Investigation study on Tundra Snow Cover Characteristic by MRS

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Abstract: By using tundra snow cover can influence local and regional scale surface water balance, energy fluxes, and ecosystem. At regional and hemispheric scales, the estimation of snow extent, snow depth and, snow water equivalent (SWE) is important because high latitude snow cover both forces and reacts to atmospheric circulation patterns. Remote sensing techniques have been employed to monitor the snow since the1960s when the visible light channels were used to map snow extent. Passive microwave data are the only currently operational sources for providing estimates of dry snow extent, SWE and snow depth. The overall objective of this research is to improve operational capabilities for estimating end of winter, pre-melt tundra SWE using satellite passive microwave data. We use the data located in the mountain area. The spatial distribution of snow depth, density and SWE in the study area is controlled by the interaction of blowing snow with terrain and land cover. Despite the spatial heterogeneity of snow cover, several inter-annual consistencies were identified. A principal component analysis (PCA) showed that there are differences in ΔTb among different EASE grids and that land cover may have an influence on regional Tb. due to the complexity of snow and terrain in high resolution footprints, it was a challenge to isolate a relationship between SWE and Tb. Despite the many challenges, algorithm development should be possible at the satellite scale.

[Alirezazahedi. **Investigation study on Tundra Snow Cover Characteristic by MRS.** *Rep Opinion* 2015;7(11):11-18]. (ISSN: 1553-9873). http://www.sciencepub.net/report. 2. doi:10.7537/marsroj071115.02.

Keywords: Passive Microwave Remote Sensing, Tundra Snow, hemispheric scale, microwave data

1- Introduction

Seasonal snow cover directly affects many aspects of our infrastructure, economy and livelihood. Snow is often viewed as a burden; however, springtime snowmelt provides much needed runoff for agriculture, potable water supply and hydroelectric generation. Furthermore, snow is an essential cryospheric element to understand and monitor as it also has several direct effects on fundamental Earth systems. The high albedo of snow cover reflects incoming solar radiation and perpetuates lower surface temperatures. Moreover, snow is also a good insulator which reduces the depth and extent of ground frost as well as reducing the net heat exchange between ground and the atmosphere. These physical changes affect the atmosphere at its lower boundary, and snow cover is recognized as an important factor which influences the climate on local, regional and global scales (Armstrong et al.,1997).Furthermore, the spatial and temporal distribution of snow extent and depth are primary controls on ecosystem carbon exchange. Moreover, recent research suggests that late winter snow depth and spring-thaw timing strongly affect the annual cycling of carbon and nutrients along with other important biogeochemical processes in the Arctic (Baghdad, et al., 1997).

The accuracy and dependability of models to predict future changes in climate and snow cover are dependent on their ability to reconstruct past and present conditions(Derksen and LeDrew, 1994). The primary limitation is that many tundrasnow cover data sets are spatially constrained and/or temporally discontinuous (Derksen, et. al., 2000).

Given the linkage of tundra snow to many physical systems, the spatial and temporal discontinuity of current data sets, and the lack of operational snow cover monitoring protocol, there is a need for developing an intensive tundra snow cover data set for

1) the improvement, development and validation of large scale satellite remote sensing algorithms,

2) the extrapolation to large scale process models, and

3) the definition of features that cannot currently be easily remotely sensed or modeled (such as snow density and snow on sub-grid scale landscape features).

Snow cover parameters of interest are the spatial and temporal distribution of 1) snow extent, 2) snow depth, and 3) SWE. Snow extent is required for climate, hydrological and ecological research as it defines the percentage of land surface occupied and influenced by a snow cover, required for quantifying land surface albedo and subsequent radiation balance. Snow depth information is an important parameter for studying energy balance, carbon cycling and ecosystem dynamics, while SWE, calculated from snow depth and density, is important for estimating snowmelt runoff, evaluating climate models, and the detection of trends related to snow mass. The seasonal evolution of the snowpack is important; however, estimates of pre-melt tundrasnow depth and SWE are most useful for both local and regional scale modeling.

Passive microwave sensors provide one of the best opportunities for providing spatially and temporally comprehensive high latitude snow cover data. These sensors have the advantage of being remotely collected with a daily frequency, extremely cost effective, and immune to atmospheric conditions (cloud cover). Furthermore, a long time series of archived data is available (1978 to present).

The overall objective of this research is to improve operational capabilities for estimating end of winter, pre-melt tundra SWE in a representative study area using satellite passive microwave data. In order to meet this objective a series of steps will beunder taken and detailed in the remaining chapters. They include:

1) outlining the importance of tundra snow and sources of snow cover data and reviewing the literature and determining theoretical limitations of passive microwave remote sensing for monitoring tundra snow cover. 2) analyzing in-situ data so that a better understanding of the distribution and properties of tundra snow can be achieved 3) evaluating the performance of current passive microwave algorithms for estimating tundra snow.

Tundra snow cover is an extremely important parameter to understand and monitor as it influences local, regional and global scale surface water balance, atmospheric dynamics, weather and climate patterns, surface energy and biogeochemical fluxes, along with ecosystem and permafrost dynamics.

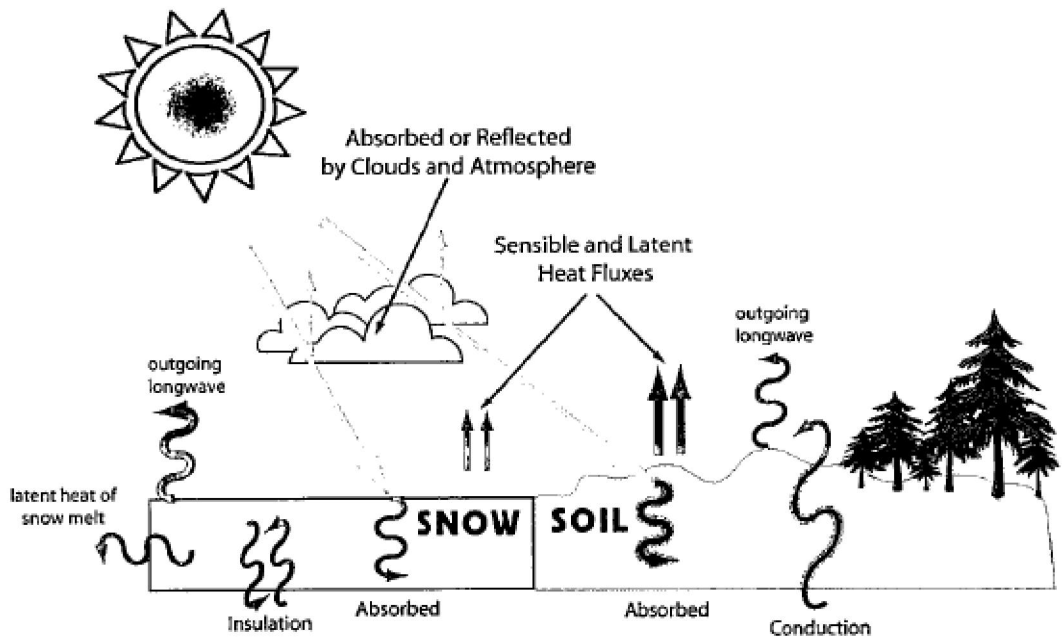

Figure 1. The comparison in shortwave energy reflection between a snow surface and bare soil

In the studied area, atmospheric dynamics are controlled in part by changes in lower boundaries. As such, snow cover is recognized as a key factor in influencing local, regional and global climates. Therefore, the spatial and temporal distribution of tundra snow is a key factor in determining the nature of winter climate. Snow has many unique surface properties which influence the surface energy balance. These include 1) a large latent heat of vaporization and fusion compared to water, 2) a low thermal conductivity, 3) a high albedo compared to soil and vegetation, and 4) a lower surface roughness compared to most land surfaces. The large scale high albedo surface of seasonal snow, prevalent for several months, significantly influences global circulation patterns. Based on the parameters discussed, Figure 1 demonstrates how the energy balance of a snow free soil surface can be compared with that of snow covered land.

In Figure 1, the incoming and outgoing energy are largely balanced over bare soil; however, there is a large energy deficit produced over the snow covered surface. This deficit exists during winter over large high latitude land areas, which results in significantly lower surface air temperatures. Cold northern snow covered regions act as a source for continental polar air masses which migrate into mid-latitude regions under large-scale circulation. These air masses are associated with cold surface temperatures. Snow cover has a large influence on the amount incoming energy lost to the atmosphere. As such, the onset of snow accumulation, the snow depth throughout the winter, the frequency of subsequent snowfall events and the timing of snow melt are key parameters which control snow-climate feedbacks. Seasonal snow cover is present on the tundra for up to 8 months of the year, and snowfall comprises over 50 percent of the total annual precipitation input to high latitude regions.

Snow ground interface temperatures can vary significantly within a few hundred meters due to differences in snow thickness. The impacts of changes in snow accumulation, extent, melt timing and duration, density, and structure on the ground thermal regime, active layer formation and permafrost have been well documented. The spatial, temporal and functional response of tundra vegetation to changes in snow cover could further influence global climate through direct impacts on radiation and energy balances. In the tundra, shrubs have been shown to modify the distribution, depth and properties of the snow pack. In areas where shrubs are more abundant, there is a greater accumulation of drifted snow, and less snow is lost throughout the winter due to sublimation. There are several ways in which tundra snow cover data have been and are currently being obtained. The data are

1) Measured from in-situ surveys,

2) Derived directly from local weather station data,

3) Modeled to form distributed data and/or extrapolated from point data, and

4) Estimated from remote sensing data.

Each method has its advantages and disadvantages, and the utility of the data isbased largely on the required spatial and temporal resolution.

2- Literature review

The total amount of microwave energy output depends on the temperature and emissivity of the object. Emissivity, e, can be defined as the microwave brightness of a graybody relative to that of a blackbody at the same temperature (Dye, 2002). Blackbodies are defined as objects that are perfect absorbers of incoming energy, and in order to remain in thermodynamic equilibrium, are also perfect emitters of that energy. Sinceobjects emit only a fraction of energy relative to a blackbody at the same physical temperature, emissivity can be further defined as

$$e = Tb/ T$$

Where Tb is the brightness temperature of a graybody, detectable with passive microwave remote sensing and T is the physical temperature of the object (Hall, et al., 2012).

2-1-Passive Microwave Sensors

Passive microwave sensors detect naturally emitted passive microwave energy. Passive microwave sensors have been deployed on operational spacebome platforms since 1972 with the launch of the Electronic Scanning Multichannel Radiometer (ESMR)aboard the Nimbus satellites. Several researchers discovered that there exists a good correlation between increasing snow depth and decreasing passive microwave emission(Leathers and Luff, 2011). Using data from the ESMR, Observations from the ESMR satellites were not extensively analyzed as early understanding of the data was hampered by the coarse spatial resolution. The improved resolution of the SMMR sensor produced more widespread interest and subsequent research initiatives with the sensor data provided the foundation for passive microwave snow research. Although the SMMR or SSM/I sensors were deployed specifically for monitoring snow cover, they have proven useful for detecting snow cover and for estimating snow depth and SWE. Limitations from the coarse resolution of the SMMR and SSM/I sensors were partially overcome by the launch of the Advanced Microwave Sounding Radiometer Earth Observing System (AMSR-E) aboard the Aqua platforms in 2002.

2-2. Passive Microwave Data

Passive microwave data can be collected on either ground based, airborne or satellite platforms. For consistency, data from each platform are usually collected at a consistent incidence angle of 50 to 53 degrees. The instantaneous field of view (IFOV) of raw data is elliptical in shape and varies in size according to the height above ground and the antenna characteristics (Figure 2).

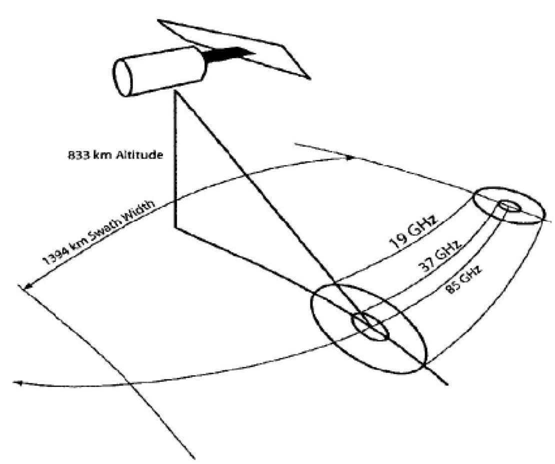

Figure 2. SSM/I scan geometry

Satellite brightness temperatures (Tb) are collected either as raw, unprocessed swath data or converted to the Equal-Area Scalable Earth Grid

(EASE-Grid) format. Swath data have the advantage of retaining the original frequency dependent imaging characteristics. However, for time series observations, changes in orbital location affect the swath level footprint location and necessitate the use of standardized EASE-Griddata (Derksen, 2008). The emission from the snow volume is influenced by many factors, including snow depth, SWE, snow density, liquid water content and snow grain size (Male, and NoI. 2005).

Within a dry snowpack, when the radii of snow grains approaches a few hundredths of the microwave wavelength, the volume scattering increases enough to produce a detectable decrease in Tb (Marshal et al., 1994).In dry snow, the presence of individual snow grains increases the amount of volume scattering and reduces the microwave emission. However, the dielectric constant is the measure used in microwave remote sensing to describe an object's electrical character. The dielectric constant for snow is a function of frequency, snow wetness, temperature and density (Van, 2005).As the dielectric constant increases, driven mainly by an increase in moisture content, the internal microwave emissivity increases, and in turn, the absorption increases (Loya, and Grogan, 1996). There have been many different passive microwave algorithms developed which can provide some estimate of snow cover properties over both hemispheric and regional scales. The common component in most operational algorithms is the use of the difference in emission over snow covered ground between a longer wavelength channel, usually 18 or 19 GHz and a shorter wavelength channel, 36 or 37 GHz. Regional algorithm development is focused on gaining a better understanding of snow-terrain-microwave emission interaction within specific environments. Regions of study have been typically subdivided based on land cover type. Primary areas of research have included open ground environments (prairies and open plains), sub-Arctic boreal forests and the sub-arctic to arctic tundra.

Currently, no operational passive microwave algorithms exist for the spatially expansive tundra and high Arctic regions due to the complexity in terrain, landscape and snow cover characteristics, along with the lack of in-situ data for development and testing. The heterogeneity of sub-grid tundra snow and terrain are definitely the limiting factors in using conventional SWE retrieval algorithm techniques. However, reliable estimates of SWE in these environments represent the final link to an otherwise nearly complete coverage of northern hemisphere snow cover monitoring and should be apriority.

It is not yet known to what extent sub-grid snow distribution will affect satellite scale Tb. Furthermore, there has been little research done to quantify within-grid tundrasnow cover variability in the context of coarse resolution algorithms and models. In order to determine the effect of snow distribution patterns on passive microwave algorithm development, a two tiered approach must be taken.

1) A better understanding of the physical processes involved in snow wind redistributionis required. For example, how do topography and wind direction control snow deposition? Can SWE and snow depth be classified according to topography and land cover? Is there any inter-annual consistency in these patterns?

2) Once snow cover distribution areas are classified within a pixel area, airborne and ground based radiometers could be employed to determine the microwave emission characteristics from each feature. This would determine the change in microwave emission across the landscape from flat tundra, through deep snow drifts to blown free ridges.

3- Satellite passive microwave data evaluation

Passive microwave sensors aboard space borne platforms have been operational since 1972 with the launch of the Electronic Scanning Multichannel Radiometer (ESMR).

The development of the Scanning Multi Channel Microwave Radiometer (SMMR) in1978, with improved resolution, resulted in interest in using passive microwave data in snow research. The SMMR sensor was followed by the Special Sensor Microwave Imager (SSM/I) in 1987 aboard the Defense Meteorological Satellite Program (DMSP) platforms. The SSM/I sensors are still in orbit and continue to provide passive microwave data. Application of SMMR and SSM/I data were restricted to large are as due to coarse spatial resolution. The Advanced Microwave Sounding Radiometer Earth Observing System (AMSR-E) sensors aboard the Aqua platforms in 2002 provide a finer spatial resolution and data at similar frequencies to those previously collected. Hence, the AMSR-E data often replace the still operational SSM/I data in current research efforts.

The time series of data provided since the launch of SMMR is of great interest for its potential to provide over 30 plus years of spatially extensive snow cover information.

Several researchers have exploited all or part of the available time series for application to hydrologie processes or evaluation of climate models (Derksen et al, 2000). Furthermore, the time series of passive microwave estimates can be merged with conventional data records dating from the early 1900s to produce an even longer time series of snow cover information (Derksen et al., 2004).

Essentially the biggest challenge is addressing the potential influence of sub-grid terrain and land cover properties on satellite Tb. However, before sub-grid heterogeneity can be resolved, there needs to be a comparison of satellite scale data with the in-situ SWE data. This is, in part, to confirm the underestimation of SWE using the conventional 37-19 GHz approach and to examine the behavior of each frequency with differing SWE. When the conventional 37 -19 GHz approach is used, there are several basic assumptions made:

1- Satellite Tb at 37 GHz changes throughout a winter season

2- Satellite Tb at 1 9 GHz does not change very much throughout a winter season

3- The Tb at 19 and 37 GHz are not systematically influenced by landscape or terrain

4- The difference between 19 and 37 GHz can be used to estimate SWE

Satellite data for the study region are available from the SMMR, SSM/I and AMSR-E platforms. The SMMR data were collected every second day, beginning with the fall/winter of 1978/79. The SMM/I data were collected daily beginning in the 1988/89season. AMSR-E data were also collected daily, starting in the 2001/02 season. The final season available at the time of analysis was 2007/08. All data were acquired in the EASE grid format from the National Snow and Ice Data Center (NSIDC). To investigate spatial patterns in Tb, an arbitrary domain of 40 EASE grid pixels was selected around the study area pixel. The domain was selected to be predominantly outside of the boreal forest and with varying lake fraction (Figure 3).

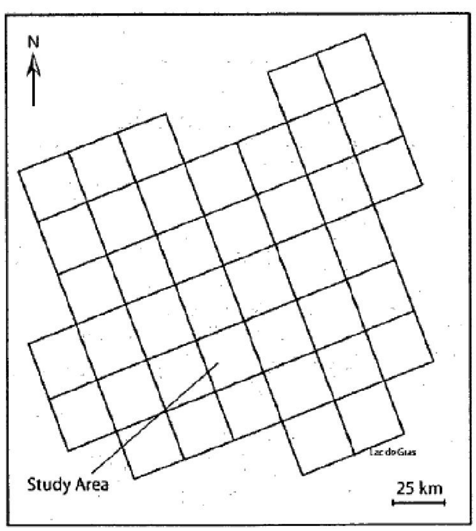

Figure 3. Spatial domain of time series EASE grids

1 - Satellite Tb at 37 GHz changes throughout a winter season

2- Satellite Tb at 19 GHz does not change very much throughout a winter season

The testing of these two assumptions is important to determine if there are in fact changes in Tb throughout a single season and from year to year. Chapter 4 showed that the mean SWE measured in the study area can reach a maximum of 171 mm at the end of the season and that mean SWE was different from year to year. If the 37 GHz Tb does not change throughout a season (from November to April) and if there are no differences in the end of season Tb from year to year, then there will obviously be serious problems in estimating SWE using passive microwave data. To examine the seasonal evolution of Tb within a single season the 37 GHz and19 GHz time series were plotted from November 1 to April 30 for the study area EASE grid pixel for each of the years with in-situ SWE data (Figure 4).

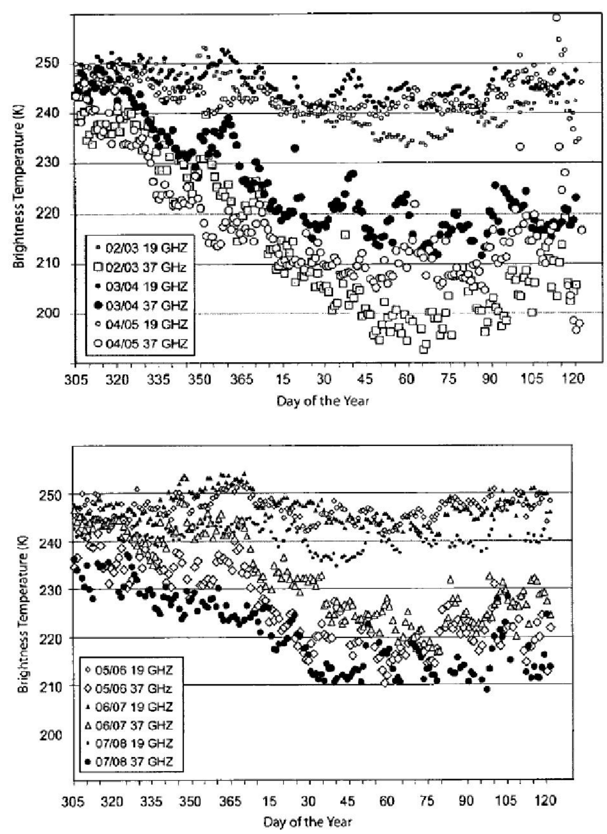

Figure 4. The seasonal evolution of 19GHz, 37 GHz

During each of the seasons plotted in Figure 4, the 19 GHz Tb values start some where between 245 and 250 K each season, dip to a minimum value of 235 to 245K around day 30 to 60 and return close to their starting point at the end of the winter. At19 GHz, the mid-winter decrease in Tb is likely a response to a decrease in air, underlying ice and ground temperatures. However, the changes in 19 GHz Tb throughout the season are not smooth. There are many jumps in Tb and, in some cases, over a relatively short period of time (for example 2003/04 from day 30 to 45).

4- Discussion

During each of the plotted seasons, the 19 GHz channel does not change very much from its original value, and there is a decrease in the 37 GHz Tb over time. This would imply that the use of a brightness temperature difference between the two frequencies should be possible. The ATb37"19 was plotted for November 1 to April 30from the study area EASE grid for each of the years with in-situ SWE data (Figure 5).

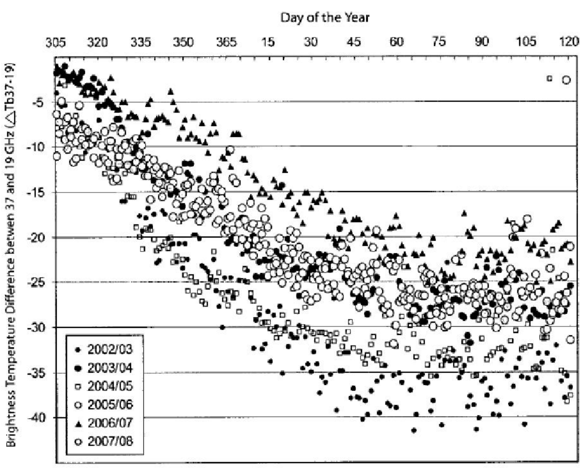

Figure 5. The seasonal evolution of the ΔTb

Figure 5 clearly shows that the ΔTb changes from near zero in early November (Day 305) to a maximum value of -20 to -42 at around days 75 to 90. This change in ΔTb throughout each season shows some sensitivity to parameters that evolve over a winter season. In the tundra, from November to April, there are several cryospheric elements which evolve: 1) changes in air temperature, 2) freezing of active layer, 3) lake ice thickness, 4) snow depth, 5) snow density, and 6) snow stratigraphy.

Eigenvalues are an output from the PCA with give precise information on the relative importance of each axis. The first component always has the highest eigenvalue followed by the second. Eigenvalues for each PC are created and often used as athreshold for determining which are most useful for interpreting the data.

By graphing eigenvalues for each factor (scree plot), the relative importance of each factor can be determined. Moreover, eigenvalues were converted into percent totalvariance explained and plotted to assist in determining how many factors should be considered (Figure 6).

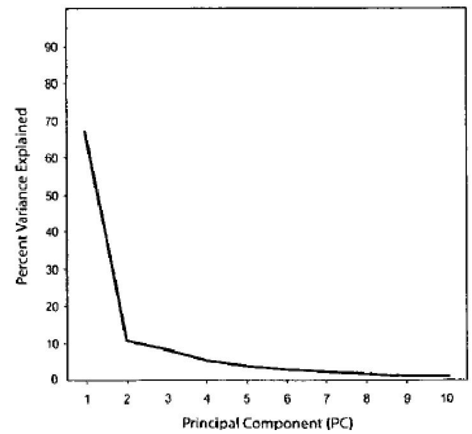

Figure 6. The percent variance explained by the first 10 components

Figure 6 shows that the first component (PC 1) explains 66 % of the total variance in ΔTb over the 30 year time series, while the second component (PC2) explains only 10 %. The variance explained diminished after the second component. Plotting eigenvalues or variance explained is useful but not the only step in selecting the number of factors. Kaiser (1960) suggests retaining all factors with eigenvalues over 1.Although this criterion is sometimes considered too strict, the PCA of ΔTb produced four components whose eigenvalues are over 1. These four components explain 88 % of the total variance in the spatial patterns of ΔTb over the entire time series.

The PCA was useful for generalizing patterns in ΔTb throughout the timeseries; however, component loadings are not useful for visualizing the spatial patterns. Itis clear that PC 1 is the dominant spatial trend; therefore, the year that loads highest into that component would be representative of the spatial pattern being summarized. In order to visualize the difference between components, the years which had the highest loadings were mapped. EASE grid data can be displayed as a grid of 25 ? 25 km cells with a single value for each cell. However, for simplicity of display and comparison, a smoothed surface was generated using inverse distance weighting (IDW) interpolation of the EASE grid centroid values (Figure 7).

The spatial pattern of ΔTb is clearly unique between the different components. The map of PC 1 (1997/98) shows a very distinct west to east longitudinal gradient in ATb37"19. The lowest values (- 39 ΔTb) are located to the west, and there is a longitudinal gradient eastward to higher values (-23 ΔTb) in the east. This pattern is somewhat different than the other PCs shown in Figure 7 and very different than the lake cover fraction. However, consistent to PC 1, PC 2, and PC 3 is that the lowest

ΔTb is located in the southwest corner of the domain. These spatial patterns and the longitudinal gradient in PC 1 suggest that there is an inter-annually consistent systematic influence on ΔTb. If the pattern is not related to lake faction then it could be related to land cover or to differences in snow accumulation.

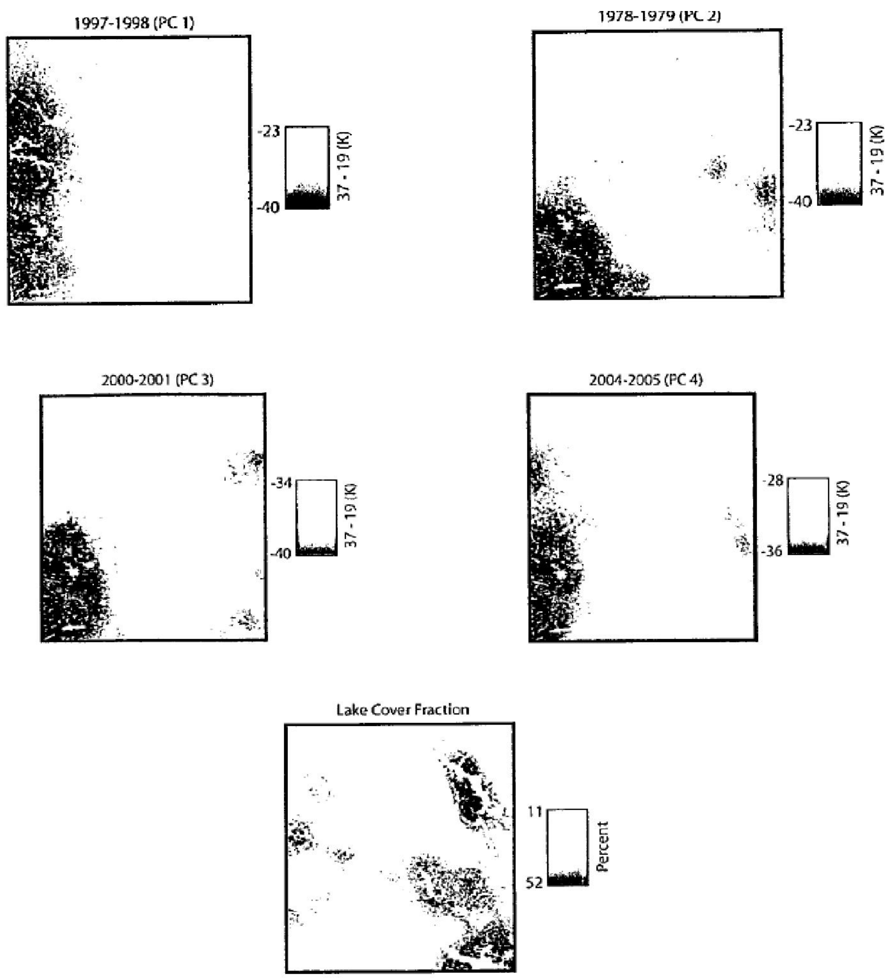

Figure 7. Maps of the seasons with the highest loading in each PC

5- Conclusion

By using tundra snow cover can influence local and regional scale surface water balance, energy fluxes, and ecosystem. At regional and hemispheric scales, the estimation of snow extent, snow depth and, snow water equivalent (SWE) is important because high latitude snow cover both forces and reacts to atmospheric circulation patterns. Moreover, snow cover has implications on soil moisture dynamics, the depth, formation and growth of the permafrost active layer, the vegetation seasonality, and the respiration of C02.Remote sensing techniques have been employed to monitor the snow since the1960s when the visible light channels were used to map snow extent. Since then, satellitere mote sensing has expanded to provide information on snow extent, depth, wetness, and SWE. However, the utility of satellite sensors to provide useful, operational tundra snow cover data depends on sensor parameters and data resolution.

Passive microwave data are the only currently operational sources for providing estimates of dry snow extent, SWE and snow depth. The heterogeneity of sub-satellite gridtundra snow and terrain are the main limiting factors in using conventional SWE retrieval algorithm techniques. Moreover, there is a lack of in-situ data for algorithm development and testing. The overall objective of this research is to improve operational capabilities for estimating end of winter, pre-melt tundra SWE using satellite passive microwave data. We use the data located in the mountain area.

During each field campaign, snow depth, density and stratigraphy are used in analysis. Multi-scale airborne passive microwave radiometer data and ground based passive microwave radiometer data were acquired. For each year, temporally coincident AMSR-

E satellite Tb were obtained. The spatial distribution of snow depth, density and SWE in the study area is controlled by the interaction of blowing snow with terrain and land cover. Despite the spatial heterogeneity of snow cover, several inter-annual consistencies were identified.

Tundra snow density is consistent when considered on a site-by-site basis and among different terrain types. When applied to site snow depths, there is little difference in SWE derived from either the site or the regional average density. SWE is more variable from site to site and year to year than density which requires the use of a terrain based Classification to better quantify regional SWE. The variability in SWE was least on lakes and flat tundra, while greater on slopes and plateaus. Despite the variability, the interannualratios of SWE among different terrain types does not change that much. The variability (CV) in among terrain categories was quite similar. The overall weighted mean CV for the study area was 0.40, which is a useful regional generalization. The terrain and landscape based classification scheme was used to generalize and extrapolate tundra SWE. Deriving a weighted mean SWE based on the spatial proportion of landscape and terrain features was shown as a method for generalizing the regional distribution of tundra SWE.

A principal component analysis (PCA) showed that there are differences in ΔTb among different EASE gridsand that land cover may have an influence on regional Tb. However, the PCA showed little relationship between end of season Δ Tb and Lake Fraction. A quadratic function was fitted to explain 89percent of the variance in SWE. The quadratic relationship provides agood fit between the data.Airborne Tb data were used to examine how different snow, land cover and terrain properties influence microwave emission. In flat tundra, there was a significant relationship between SWE and high resolution Δ Tb. On lakes and slopes, no strong relationships were found between SWE and high resolution ΔTb. Due to the complexity of snow and terrain in high resolution footprints, it was a challenge to isolate a relationship between SWE and Tb. Despite the many challenges, algorithm development should be possible at the satellite scale.

References

1. Armstrong, Richard, M. J. Brodzik, A. Varani. 2007. The NSIDC EASE-Grid: Addressing the need for a common, flexible, mapping and gridding scheme. Earth System Monitor. 7. 6-7.
2. Baghdad, N., J. P. Fortin, and M. Bernier.2007. Capability of Multitemporal ERS-1 SAR Data for Wet-Snow Mapping. Remote Sensing of the Environment. 60. 174-187.
3. Derksen, C. and E. LeDrew, 2000. Variability and change in terrestrial snow cover: data acquisition and links to the atmosphere. Progress in Physical Geography. 4. 469-498.
4. Dye, D.G. 2002. Variability and trends in the annual snow-cover cycle in Northern Hemisphere land areas, 1972-2000. Hydrological Processes. 16. 3065-3077.
5. Hall, D.K., J.L. Foster and A.T.C. Chang.2012. Freshwater ice thickness observations using passive microwave sensors. IEEE Transactions on Geoscience and Remote Sensing. GE-1 9 - 4.1 89-1 93.
6. Leathers, D., and B. I. Luff.2011. Characteristics of snow cover duration across the northeast United States of America. International journal of Climatology. 17. 1535-1547.
7. Male, S. K. and E. NoI. 2005. Impacts of roads associated with the Ekati Diamond Mine, Northwest Territories, on reproductive success and breeding habitat of Lapland longspurs. Canadian Journal of Zoology. 83. 1286-1296.
8. Marshal, S., Roads, J. O., and G. Glatzmaier. 1994. Snow hydrology in a general circulation model. Journal of Climate. 7. 1251-1269.
9. Van der Wall, R., S. Van Lieshout, D. Bos, and R. H. Drent. 2000. Are spring staging brentgeese evicted by vegetation succession? Ecography. 23. 1 .60-69.
10. Loya, M. W. and P. Grogan. 2004. Carbon conundrum on the tundra. Nature. 431. 406 -408.

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