODIS pixel to indicate the snow covered fraction. How much of the pixel is covered is known, but location within the pixel is not. Consequently, transferring the full information of the potential melt from Isnobal to the reconstruction is not possible and the melt is assumed to be uniform within a MODIS pixel. Figure 18.6 shows that this might be an acceptable assumption, but that it is not completely true; it shows the deviations of total annual melt at 30 m resolution from the total annual melt averaged over 500 m resolution. Deviations range from -40% to 60%, but these extreme values occur only rarely as shown in the inset in Figure 18.6. Most of the large deviations occur at lower elevations or along the National Park road where snow is only present for a few days of the year. 80% of the pixels deviate by less than 12% from the 500 m average.
18.6 SUMMARY AND CONCLUSIONS

A new approach to characterize the snowpack in mountainous basins using minimal ground-based measurements is proposed. The SWE reconstruction method presented does not require precipitation input, which makes it a highly attractive method to improve predictions in ungauged basins. In addition to pixel total SWE, which was estimated in previous reconstruction efforts, this model also captures the variability in SWE distribution within each modelling unit. It combines the daily change in fractional snow covered area with cumulative daily melt, computes the distribution of SWE, and summarizes its spread as the range between 25th and 75th percentile of the distribution, normalized by the median SWE.

This study further demonstrates how to separate and locate the two contributions to SWE heterogeneity: During accumulation, heterogeneity is highest in the open areas above the tree line. Once melt sets in, the heterogeneity increases also at the transition between forested and open areas.

In winter, snow accumulation is heterogeneous because of wind (Winstral et al., 2013); however, reconstruction accounts for the results of wind-redistributed snow at the beginning of the melt season, even though it does not model the actual distribution processes. Thus it provides an independent method of examining the spatial distribution of snow, which is useful to validate models of snow accumulation, either owing to redistribution (Elder et al., 1991) or to precipitation itself, such as PRISM (Daly et al., 2001; Davis et al., 2001). It is also useful in evaluating other methods to measure snow accumulation and its spatial variability, for example passive microwave. Not only does reconstruction match streamflow better than other methods (Rittger, 2012), it shows the significant negative bias of passive microwave measurements (Vander Jagt et al., 2013).

The measurement of heterogeneity can improve the way we model snowmelt. When the snowcover becomes patchy, uncovered ground will alter the advective energy exchange with the snowpack. Usually in our models, we refine the grid size down to the point where we make the cells individually homogeneous, but this strategy drives consumption of computational resources. Can we instead develop our distributed hydrologic models to account for heterogeneity in each cell (Luce and Tarboton, 2004)? This issue becomes particularly important when we incorporate snow into
land-surface interactions for climate models, because in addition to the obvious processes like snowmelt, the distribution of snow affects biogeochemical fluxes like carbon exchange (Pitman, 2003) and other elements of the land-surface interaction (Giorgi and Avissar, 1997; Liston, 2004; Swenson and Lawrence, 2012). Snow is therefore a general example of the importance of spatial patterns in the hydrologic response of catchments (Grayson et al., 2002). Improvements needed include better quantitative methods for pattern comparisons and better use of pattern information in data assimilation and modelling.

Finally, snow heterogeneity is important for a wide range of animal behaviour and vegetation patterns in the mountain environment; for example, caribou eat not the most nutritious lichen, but the lichen that are beneath the shallow snow patches (Johnson et al., 2001). Snow heterogeneity also affects the response of ecosystems to climate change, for example plant growth, arthropod communities, and carbon cycling. Winter snowcover and depth will add to spatial patterns in vegetation heterogeneity (Bokhorst et al., 2012).