A NEW STRATEGY FOR SNOW-COVER MAPPING USING REMOTE SENSING DATA AND ENSEMBLE BASED SYSTEMS TECHNIQUES

Sophie Roberge[1], Karem Chokmani[1], and Danielle De Sève[2]

[1] Institut National de la Recherche Scientifique (INRS), Centre Eau Terre Environnement, Québec (Québec), Canada

[2] Institut de Recherche d'Hydro-Québec (IREQ), Varennes (Québec), Canada

INRS Université d'avant-garde

1. Context

The snow-cover plays an important role in the hydrological cycle of Quebec (Eastern Canada). Most snow-cover mapping algorithms developed so far provides only a binary result: presence or absence of snow. Their snow detection criteria values are too rigid. It can be inappropriate to adequately map snow in some parts of the world.

2. Objectives

The main objective of this study is the **development of a snow-cover mapping algorithm strategy using remote sensing data and ensemble based systems techniques.** This mapping strategy has the advantage to provide the probability of a pixel to be snow covered and its uncertainty.

3. Data and study area

Historical dataset of NOAA-AVHRR images (1988 to 2011) taken during two critical transition phases of the hydrological cycle:

- ❑ Onset of snow cover in autumn (from October 1st to December 31st)
- ❑ Snow melting in spring (from March 16th to May 31st)
- ❑ Covering the province of Quebec and Labrador (fig. 1)

Historical data from meteorological stations

- ❑ Total of 20 stations
- ❑ Snow accumulation (in cm)

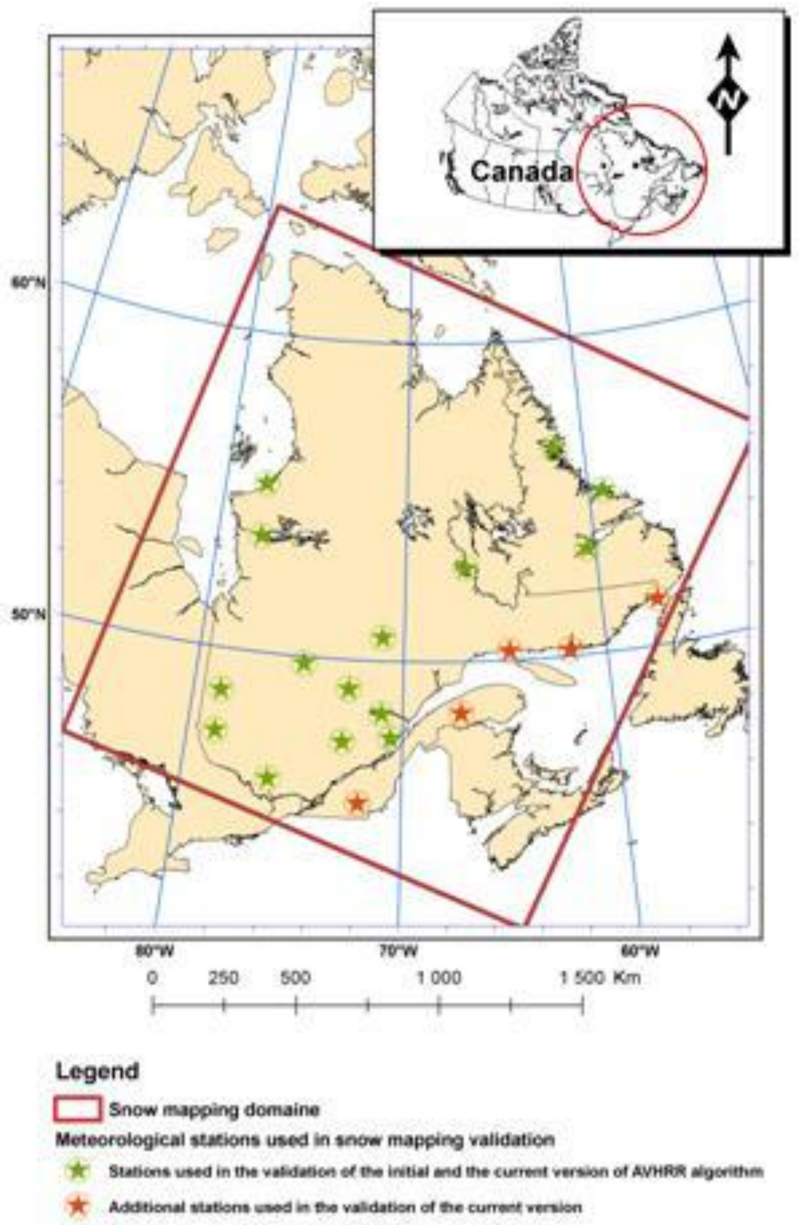

Fig 1 : Location of study area and meteorological stations

4. Calibration

The snow-cover mapping algorithm (SCMA) is made of a combination of six sequential thresholds varying according to the day of the season, going from the least restrictive to the most severe. Figure 1 shows the classification scheme.

Calibration includes:

- ❑ Pixel samples of snow, no-snow and clouds identified visually and manually extracted from an image selection containing 380 images taken during autumn and 253 during spring
- ❑ Pixel samples represent the diversity of land use prevailing in Quebec (bedrock, tundra, wetlands, boreal forest, deciduous forest, mixed forest, urban areas, agricultural areas), and diversity of climatic conditions
- ❑ Half of the pixel samples are dedicated to calibration and the remaining to validate the algorithm itself and to measure its performance
- ❑ Empirical thresholds are calculated on percentiles from radiometric data (T4, ΔT45, NDVI, ΔT34, A3, A1) of calibration pixels.
- ❑ 100 classifiers generated randomly
- ❑ Probability = amount of votes the pixel has been classified as such by all classifiers

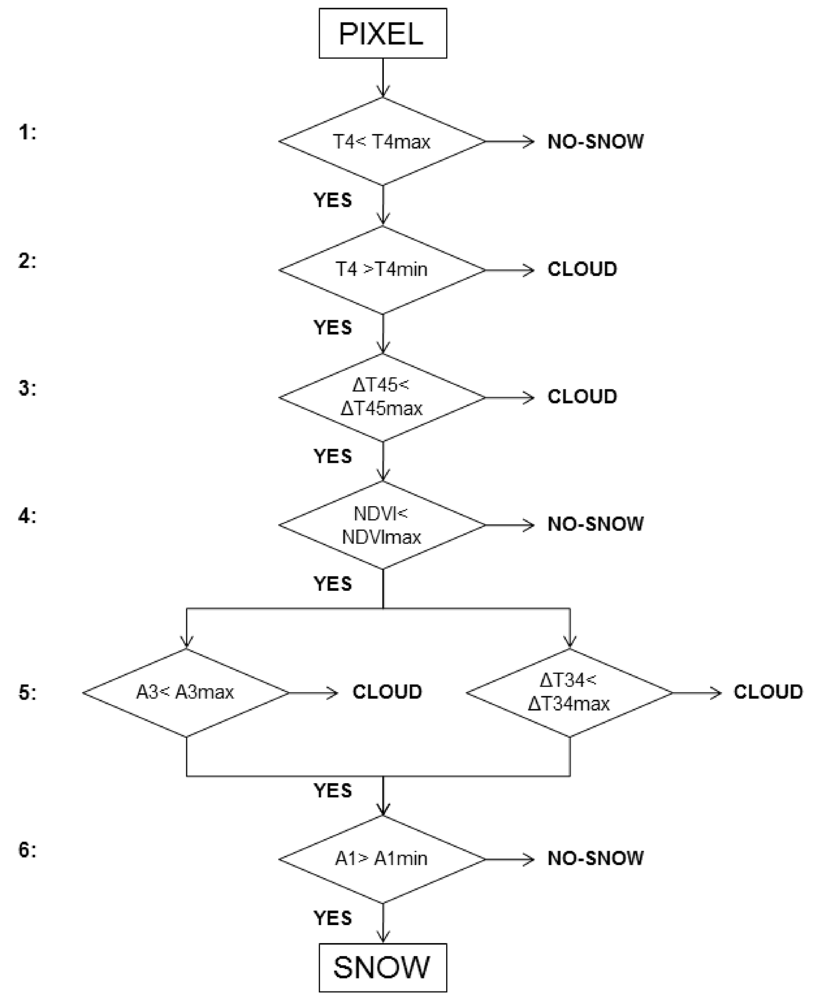

Fig 2 : SCMA classification scheme

<u>Algorithm: Generating classifiers</u>

Input:

- ❑ Calibration dataset

For *i* = 1 to 100

1. Do random permutations on input and take 2/3 of its size to create a sub-dataset
2. Choose randomly a percentile value (95, 96, 97, 98, 99)
3. Choose randomly a time-step value (3, 5, 7, 9, 11, 13)
4. Calculate empirical thresholds on sub-dataset created in (1) with parameters selected in (2) and (3)

End

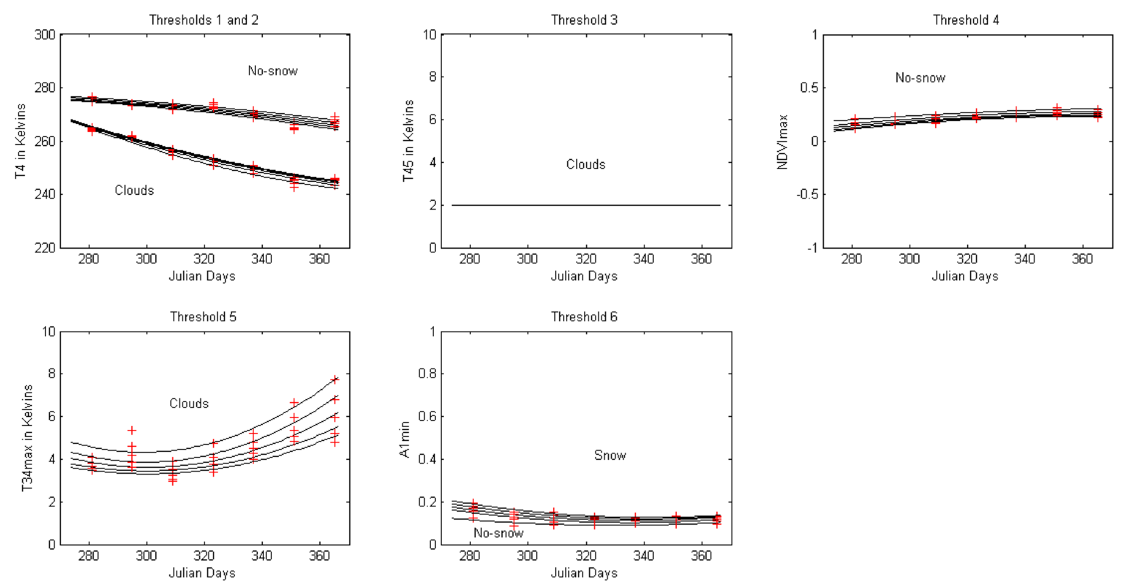

Fig 3 : Choosing randomly percentiles values to compute thresholds

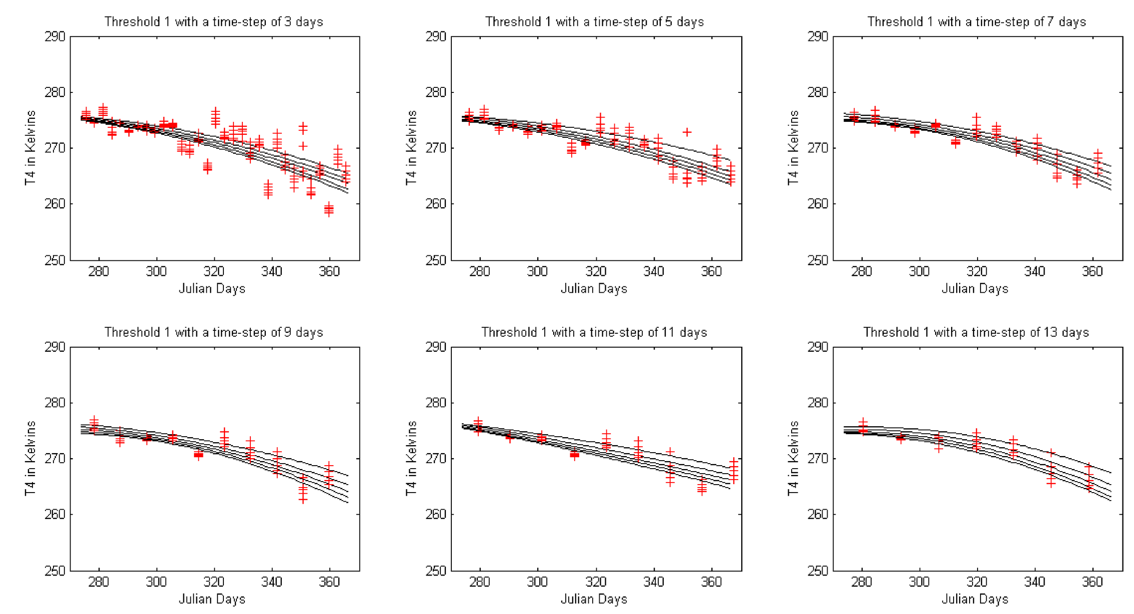

Fig 4 : Choosing randomly a time-step value to compute thresholds

5. Spatial validation

		Validation dataset					
		Snow	No-snow	Clouds	Total	Rate of success	Omission error
Calibration dataset	Snow	8930	300	643	9873	90%	10%
	No-snow	133	10223	21	10377	99%	1%
	Clouds	13	230	16251	16494	99%	1%
	Total	9076	10753	16915	36744		
	Commission error	2%	5%	4%	Overall success:		96%

		Validation dataset					
		Snow	No-snow	Clouds	Total	Rate of success	Omission error
Calibration dataset	Snow	56214	2080	4136	62430	90%	10%
	No-snow	168	14276	89	14533	98%	2%
	Clouds	113	48	62381	62542	100%	0%
	Total	56495	16404	66606	139505		
	Commission error	0%	13%	6%	Overall success:		95%

Table I : Error matrix for "autumn" (left) and "spring" (right) version of SCMA (mid-infrared channel) using a single classifier

		Validation dataset					
		Snow	No-snow	Clouds	Total	Rate of success	Omission error
Calibration dataset	Snow	8267	900	690	9857	84%	16%
	No-snow	26	10343	7	10376	100%	0%
	Clouds	26	350	16113	16489	98%	2%
	Total	8319	11593	16810	36722		
	Commission error	1%	11%	4%	Overall success:		95%

		Validation dataset					
		Snow	No-snow	Clouds	Total	Rate of success	Omission error
Calibration dataset	Snow	51145	6868	4261	62274	82%	18%
	No-snow	158	14319	56	14533	99%	1%
	Clouds	65	103	62374	62542	100%	0%
	Total	51368	21290	66691	139349		
	Commission error	0%	33%	6%	Overall success:		92%

Table II : Error matrix for "autumn" (left) and "spring" (right) version of SCMA (mid-infrared channel) using 100 classifiers

6. Conclusions

The snow-cover mapping algorithm we have developed for NOAA-AVHRR data detects snow, no-snow and clouds, with an overall success close to 96% in autumn and 95% in spring. It is reduced to 95% in autumn and to 92% in spring when one hundred classifiers are introduced in the algorithm. suggesting it is more sensitive to variations into its parameters. The rate of success for snow detection ends up to 84% in autumn and to 82% in spring compared to 90% in the single-classifier version. By creating different scenarios the algorithm tends to be more restrictive according to snow. This could explain why the rate of success of snow is lower in the ensemble based algorithm. The most significant difference between the single- and multiple-classifiers is the amount of snow pixels that becomes classified as no-snow. A possible explanation for this: these pixels have been mistaken for snow instead of snow during training sites acquisition. A validation with ground measurements will confirm or reject this hypothesis.

7. Acknowledgments

The authors would like to thank *MITACS Accelerate* and the *Institut de Recherche d'Hydro-Quebec* for their financial support.

Mitacs Hydro Québec

EGU General Assembly 2012 Vienna | Austria | 22-27 April 2012