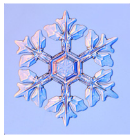

Fractional snow cover estimation in forested-alpine environments using data fusion between IKONOS, Landsat and MODIS

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Statement of Problem:

Enhanced understanding of present and future climate and water cycle changes requires accurate assessment of seasonal snow cover [1; 2].

The climatological and hydrological importance of snow cover is linked to its **(a)** high surface albedo, **(b)** significant heat capacity, **(c)** good insulating properties, **(d)** substantial water storage, **(e)** and eventual release of this storage during the melting season.

Since the middle of the 20th century, the snow pack area in the Northern Hemisphere decreased about 10%, mainly due to a decrease in precipitation falling as snow and an earlier melt season in Spring and Summer [3-7].

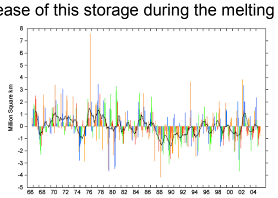


Figure 1. Changes of snow cover in the Northern Hemisphere. blue - winter , green – spring, red – summer, orange – fall, black – 12-month running meen(www.MODIS.gov)

For most of the 19th and 20th centuries, monitoring of snow cover extent (SCE) and snow water equivalent (SWE) was based on sparse ground and field measurements [8; 7]. During the last decades of the 20th century, active and passive satellite imagery enhanced and broadened monitoring of SCE and SWE on global and continental scales [9-12].

However. estimation of SCE and SWE at regional and watershed scales, in open alpine terrains and/or mountains covered by dense vegetation is still inadequate due to the complex spatial variability of many environmental factors such as: elevation, slope steepness, exposition, shadow effects, solar illumination, look geometry, snow depth and patchy snow cover [14-15] .

The main aim of the research *is to provide accurate measurements of SCE in forested and/or mountainous areas using currently available optical remotely sensed datasets. This aim is met through data fusion between daily temporal resolution images with 500 m spatial resolution (MODIS), 30 m (Landsat TM, ETM+), and 4 or 1 m (Ikonos) spatial resolution images.*

Methodology:

The research study area is in the headwaters of the San Juan River, located in the Upper Colorado River Basin, Colorado, USA. The Upper San Juan River Basin represents heterogeneous alpine and/or forested terrain with high SCE seasonal variability.

An Artificial Neural Network (ANN) is used to estimate fractional snow cover because it is a straightforward means of extracting fractional values contained in multi-spectral imagery from all image information.

The proposed ANN is a multi-layer perceptron [15].

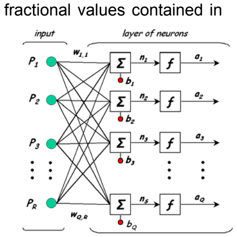


Figure 2. The architecture of one layer in a multilayer feedforward perceptron. P1, P2, .., PR – input; w1,1 .., $w_{Q,R}$ – weights; Σ- sum of the weighted inputs; b – bias; Q – number of neurons; a – network output; f - activation function; R – number of elements in input vector

The ANN training process is accomplished in two stages to bridge the 250,000:1 area ratio of MODIS 500 m pixels to 1 m Ikonos.

- high spatial resolution imaging (Ikonos, 1 m) is used to ascertain actual FSC for training the ANN estimator operating on much larger Landsat pixels (Figure 3; section A).

- FSC mapped using the Landsat estimator provides truth for training of ANN ModisFSC (Figure 3; ANN2; section B).

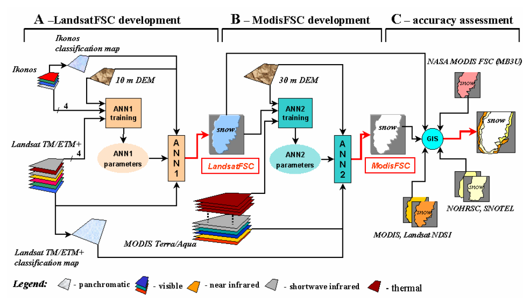


Figure 3. Information flow during the development of LandsatFSC and ModisFSC with ANN.

The inputs to the ANN are*: image data, topographic data, solar geometry, look angles, and terrain classification.*

Image data come from Landsat TM/ETM+ and MODIS Terra/Aqua sensors.

Topographic data are input as mean elevation, mean slope direction, mean and standard deviation of inclination, and computed from 10 m DEM for LandsatFSC ANN

Solar geometry are input as geographic azimuth and elevation angles, and as angles relative to the mean slope normal.

Look angles are specified in the same way as solar angles.

A classification map of the terrain are derived from the higher resolution sensors (Ikonos and Landsat respectively) using data from late Fall, prior to any snowfall (Figure 3; *Ikonos and Landsat classification maps*).

LandsatFSC and ModisFSC algorithms derived in the headwaters of the Upper San Juan River, Colorado, USA are validated in: **(1)** alpine terrains (San Juan Mountain, CO); **(2)** sub-alpine terrains (White Mountains, Arizona, USA); **(3)** deforested lowlands with patchy snow cover (Great Plains, USA); and **(4)** densely forested lowlands with patchy and fully developed snow cover (Saskatchewan, Canada).

Preliminary Results:

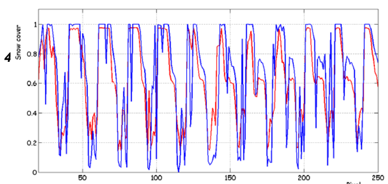
The ANN Landsat FSC ***learning process*** was performed through supervised, unsupervised and reinforcement training; however, the main focus was placed on supervised learning: performance learning with three optimization algorithms: steepest descent[1], Newton's method[2] and conjugate gradient[3] [15]. Mean square error (MSE) was used as a performance index.

In the ***training process***: log-sigmoid, tan-sigmoid and linear transfer activation functions were used: [16 -18]. The training process was conducted through two different modes: sequential and batch [15]. To protect the ANN from ***overfitting*** during the training process, an early stopping method was used.

The trained Artificial Neural Network is operational in Matlab and has produced simulated fractional snow cover for Landsat imagery. The preliminary results show a significant and consistent relationship between the snow map classification, based on the panchromatic IKONOS band, and Landsat TM5 multispectral bands: 2, 4 and 5 (Figure 4).

***Blue line* – IKONOS snow classification,**
***Red line* – simulated LandsatFSC**

Figure 4. Simulated LandsatFSC (bands: 2, 4 for south-facing slope with forest area changing from 0 to 100%.
ANN architecture: 14:34:1;
3 x sigmoid activation function;
ANN train with "traindga" function,
MSE=0.06 [15].



[1] $W_{k+1} = W_k - \alpha_k g_k$; where $g_k = \nabla F(W)|_{W=W_k}$; where $F(W)$ - performance function, α_k – learning rate parameter (stepsize);
[2] $W_{k+1}=W_k-A_k^{-1}g_k$; where: $A_k = \nabla^2 F(W)|_{W=W_k}$; $g_k = \nabla F(W)|_{W=W_k}$; $F(W)$ - performance function,
[3] $W_{k+1} = W_k + \alpha_k p_k$; where $p_k = -g_k + \beta_k p_{k-1}$; $g_k = \nabla F(W)|_{W=W_k}$; $\Delta g_k = g_{k+1} - g_k$;

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San Juan Mountains, south slopes – Wit Wisniewski summer 2006.