Analysis of Northern Hemisphere Snow Data for 1979-2014

Hester Scheepers, Thian Yew Gan

Dept. Of Civil and Environmental Engineering, University of Alberta, Edmonton, AB

FloodNet Annual General Meeting
Vaughn/Toronto, 19th to 20th September 2016

Introduction

Snowpacks affects hydrology as water from melting snow provides the spring freshet and recharges ground water supplies. In many parts of the world, snow accumulation is a major source of water for irrigation, hydro-electrical generation and drinking water. Most Canadian river basins are covered with snow in the winter which are dominated by snowmelt runoff in the spring. Snow cover and snow depth are expected to change under global warming impact. The snow water equivalent (SWE) of snowpacks represents the amount of liquid water that would result after a snowpack has completely melted. The objective of this study is to analyze SWE derived from satellite data for the Northern Hemisphere using a range of statistical techniques.

Methodology

GlobSnow SWE Data:

SWE data was obtained from the GlobSnow-2 SWE product. The SWE record combined Nimbus-7 SMMR, DMSP SSM/I-SSMIS data with ground-based synoptic weather stations. It is produced at a daily, weekly and monthly basis between 1979 and 2014, at a 25km resolution and provided for terrestrial non-mountainous regions in the Northern Hemisphere excluding Greenland.

Climate Indices:

Several different climate indices were correlated to detected changes of SWE. Climate indices are diagnostic quantities that characterize atmospheric circulation patterns obtained from analyses of geopotential height fields, sea surface pressure or sea surface temperature. Monthly climate indices used in this study included the Artic Oscillation (AO), North Atlantic Oscillation (NAO), Pacific North American pattern (PNA), Pacific Decadal Oscillation (PDO), Southern Oscillation Index (SOI) and the Niño3 index.

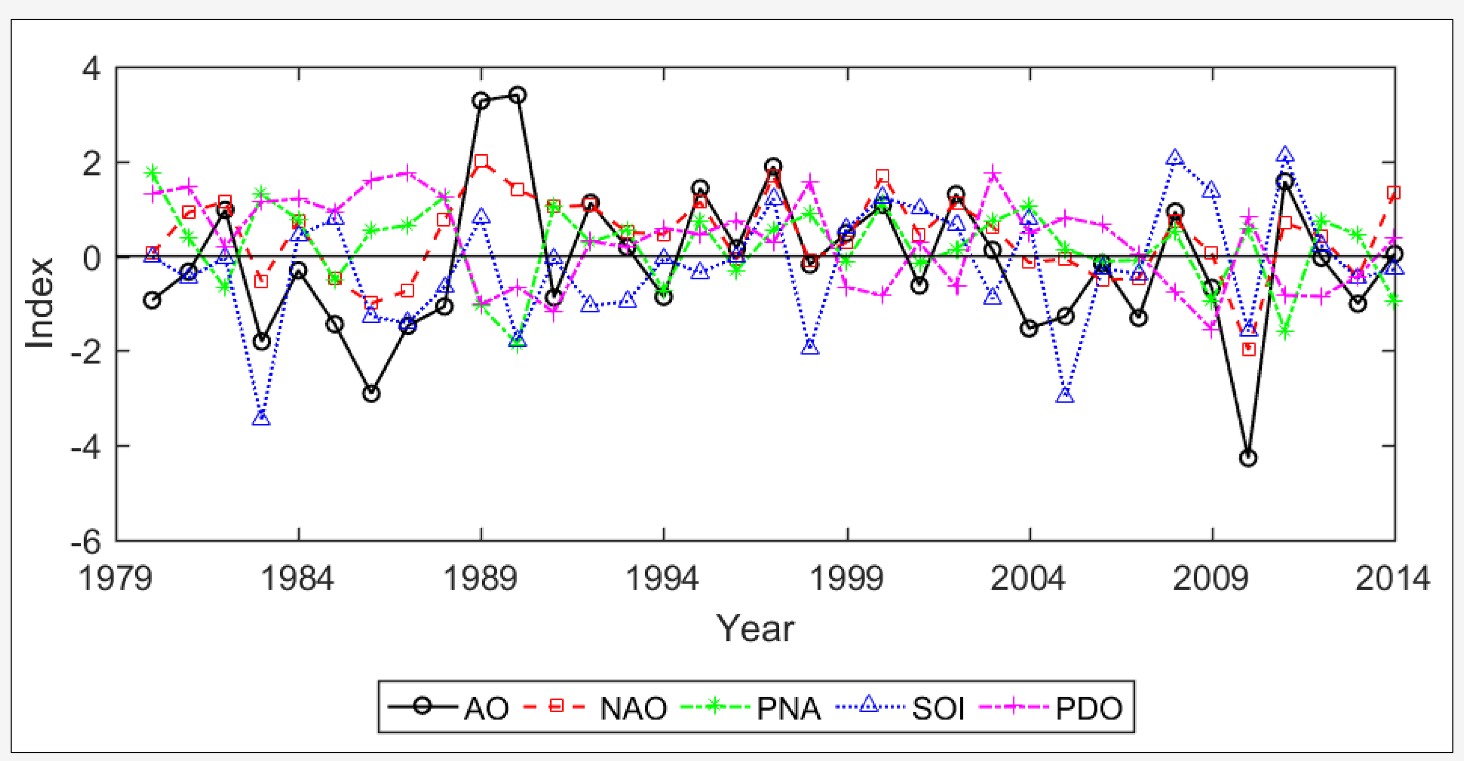

Figure 1. Monthly climatic indices for February. Positive (negative) numbers indicate the positive (negative) phase.

Trends:

Trends and trend magnitude in SWE data was tested using the non-parametric, Mann-Kendall test (Kendall, 1975; Mann, 1945) and the Theil–Sen slope estimator (Sen, 1968). which can handle non-normality, missing values, and seasonality.

Principle Component Analysis:

Principal component analysis (PCA) is a method to reduce the dimensionality of data while retaining the variability through an orthogonal transformation which identifies the principle components (PCs) along which the variation is maximal. The leading PCs were correlated with the various climate indices.

Self-Organizing Map:

The self-organizing map (SOM) (Kohonen, 2001) is a type of artificial neural network which aims to discover an underlying structure in the data through unsupervised learning to produce a two dimensional array of nodes, called a map, that are organized in such a way that similar items are close together.

Results

Trends:

The monthly SWE dataset of October-May was analyzed using the non-parametric Mann-Kendall test at 0.05 significant levels. Figure 2 shows snow covered pixels that exhibited increasing and decreasing trends for November to April.

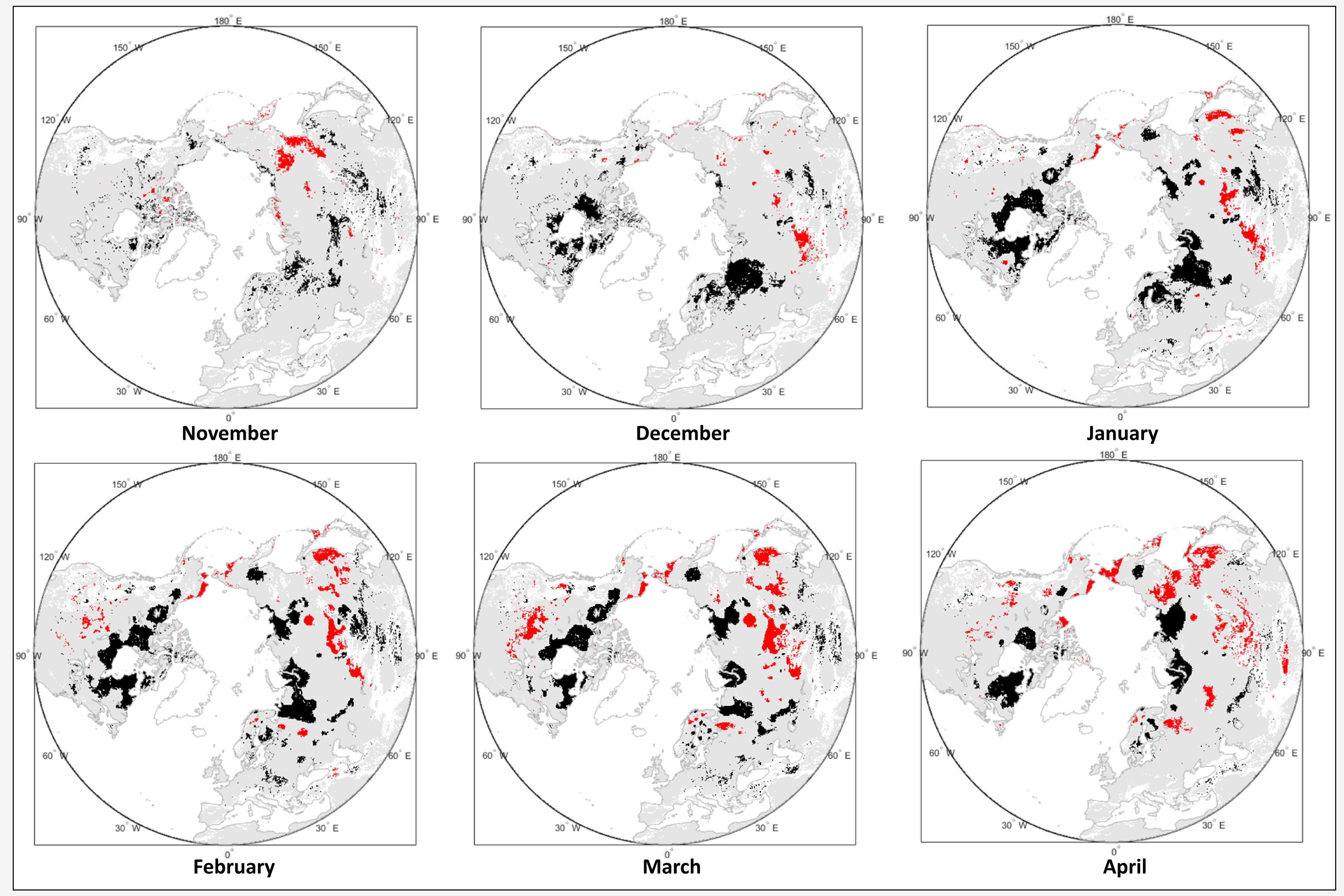

Figure 2. Northern Hemisphere monthly SWE increasing (**red**) and decreasing (**black**) trends (mm/yr) statistically significant at 0.05 level.

- Based on the total number of snow covered pixels analyzed, up to 15.5% (7.7%) of the pixels show statistically significant decreasing (increasing) trends.
- December has the largest snow cover extent and the greatest percentage of statistically significant decreasing trends, of which the majority are located north of 55° latitude. April exhibits the greatest percentage of statistically significant positive trends and most of these are located in Asia.

Principle Component Analysis:

- Scree plots (figure not shown) of the October – May 1979-2014 SWE show that in most months, about 50% of the variance is explained by the first six PCs. The leading component explains between 14.4% and 23% of the variance. Figure 3 shows the scores of the first four PCs.

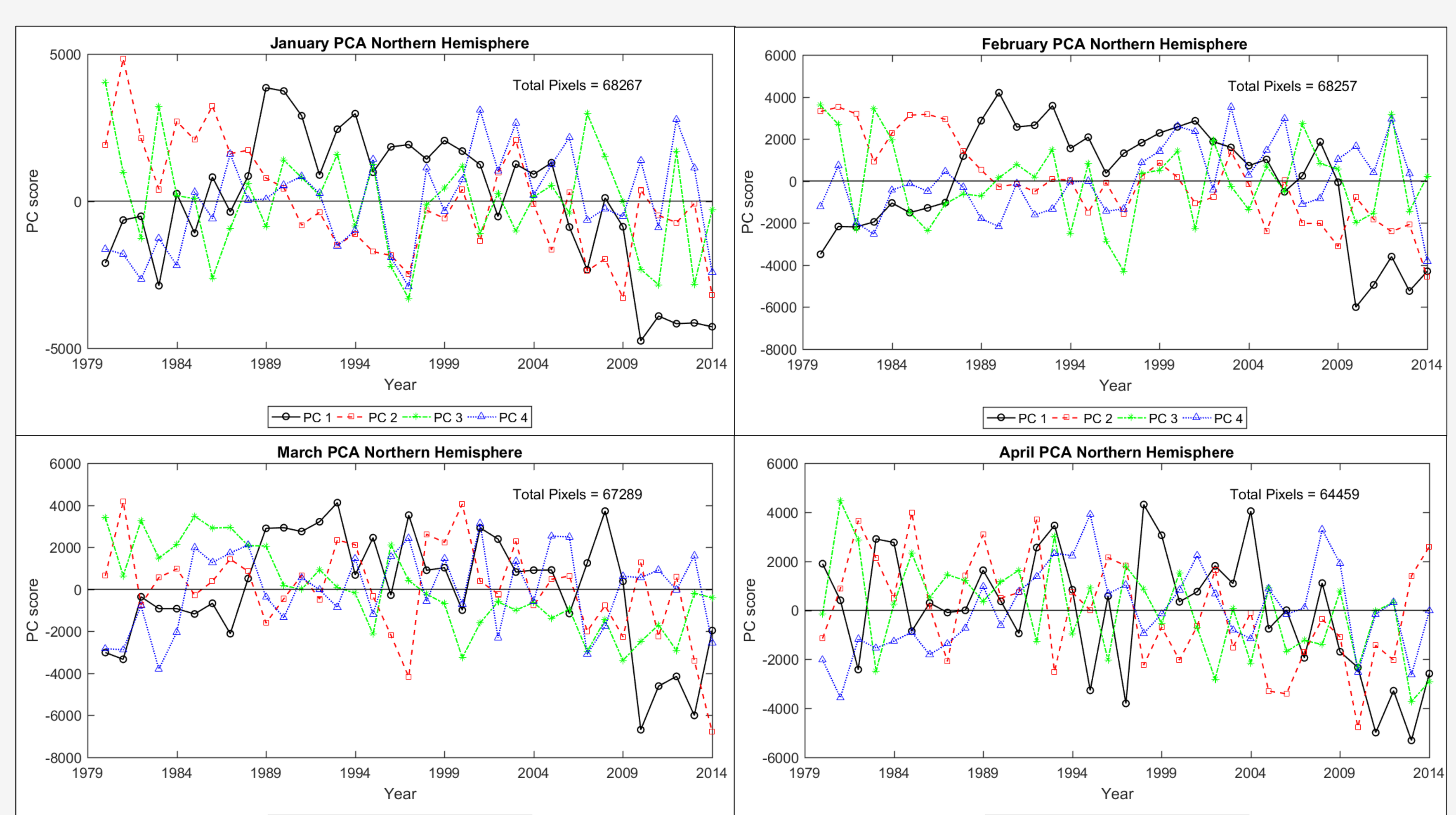

Figure 3. PC1, PC2, PC3, and PC4 of monthly SWE of 1979-2014 for January to April.

- Climate indices which were correlated with any of the first four PCs at a significance level of 0.05 are shown in Table 1 using Pearson's correlations.
- Climate indices appear to exert the greatest influence between the months of January and April.
- PC1 is mostly correlated with the AO and NAO, while the PDO and PNA are correlated with PC2 to PC4 in some months.

Table 1. Climate indices statistically significantly correlated to SWE PCs

	PC1	PC2	PC3	PC4
Oct				
Nov			PDO	
Dec				
Jan	AO, NAO, PNA	PDO	AO	PNA
Feb	AO, NAO	PDO	PNA	
Mar	AO, NAO	PNA	PDO	SOI
Apr	AO	PNA		PDO
May				

Self-Organizing Map:

- In the SOM analyses, the SWE dataset was applied such that each grid point is a different sample, and each month is a different variable.
- Similar SWE grids were associated with single neuron and similar neurons were located close together.
- K-means clustering was used to create 20 groups of similar neurons, which resulted in the map shown in Figure 4 depicting 20 regions of similar SWE pattern regions.

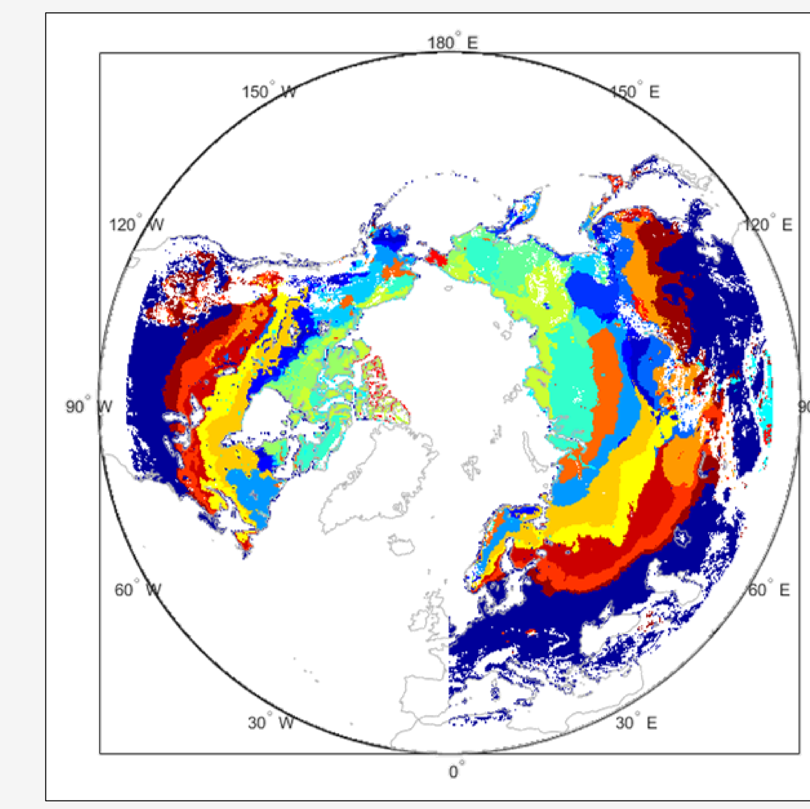

Figure 4. SWE regionalization from SOM analyses

Conclusions

- The number of snow covered pixels that show statistically significant decreasing trends are almost double the pixels that show increasing trends in December when the snow extent is the greatest. Annual SWE trends also indicate that most of the increasing SWE trends are located in Asia. Most of the decreasing trends are geographically located north of 55° latitude which may reflect the effect of polar warming.
- The mean trend magnitudes detected for October to May range from -0.18 to -1.42 mm/yr, which could mean an over reduction of snow depth of approximately 2.5 to 19.9 cm in 35 years assuming a snowpack density of 250 kg/m3, which can impact regions relying on spring snowmelt for water supply.
- ENSO (in terms of Niño3 and SOI) does not show significant correlation to principle components 1-4 of SWE on a hemispheric scale. Climate anomalies that could contribute to the SWE trends are AO, NAO, PDO, and PNA that are somewhat correlated to SWE during the months of January to April.
- SOM analyses is an alternative method for investigating SWE patterns and the atmospheric influence on SWE in the Northern Hemisphere, as well as the effects of other atmospheric variables such as temperature and precipitation.

References

Kendall, M. G. (1975), Rank Correlation Methods, Charles Griffin, London.

Kohonen, T. (2014), MATLAB Implementations and Applications of the Self-Organizing Map. Unigrafia Oy, Helsinki, Finland.

Mann, H. B. (1945), Nonparametric tests against trend, Econometrica, 13, 245–259.

Sen, P. K., 1968, Estimates of the regression coefficient based on Kendall's tau, J. Am. Stat. Assoc., 63, 1379-1389.