

1 Synergistic Use of Remote Sensing for Snow  
2 Cover and Snow Water Equivalent Estimation

3

4 Jonathan Munoz<sup>1\*</sup>, Jose Infante<sup>1</sup>, Tarendra Lakhankar<sup>1</sup>,  
5 Reza Khanbilvardi<sup>1</sup>, Nir Y. Krakauer<sup>1</sup>, Al Powell<sup>2</sup>

6

7 <sup>1</sup> NOAA-Cooperative Remote Sensing Science and Technology Center  
8 (NOAA-CREST),

9 City College of New York, 160 Convent Ave, NY 10031 USA

10 <sup>2</sup> NOAA/NESDIS/Center for Satellite Applications and Research (STAR)  
11 5200 Auth Road, WWB, Camp Springs, MD 20746, USA

12

13

14 Abstract

15

An increasing number of satellites represent an opportunity for utilizing multi-sensor techniques for improving the estimation of snowpack properties using remote sensing. In this paper, the strength of a synergistic approach of leveraging optical, active and passive microwave remote sensing measurements to estimate surface snow characteristics is discussed and examples from recent work given. Each type of sensor has specific technical constraints and limitations. The optical sensors are limited to cloud free days, whereas passive microwave sensors have coarse spatial resolution and sensitivity to multiple snow properties. Therefore, the synergistic use of multi-source and multi-temporal remote sensing data holds great promise for monitoring and analysis of snow.

16

17 *Keywords: Snow, Optical, Active, Passive, Microwave, Remote Sensing*

18

19

20 1 Introduction

21

22 Snow is a key component of Earth's energy balance, climate and  
23 environment, and also a major source of fresh water in many  
24 regions. Snow monitoring can play a significant role in seasonal  
25 flood management. One of the most common reasons for floods is  
26 rainfall over snow covered areas. During the spring, precipitation  
27 tends to occur in the form of rain rather than snow. When rain  
28 accompanies melting snow, the melting process is accelerated,  
29 causing serious floods [1,2]. Better estimation and understanding  
30 of the snowpack properties and seasonal variations therefore  
31 provide useful information for various hydrological and  
32 meteorological applications [3]. Accurate information about snow  
33 characteristics is required to increase the accuracy of water  
34 resource and flood forecasts.

35

36 Images from satellites have been used for mapping snow cover for  
37 several decades; for example, the USA National Oceanic and  
38 Atmospheric Administration (NOAA) began mapping snow using  
39 satellite-borne instruments in 1966. Snow extent is in most cases  
40 relatively straightforward to observe using visible imagery because  
41 of the high albedo of snow (up to 80% or more in the visible part of  
42 the electromagnetic spectrum) relative to most land surfaces [4].  
43 In general, visible imagery is better at detecting snow than at  
44 quantifying surface snow characteristics like snow depth or snow  
45 water equivalent. For this reason, the primary use of optical  
46 sensors is to provide accurate and spatially detailed information on  
47 the snow cover distribution. However, limitations exist. Visible  
48 imagery is limited to that portion of the surface illuminated by  
49 sunlight, and clouds can be confused with snow. As a result, snow  
50 maps generated from visible imagery can have gaps in areal  
51 coverage.

52

53 As an alternative to visible sensors and traditional station  
54 measurements, microwave remote sensing data (active and  
55 passive) have proven their value in estimating snowpack  
56 properties. Microwave sensors do not have daylight restrictions  
57 and are capable of penetrating through cloud cover, haze, and  
58 dust. This property allows for snow cover remote sensing under  
59 almost all weather and environmental conditions. Additionally,  
60 microwave remote sensing offers a great potential for snow studies  
61 due its sensitivity to snowpack and surface properties such as  
62 density, depth, grain size, temperature, melting-refreezing cycles,  
63 surface wetness and vegetation that are not easily inferred from

64 optical imagery. Nevertheless passive microwave products have  
65 much coarser (15-50 km) spatial resolution, poorly identify shallow  
66 and melting snow, and can confuse cold rocky surfaces with snow  
67 [5]. As result of these advantages, microwave products have not  
68 played a primary role in operational snow monitoring.

69

70 Despite the success of existing operational snow detection  
71 algorithms in mapping snow cover under most conditions,  
72 limitations in extending these to monitoring snow properties of  
73 interest, such as depth and water equivalent, suggest that more  
74 attention should be paid to making better use of microwave  
75 observations. This article reviews the synergistic use of optical,  
76 active and passive microwave to improving snow retrievals.

77

78 2 Remote Sensing of Snow

79

80 2.1 Optical Remote Sensing

81

82 Since surface snow properties and snow cover are rapidly changing  
83 phenomena in many regions, there is a need for frequent data.  
84 Satellite sensors such as the Advanced Very High Resolution  
85 Radiometer (AVHRR) onboard NOAA satellites, Moderate Resolution  
86 Imaging Spectro-radiometer (MODIS) onboard Earth Observing  
87 System (EOS) satellites, and Imager instruments onboard  
88 Geostationary Operational Environmental Satellites (GOES) have  
89 been used for snow cover mapping. Still, most of the optical remote  
90 sensing products are binary and just divide the surface into two  
91 classes, "snow" and "no snow".

92

93 Early optical models used threshold-based criteria tests, the  
94 normalized difference between bands, and decision rules for snow  
95 cover mapping. Kyle et al. (1978) used the ratio of radiances in  
96 1.6-0.754  $\mu\text{m}$  channels and IR band to discriminate between snow  
97 and clouds. Dozier (1989) used a more sophisticated Normalized  
98 difference band ratio of spectral reflectances measured from the  
99 Landsat Thematic Mapper for snow cover mapping. Current optical  
100 algorithms for the MODIS snow-cover products were improved and  
101 enhanced from previous operational products, allowing high  
102 resolution, daily availability, and the capability to better separate

103 snow and clouds [8]. However, detection of snow in optical  
104 wavelengths still requires clear sky conditions and sufficient  
105 daylight. For this reason and in order to mitigate these  
106 disadvantages, several authors [9] have suggested the importance  
107 of the joint use of satellite optical (visible/infrared) and microwave  
108 data to map snow extent and monitor its evolution in time and  
109 space. This is currently implemented operationally by the USA  
110 Interactive Multisensor Snow and Ice Mapping System [10], but still  
111 human and manual intervention is required.

112

## 113 2.2 Microwave Remote Sensing

114

115 Satellite observations in the microwave spectral range have also  
116 been used for the global monitoring of snow cover and surface  
117 snow properties for more than three decades. Several data sets  
118 from sensors like Electrically Scanning Microwave Radiometer  
119 (ESMR), Scanning Multichannel Microwave Radiometer (SMMR),  
120 Special Sensor Microwave/Imager (SSM/I) and Advanced Microwave  
121 Scanning Radiometer–Earth Observing System (AMSR-E) are used  
122 by the modeling community.

123

124 Models for snow-microwave interactions aim to predict the  
125 microwave radiation from a snowpack with given properties. The  
126 models describe the relationships between microwave emission  
127 and snow parameters such as mean snow grain size, density, and  
128 depth. These radiation models may be based on physical principles  
129 as well as observations, and they can be classified as empirical,  
130 semi-empirical or theoretical [11].

131

### 132 2.2.1 Passive Microwave Remote Sensing

133

134 Passive microwave sensors detect the weak microwave radiation  
135 that is constantly emitted from the surface and atmosphere of the  
136 earth. In the field of microwave radiometry, the microwave  
137 radiance is mostly expressed in terms of brightness temperature,  
138 TB at the measured frequency. Currently, there are many satellite  
139 sensors measuring brightness temperature in different microwave  
140 bands. These multi-frequency observations can be used to classify

141 snow conditions, to estimate the water equivalent of dry snow, and  
142 to determine the start of the melting period.

143

144 Early studies concluded that passive microwave is very sensitive to  
145 snow wetness [12]. Later work, analyzing snowpack transitions  
146 from dry to wet through melting conditions, showed that the  
147 microwave response for seasonal snow has a large contrast  
148 between wet and dry snow [13]. It has been confirmed that the  
149 scattering from the snow pack of microwave radiation depends on  
150 many factors, like the depth of the snow pack [14], but for a given  
151 snow depth the scattering depends on snow grain size, which  
152 increases as snow ages, decreasing the brightness temperature [15  
153 ]. For dry snow, scattering also decreases at higher microwave  
154 frequencies. In addition, snow grain size and snow temperatures  
155 have significant effects on the TB at the 37 and 89 GHz frequencies  
156 [13].

157

158 The results of several years of ground-based microwave  
159 observations along with the experience gained with satellite-borne  
160 microwave radiometers have facilitated the development of  
161 microwave emission models. Numerous research studies have used  
162 emission models along with brightness temperature at 19, 37 and  
163 85/89 GHz microwave frequencies from satellite-mounted  
164 instruments, including SSM/I and AMSR-E, for estimation of snow  
165 depth and snow water equivalent [9,16-19]. Earlier snow depth  
166 retrieval algorithms [20,21] provided an “instantaneous” daily snow  
167 depth estimate based on differences in brightness temperature  
168 between microwave frequencies. The same multi-frequency  
169 approach has been used for many years to retrieve SWE. One of  
170 the best known products is the AMSR-E global SWE product  
171 (<http://www.ghcc.msfc.nasa.gov/AMSR/>). However in assessment of  
172 the AMSR-E SWE retrievals, Tedesco and Narvekar (2010) found  
173 large errors in SWE, likely due to the static snow density assumed  
174 in the SWE algorithm, and they suggest incorporating a spatio-  
175 temporally evolving snow density and allowing for nonlinear  
176 relationships between TB and SWE.

177

178 A number of physically based models have been proposed to  
179 describe the relationships between microwave emission and snow  
180 parameters such as mean snow grain size, density, and depth  
181 [15,18,23,24] (Table 1). Still, limited understanding of the behavior

182 of snow-emitted microwave radiation throughout winter season  
183 means that existing models do not always accurately retrieve snow  
184 depth and snow water equivalent.

185

186 **Table 1 Characteristics of commonly used microwave snow emission models for**  
187 **snowpack property retrieval.**

188

<b>Model</b>	<b>Model Type</b>	<b>Characteristics</b>	<b>References</b>
Grody	Empirical	Decision tree algorithm for global snow covers map-ping from spectral gradients in SSM/I data.	Grody & Basist, (1996)
HUT	Semi-Empirical	Considers homogeneous snow or multiple layers. Includes the atmosphere, soil and vegetation.	Pulliainen et al. (1999)
MEMLS	Semi-Empirical	Considers a layered structure of the snow pack. Classical RT with Empirical scattering and absorption properties.	Wiesmann & Mätzler, (1999)
DMRT	Theoretical	Based on scattering theory. Considers snowpack as a medium consisting of scattering particles.	Tsang et al. (1992) Tsang & Kong, (2001)

189

190

### 191 **2.2.2 Active Microwave Remote Sensing**

192

193 Active microwave remote sensing, known as radar or SAR, is based  
194 on actively transmitting a powerful pulse of microwave radiation  
195 and measuring its backscatter from the target surface. Active  
196 microwave remote sensing has basically similar sensitivity to snow  
197 properties as passive microwave remote sensing using similar  
198 frequencies [27,28] but enables more precise retrievals because  
199 the power output is known. As well, active retrievals' typically  
200 achieve much better spatial resolution due to their higher signal-to-  
201 noise ratio, depending also on the antenna size. Active microwave  
202 measurements are very promising for snow remote sensing, but  
203 product improvements have been hindered by some complications,  
204 in that the backscattered energy is influenced by many other  
205 factors like soil type and soil moisture as well as the geometry of  
206 the microwave beam and receiver. Due to its higher resolution and  
207 stronger signal, studies have demonstrated that SAR can  
208 adequately distinguish snow covered areas during the snow  
209 melting period, discriminating between snow-free ground and  
210 melting snow [29].

211

212 The QuickSCAT active microwave scatterometer has been used to  
213 estimate the timing of snow melt across Greenland [30] and across  
214 Arctic lands [31] with accurate results. Furthermore, an algorithm  
215 for mapping wet snow in mountainous terrain using repeat passes  
216 of the Synthetic Aperture Radar (SAR) images showed very good  
217 correlations with snow cover retrievals [32].

218

219 Different algorithms for retrieving snow properties, including snow  
220 melting, snow depth and snow cover, based on active microwave  
221 sensors have been tested in different situations and regions of the  
222 world [18,33,34], in some cases giving accurate results, but in  
223 others offering poor to fair correlations when compared to in-situ  
224 measurements. Currently active microwave remote sensing of  
225 snow finds itself in the very peculiar situation of having long term  
226 experience on the field, a wide range of studied situations and very  
227 large data archives to analyze, but few verified operational  
228 products. The situation holds promise, but a lot more work has to  
229 be done; the possibility of incorporating more data types and  
230 sources, more complex algorithms or even more efficient and  
231 focused filtering may be pursued.

232

### 233 3 Synergistic Approach

234

235 While standalone approaches for snow estimation using individual  
236 satellite instruments have made significant progress in recent  
237 years, many of the products currently used are still based on  
238 empirical or semi-empirical relationships and are accurate only over  
239 a limited range of snow properties [35]. For this reason, some  
240 studies have explored the possibility of improving snow retrievals  
241 by incorporating the use of multi-source and multi-temporal remote  
242 sensing data. Given the technical constraints and limitations  
243 previously discussed, the synergy of satellite observations in the  
244 visible and in the microwave spectral bands is an important  
245 approach to improve the mapping and monitoring of the snow  
246 cover and snow pack properties.

247

#### 248 3.1 Snow Cover

249

250 Snow has a high reflectivity ratio in the optical range of the  
251 electromagnetic spectrum; this characteristic makes its detection  
252 very easy using different combinations of visible and infrared  
253 wavelengths. The Normalized Difference Snow Index, for example,  
254 uses the Green and Mid Infrared radiances with a threshold to have  
255 a binary detection of Snow (Covered and Non-Covered) [7]. At the  
256 same time, visible and infrared bands have the well-known  
257 limitation of allowing only clear day detection, as neither of them  
258 can penetrate clouds. Also, snowpack properties such as the snow  
259 water content can't be derived from them. A solution to the cloud  
260 problem and to inferring properties beyond snow cover is  
261 incorporating microwave data either passive or active. Both can be  
262 acquired during night or day. Although the cloud problem is  
263 removed, interpretation of microwave imagery is much more  
264 difficult compared to optical-based indices [36,37]. An example of  
265 this approach is the case of [9,38] that developed an automatic  
266 system of snow mapping with a spatial resolution of 5 km using  
267 GOES visible and infrared data and SSM/I microwave data. The  
268 method was shown to be as precise as the IMS (Ice Mapping  
269 System) products if not better especially on the level of the  
270 consistency of the time series. In general they showed the utility of  
271 the multi-sensor techniques for the improvement of the snow  
272 detection.

273

274 To improve optical-based algorithms, the use of microwave  
275 information has increased over time. One complication is that dry  
276 snow hardly emits any microwave radiation by itself, nor does it  
277 absorb radiation emitted from the underlying ground [39]. The  
278 spectral gradient between microwave frequencies is used in most  
279 algorithms for snow cover detection with microwave data. Kunzi et  
280 al. (1982) used the spectral gradient method on SMMR data to map  
281 snow cover extent and found that they were able to delimit a level  
282 of snow cover roughly corresponding to 5 cm snow depth. This level  
283 of snow cover was defined by the threshold:  $(T_{18H} - T_{37H}) > 3.8$  K.  
284 Properties affecting microwave response from snowpack include:  
285 snowpack depth and stratification, snow water equivalent, wetness,  
286 density, grain size and shape, temperature profile, snow age, and  
287 land cover. The most important of the disturbing factors are  
288 variations in snow grain size, and in some cold and dry regions it is  
289 actually the grain size, rather than snow depth, that is most  
290 important for the microwave signal [41].

291

292 It has been shown that satellite microwave data, even at very poor  
293 resolution, can be used to obtain information about average basin  
294 snow water equivalent and snow cover. In hydrology applications,  
295 a combination of passive sensors for mapping dry snow, snow  
296 water equivalent and onset of snowmelt and active sensors for  
297 mapping wet snow with better areal resolution could give the  
298 optimum information content, since the coarse resolution of  
299 passive microwave sensing can lead to large biases on very  
300 mountainous or marshy places. Venkataraman et al. (2004)  
301 combined statistically IRS LISS-III (optical) and Radarsat-1 SAR  
302 (active microwave) to improve on their already operational snow  
303 cover products, achieving better classification accuracy compared  
304 to each product individually, reducing shadow effects and  
305 correcting some errors in both products.

306

307 Goals for future work are to improve night and cloudy day  
308 detection, downscaling to better spatial resolutions, and the use of  
309 multiple instruments in different orbits in order to have better time  
310 resolution. As snow cover is currently showing rapid changes  
311 because of the climate change and it is impossible to estimate it  
312 based on ground measurements because its area is so wide  
313 globally, hydrologists are very interested in remote sensing for  
314 snow mapping, but removing biases and limitations of existing  
315 satellite products remains a challenge.

316

### 317 3.2 Snow Water Equivalent

318

319 Passive microwave data at 19 and 37 GHz (or similar frequencies)  
320 have been historically used to retrieve snow parameters such as  
321 snow water equivalent (SWE) and snow depth. Meanwhile, studies  
322 using active microwave data collected from space for snow  
323 applications have concentrated on the separation between wet and  
324 dry snow. However, a sensitivity of active microwave also exists to  
325 other parameters such as mean grain size and SWE, as has been  
326 demonstrated both theoretically and experimentally. The explicit  
327 combination of active and passive microwave data for remote  
328 sensing of snow offers therefore a strong potential for improving  
329 the retrieval of snow parameters. Hallikainen et al. (2003)  
330 combined active (QuikSCAT/SeaWinds) and passive (SSM/I/DMSP)  
331 data for monitoring key snow parameters in Finland. The results  
332 show that combined active and passive microwave sensors provide

333 useful information on diurnal and seasonal variability. These results  
334 were more accurate than those obtained by only passive  
335 microwave.

336

337 Synthetic Aperture Radar (SAR), particularly C-band SAR, has been  
338 used for monitoring snow and ice for more than two decades. In  
339 research comparing passive and active airborne microwave remote  
340 sensing of snow cover, Sokol et al., (2003) showed that SAR  
341 sensors are highly sensitive to changes in the dielectric constant  
342 and have better spatial resolution than their passive counterparts.  
343 They concluded that passive techniques estimate SWE most  
344 accurately under dry snow conditions with minimal stratified snow  
345 structures [43]. Other studies also showed that adding NDVI and  
346 QuikSCAT-ku data can increase the correlation between microwave  
347 based product and SWE [44]. Overall, there is evidence that the  
348 combination of active and passive microwave data to retrieve SWE  
349 may improve the results from those obtained just using passive  
350 microwave. Adding visible and infrared measures of snow cover  
351 may improve the spatial and temporal resolution of the retrievals  
352 further.

353

354 4 Summary

355

356 Unbiased estimates of snow properties could lead to much better  
357 understanding of hydrological processes in snow covered  
358 watersheds. This understanding is important not only for long term  
359 processes like snowmelt dependent water supply systems or snow-  
360 atmosphere interactions, but for predicting flash floods that can be  
361 caused by rapid changes in snowpack properties.

362

363 Even though significant improvements have been made to  
364 microwave emission models for snowpack properties retrieval in  
365 the last 45 years, the accuracy of the models and the retrieved  
366 data from both passive and active microwave sensors is relatively  
367 poor compared to what is needed for hydrological applications.  
368 Great advances have been achieved with combinations of different  
369 frequencies and even from data from both passive and active  
370 sensors [43]. Numbers of climate and snowpack parameters that  
371 influence brightness temperatures in the microwave range make it

372 very difficult to estimate accurate relationships from any one  
373 frequency.

374

375 For example, it has been demonstrated that passive techniques can  
376 give very good estimates of SWE, and that polarimetric Synthetic  
377 Aperture Radar (SAR) can identify complex snow structures but is  
378 affected by the SWE. Using the strength of both (passive  
379 microwave and SAR), snowpack properties can be monitored under  
380 many conditions more accurately. Azar et al. (2006) show an  
381 improvement in SWE estimation by the combination of the  
382 retrievals from both types of sensors, even though the correlation  
383 with SWE using only SAR was very low.

384

385 Future improvements include refinement of snow-cover extent  
386 measurements, minimizing SWE errors, and improving our ability to  
387 ingest remote sensing data into snow models. Also useful will be a  
388 more complete analysis of available and planned datasets from  
389 both passive and active microwave remote sensing, taking into  
390 account more parameters to improve the accuracy and temporal  
391 and spatial resolution of retrievals. These steps will help achieve a  
392 better understanding of gradual and rapid changes in the  
393 snowpack.

394

395

396 Acknowledgement

397

398 This study was supported and monitored by National Oceanic and  
399 Atmospheric Administration (NOAA) under Grant NA06OAR4810162  
400 and NA11SEC4810004. The views, opinions, and findings contained  
401 in this report are those of the author(s) and should not be  
402 construed as an official National Oceanic and Atmospheric  
403 Administration or U.S. Government position, policy, or decision.

404

405 References

406 [1] Sui J, Koehler G. Rain-on-snow induced food events in  
407 Southern Germany. *Journal of Hydrology* 2001;252:205-20.

408 [2] Marks D, Kimball J, Tingey D, Link T. The sensitivity of  
409 snowmelt processes to climate conditions and forest cover

- 410 during rain-on-snow: a case study of the 1996 Pacific  
411 Northwest flood. *Hydrological Processes* 1998;12:1569-87.
- 412 [3] Rango A. Spaceborne remote sensing for snow hydrology  
413 applications. *Hydrological Sciences Journal* 1996;41:477-94.
- 414 [4] Qu X, Hall A. What Controls the Strength of Snow-Albedo  
415 Feedback? *Journal of Climate* 2007;20:3971-81.
- 416 [5] Foster JL, Sun C, Walker J, Kelly REJ, Chang ATC, Dong J, Powell  
417 H. Quantifying the uncertainty in passive microwave snow  
418 water equivalent observations. *Remote Sensing of  
419 Environment* 2005;94:187-203.
- 420 [6] Kyle HL, Curran RJ, Barnes WL, Escoe D. A cloud physics  
421 radiometer. Third Conference on Atmospheric Radiation  
422 American Meteorological Society 28 30 June 1978, 1978, p.  
423 107.
- 424 [7] Dozier J. Spectral signature of alpine snow cover from the  
425 Landsat Thematic Mapper. *Remote Sensing of Environment*  
426 1989;28:9-22.
- 427 [8] Hall DK, Riggs GA. Accuracy assessment of the MODIS snow  
428 products. *Hydrological Processes* 2007;21:1534-47.
- 429 [9] Romanov P, Gutman G, Csiszar I. Automated monitoring of  
430 snow cover over North America with multispectral satellite  
431 data. *Journal of Applied Meteorology* 2000;39:1866-80.
- 432 [10] Helfrich SR, McNamara D, Ramsay BH, Baldwin T, Kasheta T.  
433 Enhancements to, and forthcoming developments in the  
434 Interactive Multisensor Snow and Ice Mapping System (IMS).  
435 *Hydrological* 2007;1586:1576- 1586.
- 436 [11] Tedesco M, Kim EJ. Intercomparison of Electromagnetic Models  
437 for Passive Microwave Remote Sensing of Snow. 2006.
- 438 [12] Hofer R, Schanda E. Signatures of snow in the 5 to 94 GHz  
439 range. *Radio Science* 1978;13:365-9.
- 440 [13] Lakhankar T, Muñoz J, Romanov P, Powell AM, Krakauer N,  
441 Rossow W, Khanbilvardi R. CREST-Snow Field Experiment:  
442 analysis of snowpack properties using multi-frequency  
443 microwave remote sensing data. *Hydrology and Earth System  
444 Sciences Discussions* 2012;9:8105-36.
- 445 [14] Ulaby FT, Stiles WH. The Active and Passive Microwave  
446 Response to Snow Parameters 2. Water Equivalent of Dry  
447 Snow. *Journal of Geophysical Research* 1980;85:1045-9.

- 448 [15] Grody N. Relationship between snow parameters and  
449 microwave satellite measurements: Theory compared with  
450 Advanced Microwave Sounding Unit observations from 23 to  
451 150 GHz. *Journal of Geophysical Research* 2008;113:1-17.
- 452 [16] Grody NC, Basist AN. Global identification of snowcover using  
453 SSM/I measurements. *IEEE Transactions on Geoscience and*  
454 *Remote Sensing* 1996;34:237-49.
- 455 [17] Durand M, Kim EJ, Margulis SA. Quantifying Uncertainty in  
456 Modeling Snow Microwave Radiance for a Mountain Snowpack  
457 at the Point-Scale, Including Stratigraphic Effects. *IEEE*  
458 *Transactions on Geoscience and Remote Sensing*  
459 2008;46:1753-67.
- 460 [18] Kelly RE, Chang A, Tsang L, Foster JL. A prototype AMSR-E  
461 global snow area and snow depth algorithm. *IEEE Transactions*  
462 *on Geoscience and Remote Sensing* 2003;41:230-42.
- 463 [19] Simic A, Fernandes R, Brown R, Romanov P, Park W. Validation  
464 of VEGETATION, MODIS, and GOES+ SSM/I snow-cover  
465 products over Canada based on surface snow depth  
466 observations. *Hydrological Processes* 2004;18:1089-104.
- 467 [20] Chang ATC, Kelly REJ, Foster JL, Hall DK. Global SWE  
468 monitoring using AMSR-E data. *Geoscience and Remote*  
469 *Sensing Symposium, 2003. IGARSS '03. Proceedings.*  
470 2003;1:680-2.
- 471 [21] Foster JL, Chang ATC, Hall DK. Comparison of Snow Mass  
472 Estimates from a Prototype Passive Microwave Snow  
473 Algorithm, a Revised Algorithm and a Snow Depth  
474 Climatology. *Remote Sensing of Environment* 1997;62:132-42.
- 475 [22] Tedesco M, Narvekar PS. Assessment of the NASA AMSR-E  
476 SWE Product. *IEEE Journal of Selected Topics in Applied Earth*  
477 *Observations and Remote Sensing* 2010;3:141-59.
- 478 [23] Pulliainen J, Grandell J, Hallikainen MT. HUT snow emission  
479 model and its applicability to snow water equivalent retrieval.  
480 *IEEE Trans. on Geoscience and Remote Sensing*  
481 1999;37:1378-90.
- 482 [24] Wiesmann A, Mätzler C. Microwave Emission Model of Layered  
483 Snowpacks. *Remote Sensing of Environment* 1999;70:307-16.
- 484 [25] Tsang, L., Ding, K. H. & Wen B. Dense media radiative transfer  
485 theory for dense discrete random media with particles of

- 486 multiple sizes and permittivities. Progress In Electromagnetics  
487 Research 1992;6:181-230.
- 488 [26] Tsang L, Kong JA. Scattering of Electromagnetic Waves, 3  
489 Volume Set. Wiley-Interscience; 2001.
- 490 [27] Matzler C, Schanda E, Good W. Towards the Definition of  
491 Optimum Sensor Specifications for Microwave Remote Sensing  
492 of Snow. IEEE Transactions on Geoscience and Remote  
493 Sensing 1982;20:57-66.
- 494 [28] Rott H. Synthetic aperture radar capabilities for snow and  
495 glacier monitoring. 1984.
- 496 [29] Hallikainen MT, Halme P, Takala M, Pulliainen J. Combined  
497 active and passive microwave remote sensing of snow in  
498 Finland. IEEE; 2003.
- 499 [30] Nghiem S V, Tsai W-YTW-Y. Global snow cover monitoring with  
500 spaceborne Ku-band scatterometer. IEEE; 2001.
- 501 [31] Wang L, Derksen C, Brown R. Detection of pan-Arctic  
502 terrestrial snowmelt from QuikSCAT, 2000-2005. Remote  
503 Sensing of Environment 2008;112:3794-805.
- 504 [32] Nagler T, Rott H. Retrieval of wet snow by means of  
505 multitemporal SAR data. IEEE; 2000.
- 506 [33] Yueh S, Cline D, Elder K. Airborne Ku-Band Polarimetric Radar  
507 Remote Sensing of Terrestrial Snow Cover. IEEE-INST  
508 ELECTRICAL ELECTRONICS ENGINEERS INC; 2008.
- 509 [34] Dupont F, Royer A, Langlois A, Gressent A, Picard G, Fily M,  
510 Cliche P, Chum M. Monitoring the melt season length of the  
511 Barnes Ice Cap over the 1979-2010 period using active and  
512 passive microwave remote sensing data. Hydrological  
513 Processes 2012;26:2643-52.
- 514 [35] Tedesco M, Derksen C, Pulliainen J. Hemispheric snow water  
515 equivalent: The need for a synergistic approach. Eos,  
516 Transactions American Geophysical Union 2012;93:305.
- 517 [36] Roshani N, Zouj M, Rezaei Y, Nikfar M. SNOW MAPPING OF  
518 ALAMCHAL GLACIER USING REMOTE SENSING DATA. Archives  
519 2008;37:805-8.
- 520 [37] Robinson DA, Dewey KF, Heim RR. Global Snow Cover  
521 Monitoring: An Update. Bulletin of the American  
522 Meteorological Society 1993;74:1689-96.

- 523 [38] Romanov P, Tarpley D. Enhanced algorithm for estimating  
524 snow depth from geostationary satellites. Remote Sensing of  
525 Environment 2007;108:97-110.
- 526 [39] Jiang L, Shi J, Tjuatja S, Dozier J, Chen K, Zhang L. A  
527 parameterized multiple-scattering model for microwave  
528 emission from dry snow. Remote Sensing of Environment  
529 2007;111:357-66.
- 530 [40] Kunzi KF, Patil S, Rott H. Snow-Cover Parameters Retrieved  
531 from Nimbus-7 Scanning Multichannel Microwave Radiometer  
532 (SMMR) Data. IEEE; 1982.
- 533 [41] Roy A, Royer A, Montpetit B, Bartlett PA, Langlois A. Snow  
534 specific surface area simulation using the one-layer snow  
535 model in the Canadian LAnd Surface Scheme (CLASS). The  
536 Cryosphere Discuss 2012;6:5255-89.
- 537 [42] Venkataraman G, Mahato BC, Ravi S, Rao YS, Mathur P,  
538 Snehmani S. Fusion of optical and microwave remote sensing  
539 data for snow cover mapping. Ieee; 2004.
- 540 [43] Sokol J, Pultz TJ, Walker AE. Passive and active airborne  
541 microwave remote sensing of snow cover. International Journal  
542 of Remote Sensing 2003;24:5327-2344.
- 543 [44] Azar AE, Ghedira H, Lakhankar T, Khanbilvardi R. Improvement  
544 in Estimating Snowpack Properties with SSM/I Data and Land  
545 Cover Using Artificial Neural Networks. 2006.
- 546