Dear editor, reviewers

We would like to thank you and the reviewers for the constructive and insightful comments and suggestions to improve our manuscript. We have carefully revised the manuscript according to the suggestions and comments, and provide point-by-point response following each comment and suggestion.

In the following, reviewer comments are given in black and responses are given in blue (the revised sentence was set in italics). The corresponding changes have been made in the revised paper with track changes. We mainly did following modification in the updated manuscript:

1) The revised manuscript has been proof read by a native English speaker;

2) Another two year (2008, 2009) data together with the data in 2017 were used in evaluation stage in Section 4.3; correspondingly, we revised Fig. 7.

3) We added the additional description information about the Fig. 8 in Section 4.3.

4) We added the description map on fractional snow cover distribution across North America (Figure S-9).

We think the revised manuscript has addressed all the reviewers' comments and hopefully it is now suitable for publication in The Cryosphere

Sincerely,

Xiongxin Xiao

*********************Reply to comments from anonymous reviewer 1#*********************

REVIEWER 1

This manuscript describes the development and validation of a technique to estimate fractional snow cover (FSC) from passive microwave brightness temperatures. Optical FSC estimates for algorithm training and validation were derived from MODIS Collection 6. Surface snow depth measurements and an independent passive microwave snow extent classifier were also used for evaluation. Overall, the study is comprehensive and detailed. I commend the authors for the thorough nature of the study – multiple combinations of passive microwave measurements are considered, sensitivity to various configurations of the retrieval are compared, and multiple datasets are used for evaluation. Because of this comprehensive approach, description of the analysis is sometimes unclear in some places, and the logic is not always clear on the back and forth conversion between FSC information derived via the retrieval and comparison with MODIS, and binary snow extent information used for evaluation. This can get confusing in places. But overall, the technique shows good promise, and this initial overview makes for a new contribution worthy of publication The Cryosphere.

Please note that the paper requires a thorough edit for grammar, English usage, and word choice. Edits of this nature were too numerous to identify individually in my review.

Response: Thanks for your valuable comments and suggestions to improve our manuscript. We have replied to each comment below. The manuscript has been edited by a native English speaker. Additionally, to make the description of the conversion from fractional snow cover to binary snow cover clear, we changed “random forest FSC” to “random forest SCA” in binary snow cover area information evaluation in the revised manuscript.

General comments

Please double check all the data citations in Section 2.1 and Section 2.2. Some citations are missing from the reference list. While it’s fine to provide the URL to the NSIDC webpage which hosts the data, the proper data citations (which are provided under the “Citing These Data” tab on the NSIDC webpages) must also be used.

Response: Thanks for your suggestion. We updated and added the corresponding data citations for the dataset used in Section 2.

Section 2.3.2: why is the IGBP land cover data product described here in addition to the MCD12Q1 product? This dataset does not seem to be used in the analysis: :

Response: MODIS land cover data have several classification scheme, including the IGBP classification schemes. The MODIS land cover data with IGBP classification scheme was used as the basis data of fractional snow cover retrieval model

Page 6 lines 14-23: Previous work has shown the potential for passive microwave SWE datasets, despite high uncertainty in the SWE retrievals, to provide useful snow extent information. This provides additional justification for the approach developed in this study. A brief mention of this could be added to this paragraph, including a citation to: Brown, R., C. Derksen, and L. Wang. 2010. A multi-dataset analysis of variability and change in Arctic spring snow cover extent, 1967-2008. Journal of Geophysical Research. 115: D16111, doi:10.1029/2010JD013975.

Response: Thanks for your suggestion. We cited the related literature and added the description about snow parameters (snow cover extent, snow depth and water equivalent) retrieval in page 7 lines 16-19 as follows:

"A number of published work have demonstrated the potential to derive snow depth and SWE using passive microwave radiation data (Kim et al., 2019; Wang et al., 2019). Despite the high uncertainties associated with snow depth and SWE estimations, using passive microwave data can provide useful snow cover extent information (Brown et al., 2010; Foster et al., 2011)."

Section 3.1: I was disappointed e that the analysis period was limited to January and February. This is a real limitation because the spring period is the most important with respect to the snow-albedo feedback and the contribution of snow melt to streamflow. Additionally, the snow melt period may pose significant challenges to the use of passive microwave data because of a loss of sensitivity to snow when it is wet. This limitation to the study is acknowledged in Section 5.1, but I suggest the conclusions and discussion clearly emphasize that these results are applicable to dry snow conditions, and that performance is likely to be weaker during snow melt.

Response: Thanks for your comment. We do agree that the estimation and analysis of fractional snow cover should cover the whole snow cover season (autumn, winter and spring). Noted that the fractional snow cover estimation work we're doing will cover all the year round. Additionally, we clarified the description information of applicable condition for this study in Section 6 (page 26 lines 8-10) based on your suggestion:
"These models established using several data sources in January and February had better applicability in dry snow conditions, while estimation results could be less accurate in wet snow conditions."

Section 3.2: the short-term cloud filter for single days of cloud cover is clearly described (page 8 line 21) but it's not clear how longer cloudy periods are dealt with. If cloud is present for two or more consecutive days, is that pixel masked as cloud as described on page 9 line 3? Please state this clearly.

Response: Thanks. If cloud is present for two or more consecutive days, the pixel would be masked as cloud according to short term cloud filter. Additionally, we revised and clarified the description about the short term cloud filter (page 9 lines 21-24)
"*2) Short-term temporal filter: if the status of a pixel in the input image (MCD10A1) in a given day (t) was cloud and both the preceding (t - 1) and succeeding (t + 1) days were snow-covered (or snow-free), the pixel in the output image (MCTD10A1) in the given day (t) was assigned as snow-covered (or snow-free) (summarized by Eq. 2)*..."
and revised the confused term "filter" in original sentence to
"*We adopted the most rigorous pixel filtering rule, by which one clouded pixel cannot be allowed within a 15*15 pixel window*" in page 10 lines 4-5.

Section 4.1.1: there is virtually no difference in performance between scenarios 1, 4, and 5, as summarized in Table 4, with the main difference in performance between scenarios due to the inclusion of ancillary fields (lat/lon; topography). While I agree that "location information and topographic factors play a crucial role in snowpack distribution" can a more physically-based explanation be provided for these results?

Response: Thanks for your comment. The results of Scenarios-1, 4, and 5 show that there indeed were no significant differences among these three scenarios. Generally speaking, inputting more information could make great contribution to improving the performance of snow cover parameters estimation. However, we found that inputting more information did not provide too much contribution for the performance improvement of fractional snow cover by analyzing the results of Scenarios-1, 4, and 5. Thus, we conclude that the input variables in Scenarios-1 have redundant information and it makes model establishment more time consuming. These statements have been similarly described in our manuscript "*The comparison among Scenarios -1, 4, 5 indirectly indicates that the variables used in Scenario -1 may have some information* *redundancy and slightly weaken the efficiency of the random forest retrieval model*" in page 17 lines 17-19

Additionally, we added the explanation for the "location information and topographic factors" in page 17 lines 6-9 "*In this study, the retrieval method required these five basic input variables as auxiliary information in order to learn the characteristics of snow cover under different surface conditions to assist in accurately estimating snow cover properties. In contrast, in the absence of these basic input variables, the established model has no advantage in accurately predicting the characteristics of fractional snow cover under complex surface conditions*"

Section 4.3/Figures 6 and 7: the scatterplots seem to illustrate that the retrieval is capable of identifying low snow fraction and high snow fraction, but with less skill across the intermediate values. This may be in large part due to issues with the reference snow fraction from MODIS, which seems to be clustered around low and high snow fraction values as shown in Figure 7 (with the exception of forested areas as shown in Figure 7a). Please consider adding some text to the first paragraph of Section 4.3, or strengthening the text on page 20 lines 10-20 to make clear how the performance of the retrieval can be influenced by the behaviour of the reference dataset.

Response: Thanks for your comment. In order to clarify the influence of reference dataset to fractional snow cover retrieval, we added the following statement in page 24 lines 9-11.
"*This is mainly because the established fractional snow cover retrieval model when using the training sample with relatively low diversity of fractional snow cover values does not well learn the snow cover distribution characteristics of the various surface condition.*"

Figure 8: the paper would be strengthened with more emphasis on the presentation of spatial results. Figure 8 is really important, but I found it unclear, especially panel D (the sub-panels within panel D are hard to read). Why is there so much white space in panel B? Zero snow fraction needs to have a separate colour than the range of 0 to 0.3, in order to clearly show where the retrieval estimates no snow versus very low fractions of snow (e.g. 0.1 to 0.3). I suggest a clear set of maps be presented, with emphasis on a comparison between MODIS and passive microwave estimates at the continental scale (as in panels B and C) for some key events which extended the snowline.

Response: Thank you very much for your valuable suggestion.
1) The MODIS binary snow cover image (Fig. 8A) was translated to the reference MODIS fractional snow cover (Fig. 8B) by applying the strictest pixel filtering rule at a 15*15 pixels window, meaning that the window do not allow an cloudy and water pixel when calculating the fractional snow cover. Therefore, many pixels (6.25-km) were masked as "fill value" (white in Fig. 8B). In addition, we did a test, if 5% (about 11 pixels) of cloudy and water pixels are allowed in the 15*15 pixels window, more than 6% of the white space would substitute with the intermediate values (0.1 ~ 0.9) of fractional snow cover. In other words, the number of pixels with the intermediate value (ranging from 0.1 to 0.9) will double from what it is now. The following figure show the increase percentage of the number of pixel with the fractional snow cover values in range of 0.1 and 0.9 in different land cover types if we allow 5% of cloudy and water pixels in the 15 * 15 pixels window. Furthermore, the estimated fractional snow cover would bring maximum 5% uncertainty due to these cloudy and water pixels

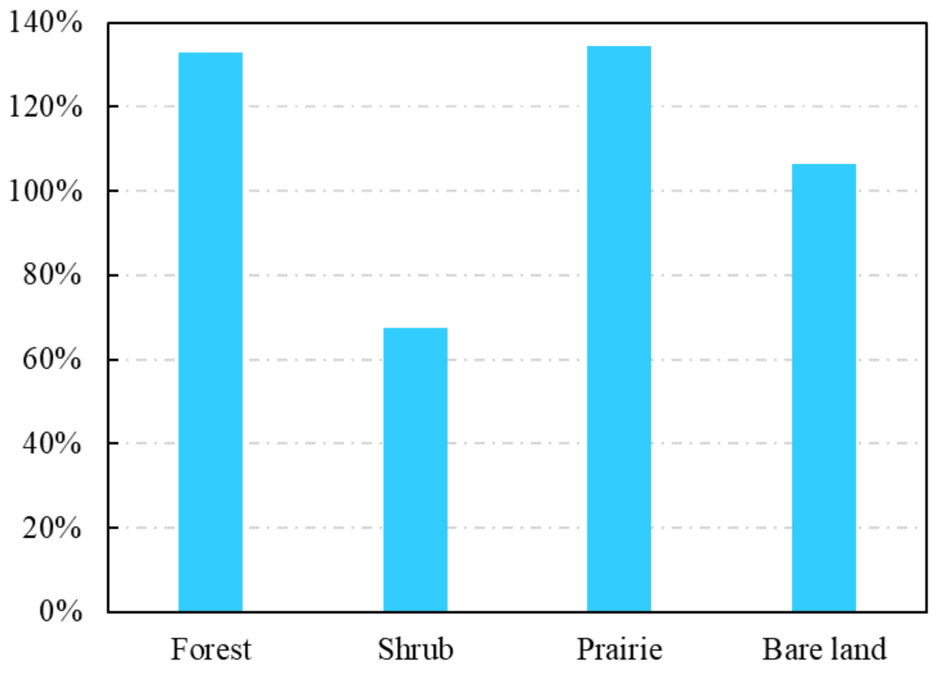


Figure R. The increase percentage of the number of pixel with the fractional snow cover values in range of 0.1 and 0.9 in different land cover types (forest, shrub, prairie and bare land) if we allow 5% of cloudy and water pixels in the 15 * 15 pixels window.

2) We modified and clarified why the separate color map was used in here.

"*Fig. 8 shows the comparison between our estimated fractional snow cover and the reference MODIS fractional snow cover, and more importantly, provides another perspective for snow cover identification in Section 4.4. Thus, Fig. 8B and 8C used 0.3 as the threshold of fractional snow cover to define snow-covered and snow-free area, and this was adopted through the experiments in Section 4.4*" in page 20 lines 18-21.

3) Moreover, according to your suggestions, we strengthened the description of spatial results in order to improve the legibility of each image (Fig. 8), and the revised statements as follows:

"*Apart from the scatter plots and statistical analysis, Fig. 8 shows the distribution pattern of snow cover from a spatial perspective, including MODIS composite binary snow cover (Fig. 8A), MODIS fractional snow cover (Fig. 8B), and the estimated fractional snow cover by the proposed algorithm (Fig. 8C). When the most rigorous pixel filtering rule at the 15*15 pixel window was applied (see Section 3.2), the large number of cloud covered pixels (yellow) in Fig. 8A resulted in most areas of the MODIS fractional snow cover image (Fig. 8B) being represented by a "fill value". Additionally, the number of intermediate values for MODIS fractional snow cover in winter would be much lower than the number of values near the two extreme values (0 and 1). In contrast, the estimated fractional snow cover from passive microwave brightness temperature data can provide almost complete coverage and continuous spatial information on snow cover (Fig. 8C; Fig. S-7 in the Appendix). Fig. 8 shows the comparison between our estimated fractional snow cover and the reference MODIS fractional snow cover, and more importantly, provides another perspective for snow cover identification in Section 4.4. Thus, Fig. 8B and 8C used 0.3 as the threshold of fractional snow cover to define snow-covered and snow-free area, and this was adopted through the experiments in Section 4.4. This means that the pixel was identified as snow cover when fractional snow cover value was less than 0.3. From Fig. 8A – C, the spatial pattern of estimated fractional snow cover from the proposed method seems to accurately capture the distribution of snow cover from MODIS under clear-sky conditions, such as the snow-free area in most areas of North America, and snow-covered areas in northern Canada. Fig. 8D presents a specific example comparing these two fractional snow cover datasets and MODIS composite binary snow cover products in central Canada on February 27th, 2017. Based on this example, we find that our estimated fractional snow cover was capable of obtaining snow cover distribution when most of the area was covered by cloud, which was not the case for MODIS. This example also show that the extent of snowline observed in the MODIS binary snow cover image (500 m), which was the boundary between snow-covered and snow-free, was well described and exhibited by the estimated fractional snow cover (6.25 km)*" in page 20 lines 10-30.

Moreover, the estimation results comparison of fractional snow cover for MODIS and our proposed algorithm in continuous value has been shown in the supplement file:

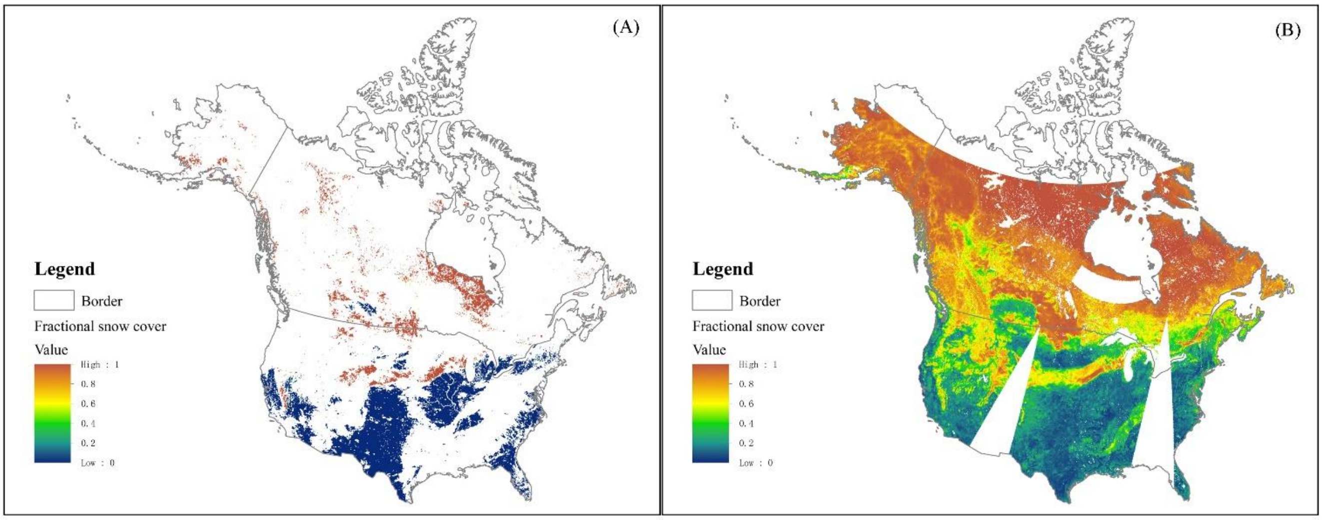


Figure S-7. Comparison of the reference MODIS fractional snow cover (A) with our estimated fractional snow cover (B) in continuous value (6.25-km) on February 27th, 2017 (2017058)

Page 18 lines 3-6/Page 19 lines 27-28/Page 22 lines 1-3: the explanation for the potential over-identification of snow in the microwave retrievals (compared to the Grody product) is not convincing. The misclassification of snow extent due to non-snow scatterers (like cold deserts/frozen ground) is not a prevalent issue in North America. To better understand the statement that "the non-snow scatterer is the major source of snow cover misclassification for random forest FSC results" it would be clearer to show a map of locations where the RF classifier identifies snow and the Grody algorithm does not. This aspect needs to be explored in more detail in the final manuscript.

Response: Thanks for your comment. Although the commission error of the proposed algorithm in snow cover identification only have 0.17, we provided additional information to explain this kinds of error. As you say, the non-snow scatters (like cold deserts, frozen ground) is not a prevalent issue in North America. According to our analysis results, we can also conclude that the snow cover misclassification effected by cold deserts and frozen ground is not prevalent issue in North America. We specified the different source error for commission error and revised the statement as follows:

"*The records, which were misclassified as snow cover by random forest SCA, although they are non-snow scatter components (precipitation, cold desert, and frozen ground), account for 70.1% of total misclassification records (CE = 0.17), of which 63.0% comes from precipitation, 6.4% from cold desert, and 0.7% from frozen ground*" in page 23 lines 12-15.

Following your suggestion, we first analyzed the confidence of the comparison results between Random forest SCA and Grody's algorithm SCA, when the in-situ station observation is absent. We provided the following statistical metrics (Table A) using the data in 2017. We can see that the percentage of "True observation" for Grody's algorithm only is 24.9% when RF classifier identifies snow-covered and the Grody's algorithm does not (Condition B); inversely, it should be classified as snow-covered. If we do not use the in-situ observation as the "true" observation, we do not have high confidence to say that the detection results by our proposed algorithm in Condition B are not right. Moreover, we show an example that provides a map for different condition combinations of Random forest SCA and Grody's algorithm SCA (Fig. S-9). The inconsistencies between Random forest SCA and Grody's algorithm SCA usually occurred in the mid-latitude region, in which it has the low fractional snow cover (Figure S-7). And also we revised the statement to

"*For different results for these two snow cover mapping algorithms, we have used an example to show the inconsistencies and consistencies in mapping between the random forest SCA and Grody's algorithm SCA (Fig. S-9)*" in page 23 lines 17-18.

Table A. The effect of precipitation, cold desert and frozen ground in snow cover misclassification. FP is false positive that means it is the number of pixels that are misclassified as snow cover by Random forest FSC. $SD_{obs} = 0$ denotes snow-free measured in station, otherwise, it is snow-covered; $SC_{Grody} = 0$ denotes snow-free (precipitation, cold desert and frozen ground) determined by Grody's algorithm, otherwise it is snow-covered; $FSC \leq 0.3$ denotes snow-free cover detected by our method, otherwise, it is snow-covered.

No.	Conditions	Observation		Percentage of "True observation"	
		$SD_{obs} = 1$	$SD_{obs} = 0$	Random Forest	Grody's algorithm
A	$SC_{Grody} = 0$ & $FSC \leq 0.3$	17435 (13%)	116069 (87%)	87%	87%
B	$SC_{Grody} = 0$ & $FSC > 0.3$	60601 (75.1%)	20063 (24.9%)	75.1%	24.9%
C	$SC_{Grody} = 1$ & $FSC \leq 0.3$	4379 (51.5%)	4120 (48.5%)	48.5%	51.5%
D	$SC_{Grody} = 1$ & $FSC > 0.3$	80167 (90.3%)	8575 (9.7%)	90.3%	90.3%

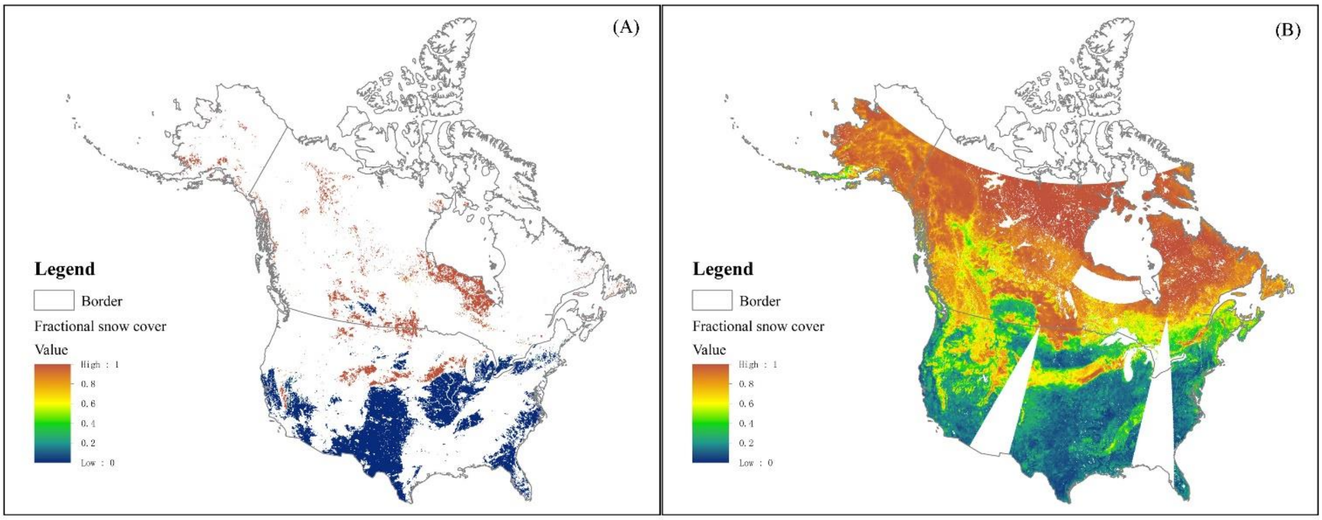


Figure S-7. Comparison of the reference MODIS fractional snow cover (A) with our estimated fractional snow cover (B) in continuous value (6.25-km) on February 27th, 2017 (2017058)

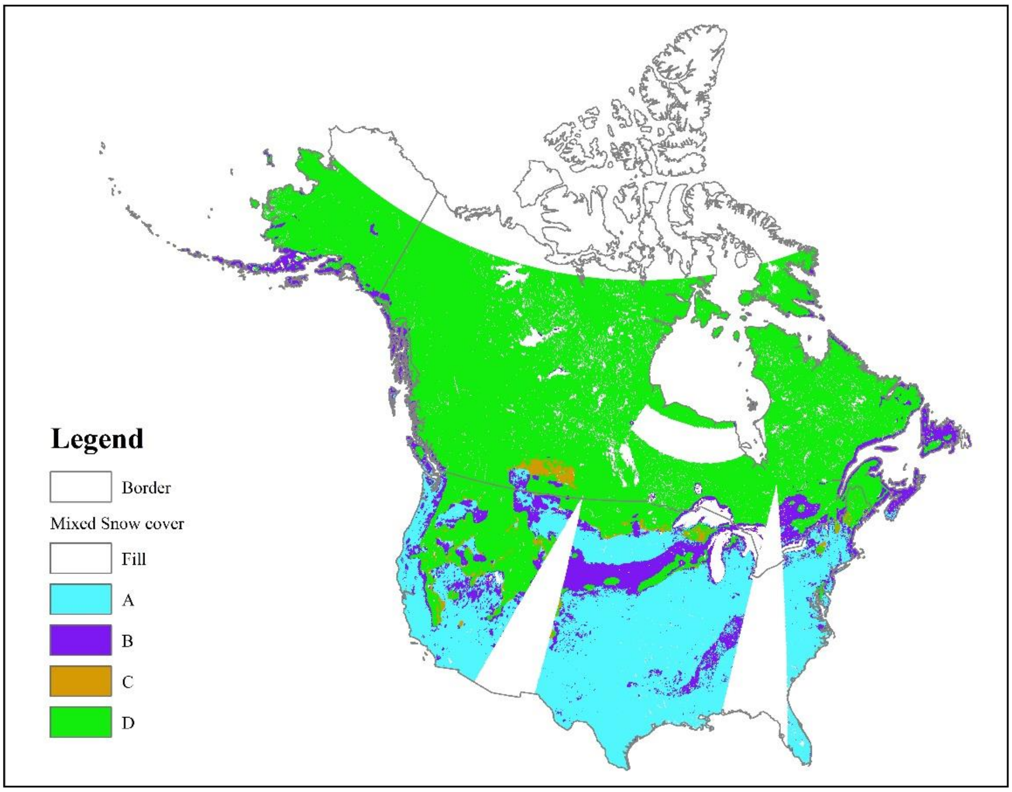


Figure S-9. The mixed snow cover detection map for different condition combinations of Random forest SCA and Grody's algorithm SCA on February 27th, 2017 (2017058) (the meaning of A-B can refer to Table A).

Editorial comments:

Abstract line 23: change '0.31 million' to '310 000'

Response: Thanks. "0.31 million" was changed to "*310 000*" in page 1 line 30.

Abstract line 26: I suggest not referring to the passive microwave dataset used for comparison as 'Grody's snow mapping algorithm' in the abstract.

Response: Thanks. We changed the statement to "*There was significant improvement in the accuracy of snow cover identification using our algorithm; the overall accuracy had increased by 18% (from 0.71 to 0.84), and the omission error had reduced by 71% (from 0.48 to 0.14), when the threshold of fractional snow cover was 0.3*" in abstract.

Page 2 line 2: change 'cycles' to 'cycle'

Response: we changed "cycles" to "*cycle*" in page 2, line 11.

Page 2 line 5: 'vast number of water resources' awkward wording

Response: we rephrased the sentence to "*Snowpack also stores a huge amount of water…*" in page 2, lines 13-14.

Page 3 lines 20-25: when possible, try to use product names instead of the author names. For example, the Kelly (2009) reference refers to the NASA standard AMSR-E snow water equivalent product. The citations should be retained, just the product names changed.

Response: Thanks you for your comment. We inquired each algorithm and tried to find their products. If the corresponding products were not found, author's name was used as the name of the algorithm. We revised the statement to "*Specifically, they involved the application of common passive microwave snow cover mapping algorithms, such as Grody's algorithm (Grody and Basist, 1996), National Aeronautics and Space Administration (NASA) Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) SWE algorithm (Kelly, 2009), Singh's algorithm (Singh and Gan, 2000), Neal's algorithm (Neale et al., 1990), the FY3 algorithm (Li et al., 2007), and the South China algorithm (Pan et al., 2012) …*" in page 4 lines 4-8.

Page 3 line 28 and page 20 line 17: change 'patch' to 'patchy'

Response: the word "patch" was revised to "*patchy*" in page 4, line14 and page 24 line 14.

Page 4 line 7: change ' predict' to 'retrieve'

Response: we changed "predict" to "*retrieve*" in page 4 line 25.

Page 5 line 7: change 'America' to 'United States'

Response: We changed "America" to "*United States*" in page 5 line 26.

Page 8 line 4: not clear what is meant by 'fill'

Response: We changed to "*fill value*" in page 9 line 4.

Page 18 lines 10-14: this text is unclear and seems very anecdotal. I think it can be removed.

Response: Thank you. We removed these unclear statements.

Figure 1: Add units to the legend. Why is there negative elevation?

Response: Thanks. We updated Figure 1. The negative value is located in the lake region which is under the land surface.

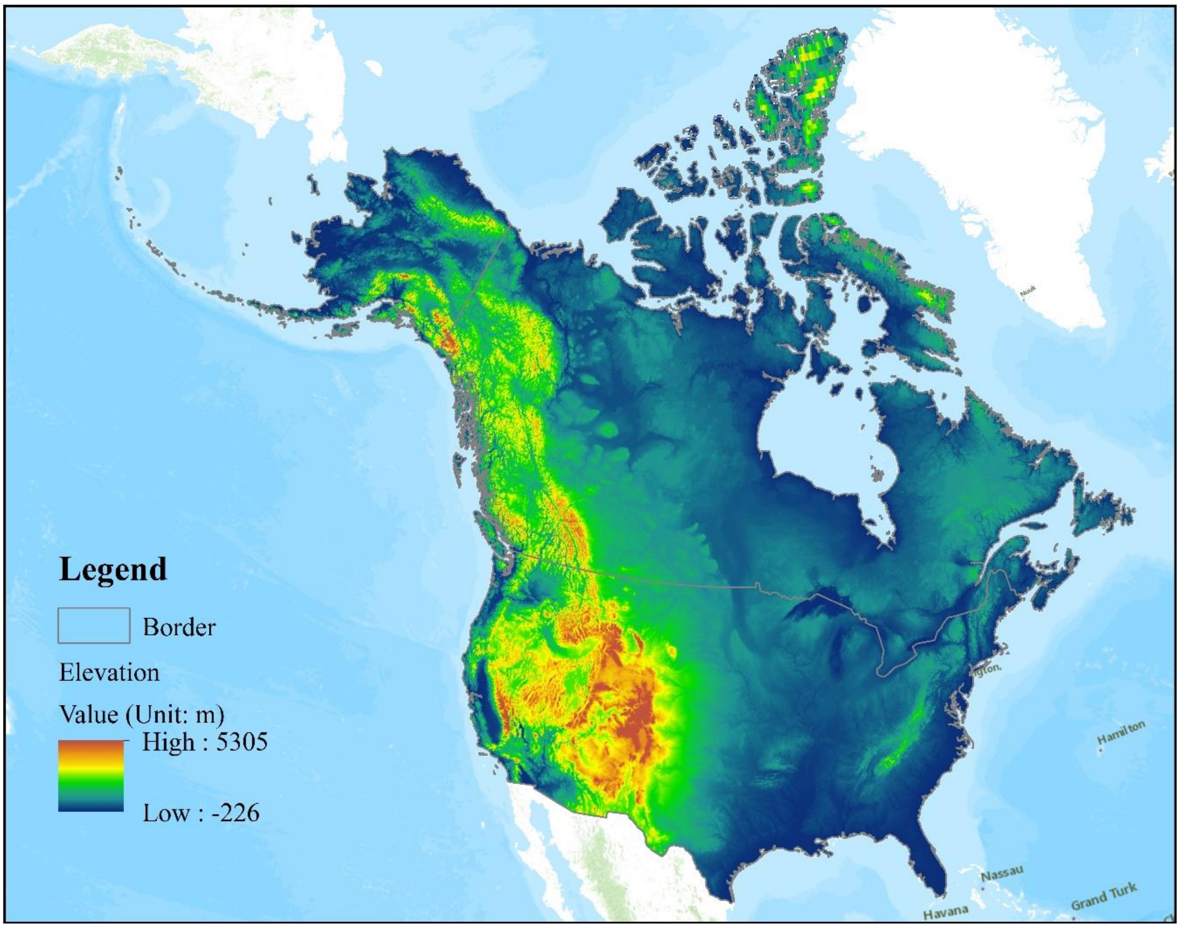


Fig. 1 Topographic map of North America.

Figure 4: caption is not clear

Response: The caption of Fig. 4 changed to "*The performance of random forest models with increasing the size of training sample for shrub type*"

Figure 9: add x-axis label to indicate snow depth

Response: Thanks. We added x-axis label to Fig. 9

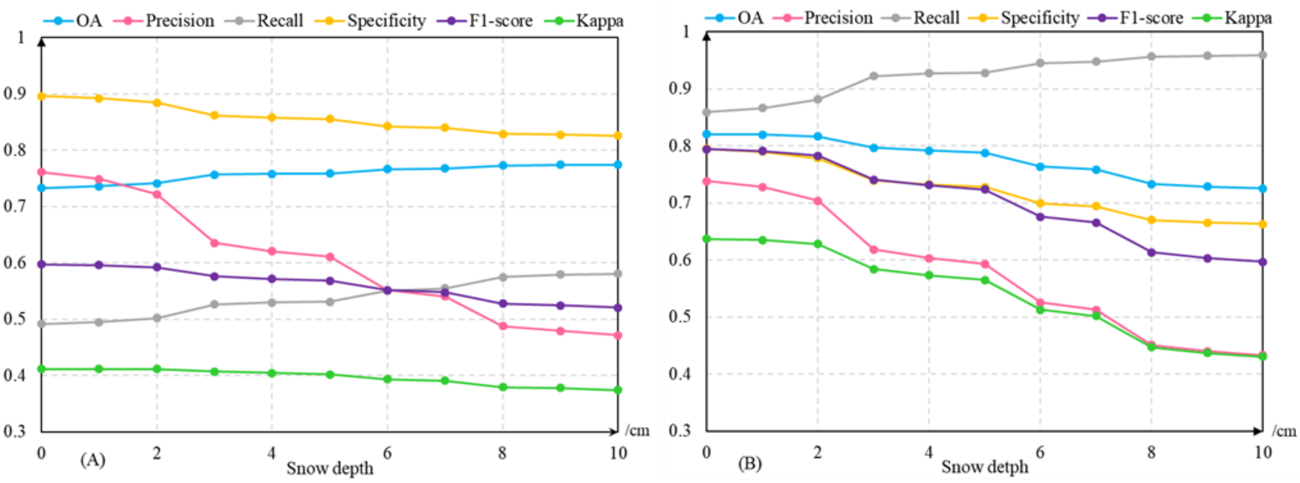
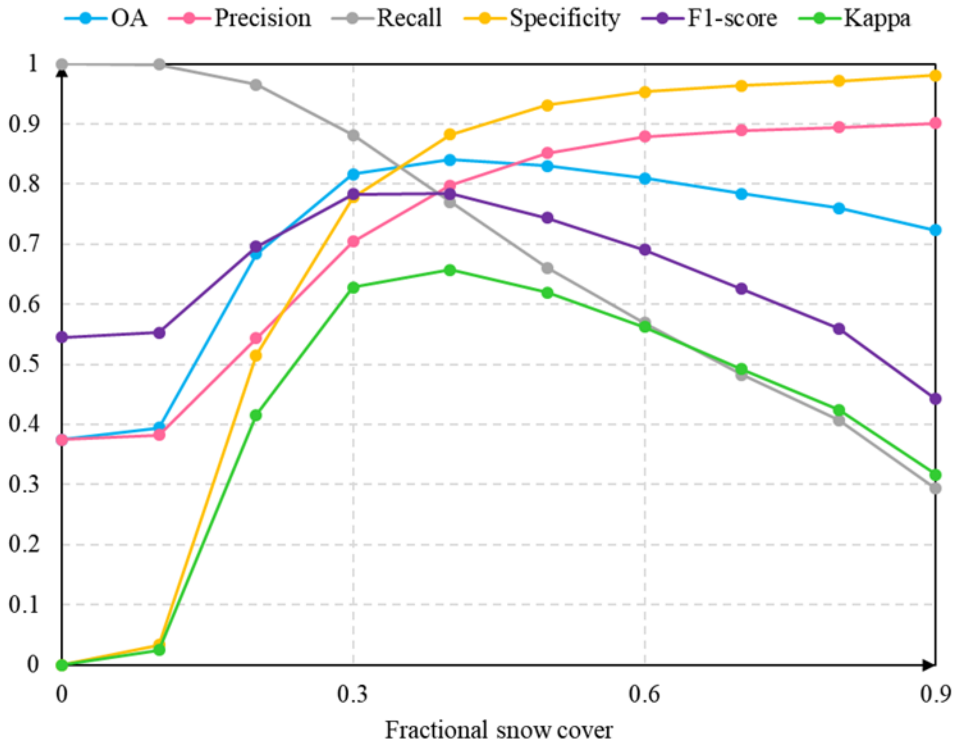


Figure 10: add axis labels

Response: Thanks. We updated the Fig. 10.



********************Reply to comments from anonymous reviewer 2#********************

REVIEWER 2#

Overview and General Comments

This manuscript describes a new approach of estimating fractional snow fraction from satellite-based passive microwave (PM) sensors and higher resolution MODIS snow cover estimates. The authors present different regression and machine learning type algorithms, including multi-regression, artificial neural networks (ANN), and a random forest regression technique, for estimating the PM-based snow cover fraction using the MODIS snow cover as a reference input to the algorithms along with accounting for different PM retrieval and ancillary datasets, like vegetation types. The methods are demonstrated and validated against independent in situ measurements across the region of interest (Canada and the US).

Overall, the paper includes comprehensive descriptions of the data and methods used, and detailed background and justification for the work presented. It also is within the scope and appropriate for the journal, The Cryosphere. The supplementary material does help support the overall findings in the paper. However, some of the methods and conclusions may require some revision and may not be conclusive enough as there is a limitation on the years evaluated and the wintertime period focused on. A few major and minor comments are noted in this review that hopefully help to strengthen the paper and the organization of the methods and results presented. There are a few sections that were difficult to follow and some of the English grammar and syntax was unclear.

Response: Thanks for your constructive suggestions and positive comments. According to you suggestion and comments, we have carefully revised the manuscript and provided point-by-point response following each comment.

One downside to this study is that the authors only focused on seven years of available passive microwave and optically based snow cover observations and then just the peak snow months of January and February. Though it seems to make sense to focus only on when the snowpack is at the peak months and more spatially continuous, however, it is also worthwhile to capture the temporal and spatial heterogeneity in the accumulation and ablation seasons and more fully test the algorithms described and applied in this study. Otherwise, the algorithms are only somewhat effective for peak wintertime in US and Canada and not applicable for studies, like prescribing observational snow cover conditions in climate projection or snow-land-atmosphere climate interaction studies, which are pointed out as one primary reason to perform this present study.

Response: Thanks you very much. We do agree with your comment on extending the study period to the snow cover accumulation and ablation stages/seasons for the fractional snow cover retrieval models. For this issue, we have discussed in Section 5.1 and provided the detailed discussions

"*...In this study's datasets, a greater number of records were located near the extreme values of the fractional snow cover (0 and 1). Thus, it is reasonable to use stratified random sampling (Dobreva and Klein, 2011), however, not the proportional distribution of target values suggested by previous studies (Nguyen et al., 2018; Millard and Richardson, 2015). Even in this cases, the overestimation and underestimation often occur in the results of training datasets (Fig. 7 A – D) and evaluation datasets (Fig. 7 a – d), respectively. This is mainly because the established fractional snow cover retrieval model using the training sample with relatively low diversity of fractional snow cover values does not well learn the snow cover distribution characteristics of the various surface condition. Therefore, it is necessary for future studies to increase the amount of samples by extending the study period to the snow accumulation and snow ablation stages (Xiao et al., 2018), where there is much more shallow snow and "patchy" snow cover. Another option is using data from multi-source sensors to generate reference snow cover data (e.g., Sentinel -1 Synthetic Aperture Radar data). By doing this, the proportion of fractional snow cover* *values in the training sample may be distributed as evenly as possible (Colditz, 2015; Jin et al., 2014; Lyons et al., 2018).*" in page 24 lines 5-16.

In fact, the same idea on "It is also worthwhile to capture the temporal and spatial heterogeneity in the accumulation and ablation seasons and more fully test the algorithms described and applied in this study" has been one major task of our ongoing work. Specifically, it is to establish different fractional snow cover retrieval models on different snow cover stages (snow cover accumulation stage, snow cover stabilization stage and snow cover ablation stage), and to analyze the spatiotemporal variation characteristics of the estimated fractional snow cover.

Also, in relation to the timeframe of the training and validation data years, only having one year to perform the validation seems quite limiting, as a given year can be hard to note overall performance given snow cover can vary greatly from year to year (e.g., snow drought conditions). This is somewhat reflected in Figure 7 (right column panels), which show how highly variable and not as predictable in the validation year (2017). Please explain why a longer period of record is not used, e.g., 2002-2019 (Terra+Aqua MODIS combined) and the passive microwave combined product by Brodzik et al. (2018), to perform the training and validation period. Perhaps, use Water Years (WY) 2002-2013 for training and WY 2014-2018 for validation?

Using only one year for testing and a second year for validation is very limiting for this study, and it is highly recommended for additional years to be included. Also, for the four different approaches of estimating the fractional snow cover from passive microwave should have longer evaluations performed in this context as the summary of the results would be inconclusive for one year of validation.

Response： Thanks for your comments and suggestions. In the absence of available published materials on fractional snow cover estimation from passive microwave data, the first subject of this study is to explore the possibility and feasibility of estimating fractional snow cover estimation from passive microwave brightness temperature data. Therefore, we conducted a series of experiments with 10 years data (January and February only) to demonstrate the feasibility of estimating fractional snow cover from passive microwave data, as described in Section 6 (page 26 lines 11-18)
"*Numerous studies have investigated the relationship between common snowpack physical properties (e.g., snow depth and water equivalent) and passive microwave brightness temperature at different frequencies and polarizations (Chang et al., 1987; Dietz et al., 2011; Kim et al., 2019; Xiao et al., 2018). Unlike many previous studies, this study innovatively used passive microwave data to directly estimate fractional snow cover. The results showed that it is possible to directly obtain an estimated fractional snow cover with high accuracy from high-spatial-resolution passive microwave data (6.25 km) under all weather conditions. Further detailed study on the use of high spatial resolution passive microwave data for fractional snow cover estimation presents itself as an interesting research direction for the development of the studies on fractional snow cover estimation*". Overall, we has basically achieved the preset goals of this study.

Moreover, at the beginning of our experiment, we also tested the performance of fractional snow cover retrieval model with the remaining data of 2011-2016 (excluding the dataset used for training samples); its conclusion is consist with that of the current experiment (using a single year of data), and the accuracy indexes (MAE and RMSE) are not significantly different. To make sure that each experiment is completely independent, we then gave up the above experimental design and adopted that the data of different years were used in different phases. As a basis of estimating fractional snow cover from passive microwave data, there will be a lot of researches to carry out in future studies, such as to apply this algorithm to other study region and other study period, to improve the fractional snow cover retrieval algorithm, and to generate a high accuracy product for change characteristics analysis of snow cover area.

Furthermore, one issue that has to be explained in detail is the use of the data in this study. As to Fig. 7, the major reason for the relatively even distribution of the data used in the left column panels with capital letters (A-D) is that these training data are obtained by applying a stratified random sampling strategy in the 6 years total available data (2011-2016; January and February). Following your suggestion, we added another two years data for evaluating the performance of the retrieval models

(Fig. 7). The right column panels with lowercase letters (a-d) in the revised Fig. 7, the updated evaluation datasets, which were randomly selected from the datasets in 2008 – 2009 and 2017 and the selecting rule is same as the training sample, were used to further evaluate the predictive capability of random forest models in all range values. Correspondingly, we modified the statistic indexes in Table 6 and the description in Section 4.3 as following:

"*The independent data, which was randomly selected from the datasets in 2008 – 2009 and 2017 and the selecting rule is same as the training sample, was used to further evaluate the predictive capability of random forest models in all range values. In this part, we analyzed the results from the training and evaluation stage for four land cover types (Table 6, Fig. 7). Fig. 7A and 7a show that fractional snow cover around 1 are distinctly underestimated and few are above the 1:1 line. The model for forest type had the poorest performance with the lowest R (0.636) and the highest RMSE (0.221) for the evaluation dataset (Table 6). The retrieval model on the prairie type had the best performance on the evaluation data (R: 0.752; MAE: 0.148; RMSE: 0.189). In shrub and bare land types (Fig. 7B, 7b, 7D and 7d; Table 6), the retrieval models have similar performance in evaluation datasets (R: 0.712 and 0.719; MAE: 0.160 and 0.165; RMSE: 0.212 and 0.216, respectively); "true" fractional snow cover values in the training and validation datasets were more distributed at two polar ends (0.0~0.3 and 0.9~1.0) in these two land cover types. When comes to the results in the training stage and the evaluation stage, we can found that the estimation performance of the retrieval model in evaluation datasets are highly dependent on the quality of training sample which was used to establish the retrieval models. Fig. 7 show that the established models in four land cover types can properly capture the characteristics of all range of fractional snow cover values.*"

Table 6. The performance of random forest models on training and validation data under four land cover types.

Land cover type	Training			Validation		
	R	MAE	RMSE	R	MAE	RMSE
Forest	0.702	0.166	0.207	0.636	0.180	0.221
Shrub	0.772	0.146	0.191	0.712	0.160	0.212
Prairie	0.807	0.142	0.182	0.752	0.148	0.189
Bare land	0.807	0.144	0.190	0.719	0.165	0.216

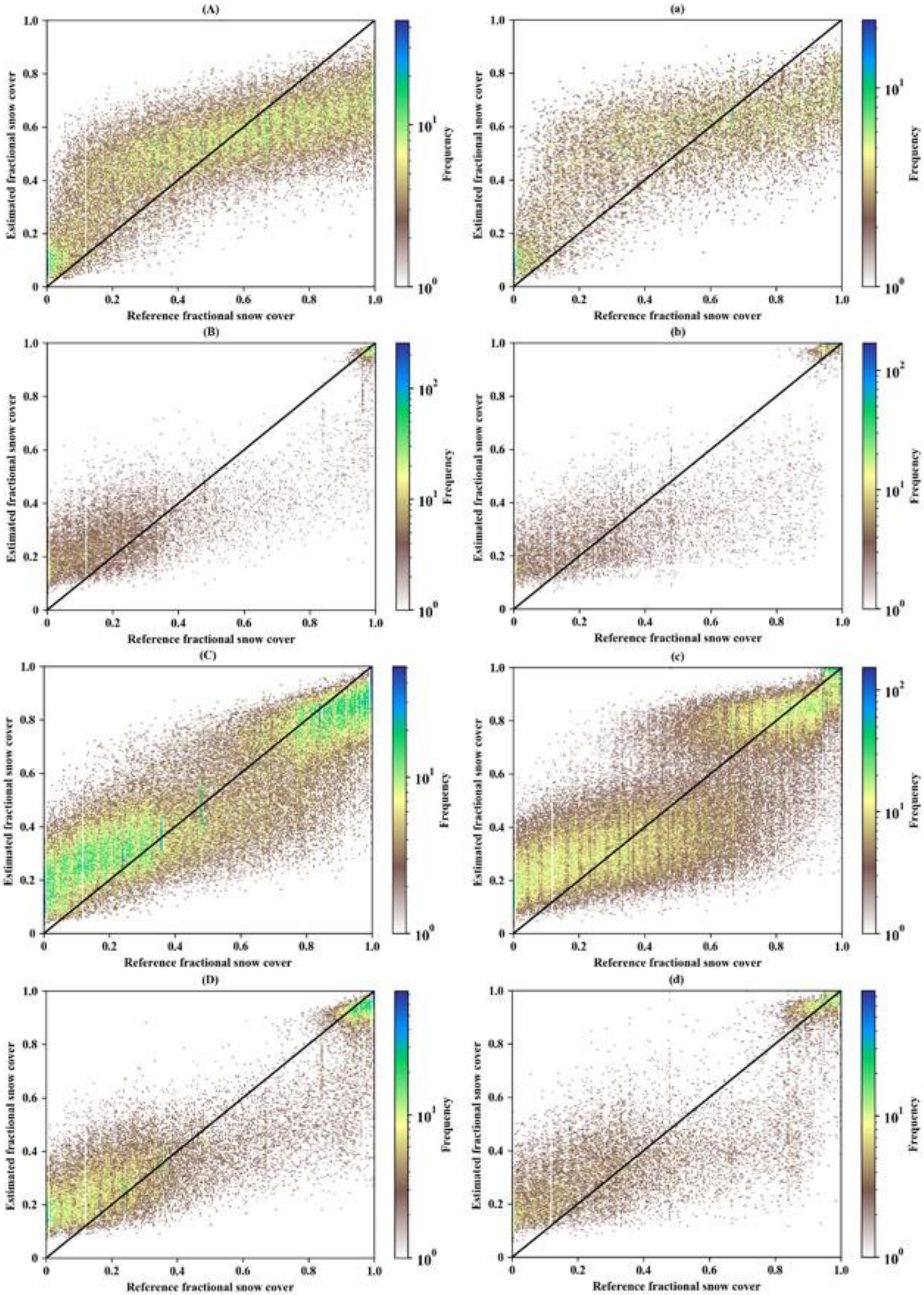


Fig. 7. The color-density scatter plots between the estimated fractional snow cover and MODIS-derived fractional snow cover for four land cover types (forest: A, a; shrub: B, b; prairie: C, c; bare land: D, d). Left column with capital letters is the

results in the training stage (A-D); right column with lowercase letters is the results in the evaluation stage (a-d).

Some of the methods sections are hard to follow, though the authors provide many details there and in the Supplemental material. For example, Section 3.3.1 of "Selecting input variables" was at times hard to follow and why each scenario was selected. Improving the organization of the sections to flow better in terms of their logic and why different experiments were performed would be helpful for the overall background and discussions of this study.

The English grammar and syntax used require additional review and editing by editorial services to help correct these issues before resubmitting. A few suggested corrections are offered below in the technical corrections section.

Response: Thanks for your positive comment to improve our manuscript. The revised manuscript has been proof read by a native English speaker. Additionally, we clarified the background of the variables selection and setting for each scenarios, and revised the statement about why different experiments were performed in Section 3.3.1 (from page 10 lines 19 to page 11 line 14).

"*A decision tree was established using all variables shown in Scenario -1 (Table 1), and was utilized to compare with five scenarios in terms of prediction performance and efficiency. Note that these 19 input variables were determined by using the Correlation Attribute Evaluation method in the Waikato Environment for Knowledge Analysis 3.8.3 (WEKA) data mining software. This method evaluates the worth of the attribute by measuring the correlation between the attribute and the target (Frank et al., 2004; Eibe Frank, 2016). The brightness temperature and its linear combination can also directly be used to detect snow cover based on Xu et al. (2016) study; thereby, Scenario -2 only contained brightness temperature and its linear combination without consideration to the effects of location and topographic factors. Wiesmann and Mätzler (1999) reported that V and H polarizations were dominated by scattering and snow stratigraphy, respectively. Thus, Kim et al. (2019) only assimilated V polarization with an ensemble snowpack model to estimate snow depth. Therefore, in Scenario -3, we attempted to evaluate the performance of the established retrieval model by only using the brightness temperature in 19, 37 and 91 GHz (V polarization) based on Wiesmann and Mätzler (1999) and Kim et al. (2019). In Scenario -4, we used similar input variables to those used for snow depth estimation in Xiao et al. (2018), and examined whether these same parameters can or cannot estimate the fractional snow cover. In Scenario -5, unlike the variables used in Scenario -4, we attempted to use the basic input variables coupled with the brightness temperature linear combination for fractional snow cover retrieval.*

There are other variable selection strategies based on the importance rank when using random forest method. For example, Mutanga et al. (2012) implemented a backward feature elimination method to progressively eliminate less important variables, whilst Nguyen et al. (2018) summarized the grade of the variable and selected the top eight important variables as the input variables in the training model. Similarly, this study assessed the importance of input variables on four land cover types using the same size of the training sample (15 000) (Xiao et al., 2018). We then counted the number of times of each variable that was ranked in the top nine important variables (summarized in Table S2, Appendix), which were then used as the input variables for Scenario -6 (listed in Table 1). By assessing the performance of models established by these six scenarios, an optimal combination of input variables for the fractional snow cover retrieval model may be selected (see Section 4.1.1). All input variables were normalized to [0, 1]."

Specific Comments

Abstract: The authors introduce "Grody's snow cover mapping algorithm" towards the end of the abstract without any other background. Perhaps they could provide one introductory phrase on this algorithm within the abstract to give more context.

Response: Thanks for your comment. We revised the original sentence to "*There was significant improvement in the accuracy of snow cover identification using our algorithm; the overall accuracy had increased by 18% (from 0.71 to 0.84), and the omission error had reduced by 71% (from 0.48 to 0.14), when the threshold of fractional snow cover was 0.3* " in Abstract

Page 2, Lines 9-10: The authors mention that snow cover data from station measurements are “time-consuming, [and] cumbersome,”. What do the authors mean by these adjectives? Please clarify here. Any dataset, including satellite, requires time and careful derivation of the final product. However, in situ snow cover data are spatially discontinuous and require more time to maintain.

Response: Thank you. According to your suggestion, we clarified the sentence to “*Snow cover data is typically obtained from meteorological stations or in-situ manual measurements, which is spatially discontinuous and labor intensive*” in page 2 lines 17-18.

Page 6, lines 11-12: Would like to point out here that North America includes Mexico as well. The authors should specify that their study domain spans the continental U.S. and Canada only.

Response: Thank you. We specified the study domain definition and revised the original sentence to “*Fig. 1 shows the elevation pattern for North America, limited to Canada and United States in this study.*” in page 7 lines 3-4.

Page 7, lines 10-11: Authors state here that “to the best of our knowledge, there are no researchers have developed fractional snow cover : : : using passive microwave data.” Please take a look at the following references and cite appropriately:

Foster, J.L., D. K. Hall, J. B. Eylander, G. A. Riggs, S. V. Nghiem, M. Tedesco, E. Kim, P.M. Montesano, R. E. J. Kelly, K. A. Casey and B. Choudhury (2011): A blended global snow product using visible, passive microwave and scatterometer satellite data, International Journal of Remote Sensing, 32:5, 1371-1395, DOI: 10.1080/01431160903548013

Response: Thanks for your comment. The study carried out in Foster et al. (2011) was to yield a blended snow cover product with a 25-km resolution by combining MODIS snow cover product, AMSR-E snow water equivalent product, and QSCAT data, which have several parameters including snow cover extent, snow water equivalent, fractional snow cover, onset of snowmelt and areas of snow cover that are actively melting. We find that there is essential difference between Foster’s study and our work in fractional snow cover estimation. In contrast, current study devoted to retrieving fractional snow cover from passive microwave brightness temperature at 6.25-km resolution, which means that the estimated results are based on passive microwave data. We changed it to “*Second, to the best of our knowledge, there are few attempts to directly develop fractional snow cover from passive microwave data*” in page 8 lines5-6

Page 8, lines 24-27: It would be helpful here to provide a lead in sentence to introduce your first two equations.

Response: Thanks your valuable suggestion. We revised and clarified the description about these two equations as follows (in page 9 line 16-26):

“*1) Combining snow cover images from two sensors on a given day: the first simple filter was applied under the assumption that snowmelt and snowfall did not occur within the two sensor observations. Whether a pixel in Terra (S_t^{Aqua}) or Aqua (S_t^{Terra}) snow cover image in a given day (t) was observed as snow cover or snow-free, the pixel in the output image (MCD10A1) was assigned the same ground status (shown in Eq. 1). The results showed about 3% of cloud cover was removed compared to MOD10A1 (Gafurov and Bárdossy, 2009).*

2) Short-term temporal filter: if the status of a pixel in the input image (MCD10A1) in a given day (t) was cloud and both the preceding (t - 1) and succeeding (t + 1) days were snow-covered (or snow-free), the pixel in the output image (MCTD10A1) in the given day (t) was assigned as snow-covered (or snow-free) (summarized by Eq. 2). Compared to the first filter, this short-term temporal filter may markedly reduce the number of days (10% ~ 40%) for cloud coverage and increase the overall accuracy of snow cover detection (Gafurov and Bárdossy, 2009; Tran et al., 2019)…” in page 8 lines 22-30.

Page 8, last line: “Calculation areas should be in a larger feet : : :” What is meant here by “feet”? It does not seem to make sense to use this word here, but perhaps “footprint area” makes more sense? Please correct.

Response: Thanks for your suggestion. We corrected the sentence to “*Calculated areas should be a larger footprint area than the pixel resolution to avoid MODIS geolocation uncertainties…*” in page 10 lines 1-2.

Page 11, lines 2-3: MODIS Collection 5 products are considered older and not “current”, as they have been replaced by Collection 6. Recommend removing “current” here.

Response: Thank you. We removed “current” and revised the sentence to “*This type of regression method has been applied in generating the standard MODIS fractional snow cover product Collection 5…*” in page 12 lines 12-13.

Subsection 3.4.1: The authors discuss both the linear and multi-linear regression methods here, which makes the discussion confusing to follow. They then have the reader refer to the Supplementary material for more information. It is recommended that the authors better describe in this subsection how the “linear regression” is applied. Was it based on the equations in Salomonson and Appel (2004) or new linear equations and parameters derived for the four different vegetation categories? Please try to better organize and explain this linear method in this subsection.

Response: Thanks for your comment and suggestion. We revised the statement about linear regression method as follows: “*For optical remote sensing studies, there is a classical and general linear regression method used to estimate the sub-pixel snow cover area in medium- to high-spatial-resolution image. This only involve the relationship between NDSI and fractional snow cover derived from high-resolution snow cover maps (Salomonson and Appel, 2004; Salomonson and Appel, 2006). This type of regression method has been applied in generating the standard MODIS fractional snow cover product Collection 5. Similarly, the multiple linear regression method was used as a reference method in this study to estimate fractional snow cover based on passive microwave data. The inputs were the same as the other three methods in this study…*” in page 12 lines 8-15.

Page 14, lines 10-11: Please provide citations and references where possible for the metrics, especially Cohen’s kappa coefficient and the F1 score.

Response: Thanks. We add the citation for the metrics and correspondingly the sentence was revised to “*Six accuracy assessment indices were used for the analysis of snow cover detection capability (Liu et al., 2018; Gascoin et al., 2019); overall accuracy (OA), precision (that is, a positive prediction value), recall, specificity (that is, the true negative rate), F1 score (Zhong et al., 2019), and Cohen's kappa coefficient (Foody, 2020).*” in page 16 lines 4-7.

Page 15, Lines 11-12: Authors indicate here that their “Scenario-6” variable sensitivity case “generated the worse performance, with the low R, the great MAE and RMSE”. When looking at Table 4 results, Scenario-6 appears to perform rather well overall. Perhaps it would help if the authors specify here that of the Scenarios of 1, 4-5 and 6, Scenario-6 performs the “worst”. It is also recommended to change the last part of that sentence to: “ this scenario’s setting had the third worst performance with lower R values and higher MAE and RSME values.”

Response: Thank you very much for your suggestion. We revised the statement to “*Moreover, when compared to Scenarios-1, 4, 5, the setting in Scenario-6, where input variables were selected by importance, had the third poorest performance, with a low R, and a high MAE and RMSE*” in page 17 lines 13-16.

Page 15, line 31 to top of Page 16: Make “Figure” plural and change the last part of this sentence to something like: “show that this finding was not coincidental.” This sentence is a bit hard to understand in what is meant by “not coincidental”. Please elaborate or better explain the meaning here.

Response: Thanks. We clarified the statement and revised to “*Interestingly, the 0.3% training sample size had the shortest modeling time of the three sample size (Fig. 4); Figs. S-1, 2, 3 also exhibit similar findings on modeling time.*” in page 18 lines 5-7.

Page 16, line 29: Please clarify here what is meant by “neglected to assess the rationality of estimated value : : :”. Are you referring to the out-of-bounds events that occur in the other methods, other than the random forest approach and that that “rational” was not well checked?

Response: Thanks for your suggestion and comment. We revised the sentence to “*Previous studies have generally neglected the analysis and evaluation of whether the estimated value is out-of-range*” in page 19 lines 8-9.

Page 21, line 1: Authors state that only a few studies validate the accuracy of MODIS snow cover products in forested areas. Actually, there are several in addition, including:

Arsenault, K.R., P.R. Houser and G. J.M. De Lannoy, 2014: Evaluation of the MODIS snow cover fraction product, Hydro. Proc., 30, 3, pps. 980-998. https://onlinelibrary.wiley.com/doi/full/10.1002/hyp.9636

Kostadinov, T. S., and T. R. Lookingbill, 2015: Snow cover variability in a forest ecotone of the Oregon Cascades via MODIS Terra products, Rem. Sens. Env., 164, pps. 155-169. https://www.sciencedirect.com/science/article/pii/S0034425715001303

Response: Thank you very much for your suggestion. We added the suggested literatures and revised the statement to “*Several studies have validated and evaluated the accuracy of MODIS snow cover products, particularly in forested areas (Parajka et al., 2012; Zhang et al., 2019; Arsenault et al., 2014; Kostadinov and Lookingbill, 2015)*” in page 24 lines 27-29.

Page 22, lines 14-16: The first statement here about the “strong limitations in the understanding of physical mechanism” is a bit hard to understand. Are the authors referring to the underlying physics and characteristics that relate the fractional snow to the signature of the passive microwave bright temperature responses? Perhaps, it might be better to frame these concluding statements more in that way vs. “mechanisms”.

Response: Thanks for your constructive suggestion. We clarified and revised the sentence to “*However, it also contains significant limitations in understanding the physics that relates fractional snow cover to the signature of passive microwave brightness temperature (Cohen et al., 2015; Che et al., 2016). Future studies need to use physical snowpack models and radiation transfer theory to explore the physical mechanistic relationships between microwave brightness temperature and fractional snow cover (Pan et al., 2014)*” in page 26 lines 23-27.

Table 1: In the row of references, does the Xiao et al. (2018) paper cover both Scenario-4 and -5 columns in the table? If so, it might be helpful to specify this in the body of the paper.

Response: Thanks. Xiao et al. (2018) study only cover the variables used in Scenario-4, not in Scenario-5. Thus, we did not provide the related reference for Scenario-5.

Figure 8: In panel A, more binary MODIS snow cover present (e.g., large green pixeled areas in Canada), but that does not

seem to get translated over to panel B for the fractional MODIS snow cover (mostly filled in with no fractional values). Please explain why most of the derived MODIS snow cover fraction is removed here, especially over Canada? Also, for the MODIS snow fractional product, there is no fractional snow representation between 0.3 and 0.8, the other two categories shown in panel B. What is happening here in that regard – no fractional snow within 0.3 and 0.8 at any noticeable gridcells? Please provide an explanation in the text as well.

Response: Thanks for your suggestions to improve our manuscript.
1) The MODIS binary snow cover image (Fig. 8A) was translated to the reference MODIS fractional snow cover (Fig. 8B) by applying the strictest pixel filtering rule at a 15*15 pixels window, meaning that the window do not allow an cloudy and water pixel when calculating the fractional snow cover. Therefore, many pixels (6.25-km) were masked as "fill value" (white in Fig. 8B). In addition, we did a test, if 5% (about 11 pixels) of cloudy and water pixels are allowed in the 15*15 pixels window, more than 6% of the white space would substitute with the intermediate values (0.1 ~ 0.9) of fractional snow cover. In other words, the number of pixels with the intermediate value (ranging from 0.1 to 0.9) will double from what it is now. The following figure show the increase percentage of the number of pixel with the fractional snow cover values in range of 0.1 and 0.9 in different land cover types if we allow 5% of cloudy and water pixels in the 15 * 15 pixels window. Furthermore, the estimated fractional snow cover would bring maximum 5% uncertainty due to these cloudy and water pixels

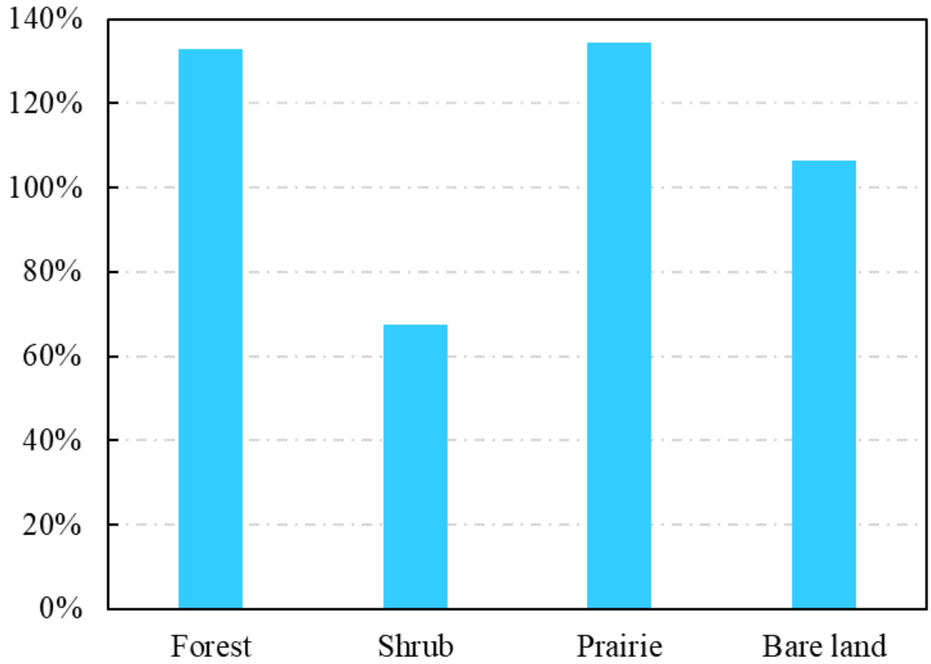


Figure R. The increase percentage of the number of pixel with the fractional snow cover values in range of 0.1 and 0.9 in different land cover types (forest, shrub, prairie and bare land) if we allow 5% of cloudy and water pixels in the 15 * 15 pixels window.

2) Each category (0-0.3; 0.3-0.5; 0.5-0.8; 0.8-1) was exhibited in MODIS fractional snow cover image (Fig. 8B), just the difference in the amount of pixels. The intermediate values of fractional snow cover usually can be found at the edge of the two extreme values area (0 and 1).
Based on your suggestion, we revised the description about Fig. 8 as follows:
"*Apart from the scatter plots and statistical analysis, Fig. 8 shows the distribution pattern of snow cover from a spatial perspective, including MODIS composite binary snow cover (Fig. 8A), MODIS fractional snow cover (Fig. 8B), and the estimated fractional snow cover by the proposed algorithm (Fig. 8C). When the most rigorous pixel filtering rule at the 15*15 pixel window was applied (see Section 3.2), the large number of cloud covered pixels (yellow) in Fig. 8A resulted in most areas of the MODIS fractional snow cover image (Fig. 8B) being represented by a "fill value". Additionally, the number of intermediate values for MODIS fractional snow cover in winter would be much lower than the number of values near the two extreme values (0 and 1). In contrast, the estimated fractional snow cover from passive microwave brightness temperature data can provide almost complete coverage and continuous spatial information on snow cover (Fig. 8C; Fig. S-7 in the*

Appendix). Fig. 8 shows the comparison between our estimated fractional snow cover and the reference MODIS fractional snow cover, and more importantly, provides another perspective for snow cover identification in Section 4.4. Thus, Fig. 8B and 8C used 0.3 as the threshold of fractional snow cover to define snow-covered and snow-free area, and this was adopted through the experiments in Section 4.4. This means that the pixel was identified as snow cover when fractional snow cover value was less than 0.3. From Fig. 8A – C, the spatial pattern of estimated fractional snow cover from the proposed method seems to accurately capture the distribution of snow cover from MODIS under clear-sky conditions, such as the snow-free area in most areas of North America, and snow-covered areas in northern Canada. Fig. 8D presents a specific example comparing these two fractional snow cover datasets and MODIS composite binary snow cover products in central Canada on February 27th, 2017. Based on this example, we find that our estimated fractional snow cover was capable of obtaining snow cover distribution when most of the area was covered by cloud, which was not the case for MODIS. This example also show that the extent of snowline observed in the MODIS binary snow cover image (500 m), which was the boundary between snow-covered and snow-free, was well described and exhibited by the estimated fractional snow cover (6.25 km)." in page 20 lines 10-30.

Finally for Figure 8, it would be helpful to assign a different color and category for the non-snow pixels (at fractional value of 0.) in panels B and C to better discriminate the non-snow areas from the snow-based areas. Currently, snow-free pixels are lumped in with the low snow fraction category of 0 to 0.3.

Response: Thanks for your comment. In this study, we clarified why 0.3 is adopted as the threshold of fractional snow cover. "*Fig. 8 shows the comparison between our estimated fractional snow cover and the reference MODIS fractional snow cover, and more importantly, provides another perspective for snow cover identification in Section 4.4. Thus, Fig. 8B and 8C used 0.3 as the threshold of fractional snow cover to define snow-covered and snow-free area, and this was adopted through the experiments in Section 4.4*" in page 20 lines 18-20.

In addition, a comparison example of the reference MODIS fractional snow cover with our estimated fractional snow cover in continuous value (Figures S-7 vs Fig 8.) in the supplement have been provided to show the continuous change characteristics of fractional snow cover in the Norther America on February 27th, 2017 (2017058).

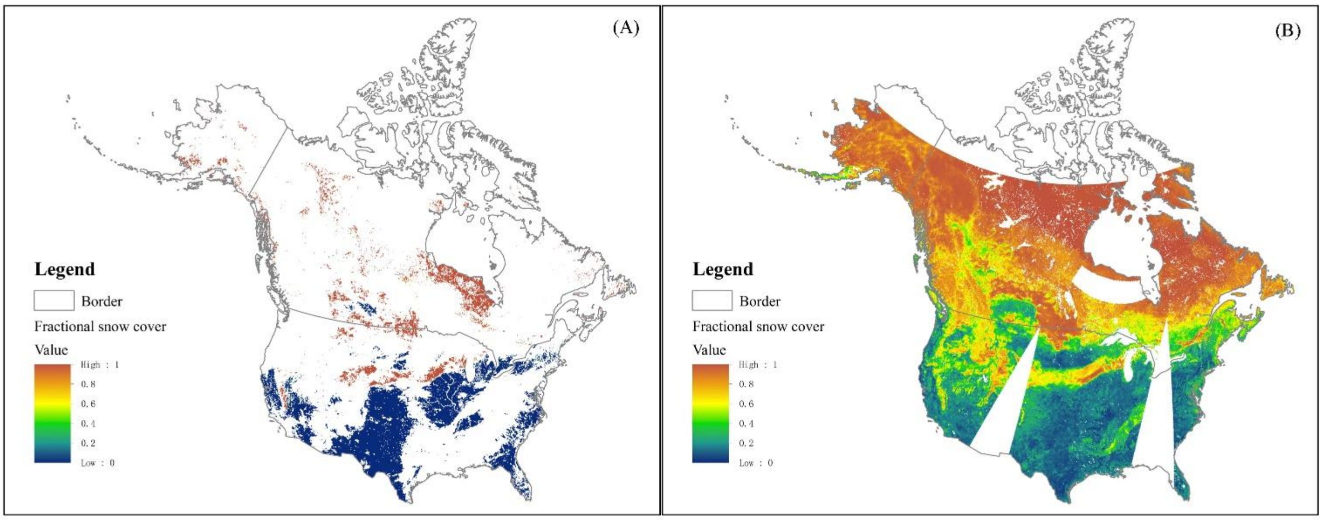


Figure S-7. Comparison of the reference MODIS fractional snow cover (A) with our estimated fractional snow cover (B) in continuous value (6.25-km) on February 27th, 2017 (2017058)

Fig. 11: This is a nice figure that summarize and present these results well.

Response: Thanks for your positive comments.

Technical corrections

Page 2, line 25: Please specify what “FY” stands for in “FY series sensors”.

Response: We revised the sentence to “*...Fengyun (FY) series sensors....*” in page 3 line 7.

Page 3, line 25: Awkward phrasing here: “To unite resolution, : : :” Perhaps try: “ To be at a common resolution, : : :”

Response: Thanks for your suggestion. We revised the sentence to “*To achieve a common resolution, bilinear interpolation was used to aggregate the 3.125 km spatial resolution data to 6.25 km*” in page 5 lines 15-16.

Page 5, line 7: Recommend here to separate the two phrases here with either a semi-colon (between “collected” and “all available”) or place the conjunction “and” after the comma.

Response: Thanks. We revised the sentence to “*... Canada and United States were collected, and all available records from these sites were included in this study.*” in page 5 lines 26.

Page 6, line 6: Please specify what “ETOPO1” stands for.

Response: Thanks. The elevation dataset’s name is called ETOPO1 refer to the website (https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ngdc.mgg.dem:316), and do not have more full name for these characters.

Page 6, line 11: Add citation and reference for “ArcGIS 10.5” software.

Response: We cited the related reference and revised the sentence to “*The slope and aspect data were obtained from ETOPO1 data by ArcGIS 10.5 (Buckley, 2019)*” in page 7 lines 2-3.

Page 6, line 17: Replace “heterogeneous” with the noun, “heterogeneity”.

Response: Thanks. We replace “heterogeneous” with “*heterogeneity*” in page 7 line 9.

Page 7, line 7: MODIS misspelled here as “MODSI”.

Response: Thanks. We changed “MODSI” to “*MODIS*” in page 8 line2.

Page 7, line 31: Remove “with” before “accurate”.

Response: Thank you. We removed “with” before “*less accurate*” in page 8 line 30.

Page 9, line 21: Either replace the semicolon with a period, or make the word, “Thereby”, lower-case.

Response: Thanks. We changed “Thereby” to “*thereby*” in page 10 line 25.

Page 9, line 27: Change the “not” in this line to “cannot”. Also on that same line, the word use of “Correspondingly” here does not seem to make sense.

Response: Thanks. We revised the sentence to “*... can or cannot estimate the fractional snow cover. In Secenatio-5 ....*” in page 11 line 1.

Page 10, line 5: Make “variable” plural here in “an optimal combination of input variables”.

Response: Thanks. We changed “variable” to “*variables*” in page 11 line 13.

Page 13, line 6: “researches” should be changed to “researchers”.

Response: Thanks you. We changed “researches” to “*researchers*” in page 14 line 23.

Page 18, line 5: Remove “be” before “misclassified” and change “into” to “as”. Also, please remove the phrase, “As we all know”, and change the start of the second sentence there to: “Permafrost is known to be widely distributed in the northern part of…”

Response: Thank you. We removed “be” before misclassified and changed “into” to “as”, accordingly, the sentence changed to “*... these scatters were easily misclassified as snow cover in less snow cover conditions...*” in page 21 lines 14-16. And we have removed the description “Permafrost is known to be widely distributed in the northern part of…” based on the revised needs

Page 20, line 4: Change “researches” to “studies”.

Response: We changed “researches” to “*studies*” in page 23 line 27.

Page 21, lines 23-24: Change “were” to “was” in relation to “The accuracy of the proposed algorithm was further : : :”.

Response: Thank you. The sentence was changed to “*The results of the evaluation using the reference fractional snow cover data in 2017 showed that ....*” in page 25 lines 26-27.

Table 2 caption: “unite” should be “unit”, and “clod desert” should be “cold desert”.

Response: Thank you very much. We changed “unite” to “*unit*” and modified “clod desert” to “*cold desert*” in Table 2

Figure 7: The use of the capitalized and lower-case plot labels is fine but not conventional. Would it make more sense to simply use, “A, B” then “C, D”, etc., for the paired columns?

Response: Thanks for your comment. Horizontally, the capital letters indicate the results in the training stage, while the lowercase letters represent the results in evaluation stage; from the vertical perspective, the results in two stages in each row are the same type of land cover which was represented by the same level of letters that are easily distinguished. The caption of Fig. 7 was modified to “*... Left column with capital letters is the results in the training stage (A-D); right column with lowercase letters is the results in the evaluation stage (a-d).*

Estimating fractional snow cover from passive microwave brightness temperature data using MODIS snow cover product over North America

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Abstract: The dynamic characteristics of seasonal snow cover are critical for the hydrology management, the climate system, and the ecosystem functions. ~~Although optical~~ Optical satellite remote sensing has proven~~d~~ to be an effective tool for monitoring global and regional variations of snow cover. However, ~~it is still problematic to~~ accurately capturing~~e~~ the characteristics of snow dynamics ~~characteristics~~ at a finer spatiotemporal resolution continues to be problematic as~~, because~~ ~~the~~ observations from optical satellite sensors are ~~seriously~~ greatly impacted ~~affected~~ by clouds and solar illumination. ~~Besides,~~ T~~t~~raditional methods of mapping snow cover from passive microwave data only provide binary information ~~with~~ at a spatial resolution of 25~~-~~ km ~~spatial resolution~~. T~~In t~~his ~~study, we~~ innovative study applies the random forest regression technique to enhanced-resolution passive microwave brightness temperature data (6.25 km) to ~~first present an approach to predict~~ estimate fractional snow cover over North America under all-weather conditions~~, derived from the enhanced resolution passive microwave brightness temperature data (6.25 km)~~. Many influent factors, including land cover, topography, and location information, were incorporated into the retrieval models. ~~This estimation algorithm used~~ Moderate Resolution Imaging Spectroradiometer (MODIS) snow cover products between 2008~~10~~ and 2017 were used to create the reference fractional snow cover data as the "true" observations in this study. ~~Further, the influence of many factors, including land cover, topography, and location, were incorporated into the retrieval models. The results show that~~ T~~t~~he proposed retrieval ~~models~~ algorithm out-~~based on random forest regression technique~~ performed the other three approaches (linear regression, artificial neural networks, and multivariate adaptive regression splines), ~~much better~~ using independent test data for all land cover classes, with higher accuracy and no out-of-range estimated values~~, when compared to the other three approaches (linear regression, artificial neural networks (ANN), and multivariate adaptive regression splines (MARS))~~. The method enabled the ~~The results of the output~~ evaluation of~~ed~~ the estimated fractional snow cover ~~by~~ using ~~using~~ independent datasets, where ~~from 2017~~ ~~indicate that~~ the ~~the~~ root-mean-square error of evaluation results ~~(RMSE) of the estimated fractional snow cover~~ ranged~~es~~ from 0.189~~16.7%~~ to 0.221~~19.8%~~. ~~In addition,~~ T~~t~~he snow cover detection capability of the proposed algorithm ~~estimated fractional snow cover~~ was~~is~~ validated~~erified~~ ~~in the snow mapping aspect by~~ using ~~snow cover observation data from~~ meteorological station~~s~~ observations with greater~~(more~~ than ~~0.~~310 000 ~~million~~ records~~)~~. We found~~The result shows~~ that ~~the~~ binary snow cover obtained from the estimated fractional snow cover ~~by the proposed retrieval algorithm~~ was~~is~~ in ~~a~~ good agreement with ~~the~~

ground measurements (kappa: 0.67). There was significant improvement in the accuracy of snow cover identification using our~~our~~ algorithm; ~~estimation in the snow cover identification shows significant improvement when benchmarked against the Grody's snow cover mapping algorithm:~~ the overall accuracy had ~~is~~ increased by 18% (from 0.71 to 0.84), and the omission error had ~~is~~ reduced by 71% (from 0.48 to 0.14), when the threshold of fractional snow cover was 0.3. The~~According to our~~ experimental results show~~, we can conclude~~ that ~~it is feasible for estimating fractional snow cover from~~ passive microwave brightness temperature data may potentially be used to estimate fractional snow cover directly.~~,~~ ~~and~~ where this~~is~~ retrieval strategy ~~also~~ offers~~has~~ a ~~great~~ competitive advantage in ~~detecting~~ snow cover ~~area~~detection.

1. Introduction

Snow cover is a critical indicator of climate change, ~~and~~ playing~~s~~ a vital role in the global energy budget (Flanner et al., 2011), water cycle~~s~~ (Gao et al., 2019), and atmospheric circulation (Henderson et al., 2018). Snow cover directly modulates the release of carbon and methane from ~~the~~ underlying soil (Zhang, 2005; Zona et al., 2016), and influences ~~the~~ permafrost conditions and active layer dynamics (Zona et al., 2016). ~~Moreover, snowpack~~ Snowpack also stores ~~a~~a huge ~~vast~~ amount~~number~~ of water ~~resources~~ providing ~~water~~ for both domestic and industrial water ~~use~~ needs (Sturm, 2015; Cheng et al., 2019). Accurate and timely monitoring of the spatiotemporal variation of snow cover~~spatiotemporal variation~~ is beneficial for hydrologic forecasting, climate predictions and water resources management (Barnett et al., 2005; Bormann et al., 2018).

~~Usually, S~~Snow cover data is typically obtained from meteorological stations or in-situ manual measurements, which is spatially discontinuous and labor~~are time-consuming, cumbersome, and~~ intensive~~spatially discontinuous~~. Remote sensing has become an attractive alternative tool to ground-based measurements as it is able to~~can~~ cover a wide area and is capable of high frequency observations~~; therefore, it has been an attractive alternative tool to ground-based measurements~~. Numerous studies have focused on snow cover detection and snow cover products used optical and microwave satellite data (Tsai et al., 2019; Liu et al., 2018; Hori et al., 2017). Most of these snow cover products provide binary information at the pixel-level;~~,~~ ~~either~~ snow-covered or snow-free. However, snow cover often varies within a limited scale area, ~~showing~~ characterized by high spatial heterogeneity, especially in alpine terrain areas. Dobreva and Klein (2011) demonstrated that the use of binary snow cover classification in snow cover area estimation ~~could~~ may produce considerable uncertainties. ~~The binary~~ Binary snow cover lacking fractional features hinders ~~the capabilities of~~ accurate~~ly~~ characterization of~~ing~~ the spatial distribution of snow cover and cannot accurately capture variations in~~s~~ ~~the~~ seasonal snow cover dynamics~~ variations~~. ~~From~~ In terms of the energy budget perspective, binary snow cover ~~will bring~~introduces significant uncertainties into the global energy budget estimation because of ~~due to huge~~the large surface albedo differences~~ in surface albedo~~ between snow-covered and snow-free surfaces (He et al., 2014). Thus, there is an urgent need to acquire snow cover area within a sub-pixel to ~~is urgently needed for~~ provide~~ing~~ accurate snow cover information. ~~Therefore, focusing on f~~Fractional ~~instead of binary~~ snow cover allow for the ~~is~~ derivation of snow cover area at the sub-pixel level; this is a better option compared to binary snow cover~~, which means deriving the snow cover area at the sub-pixel level~~ (Salomonson and Appel, 2004).

Fractional snow cover maps derived from optical imagery have been produced for over 40 years. ~~It is generally well known that O~~Optical satellite observations have been recognized for their~~are~~ suitability in~~le for~~ estimating fractional snow cover because of their high spatial resolution. Moderate- to high- resolution optical observations have been~~are~~ popular in previous snow cover studies, for example ~~FY~~Fengyun (FY) series sensors (0.5–~~~~~4 km) (Wang et al., 2017), Moderate Resolution Imaging Spectroradiometer (MODIS) (500 m) (Kuter et al., 2018), and Landsat (30 m) (Berman et al., 2018). There are also many predictive methods for ~~predicting~~ fractional snow cover, such as~~,~~ linear regression (Salomonson and Appel, 2004; Salomonson and Appel, 2006),~~;~~ spectral mixture analysis (Wang et al., 2017; Rosenthal and Dozier, 1996)~~;~~, machine learning~~,~~ (e.g., artificial neural network, ~~(~~ANN) (Liang et al., 2017; Moosavi et al., 2014),~~;~~ and multivariate adaptive regression splines (MARS) (Kuter et al., 2018). A simple linear regression cannot fully describe the complex~~ity of the~~ relationship between satellite observations and fractional snow cover. As such~~; thus~~, non-linear approaches ~~were~~ have recently been developed to replace this traditional method (Berman et al., 2018). Kuter et al. (2018) estimated fractional snow cover from MODIS data using the MARS technique, where the Landsat 8 binary snow cover data served as the reference fractional snow cover data. They found ~~results indicated~~ that the estimated fractional snow cover using ~~from~~ MARS method was~~is~~ in good agreement with the reference fractional snow cover, with the average correlation coefficient being ~~values of~~ R = 0.93 ~~(correlation coefficient)~~ (Kuter et al., 2018). However, polar regions contend with clouds and ~~the~~ limited solar illumination, which are ~~in polar regions have become~~ the greatest challenges ~~in~~ for snow cover detection ~~from~~ using optical satellite data. This has~~,~~ result~~ing~~ed in snow cover maps with incomplete spatial coverage, at times with gaps of ~~sometimes~~ up to 70% (Parajka and Blöschl, 2008). Although there have been c~~C~~onstant efforts ~~have been made~~ to fill the gaps mainly caused by cloud contamination by fusing multi-source data (Chen et al., 2018), such as passive microwave snow cover products (Hao et al., 2018; Huang et al., 2016), and different spatiotemporal ~~and spatial~~ information ~~of~~ on snow cover (Dong and Menzel, 2016; Gafurov and Bárdossy, 2009)~~; however~~, most ~~of these~~ studies have focused on binary snow cover.

When there are consecutive cloud~~ys appear in consecutive~~ days, the use of ~~the before-mentioned~~ data fusion technology ~~would~~ introduces ~~cause~~ significant uncertainties in detecting snow cover from optical imagery. Passive microwave sensors are largely ~~The primary~~ advantageous ~~of passive microwave sensors~~ because they have~~is that they are~~ capacity~~ble~~ to~~f~~ measur~~eing~~ microwave radiation emitted from the ground under the clouds and in darkness. Compared with active microwave sensors~~Besides~~, passive ~~microwave~~ sensors~~, compared with active~~, have a large swathe width and generate a massive amount of daily observations ~~data~~ that extends for several decades (Cohen et al., 2015). To date~~Nowadays~~, passive microwave brightness temperature data ~~have~~ has been widely applied in monitoring soil moisture (Qu et al., 2019), sea/lake ice (Peng et al., 2013), frozen soil (Han et al., 2015), and snow cover. Previous studies ~~about~~ on snow cover usually have typically focused on snow depth (Xiao et al., 2018; Che et al., 2008), snow water equivalent (SWE) (Takala et al., 2011; Lemmetyinen et al., 2018) and snow cover area (Liu et al., 2018; Xu et al., 2016). All ~~these~~ studies on snow cover area were limited to binary information. Specifically, they involved the application of ~~seven~~ common passive microwave snow cover mapping algorithms, such as Grody's algorithm (Grody and Basist, 1996), National Aeronautics and Space Administration (~~Kelly's~~ NASA) Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) SWE algorithm (Kelly, 2009), Singh's algorithm (Singh and Gan, 2000)~~, Hall's algorithm ,~~ Neal's algorithm (Neale et al., 1990), the FY3 algorithm (Li et al., 2007), and the South China algorithm (Pan et al., 2012).~~,~~ ~~all~~ All these algorithm~~of which~~ utilize different thresholds for ~~the~~ brightness temperature to identify binary snow cover. Recently, Xu et al. (2016) applied the brightness temperatures of different channels and their linear combinations into the Presence and Background Learning (PBL) algorithm ~~for~~ to identify~~ing~~ global binary snow cover.

As~~Because of~~ the effect of environmental factors (e.g.,~~such as~~ vegetation, topography, and wind) on snow cover distribution produces~~results in~~ great~~a vast~~ heterogeneity, snow cover monitoring still bears larger uncertainties when only using passive microwave data. These large uncertainties may result from "patchy" (shallow/discontinuous) snow cover and the use of coarse resolution (25 km) (Xiao et al., 2018). ~~Albeit with its~~Despite the coarse resolution of passive microwave sensors, ~~the~~ its ~~cap~~ability to~~of~~ detect~~ing~~ snow cover in the presence of clouds ~~makes passive microwave sensors an~~demonstrates its effectiveness as a snow cover monitoring tool. There is an urgent need for d~~D~~aily time-series and full space-covered sub-pixel snow cover area data ~~are urgently needed~~ for climate and reanalysis studies. Thus, it is necessary to derive high resolution fractional snow cover that can describe snow cover distribution patterns and capture its rapid evolution processes. Brodzik et al. (2018b) recently published the Calibrated Enhanced-Resolution Passive Microwave Daily Equal-Area Scalable Earth Grid (EASE-Grid) 2.0 Brightness Temperature data (see S~~s~~ection 2.1 below), which has~~ve~~ high spatial resolution (3.125~~ km~~ and~~,~~ 6.25 km) depending on frequency (Brodzik et al., 2018a; Long and Brodzik, 2016). This passive microwave data with enhanced resolution ~~enhanced passive microwave data~~ provides an opportunity for fractional snow cover estimation.

The main objective of this study is to develop a feasible method utilizing the enhanced-resolution passive microwave brightness temperature data to retrieve~~predict~~ daily fractional snow cover ~~with~~ at a 6.25 km resolution. The datasets used in this study are described in Section 2, including~~e~~ the enhanced-resolution passive microwave data, ground-based measurements, MODIS snow cover and land cover products, and topographic data ~~are described in section 2~~. Section 3 details the proposed retrieval algorithm ~~with~~ using the random forest method as a retrieval function. Section 4 presents the results from the methods comparison, evaluation, and validation experiments. Finally, ~~section~~ Section 5 discusses the possible factors that impact on~~affect~~ the accuracy of the fractional snow cover estimates derived from passive microwave data.

2. Datasets

2.1 The enhanced-resolution passive microwave data

The NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) program provides ~~one~~ a new version of passive microwave brightness temperature data ~~called~~ known as the Calibrated Enhanced-Resolution Passive Microwave Daily EASE-Grid 2.0 ~~(Equal-Area Scalable Earth Grid)~~ Brightness Temperature. This~~ese~~ passive microwave gridded data spans from 1978 to mid-2017, using~~e~~ the Level-2 satellite records from multiple passive microwave sensors~~, time span from 1978 to mid-2017~~ (Brodzik et al., 2018b; Brodzik et al., 2016, Updated 2018.). This enhanced-resolution data ~~can~~ may be downloaded from the National Snow and Ice Data Center (NSIDC, https://nsidc.org/data/NSIDC-0630/versions/1). We used data from January and February of 2008~~10~~ – ~~to~~ 2017 ~~(January–February only)~~ to explore the feasibility of estimating fractional snow cover using passive microwave data. The Special Sensor Microwave/Imager (SSMIS) sensor (F-16) used in this~~e~~ present study offers three channels (19~~-~~, 37~~-~~ and, 91 -GHz) in both horizontal (H) and vertical (V) polarization, and 22 -GHz with vertical polarization. These datasets were gridded into EASE-Grid 2.0 projections at two spatial resolutions (19~~-~~ and~~,~~ 22 -GHz with 6.25 km,~~;~~ 37~~-~~ and~~,~~ 91 -GHz with 3.125 km). Only observations from descending orbit (morning, 03:52) were used~~In order~~ to avoid the effects of wet snow as much as possible~~ wet snow effects, only observations from descending orbit (morning, 03:52) were used~~ (Derksen et al., 2000). To achieve a common~~unite~~ resolution, ~~a~~ bilinear interpolation was used to aggregate the 3.125 km spatial resolution data to 6.25 km.

2.2 Ground measurements

Although ground measurements of snow cover have limited spatial representation~~iveness~~ in passive microwave coarse spatial resolution, ~~the~~ in-situ measurements continue to be~~are still~~ the most authentic and reliable data source for snow depth estimation or snow cover detection (Chen et al., 2018; Sturm et al., 2010). ~~The g~~Ground measurements from the Global Historical Climatology Network-Daily (GHCN-Daily) data were used to assess the snow cover detection capability (Menne et al., 2012a). The GHCN-Daily dataset wa~~is~~s provided by the National Climatic Data Center (available in http://doi.org/10.7289/V5D21VHZ), and~~; it~~ integrates daily observations from approximately 30 different data sources. The new version data was~~,~~ updated on June 13, 2018, and contained~~s~~ measurements from over ~~one hundred thousand~~100 000 stations worldwide. These stations record various aspects ~~a variety elements~~ of meteorological observations, including snow depth and snowfall (Menne et al., 2012b). Data for more than 50 000 measurement sites across Canada and ~~America~~United States were collected, and~~,~~ all available records from these sites were included in this study.

2.3 MODIS land surface products

2.3.1 Snow cover product

MODIS snow cover products were considered the most suitable reference data b~~B~~ecause of ~~its~~ their wide application, high accuracy (Hall and Riggs, 2007; Zhang et al., 2019; Coll and Li, 2018), and high spatiotemporal resolution (1 ~~-~~day; 500 ~~-~~m)~~, MODIS snow cover products were considered as the most suitable reference data~~. The accuracy of the version 6 MODIS snow cover products ~~(version 6)~~ has ~~been~~ improved compared to that of version 5 (Dong et al., 2014; Huang et al., 2018). The most noticeable change for version 6 is that the Normalized Difference Snow Index (NDSI) snow cover has replaced fractional snow cover, while ~~the~~ binary snow covered area (SCA) datasets are~~is~~ no longer available (Riggs and Hall, 2016). A snow cover detection method using NDSI was applied in version 6 to alleviate commission errors (Riggs et al., 2017). The NDSI index ~~contributes~~ helps to distinguish snow from other surface features and to describe the presence of snow (Hall et al., 1998; Hall et al., 2001). These products ~~are~~ were available from NSIDC website (MOD10A1: https://nsidc.org/data/MOD10A1; MYD10A1: https://nsidc.org/data/MYD10A1)(Hall and Riggs, 2016a, b). The local equatorial crossing times of MODIS onboard the Terra and Aqua satellites are approximately 10:30 a.m. and 01:30 p.m., respectively. This~~In the present~~ study used~~,~~ both MOD10A1 and MYD10A1 NDSI snow cover products ~~were used~~ to generate reference fractional snow cover ~~over~~ for North America. The NDSI snow cover data ~~were~~ was initially~~firstly~~ converted to binary snow cover for~~in order to~~ aggregation~~e~~ into ~~the~~ fractional snow cover data ~~with~~ at ~~a~~ 6.25 km spatial resolution (see S~~s~~ection 3.2).

2.3.2 Land cover product

Generally, the retrieval accuracy of snow cover parameters is strongly dependents~~s~~ on the land cover type~~s~~ (Xiao et al., 2018; Kuter et al., 2018; Dobreva and Klein, 2011; Huang et al., 2018). W~~Thus, w~~e indirectly considered the land cover effect when estimating fractional snow cover by establishing retrieval models on different land cover classes derived from MODIS land cover data (2008~~10~~ – ~~—~~2017). MODIS Land Cover Type Yearly Product (MCD12Q1, version 6) incorporates five different classification schemes and is globally available at a 500 ~~-~~m spatial resolution ~~from~~ spanning 2001 to the present (https://search.earthdata.nasa.gov/). The International Geosphere–Biosphere Program (IGBP) classification scheme categorizes land cover into 17 classes (Sulla-Menashe and Friedl, 2018). In this~~e~~ study, MCD12Q1 data was resampled into the 6.25 km grid using a simple majority method, ~~and~~ then ~~it was~~ integrated into five classes:~~.~~ forest, shrub, prairie, bare land, and water (refer to Xiao et al. (2018)). ~~The~~ F~~f~~ractional snow cover retrieval models were established for ~~the previously mentioned~~ four of these land cover types, ~~except~~ excluding ~~for~~ water.

2.4 Topographic data

Previous studies have demonstrated that topography plays an important role in snowpack distribution (Dai et al., 2017) and snow evolution (Savoie et al., 2009). The ETOPO1 data was used as the topographic auxiliary data; this data~~. ETOPO1~~ has a 1 arc-min~~ute~~ spatial resolution and was developed by the National Geophysical Data Center of the~~,~~ National Oceanic and Atmospheric Administration (NOAA) (Amante and Eakins, 2009)~~. This data is available from the website (https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ngdc.mgg.dem:316)~~. This study also considered elevation, ~~not only~~

~~elevation but also~~ slope, and aspect factors. ~~The e~~Elevation was directly acquired from ETOPO1, which was re-projected and resampled into the grid ~~at~~at the ~~-~~6.25 km spatial resolution. The slope and aspect data were ~~processed~~ obtained from ETOPO1 data by ArcGIS 10.5 (Buckley, 2019)~~ as a derivative product of ETOPO1 data~~. Fig. 1 shows the elevation pattern for~~of our study region,~~ North America, limited to Canada and United States in this study.

3. Methodology

Microwave radiation constantly emitted from the substratum can be measured by passive microwave sensors. However, the overlying snowpack attenuates the upward microwave radiation (Chang et al., 1987). This microwave radiation attenuation was mainly dominated by volume scatter relying on ~~the~~ properties of the snow cover. ~~However, P~~Previous studies have demonstrated that there is great heterogeneity in ~~the~~ snow properties and the distribution of snow cover, both of which~~ show great heterogeneous and~~ may be influenced by many factors (Xiao et al., 2019), including~~, but not limited to~~, the most prevalent land-cover (Che et al., 2016; Kim et al., 2019), topography (e.g., elevation, topographic relief) (Smith and Bookhagen, 2016; Revuelto et al., 2014), time (Sturm et al., 2010; Dai et al., 2012), and climatic conditions (e.g., wind speed, near-surface soil temperature and air temperature) (Dong et al., 2014; Grippa et al., 2004; Josberger and Mognard, 2002). Satellite sensors receive reduced upwelling microwave radiation in proportion to a greater snow cover area or a larger mass of snowpack ~~As a result, the more covered area or the more mass magnitude of the snowpack, the less upwelling microwave radiation was received by the satellite sensors~~ (Chang et al., 1987; Dietz et al., 2011; Saberi, 2019). A number of published work have demonstrated the potential to derive snow depth and SWE using passive microwave radiation data (Kim et al., 2019; Wang et al., 2019). Despite the high uncertainties associated with snow depth and SWE estimations, using passive microwave data can provide useful snow cover extent information (Brown et al., 2010; Foster et al., 2011).

3.1 Overview

T~~In order t~~o develop a fractional snow cover prototype retrieval method combined with optical and passive microwave data, we only used the January and February datasets, ~~because~~ as ~~during this period the~~ snow cover areas ~~reach~~ are at a ~~its~~ maximum and ~~the~~ snowpack properties are relatively stable during this period (Xiao et al., 2018). The influential factors~~ as mentioned above~~ on snow cover, including topography factor, land cover, location and time, were indirectly or directly considered during ~~the~~ retrieval of the fractional snow cover. To date~~So far~~, many researchers have applied machine learning techniques ~~in~~ for the retrieval of snow cover parameters ~~retrieval~~ to explore the relationship between passive microwave signals and snow properties~~y~~ (Xiao et al., 2018; Tedesco et al., 2004). In this study~~Here~~, random forest regression (described in S~~s~~ection 3.4.4) was selected as the retrieval ~~function~~ method to mine the relationship between passive microwave brightness temperature and fractional snow cover. Fig. 2 ~~shows~~ provides an overview of the workflow that consists of four parts:

First, a ground "truth" observation was~~is~~ necessary ~~for~~ to produce~~ing~~ snow cover areas in sub-pixel. Under clear-sky conditions, the reference fraction of snow cover was~~ere~~ generated within a 6.25 ~~-~~km pixel cell by applying the aggregation method to the MOD~~S~~IS binary snow map (see S~~s~~ection 3.2). To make the experiment to be fully independently, t~~T~~he reference fractional snow cover data was divided into three parts: the data from 2011 to 2016, used in the training stage; the data from 2010, used in the testing stage; and the 2008 – 2009 and ~~the~~ 2017 data, used in the evaluation stage.

Second, to the best of our knowledge, there are few attempts to directly develop ~~no researchers have developed~~ fractional snow cover ~~retrieval methods using~~ from passive microwave brightness temperature data. This meant~~us,~~ ~~a~~ a series of sensitivity experiments of input variables selection ~~is~~ were required~~needed~~. ~~The i~~Input parameters were selected based on a series of ~~the~~ tests described in S~~s~~ection 3.3.1. Moreover, we conducted several sensitivity experiments to determine the optimal training sample size for the retrieval method used in this study (Section 3.3.2).

Third, many studies ~~have~~ found that the separate estimation of fractional snow cover (Dobreva and Klein, 2011) and snow depth (Xiao et al., 2018) on different land cover types ~~has~~ produced better results than those obtained from the combined retrieval model. ~~Hence~~As such, the random forest models were developed separately ~~developed~~ for the four land cover types.

Fourth, the last stage consisted of ~~is the~~ evaluation and validation of the established model. ~~The D~~Data from 2010 ~~were~~ was used to assess the performance of four different approaches for estimating fractional snow cover. Additionally, the independent datasets in 2008 –2009 and 2017 were ~~employed~~ used to evaluate the performance of the random ~~-~~forest-based retrieval algorithm for the four land cover types. ~~The I~~Independent validations of snow cover detection capability were conducted using the 2017 retrieval results and station snow depth measurements across North America. There were ~~and~~ compared with the results of Grody's snow cover mapping algorithm.

3.2 Preprocessing of MODIS snow cover products

The base data for this study was t~~T~~he reference fractional snow cover data obtained from the interpretation of MODIS snow cover products ~~is the base data for our work~~. The ~~top~~ highest priority ~~issue~~ was~~is~~ to produce daily binary snow cover area from NDSI snow cover. Previous snow cover detection studies recommend a 0.4 NDSI threshold on global and regional scale snow cover investigations (Parajka et al., 2012; Hall et al., 1995); However, for the new version of MODIS snow cover products, several ~~previous~~ studies ~~researches~~ employed a threshold of NDSI > 0 to identify snow cover (Dong et al., 2014; Riggs et al., 2017; Huang et al., 2018). The NDSI of other features (e.g., cloud-contaminated pixels at the edges of cloud, salt pans, and ~~the~~ pixels with very low visible reflectance) ~~can~~ may also be greater than 0 (Riggs et al., 2017). For this reason, Zhang et al. (2019) demonstrated that a 0.1 NDSI threshold was~~is~~ more reasonable than 0.4 for snow cover identification in no-forest regions, whereas, forest-covered regions insufficient ~~lack enough~~ station measurements ~~to do~~for a reliable and complete evaluation. MODIS snow cover performance is~~s~~ better ~~in~~ for no-forest landscapes than forest-covered~~-~~ counterparts~~landscapes~~, wherein ~~which~~ it is ~~with~~ less accurate for snow cover identification (Hall and Riggs, 2007; Parajka et al., 2012).

T~~In t~~his study selected conservative~~,~~ ~~the~~ NDSI thresholds of 0.1 and 0.4 for~~, in~~ no-forest-covered areas~~, and 0.4,~~ ~~conservatively~~ and ~~chosen~~ for forest-covered ~~areas~~areas, respectively (Riggs and Hall, 2016) to~~, were used for~~ determine~~ing~~ “snow-covered” or “snow-free” areas. The original NDSI snow cover layer classes were reclassified into five types:~~;~~ snow-covered, snow-free, water, cloud, and fill value (refer to Table S1 in Appendix). In addition, MCD12Q1 datasets (500~~-~~ m) ~~were~~ were used as auxiliary data to mask water bodies (Fig. 3) in order to alleviate the uncertainty caused by frozen water bodies when using passive microwave data to detect snow cover (Tedesco and Jeyaratnam, 2016). The MODIS binary snow cover data ~~were~~ was generated based on the NDSI snow cover basic quality assessment (QA), with values of 0 (best), 1 (good) and 2 (OK) (Liang et al., 2017).

Despite the~~Even if MODIS snow cover products have a~~ high spatiotemporal resolution and overall accuracy of snow cover detection (85% – 99%) using MODIS snow cover products (Parajka et al., 2012; Tran et al., 2019; Zhang et al., 2019), the cloud effect hinders its widespread applicability. Previous studies have reported that clouds may~~could~~ cover more than 40% of ~~the~~ MODIS snow cover data, in some cases ~~even~~ exceeding 60% (Dong and Menzel, 2016; Yu et al., 2016; Parajka and Blöschl, 2006). As such, c~~C~~loud removal processing is essential to mitigate the cloud obstruction of MODIS products. This study adopted t~~T~~he cloud removal method combining the MOD10A1 and MYD10A1 snow cover products, as proposed by Gafurov and Bárdossy (2009)~~, was adopted~~. This method consists of two main filters as shown in Fig. 3:

1) Combining snow cover images from two sensors on a given day:~~.~~ t~~T~~he first simple filter was applied under the assumption that snowmelt and snowfall did not occur within the two sensor observations. Whether a pixel i~~o~~n Terra (S_t^{Aqua}) or Aqua (S_t^{Terra}) snow cover image in a given day (t) was~~is~~ observed as snow cover or snow-free, the pixel in the ~~combined~~ output image (MCD10A1) ~~will~~ was~~be~~ assigned the same ground status (shown in Eq. 1). The results showed about 3% of cloud cover was removed compared to MOD10A1 (Gafurov and Bárdossy, 2009).

2) Short-term temporal filter:~~.~~ i~~I~~f the status of a pixel in the input image (MCD10A1) in a given day (t) was~~is~~ cloud and both the preceding (t - 1) and succeeding (t + 1) days ~~–~~were~~are~~ ~~both~~ snow-covered (or snow-free), the ~~cloud~~ pixel in ~~the current MCTD10A1~~the output image (MCTD10A1) in the given day (t) ~~will be~~was assigned as snow-covered ~~status~~ (or snow-free) (summarized by Eq. 2). Compared to the first filter, this short-term temporal filter may ~~strikingly~~ markedly reduce the number of days (10% ~ 40%) for cloud coverage and increase the ~~in~~ overall accuracy of~~for~~ snow cover detection (Gafurov and Bárdossy, 2009; Tran et al., 2019).

$$S_{(output,t)} = max\left(S_t^{Aqua}, S_t^{Terra}\right) \quad (1)$$

$$S_{(output,t)} = 1 \;\; if\left(S_{(t-1)} = 1 \;\; and \;\; S_{(t+1)} = 1\right) \quad (2)$$

where, t is the time and S represents the ground status observed in the image (0 or 1);~~.~~ 0 denotes cloud presence and~~;~~ 1 indicates snow-covered or snow-free.

Theoretically, the MODIS fractional snow cover map should calculate the percentage of snow cover in a strictly delimited area of the passive microwave pixel. Calculated~~ion~~ areas should be ~~in~~ a larger ~~feet~~ footprint area than the pixel resolution to avoid MODIS geolocation uncertainties (Wolfe et al., 2002; Dobreva and Klein, 2011). In this study, a window of 15*15 pixels of MODIS binary snow cover data (MCTD10A1; 500~~-~~ m) was used ~~for~~ to calculate~~ing~~ the fraction of snow cover in a 6.25~~-~~ km pixel. We ~~decided to~~ adopted the most rigorous pixel filtering rule, by~~in~~ which one clouded pixel ~~can not~~cannot be allowed within a 15*15 pixel~~s~~ window. This~~It~~ is ~~somewhat~~ slightly different from a previous study that allowed 10% of clouds (Dai et al., 2017).

3.3 Sensitivity study

3.3.1 Selecting input variables

After determining the retrieval function, ~~a major challenge is to~~ selecting the fewest number of variables ~~and~~ to ~~then~~ establish~~provide~~ an efficient estimation model is a major challenge (Mutanga et al., 2012). Many factors influence snowpack distribution, and the consideration of all factors in snow cover properties estimation ~~it~~ is unrealistic~~ to consider all factors into the snow cover properties estimation~~. Therefore, we conducted six scenarios to evaluate and finally screen ~~the~~ input variables. ~~According to previous study,~~ The topographic factors (digital elevation model (DEM), slope, aspect) (Revuelto et al., 2014) and location information (longitude and latitude) (Xiao et al., 2018; Sturm et al., 2010) were directly take as the basic input variables. Additionally, consideration was also given to the passive microwave brightness temperature (19~~-~~ GHz, 37~~-~~ GHz, and 91~~-~~ GHz; both H and V polarization) (Xiao et al., 2018; Xu et al., 2016) and the difference of brightness temperature between different channels (Xu et al., 2016; Liu et al., 2018) ~~were also considered~~ (listed in Table 1). The 22~~-~~ GHz channel was excluded because it is sensitive to water vapor.

A~~The~~ decision tree was established using all variables shown in Scenario -1 (Table 1), ~~which~~ and was ~~used~~ utilized to compare with ~~the following~~ five scenarios in terms of prediction performance and efficiency. Note that these 19 input variables were determined by using the Correlation Attribute Evaluation method ~~in~~ in the Waikato Environment for Knowledge Analysis ~~WEKA~~ 3.8.3 (WEKA~~Waikato Environment for Knowledge Analysis~~) data mining software. This method evaluates the worth of the attribute by measuring the correlation between the attribute and the target (Frank et al., 2004; Eibe Frank, 2016). The brightness temperature and its linear combination can also ~~be~~ directly be used to detect snow cover based on Xu et al. (2016) study;~~;~~ t~~T~~hereby, Scenario -2 only contained~~s~~ brightness temperature and its linear combination without consideration to the effects of~~ing~~ location and topographic factors~~ effects~~. Wiesmann and Mätzler (1999) reported that ~~vertical~~ V and ~~horizontal~~ H polarizations ~~are~~ were dominated by scattering and snow stratigraphy, respectively. Thus, Kim et al. (2019) only assimilated ~~vertical~~ V polarization with an ensemble snowpack model to estimate snow depth. Therefore, i~~I~~n Scenario -3, we attempted to evaluate~~d~~ the performance of the established retrieval model ~~established~~ by only using the brightness temperature in 19~~-GHz~~, 37~~-GHz~~ and 91- GHz (V polarization) based on Wiesmann and Mätzler (1999) and Kim et al. (2019). I~~I~~n ~~the~~ Scenario -4, we used similar input variables to those used for snow depth estimation in Xiao et al. (2018), and examined whether these same parameters can or cannot estimate the fractional snow cover.~~ Correspondingly, in ~~ In Scenario -5, unlike the variables used in Scenario -4~~Scenario 5~~, we attempted to use~~d~~ the basic input variables coupled with the brightness temperature linear combination for fractional snow cover retrieval.~~ ~~

~~The importance rank of the input variable was generated during the training stage of the random forest model (refer to section 3.4.4).~~There are other variable selection strategies b~~B~~ased on the importance rank when using random forest method. For example~~, —~~, Mutanga et al. (2012) implemented a backward feature elimination method to progressively eliminate less important variables, whilst~~;~~ Nguyen et al. (2018) summarized the grade of ~~v~~the variable and selected the top eight important variables as the input variables in the training model. Similarly, ~~we~~ this study assessed the importance of input variables on four land cover types using the same size of the training sample (15 000) (Xiao et al., 2018). We then counted the number of times of each variable that was~~is~~ ~~in the~~ ranked in the top nine important variables (summarized in Table S2~~, in the~~ Appendix)~~.~~, ~~Scenario 6 shows the selected the top nine important variables~~ which were then used as the input variables for Scenario -6 (listed in Table 1). By ~~analyzing~~ assessing the performance of models established ~~using the variables in~~ by these six scenarios, ~~we will select~~ an optimal combination of input variables for the fractional snow cover retrieval model may be selected (see ~~section~~ Section 4.1.1). All input variables were normalized to [0, 1].

3.3.2 Determining sample size

Although the random forest method can avoid overfitting (Breiman, 2001), it is important to evaluate ~~the~~ its sensitivity to sample selection types and the size of the training sample (Belgiu and Drăguț, 2016; Millard and Richardson, 2015; Nguyen et al., 2018; Colditz, 2015). The performance of predicted models trained by machine learning methods is strongly dependent on the quality of the training sample (Dobreva and Klein, 2011). G~~A g~~ood quality training samples indicate that the sample data ~~cannot~~ is not ~~be~~ biased towards a certain value. The distribution of the fractional snow cover value from our dataset shows that more than 70% of ~~the~~ values were~~are~~ near 0 and 1. ~~Hence~~As such, the use of the random selection or equal proportional selection method (Millard and Richardson, 2015; Lyons et al., 2018; Nguyen et al., 2018) would hinder the interpretation of the final fractional snow cover estimation model by ~~making~~ reducing the accuracy of the estimation~~ less accurate~~. ~~Therefore~~To address this, we adopted ~~the~~ stratified random sampling as a sample selection strategy (Xiao et al., 2018; Dobreva and Klein, 2011), where~~.~~ s~~S~~tratification was performed on the~~ value of~~ fractional snow cover ~~with~~ at ~~n~~0.01 increments~~ of 0.01~~.

From previous studies, ~~we know~~ the sample size, approximately 0.25% of the total study area, was adopted by Colditz (2015) when using the random forest method. T~~Moreover, t~~his value has also been evaluated in optical and active remote sensing studies (Nguyen et al., 2018; Du et al., 2015). In this study, we ~~separately~~ generated the training sample datasets separately from 0.15% to 0.35% of the total cover area for~~of~~ each land cover class (in 0.05% increments). Then, ~~the~~ sensitivity tests were carried out for the four land cover types.~~;~~ ~~in~~ T~~t~~his means~~ way,~~ the training dataset would represent the values of fractional snow cover categories for each land cover type (see S~~s~~ection 4.1.2). All ~~the~~ selection operations were completely random.

3.4 Description of different estimation methods

In this study, we compared the random forest method with the other three methods for retrieving fractional snow cover, including linear regression, ANN, and MARS. ~~It should be~~ N~~n~~ote~~d~~ that the four methods input the same ~~input~~ variables ~~of the four methods are the same and are~~ selected by the sensitivity test, including 12 characteristic variables and one target variable (see ~~section~~ Section 3.3.1 and 4.1.1).

3.4.1 Linear regression

For optical remote sensing studies, there is a classical and general linear regression method used to estimate the sub-pixel snow cover area in medium- to high-spatial-resolution image. This only involve the ~~A sub-pixel snow cover area estimation method has been developed for optical remote sensing studies by establishing a linear~~ relationship between NDSI and fractional snow cover derived from ~~high~~ high-resolution snow cover maps (Salomonson and Appel, 2004; Salomonson and Appel, 2006). This type of regression method has been applied in generating the ~~current~~ standard MODIS fractional snow cover product Collection 5. Similarly, ~~T~~the~~is~~ multiple linear regression method~~, which uses least squares,~~ was used~~employed~~ as a reference method in this study to estimate fractional snow cover ~~from~~ based on passive microwave data. The inputs were the same as the other three methods in this study. This method was ~~complete~~ undertaken in WEKA 3.8.3 and did~~o~~ not use any attribute selection method. In the Appendix, we present~~ed~~ the linear regression formulas of fractional snow cover estimation for the four land cover types (Eq. S-1 and Table S6).

3.4.2 ANN

ANN is a popular machine learning technique ~~that has been~~ widely applied in remote sensing studies. Tedesco et al (2004) developed an ~~snow water equivalen~~SWE~~t~~ and snow depth retrieval algorithm based on an ANN technique using passive microwave brightness temperature. ~~ANN also was involved in~~ Xiao et al. (2018) also sued ANN ~~study~~ to derive snow depth, and Kuter et al. (2018) and Czyzowska-Wisniewski et al. (2015) used ANN ~~study~~ to retrieve fractional snow cover from MODIS data.

ANN consists of multiple layers; an input layer, one or more hidden layers, and an output layer (Hecht-Nielsen, 1992). The network with multi~~ple~~ layer perceptron can easily handle the nonlinear relationship between the input and output without any prior knowledge (Haykin, 2009). The inputs of each neuron were~~are~~ multiplied and summed by the connection weight.~~,~~ ~~and then~~ T~~t~~he output results were subsequently ~~are~~ computed ~~through~~ using a nonlinear logistic sigmoid transfer function. For numerical data, the transfer function in WEKA substitutes the pure linear unit function for the logistic sigmoid.

~~Apart~~Aside from ~~the~~ data preprocessing, a crucial step in this process is to design and optimize the ANN ~~network~~ structure for ~~a better~~improved estimation performance and good generalization capability (Kuter et al., 2018). Kuter et al. (2018) demonstrated that multidimensional function modeling can ~~be done~~ successfully achieved with one hidden layer network. All parameters were set ~~as~~ to the default with the exception of ~~for~~ the learning rate, which was optimized through a simple trial-and-error method. ~~From~~ Based on the accuracy index and the modeling speed ~~aspect~~, Table S3 ~~in the~~ (Appendix) shows that a learning rate of 0.2 ~~as the learning rate~~ generated the best performance ~~of~~ for the ANN-retrieval model.

3.4.3 MARS

The MARS technique has been applied in ~~quite~~ a number ~~plenty~~ of studies and in many fields, such as~~e.g.,~~ classification and mapping (Quirós et al., 2009), atmosphere correction (Kuter et al., 2015), pile drivability prediction (Zhang and Goh, 2016), and fractional snow cover estimation (Kuter et al., 2018). Unlike ANN, the modeling process of MARS is flexible and straightforward. Friedman (1991) first proposed ~~the~~ a MARS technique that organizes a simple model for the complex and high-dimensional relationship between ~~the~~ input variables and the target by ~~having~~ smoothly connecting ~~simply~~ piecewise linear polynomials (known as basis functions (BFs)) ~~smoothly connected~~. The ranges of the input variables ~~a~~were~~re~~ cut into a series of sub-ranges by ~~the~~ knots; these were ~~that~~ the ~~is~~ connection points for two pieces of BFs. A simple BFs format of MARS is expressed ~~as showing~~ in Eq. 3, where~~.~~ $max(\cdot)$ indicates that only positive parts ~~are~~ were take; otherwise, it ~~is~~ was assigned a~~s~~ zero; and~~.~~ τ is a univariate knot.

$$max(0, x-\tau) = \begin{cases} x-\tau, & if \;\; x > \tau \\ 0, & otherwise \end{cases} \tag{3}$$

The MARS method involves two ~~stages~~ phrases to establish a regression model; (forward phase and backward phase~~) for establishing a regression model~~. In the forward phase, ~~the~~ BFs were generated ~~by~~ using a~~the~~ stepwise search of all univariate candidate knots and all variables interactions. These adopted knots and ~~its~~ their corresponding pair of BFs should produce the greatest decrease in residual error. The BFs were successively added to the model until it reached the maximum number of BFs ~~was reached~~,~~.~~ ~~As a~~ resulting in an~~, the~~ over-fitted and complicated model ~~is over-fitted and complicated~~. In the backward phase, the redundant BFs that ~~make the~~ least contribute~~ions~~ to ~~for~~ model prediction~~ive is~~ are completely excluded from the regression model. These two phases are an iterative process (Kuter et al., 2018; Zhang and Goh, 2016).

Two important parameters of MARS determine the model "growing" and "pruning" processes;~~.~~ ~~The first is~~ the maximum number of basis functions (max_BFs), and ~~the second is~~ the maximum degree of interactions among ~~the~~ input variables (max_INT) (Kuter et al., 2018). Kuter et al. (2018) reported that the increase in the structural complexity of the model does not significantly contribute to improving~~e~~ the performance of the MARS model. We ~~did~~ conducted several tests to optimize the structure of MARS and found that more complex structures had a longer modeling time, ~~but~~ however, ~~the performance of the model~~ did not significantly improve model performance. Specifically, the modeling time of the complex structure (max_BFs = 100, max_INT = 2) was~~is more than~~ four times greater than ~~that of~~ the simple structure (max_BFs = 40, max_INT

= 2) based on our analysis experiments. ~~Thereby~~As such, the simple structure was chosen, as per ~~following~~ Kuter et al. (2018)~~,~~ ~~the simple structure was chosen~~. We implemented an open MARS MATLAB source code available from Jēkabsons (2016) for fractional snow cover estimation. These codes were compiled on a 2.40 GHz Intel Xeon Central Processing Unit (CPU) server.

3.4.4 Random forest

Random forest is an ensemble learning method, gaining the attention of~~which has drawn~~ many researchers~~' attention~~ because it is more efficient and robust than the single method (Breiman, 2001). As a classifier, random forest has been successfully used to detect snow cover (Tsai et al., 2019), land cover (Rodriguez-Galiano et al., 2012), and woody invasive species (Kattenborn et al., 2019). The random forest regression method can also ~~provides a~~ successfully estimat~~e~~ion ~~of~~ land surface temperature (Zhao et al., 2019), biomass (Mutanga et al., 2012), and soil moisture (Qu et al., 2019).

Random forest buil~~ds~~t a large series of decision trees by applying the bootstrap sampling method. ~~In~~ During the training stage, each tree grows by randomly selecting several variables and samples from input datasets (Mutanga et al., 2012). ~~The~~ I~~i~~nput data was repeatedly split into training and test data using the bootstrapping method. Each randomly selected bootstrap sample in each iteration contain~~eds~~ approximately 2/3 of the input elements. The remaining data, ~~called~~ referred as out-of-bag (OOB) data, was~~is~~ used for validation. The predicted value of OOB data was~~is~~ produced from all the ~~produced~~ tree~~s~~ results that were generated and the OOB error was subsequently~~is~~ calculated. For classification, the output was~~is~~ determined by voting the results from all decision trees,~~;~~ whereas for regression, the output results were determined~~is~~ by averaging. The random forest was ~~performed~~ conducted in WEKA 3.8.3. As s~~S~~everal attempts to optimize the parameters of random forest structure had failed~~. Thus~~, all ~~the~~ parameters used were the default values ~~here~~.

3.5 Snow cover identification

The microwave radiation characteristics of precipitation, cold deserts and, frozen ground are similar to ~~that~~ those of snow cover (Grody and Basist, 1996), and as such~~. As a result~~, ~~the~~ snow cover area is likely to be overestimated. Grody and Basist (1996) proposed a snow cover identification algorithm, ~~which can~~ distinguishing snow cover from precipitation, cold desert, and frozen ground. ~~Consequently, many~~ Many researchers have since used Grody's algorithm and its derivative algorithm to detect snow cover (Che et al., 2008; Xiao et al., 2018; Wang et al., 2019). Liu et al. (2018) reported ~~that~~ on the assessment ~~results~~ of different passive microwave snow cover detection algorithms and ~~showed~~ demonstrated that Grody's algorithm had a higher precision (positive predictive value) than those of other algorithms. We adopted the revised snow cover decision tree of Grody's algorithm (Table 2) ~~Due to~~as the highest frequency in this study was~~is~~ 91- GHz instead of 81- GHz in Special Sensor Microwave Images/Sounder (SSMIS) sensors~~, we adopted the revised snow cover decision tree of Grody's algorithm (Table 2)~~ (Che et al., 2008).

There were~~are~~ two main objectives for using the revised Grody's algorithm (hereafter referred to Grody's algorithm) in this ~~work~~study. The first was~~is~~ to compare the snow cover identification capability of the proposed fractional snow cover estimation algorithm with respect to ground snow depth measurements (see S~~s~~ection 4.4).~~;~~ The second purpose was to assess the effect of non-snow scatterer in estimating fractional snow cover, due to~~On account of~~ this algorithm's special ~~cap~~ability to distinguish the non-snow scatterer (i.e., precipitation, cold desert, and frozen ground)~~, the second purpose is to assess the affect of non-snow scatterer in estimating fractional snow cover~~. In both optical and microwave remote sensing research, ~~the~~ capability assessment of snow-free detection has been regularly neglected in most ~~of the previous~~ snow cover detection studies.

3.6 Validation of snow cover identification

When using the in-situ snow depth (or ~~snow water equivalent~~SWE) measurements to quantitatively validate the accuracy of snow cover area data, ~~the first challenge is how to~~ converting snow depth into binary snow cover using an appropriate threshold is the first challenge. ~~Numerous~~ Many different ~~values of~~ depth thresholds have been suggested in ~~published~~ previous studies,~~:~~ for instance 2 cm for 20 m spatial resolution (Gascoin et al., 2019); 0 cm (Parajka et al., 2012),~~;~~ 1 cm (Zhang et al., 2019), 3 cm (Hao et al., 2018), 4 cm (Huang et al., 2018; Wang et al., 2008) and, 15 cm (Gascoin et al., 2015) for 500 m spatial resolution;~~,~~ 2.5 cm for 5 km spatial resolution (Hori et al., 2017);~~,~~ 3 cm (Xu et al., 2016) and~~,~~ ~~4 cm,~~ 5 cm for 25 km spatial resolution (Liu et al., 2018); and~~,~~ 2 cm for 0.75° grid resolution (Brown and Derksen, 2013). ~~Because of this~~Due to these significant ~~vigorous~~ disagreements in the ~~in the~~ depth threshold~~-~~s~~value~~, Gascoin et al. (2019) conducted a sensitivity experiment that tested the agreement between in-situ measurements and optical snow cover area products.~~ Similarly,~~ T~~t~~he sensitivity of passive microwave snow cover identification results to ~~the~~ snow depth at 6.25 km spatial resolution was also tested by computing the accuracy metrics with snow depth ~~value~~ increasing from 0 ~~cm~~ to 10 cm.

Then, we needed~~The next problem is~~ to determine the threshold for converting fractional snow cover to binary snow cover. To date~~Up to now~~, ~~there are~~ few studies exist on fractional snow cover from the passive microwave pixel-level. Dai et al. (2017) considered~~took the grid~~ ~~consider as~~ snow cover on the grid if ~~the~~ fractional snow cover (25~~-~~ km) was~~is~~ larger than 10%. I~~Additionally, i~~f the fraction of snow cover was~~is~~ less than 0.25, the ~~snow water equivalent (~~S~~E~~WE~~)~~ was~~is~~ set to 0 mm ~~for~~ to correct the~~ing~~ snow cover area in the daily SWE product ~~according to~~based on Luojus et al. (2018)~~ study~~. However, optic remote sensing studies often adopted 0.5 ~~often~~ as ~~is~~ the ~~used~~ threshold of fractional snow cover~~ adopted in optic remote sensing studies~~ (Hall and Riggs, 2007). Sensitivity experiments of fractional snow cover similar to ~~ground-based~~ snow depth were ~~employed in order~~conducted to obtain the optimum conversion threshold. Both sensitivity experiments were carried out using 2017 bare land type datasets in S~~s~~ection 4.4.

3.7 Performance accuracy assessment

When evaluating the estimation performance of fractional snow cover in S~~s~~ection 4.1-4.3, we used conventional accuracy metrics;~~:~~ correlation coefficient (R; Eq. 4), mean absolute error (MAE; Eq. 5) and root mean squire error (RMSE; Eq. 6). Where

$\bar{x}$ is the mean value of all predicted values x_i; $\bar{y}$ is the mean value of all target values, y_i; and n denotes the number of used data.

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{6}$$

We ~~not only~~ evaluated the predicted accuracy of fractional snow cover~~,~~ and ~~but also~~ assessed ~~the~~ snow cover identification performance (see S~~s~~ection 4.4). Six accuracy assessment indices~~exes~~ were used for the analysis of snow cover detection capability ~~analysis~~(Liu et al., 2018; Gascoin et al., 2019);~~:~~ overall accuracy (OA), precision (that is~~a.k.a.~~, a~~.~~ positive prediction value), recall, specificity (that is, the~~a.k.a.~~ true negative rate), F1 score (Zhong et al., 2019), and Cohen's kappa coefficient (Foody, 2020). OA refers to the proportion of correctly classified pixels as snow-covered and snow-free. The F1 score is a weighted average measurement of precision and recall ranging from 0 to 1 ~~for~~ to measure~~ing~~ the accuracy of binary classification. Cohen's kappa coefficient measures the agreement between ~~the~~ snow cover products and ground measurements. All ~~of~~ these indices~~exes~~ w~~ean b~~ere calculated from the confusion matrix (Table 3). OE is the omission error; CE is the commission error.

4. Results analysis

4.1 Sensitivity in the training sample

4.1.1 Influence of input variables on model performance

We evaluated the results from 24 random forest fractional snow cover retrieval models (four types * six scenarios) t~~T~~o better understand which input variables have a good relationship with fractional snow cover and the combination of the variables that ~~combination~~ can improve ~~the~~ retrieval model performance~~, we evaluated the results from 24 random forest fractional snow cover retrieval models (4 types * 6 scenarios)~~. The data used for variable sensitivity tests in this part ~~merely~~ spanned only ~~involved~~ two years (2014 – ~~-~~ 2015) ~~since~~ as the 91~~-~~ GHz ~~horizontal~~ H polarization data was~~is~~ missing over the area south of 50° N for~~in~~ 2016 – ~~-~~2017. The OOB error and 10-fold cross-validations error were used to measure the performance of fractional snow cover retrieval models in each scenario (Mutanga et al., 2012). Table 4 shows the results of the six scenarios for~~on~~ the bare land type datasets.

The variable selection tests ~~ar~~were~~e~~ used to ~~seek~~ identify a better combination of different variables (Table 4). ~~At first glance,~~ Scenario -3, which only involves ~~vertical~~ V polarization data, yielded~~s~~ the smallest R (0.590) and the largest MAE (0.197) and RMSE (0.248) of OOB error, and also for 10-fold cross validation error (R: 0.596; MAE: 0.197; RMSE: 0.246).

Scenario 3 performed the poorest of the ~~When compared to the other fiv~~six~~e~~ scenarios, ~~Scenario 3 had the worst performance,~~ which may be due to the lack of further~~no more~~ available information from input variables that ~~can~~ could be fully exploited (Xiao et al., 2018). Scenario -2, ~~that~~ only containing~~s~~ passive microwave brightness temperature data similar to ~~that is nearly same as~~ the variables used in Xu et al.(2016)~~ study~~, had the second ~~worst~~ poorest performance. This shows~~It has proven~~ that ~~the~~ location information and topographic factors play a crucial role in snowpack distribution (Revuelto et al., 2014; Czyzowska-Wisniewski et al., 2015; Sturm et al., 2010). In this study, the retrieval method required these five basic input variables as auxiliary information in order to learn the characteristics of snow cover under different surface conditions to assist in accurately estimating snow cover properties. In contrast, in the absence of these basic input variables, the established model has no advantage in accurately predicting the characteristics of fractional snow cover under complex surface conditions. The major difference between Scenarios -1, 4, 5, ~~-5,~~ 6 and Scenario -2 and~~,~~ 3 (Table 1) was~~is~~ whether or not considering ~~the consideration of~~ the basic input variables (location information and topographic factors). ~~-~~ T~~hereby, t~~he comparison results (i.e., Scenarios -1, 4, 5, ~~-5,~~ 6 vs. Scenarios -2 and~~,~~ 3) ~~further~~ indicate that the effect of location information and topography need to be considered ~~for~~ to estimate snow parameters ~~estimation~~. Moreover, when compared to Scenarios-1, 4, 5, ~~Even though the input variables of Scenario-6 is selected by importance,~~ the setting in~~is~~ Scenario-6~~setting~~, where input variables were selected by importance, ~~generated~~ had the third ~~worse~~ poorest performance, with ~~the~~ a low R, ~~the~~ and a high~~great~~ MAE and RMSE. ~~As for~~ Scenarios -1, 4 and 5, generated~~they gave~~ better results; there were no ~~obvious~~significant differences in R, MAE and RMSE ~~values~~ for the tests on the four land cover types ~~tests~~ (Table 4; Tables S4 and S5 in Appendix). The~~is~~ comparison among Scenarios -1, 4, 5 indirectly indicates that the variables used in Scenario -1 may have some information redundancy and slightly weaken the efficiency of the random forest retrieval model. ~~While~~ Although the selection methods of Scenario -4 and ~~Scenario~~ 5 performed well (in terms of modeling time and accuracy of predicted target), only one scenario was selected;~~,~~ the other ~~one~~ may ~~can~~ be used as an alternative in ~~the~~ future. ~~Finally~~To this end, the variable combinations in Scenario -5 were selected for further analysis.

4.1.2 Determination of sample size

The datasets from 2014 – ~~-~~2016 were used to examine ~~the~~ sensitivity to training sample size where~~.~~ t~~T~~he ~~used~~ accuracy metrics ~~are~~ used were the same as ~~in~~ S~~s~~ection 4.1.1. ~~On account of~~As the values and variation trends of the accuracy metrics of the OOB error and 10-fold cross validation error ~~are~~ were almost ~~same~~equivalent, ~~thus,~~ only the OOB error ~~were~~ is shown in Fig. 4 and Fig~~ures~~s. S-1, 2, 3 (in the A~~a~~ppendix). We compared the performance of the random forest-based models altering the training sample size for the four land cover types.

Fig. 4 illustrates that there is a slow increase in ~~the~~ R ~~slow increase~~ and a slight decrease in ~~the~~ MAE and RMSE ~~slight decrease with~~when the training sample size increased from 0.15% to 0.25% on the shrub type, whilst there was a significant increase in~~. Meanwhile, the~~ modeling time ~~has a significant increase~~. As the sample size ~~goes~~ increase from 0.25% to 0.35%, the model~~ shows a~~ consistently estimates ~~accurate performance of~~ fractional snow cover accurately ~~estimation~~ (higher R and ~~less~~ lower MAE and RMSE). This finding appears to be consistent with previous studies (Colditz, 2015; Nguyen et al., 2018). An applicable and eligible sample selection scheme, which can achieve an acceptable target prediction accuracy ~~level~~ and an adequate execution time, is essential for the implementation of a random forest model with superior predictive capability. One noticeable distinction between the three sample sizes (0.25% ~ 0.35%) was~~is the~~ modeling time. Interestingly, the 0.3% training sample size had the ~~lowest~~ shortest modeling time of the three sample size (Fig. 4);~~.–~~ Fig~~ures~~s. S-1, -2, -3~~,~~ also ~~show~~ exhibit similar~~that this~~ findings on modeling time ~~was not be coincidental~~. The ~~explanation~~ reasons underpinning ~~for~~ the difference in modeling time is beyond the scope of this study and requires further research. We used the sample dataset covering 0.30% of the study area of each class as a suitable size to randomly select training samples.~~ Subsequently,~~ W~~w~~e subsequently extracted the training samples for each land cover type from the 2011–~~-~~2016 dataset to establish the retrieval models.

4.2 Comparison of the four retrieval methods

In this section, the independent testing datasets from 2010 were used to assess the predictive performance of the random forest-based models and the other three models (based on linear regression, ANN and MARS). ~~When~~ A comparison of~~ng~~ the modeling time ~~of~~ for the four methods (Table 5) showed that~~,~~ linear regression ~~shows~~ had the shortest time, with less~~-~~ than 1 s for the four land cover types, followed by ANN ~~that i~~with~~s~~ approximately 51 s (forest), 22 s (shrub), 156 s (prairie) and 35 s (bare land). Random forest modeling times~~,~~ were~~are~~ very close to ANN modeling times for each land cover type. ~~By~~ In contrast, ~~the~~ MARS was~~is~~ the most time consuming, ~~takes~~ with the longest time (~~about~~ approximately 6.5 h~~ours~~) for the prairie type and the shortest (19 min~~utes~~) for the shrub type. The absolute value of ~~the~~ modeling time would vary under different computing~~er~~ capabilities.

Table 5 and Fig. 5 ~~exhibit~~ present the results of the four retrieval methods for the four land cover types. The retrieval models of the shrub type ~~almost~~ predominantly have the lowest RMSE in contrast with the other three land cover types ~~for~~ using the four methods (Table 5; cf. Fig. 5 and Figs.~~ure~~ S-4, 5, 6 in the Appendix).~~ For forest (Table 5; Fig. 5 and 6);~~ T~~t~~he random forest model had~~s~~ the highest R (0.916), lowest MAE (0.202) and RMSE (0.245), and no out-of-range records f~~F~~or the forest type (Table 5; Fig. 5 and 6)~~;~~. The distribution and variation of MAE and RMSE for the four methods were~~are~~ ~~nearly the same~~ similar under different land cover types, with the exception of ~~for~~ the shrub type (Table 5; Fig. 5). ~~Apart from~~With the exception of ANN, the ranking ~~of results accuracy (MAE and RMSE)~~ of the three algorithms based on the accuracy of results (MAE and RMSE) ~~on~~ for the shrub test data was also ~~is~~ the same as ~~that~~ under other land cover types (i.e., Random forest > MARS > linear regression). ~~For the~~ R~~, r~~andom forest ~~shows~~ had the greatest R value, followed by ANN, then MARS, and ~~finally~~ for most of the land cover types the smallest R~~r~~ value was~~is~~ from the linear regression. ~~As showed in~~ Fig. 6 illustrates that the~~,~~ random forest (Fig. 6D) produced a relatively small number of overestimated (~ ~~around~~ 0) and underestimated (~~around~~ ~1) values compared with the other three models (Fig. 6A – ~~-~~ 6C). The MAE (0.315) and RMSE (0.401) of ANN were~~are~~

greater than ~~those of~~MARS (MAE = 0.208, RMSE = 0.254). The number of out-of-range estimated values of ANN (36.62%; 161260) was~~is~~ also greater than ~~that of~~ MARS (2.65%; 11667), which may be attributed ~~due~~ to ~~the~~ a major underestimation of the fractional snow cover ~~were~~ using ~~seriously underestimated by~~ the ANN method. The maximum and minimum of ANN and MARS on the forest type were~~are~~ 0.949 (-0.52) and 2.132 (-0.122), respectively. For the other three land cover types, the numbers of out-of-range pixels of the four methods ~~have~~ were almost in the same order (r~~R~~andom forest < ANN < MARS < linear regression).

The random forest-based models had~~ve~~ the best performance with the highest R, and lowest MAE and RMSE (Table 5). Previous studies have generally ~~usually neglected~~ neglected the analysis and evaluation of whether the estimated value is out-of-range~~to assess the rationality of estimated value~~ (Liang et al., 2017; Wang et al., 2017; Hao et al., 2019; Masson et al., 2018). ~~From~~ Table 5~~,~~ ~~we know~~show that the random forest models for the four land cover types produced reasonable fractional snow cover values ~~that~~ ranging~~e~~ between 0 and 1. In comparison, the estimated fractional snow cover from the other three methods (linear regression, ANN and MARS) was beyond this range. From the number of out-of-range records, the linear regression method generated the largest number of out-of-range fractional snow cover estimates, with more than 0.85 million pixels (18.69%). Although the number of out-of-range records of ANN (12.31%) was~~is~~ less than ~~that of~~ MARS (16.39%), both numbers exceed 0.5 million. ~~The results from~~ Kuter et al. (2018)~~,~~ ~~which~~ estimated fractional snow cover using MARS and ANN techniques, also yielded ~~the~~ similar out-of-range values. The ~~performance of the~~ linear regression method had the poorest performance in estimating fractional snow cover from passive microwave data, with ~~is the worst; it shows~~ the lowest R and the largest number of out-of-range records. These results indicate that~~us,~~ nonlinear methods should ~~thus are~~ first ~~encouraged to~~ be used. Xiao et al. (2018) demonstrated the nonlinear relationship between passive microwave brightness and snow depth. ~~Besides,~~ De Lannoy et al. (2012) provided an exponential function for converting ~~from snow water equivalent~~ SWE to fractional snow cover. Thus, it is reasonable that a ~~for the~~ non-linear-relationship exists between fractional snow cover and passive microwave brightness temperature.

4.3 Evaluation of fractional snow cover

~~To further investigate the predictive capability of the random forest models, we conducted the evaluation using~~ The independent data, which was randomly selected from the datasets in 2008 – 2009 and 2017 and the selecting rule is same as the training sample, was used to further evaluate the predictive capability of random forest models in all range values. In this part, we analyzed the results from the training and evaluation stage ~~results~~ for ~~the~~ four land cover types (Table 6, Fig. 7). ~~As shown in~~ Fig. 7A and 7a show that~~,~~ ~~the~~ fractional snow cover ~~values~~ around 1 are distinctly underestimated and few are above the 1:1 line. The model for forest type ~~exhibits~~ had the ~~worst~~ poorest performance with the lowest R (0.636~~932~~) and the highest RMSE (0.221~~199~~) ~~on~~ for the ~~validation~~ evaluation dataset (Table 6). The retrieval model on the ~~shrub~~ prairie type ~~obtained~~ had the best performance on the ~~validation~~ evaluation data (R: 0.752~~971~~; MAE: 0.148~~2~~; RMSE: 0.189~~67~~). ~~In addition to forest,~~

~~prairie shows more underestimation (around 0) and overestimation (around 1) records (R = 0.946, MAE = 0.163, RMSE = 0.198) than the other two land cover types (shrub and bare land) (Table 6; Fig. 7b – 7d). For~~ In shrub and bare land types (Fig. 7B, 7b, 7D and 7d; Table 6), the retrieval models have similar performance in evaluation datasets (R: 0.712 and 0.719; MAE: 0.160 and 0.165; RMSE: 0.212 and 0.216, respectively); "true" fractional snow cover values ~~values~~ in the training and~~or~~ validation datasets ~~are~~ were more distributed at two polar ends (0.0~0.3 and~~;~~ 0.9~1.0) in these two land cover types. When comes to the results in the training stage and the evaluation stage, we can found that the estimation performance of the retrieval model in evaluation datasets are highly dependent on the quality of training sample which was used to establish the retrieval models. Fig. 7 show that the established models in four land cover types can properly capture the characteristics of all range of fractional snow cover values.

Apart from the scatterplots and statistical analysis, Fig. 8 shows~~s~~ the ~~spatial~~ distribution pattern~~s~~ of snow cover from a spatial perspective, including MODIS composite binary snow cover (Fig. 8A), ~~the calculated~~ MODIS fractional snow cover (Fig. 8B), and the estimated fractional snow cover by the proposed algorithm~~from passive microwave brightness temperature data~~ (Fig. 8C). When the most rigorous pixel filtering rule at the 15*15 pixel window was applied (see Section 3.2), the large number of cloud covered pixels (yellow) in Fig. 8A resulted in most areas of the MODIS fractional snow cover image (Fig. 8B) being represented by a "fill value". Additionally,~~,~~ ~~a~~the number of intermediate values for MODIS fractional snow cover in winter would be much lower than the number of values near the two extreme values (0 and 1). In contrast, the estimated fractional snow cover from passive microwave brightness temperature data can provide almost complete coverage and continuous spatial information on snow cover (Fig. 8C; Fig. S-7 in the Appendix). Fig. 8 shows the comparison between our estimated fractional snow cover and the reference MODIS fractional snow cover, and more importantly, provides another perspective for snow cover identification in Section 4.4. Thus, Fig. 8B and 8C used 0.3 as the threshold of fractional snow cover to define snow-covered and snow-free area, and this was adopted through the experiments in Section 4.4. This means that the pixel was identified as snow cover when fractional snow cover value was less than 0.3. From Fig. 8A – C, t~~T~~he spatial pattern of estimated fractional snow cover from the proposed method seems to accurately capture the distribution of snow cover from MODIS under clear-sky conditions, such as the snow-free area in most areas of North America, and snow-covered areas in northern Canada ~~(Fig. 8)~~. Fig. 8D presents a specific example compari~~so~~ng ~~example of~~ these two fractional snow cover datasets and MODIS composite binary snow cover products in ~~the c~~Central Canada ~~area~~ on February 27th, 2017. Based on this example, we find that our estimated fractional snow cover was capable of obtaining snow cover distribution when most of the area was covered by cloud, which was not the case for MODIS. T~~In addition, t~~his ~~case~~ example also show that the extent of snowline observed in the MODIS binary snow cover image (500 m), which was the boundary between snow-covered and snow-free, ~~can be~~was well described and exhibited by the estimated fractional snow cover (6.25- km). ~~The spatial pattern of estimated fractional snow cover from the proposed method seems to accurately capture the distribution of snow cover from~~

~~MODIS under clear-sky condition (Fig. 8).~~

Thus far, we have evaluated the performance of random forest-based models on independent datasets from 2010 and 2017 on each land cover type. ~~Seeing~~ T~~t~~he results from the random forest (Table 5; Fig. 6D; Figs~~ure~~ S-4 – ~~-~~ 6; Fig. 7) show that~~, we find~~ the minimum estimates were~~are~~ higher than 0 and approximately 0.01. This may be because the random forest uses a results output principle where the regression output results are obtained by averaging results from multiple trees ~~One possible reason is that the results output principle of random forest that the regression output results are obtained by averaging the results from multiple trees~~ (see S~~s~~ection 3.4.4) (Breiman, 2001; Belgiu and Drăguţ, 2016). Although MODIS snow cover products ~~have~~ are highly accurate~~cy~~ in snow cover identification (Tran et al., 2019), the estimated results indicate that a large number of fractional snow cover values were overestimated (~0) ~~around 0~~ and underestimated (~0)~~around 1~~. Some fractional snow cover estimates, at~~in~~ the individual pixel level, show~~s~~ a large discrete distribution near the 1:1 line (Fig. 7). These misestimates are not confined to~~appear not just in~~ the results of the random forest model, but also appear in results of the other three methods ~~result~~ (Fig. 6; Fig. S-4 – 6 in the A~~a~~ppendix). Other non-snow scatterers (i.e., precipitation, cold desert, frozen ground) may potentially~~largely control~~ contribute to the overestimation of~~es~~ snow cover area~~in low snow coverage region~~ as ~~because in this regions~~ these ~~non-snow~~ scatters were easily ~~be~~ misclassified ~~into~~ as snow cover~~. As we all know, permafrost widely distributed in North America , and it would offer great contributions to the misclassification of snow cover~~ in less snow cover conditions (Grody and Basist, 1996). A~~The more~~ detailed analysis ~~of~~ on the misclassification is ~~discussed~~ provided in S~~s~~ection 4.4~~. Moreover, the difference in satellite overpass time may also result in~~ Satellite sensors may provide completely different snow cover information because of different satellite overpass time~~measured by satellite sensors~~. In this study, the difference in the equator crossing time between MODIS and passive microwave sensor was close to 6.5 and 9.5 h (refer to Section 2.1 and 2.3.1). Generally, t~~T~~he error caused by~~is~~ the differences in the satellite overpass time ~~can be~~may easily neglected when using multi-sensor observations for data fusion. ~~We know the difference of equator crossing time between MODIS sensors and passive microwave is close to 6.5 hours and 9.5 hours (refer to section 2.1 and section 2.3.1). Time-lapse photography from camera network was utilized to monitor snow processes in the Upper Rhine Region . According to measurements, snow depth may exhibit great dynamics within hours under a snowstorm, continuous snowfall conditions, resulting in fractional snow cover changes rapidly . Thereby, the inconsistent observations occurred between the passive microwave sensor and MODIS.~~

4.4 Validation using ground measurements

In winter with clouds and snow cover, the MCTD10A1 data still contained a large number of clouds (Fig. 8A; yellow) despite~~even after~~ the implementation of the cloud removal and filling process for MODIS snow cover data~~, MCTD10A1 data still presents a large number of clouds (Fig. 8A; yellow)~~. ~~After~~ When applying the rigorous pixel filters (see S~~s~~ection 3.2), there was~~is~~ very little snow cover data for further model training and results analysis in one imagery (Fig. 8B). To evaluate and validate the estimated fractional snow cover ~~Under~~ in the absence of reference MODIS fractional snow cover~~, how can~~ we~~ evaluate and validate the estimated fractional snow cover~~ conducted~~?~~ f~~F~~urther analysis ~~from~~ on~~the~~ snow cover detection capability~~ aspect was performed~~. The ground snow depth measurements were utilized to investigate the accuracy of snow cover identification from two snow cover data;~~:~~ the snow cover detected by Grody's algorithm and ~~the~~ fractional snow cover derived from random forest. We collected all available meteorological station snow depth measurements of 2017 (January and February) over North America, obtaining more than 311 000 pairs of records.~~,~~ ~~which~~ This includes the snow depth measurements, ~~the~~ snow cover area converted from the estimated fractional snow cover (hereafter referred to ~~Random forest FSC~~random forest SCA), and~~,~~ snow cover area derived from Grody's snow cover mapping algorithm (hereafter referred to Grody's algorithm SCA).

The sensitivity to ground-based snow depth in the snow cover detection results were tested by computing the accuracy metrics. Fig. 9 ~~presents~~ shows that the accuracy metrics vary with increasing snow depth, whereby~~. We can see that~~ the ~~accuracy~~ metrics change significantly when snow depth exceeds 2 c~~m~~, and ~~they~~ reach a relative optimum ~~value~~ when snow depth is equal to 2 cm. Che et al. (2008) stated that snow cover ~~can~~ may be detected by passive microwave sensors when snow depth is greater than 2 cm. ~~Consequently~~For this reason, we adopted 2 cm as the optimum depth threshold to transform ground snow depth measurements to snow-covered or snow-free information. ~~Moreover, we~~ We also conducted a series of sensitivity experiments ~~were conducted~~ to search the optimum threshold for converting fractional snow cover to binary snow cover (Fig. 10). Fig. 10 shows that recall and precision have opposing~~ite~~ variation trends; the~~.~~ F1-score is up to the maximum value when FSC = 0.3. In additional, the other two indicators (OA, kappa) also reached their maximum ~~value~~ when the FSC value were ranging~~es~~ between 0.3 and 0.4. As expected, 0.3 was ~~taken~~ used as the conversion threshold for fractional snow cover. Nevertheless, the conversion thresholds of snow depth and fractional snow cover need to be optimized with more data in the future.

We used a 2 cm snow depth threshold and a 0.3 fractional snow cover threshold to calculate the confusion matrix for Grody's algorithm SCA and ~~Random forest FSC~~random forest SCA against ground snow depth measurements (Fig. 11 and Fig. S-8). Fig. 11 illustrates that the overall accuracy of snow cover identification ~~is~~ had significantly improved by 18%, from 0.71 for Grody's algorithm SCA to 0.84 for ~~Random forest FSC~~random forest SCA, indicating that the latter's~~Random forest FSC~~ results ~~have a promising~~were in goo agreement with ground snow cover measurements (kappa = 0.67). For the ~~Random forest FSC~~random forest SCA, ~~the~~ precision (0.83) was~~is~~ lower than the recall (0.87), which means that snow cover area was~~is~~ more likely to be overestimated (CE = 0.17) than~~ to be~~ underestimated (OE = 0.13), with respect to in-situ measurements. In contrast,~~;~~ f~~F~~or Grody's algorithm SCA,~~ on the contrary,~~ ~~the~~ precision (0.87) was~~is~~ larger than the recall (0.52). By utilizing the proposed method, the OE of snow cover identification ~~is~~ had reduced by 71% ~~in compari~~compared~~son~~ to the OE for Grody's algorithm SCA. The snow cover identification accuracy for the four land cover types ~~were~~ are illustrated in Fig.~~ure~~ S-8 (in the

Appendix) by radar charts. Additionally, Fig. 8 presents~~ovide~~ a simple example of the snow cover identification results of the ~~Random forest FSC~~random forest SCA (Fig. 8C) compared with MODIS composite binary snow cover products (Fig. 8A) on February 27th, 2017. ~~From~~ Fig. 8 shows~~, we can find~~ that the cloud-free area (snow-cover and snow-free area) in MODIS was almost ~~be~~ captured by our estimated results.

~~Subsequently,~~ W~~w~~e subsequently explored the influence of non-snow scatterers in estimating fractional snow cover. The CE of Grody's algorithm (CE = 0.13) was~~is~~ lower than r~~that of Random forest FSC~~andom forest SCA (CE = 0.17). Fig. 11 shows that the overall snow-free identification capability of Grody's algorithm SCA (specificity = 0.92) was~~is~~ significantly superior to the ~~Random forest FSC~~random forest SCA (specificity = 0.81), which was~~is~~ also apparent for the four land cover types (Fig.~~ure~~ S-8). Th~~It~~is may possibly be due to ~~the~~ Grody's algorithm filtering out non-snow scatter signature (precipitation, cold desert, and frozen ground) (Grody and Basist, 1996).~~ Thereby,~~ W~~w~~e counted the number of records ~~that~~ in which a pixel had been~~was~~ detected as snow-free by the station and ~~the~~ Grody's algorithm, however, was considered ~~but~~ snow-covered by ~~the Random forest FSC~~random forest SCA. The records, which~~,~~ ~~which are~~were misclassified as snow cover by ~~Random forest FSC~~random forest SCA, although they are~~but should be~~ non-snow scatter components (precipitation, cold desert, and frozen ground),~~,~~ account for 70.1% of total ~~number of~~ misclassification records (CE = 0.17), of which 63.0% comes from precipitation, 6.4% from cold desert, and 0.7% from frozen ground ~~by Random forest FSC~~. ~~This proportion of~~ For forest, shrub, prairie and, bare land types, this misclassification proportion because of the non-snow scatters were~~is~~ 77.7~~8~~%, 93.5%, 70.6~~1~~% and 67.3%, respectively (Table 7). ~~.~~For different results for these two snow cover mapping algorithms, we have used an example to show the inconsistencies and consistencies in mapping between the random forest SCA and Grody's algorithm SCA (Fig. S-9)~~.~~. These results~~In conclusion,~~ demonstrate that the non-snow scatterer is the major source of snow cover misclassification for random forest FSC results (Grody and Basist, 1996). Therefore, it is necessary to first distinguish the scattering signature of snow cover from other non-snow scattering signatures when using passive microwave data to identify snow cover. Similar preprocessing has been applied into snow depth estimation to minimize its uncertainties (Xiao et al., 2018; Wang et al., 2019; Tedesco and Jeyaratnam, 2016).

5. Discussions

5.1 Sensitivity to training sample size and quality

The size and quality of training samples may contribute to a large error at the individual pixel level (Dobreva and Klein, 2011; Kuter et al., 2018; Nguyen et al., 2018; Belgiu and Drăguţ, 2016). Previous studies~~researches~~ have investigated the sensitivity to sample size and sample quality (Nguyen et al., 2018; Colditz, 2015; Lyons et al., 2018). While some studies indicate that a larger training sample size ~~of training sample~~ improves the accuracy of estimates~~d results accuracy~~, we found that a training sample dataset covering about 0.3% of the total study area ~~is enough~~was sufficient to achieve high accuracy in the estimation of fractional snow cover. When comparing to previous sensitivity tests on sample size (Nguyen et al., 2018), the major difference was~~is~~ taking ~~the~~ modeling time as ~~one~~ an index in this study.

The estimation results of the random forest model on training and evaluation (test) datasets (S~~s~~ections 4.2 and 4.3) showed that~~, in~~ generally, the prediction performance of the random forest model was~~is~~ closely related to the quality of training sample. In this study's datasets, a greater number of ~~more~~ records were~~are~~ located near the extreme values of the fractional snow cover (0 and 1). Thus, it is reasonable to ~~employ~~ use~~the~~ stratified random sampling (Dobreva and Klein, 2011), however, ~~but~~ not the proportional distribution of ~~the~~ target values suggested by previous studies (Nguyen et al., 2018; Millard and Richardson, 2015). Even~~ then~~ in this cases~~,~~ the overestimation and underestimation often occur ~~near 0.0 and 1.0~~ in the results of training datasets (Fig. 7 A–~~-~~D) and ~~in~~ evaluation datasets (Fig. 7 a–~~-~~d), respectively. This is mainly because the established fractional snow cover retrieval model using the training sample with relatively low diversity of fractional snow cover values does not well learn the snow cover distribution characteristics of the various surface condition. ~~For future studies~~Therefore, it is~~will be~~ necessary for future studies to increase the amount of samples ~~data~~ by extending the study period to the ~~the~~ snow accumulation and snow ablation stages~~s~~ (Xiao et al., 2018), ~~in~~ where there is ~~which have~~ much more ~~of~~ shallow snow and "patchy" snow cover. Another option is using data from multi-source sensors ~~data~~ to generate ~~the~~ reference snow cover data~~,~~ (e.g., Sentinel-1 ~~SAR (~~Synthetic Aperture Radar~~)~~ data). By doing this, the proportion of ~~the~~ fractional snow cover values in the training sample ~~can~~ may be distributed as evenly as possible (Colditz, 2015; Jin et al., 2014; Lyons et al., 2018).

5.2 Effects of vegetation

Snow cover detection can be partially or completely obscured (or intercepted) by dense vegetation canopies. This introduces major~~It bring great~~ uncertainties in accurate detection of ~~on~~ snow cover ~~accurate detection~~ (Che et al., 2016; Hall et al., 2001; Parajka et al., 2012). Forest cover is an influential factor that cannot be ignored in optical and microwave remote sensing studies (Metsämäki et al., 2005; Cohen et al., 2015). It is evident that ~~the~~ fractional snow cover retrievals ~~almost~~ typically have the least accuracy under the forest type ~~with respect to~~in comparison to ~~under~~ other land cover types (Table 5; Figs. 6 and ~~Fig.~~ 7). There are two reasons that may be attribute to ~~can explain~~ this error~~ initially~~;~~:~~ one is the accuracy of the reference "true" fractional snow cover data in a forested area (Riggs and Hall, 2016), and the other is the microwave radiation attenuation caused by forests (Che et al., 2016).

Previous studies have reported that lower accuracy of MODIS snow cover products was~~is~~ found in forest covered areas and complex terrain (Hall and Riggs, 2007; Tran et al., 2019; Coll and Li, 2018).~~ There are few~~ Several studies have ~~that~~ validated and evaluated the accuracy of MODIS snow cover products, particularly ~~–~~in forested areas (Parajka et al., 2012; Zhang et al., 2019; Arsenault et al., 2014; Kostadinov and Lookingbill, 2015). In term of~~As for~~ the NDSI threshold in forested areas (S~~s~~ection 3.2), we used 0.4 as a conservative~~ly took 0.4 as the~~ threshold. According to previous studies, our operation (merely using NDSI as the criterion) in forest-covered areas would produce greater~~result in more~~ commission errors ~~in~~

compared with using the Normalized Difference Vegetation Index (NDVI) as auxiliary information (Hall and Riggs, 2007). The retrieval results indicated that~~e~~ the NDSI threshold ~~of NDSI~~ in forested areas needs ~~to be~~ optimization~~ed~~ using ~~-~~numerous data (Riggs et al., 2017; Xin et al., 2012). In addition to the influence of forests ~~influence~~ on MODIS data, forests also hamper~~s~~ the upwelling microwave radiation emitted from the ground. Snow cover in forested areas ~~can~~ may be divided into under-forested and over-forested snow cover (Xin et al., 2012). This apparently distinguishes~~ereby,~~ the interference effects of evergreen forests and deciduous forests on snow cover ~~are apparently different~~ (Gascoin et al., 2019; Romanov and Tarpley, 2007). Additionally, there are major differences in ~~forested area,~~ the observation ~~way of~~means for optical and passive microwave sensors in forested areas ~~has great differences~~. The capacity for o~~O~~ptical sensors ~~capability~~ to observe over-forested snow cover is mainly dependent~~s~~ on the vegetation canopy density (Kuter et al., 2018), while microwave sensor may ~~can~~ obtain information ~~of~~ on snow cover under vegetation canopy (under-forested snow cover) (Che et al., 2016; Cohen et al., 2015). Overall, the~~is~~ combination of these two effects ~~could~~ may ~~cause~~ produce ~~the~~ low estimation accuracy for ~~in estimating~~ fractional snow cover.

6. Conclusions

Many previous studies have focused on ~~the~~ estimating~~on of~~ fractional snow cover utilizing optical remote sensing imagery, which suffers from cloud contamination during~~in~~ data acquisition. In contrast, ~~the~~ microwave sensors offer attractive advantages of working under all weather conditions and around the clock.~~-~~ In this study~~Thus~~, we ~~tried~~ attempted to develop~~ed~~ an algorithm for ~~estimating fractional snow cover from~~ applying the enhanced-resolution passive microwave brightness temperature data (6.25~~-~~ km) to fractional snow cover estimation during January and February of 2010 to 2017. ~~The proposed algorithm took into account a series of influential factors, including topography, land cover, and location.~~ Using the reference fractional snow cover stem from MODIS snow cover products as the "true" observation, we established ~~the~~ fractional snow cover retrieval models for four land cover types (forest, shrub, prairie and bare land) inputting 12 variables selected by 24 sensitivity experiments. The~~e~~ proposed algorithm ~~took into~~ accounted for a series of influential~~tial~~ factors~~,~~ including topography, land cover, and location information. Compared with the other three methods (linear regression, ANN~~ANN~~ and ~~MARS~~MARS), the random forest-based algorithm had the best performance with high accuracy (highest R, and lowest MAE and RMSE) and no out-of-range retrievals. ~~The accuracy of the proposed algorithm were further assessed using MODIS reference fractional snow cover data of 2017, and T~~The results of the evaluation ~~results~~ using the reference fractional snow cover data in 2017 showed that ~~random forests models~~ our proposed algorithm had~~ve a~~ good retrieval performance in estimating fractional snow cover, with RMSEs ranging from 0.167 to 0.198~~207~~. Moreover, i~~I~~n-situ snow depth measurements were used to validate the accuracy of the ~~estimated~~ proposed fractional snow cover estimation algorithm~~results~~ in snow cover mapping ~~comparing them with the snow cover detection results from Grody's algorithm~~. Snow cover ~~identification~~ detection capability of the ~~random~~ random forest-based method was~~is~~ superior (OA =0.84, kappa = 0.67) to that of Grody's algorithm, with overall accuracy increasing by 18% (from 0.71 to 0.84), and omission error reducing by 71% (from 0.48 to 0.14), when the fractional snow cover threshold was 0.3~~, indicating that the proposed approach detects snow cover with considerable accuracy~~. Although the ~~random~~ random forest-based models achieved an acceptable accuracy, the fractional snow cover ~~are~~ was more likely to be overestimated (CE = 0.17) than ~~to be~~ underestimated (OE = 0.~~14~~13). In addition, ~~As Grody's algorithm yielded good prediction on snow-free class, the~~ the effect of the non-snow scatterer was evaluated on fractional snow cover predictions by means of the good prediction of Grody's algorithm on snow-free class; the results indicated~~it was found~~ that more than 70% of CE was caused by misclassifying the non-snow scatterer (precipitation, cold desert, frozen ground) as snow cover. These models established using several data sources in January and February had better applicability in dry snow conditions, while estimation results could be less accurate in wet snow conditions.

Numerous studies have investigated the relationship between common snowpack physical properties (e.g., snow depth and water equivalent) and passive microwave brightness temperature ~~in~~ at different frequencies and polarizations (Chang et al., 1987; Dietz et al., 2011; Kim et al., 2019; Xiao et al., 2018). ~~However~~Unlike many previous studies, this study innovatively used passive microwave data ~~was the first attempt~~ to directly estimate fractional snow cover ~~using passive microwave data~~. The results ~~demonstrated~~ showed that it is possible to directly obtain an estimated fractional snow cover ~~directly~~ with high accuracy from high-spatial-resolution passive microwave data (6.25 km) under all weather conditions. ~~Thus,~~ Further detailed study on the use of high spatial resolution passive microwave data for fractional snow cover estimation ~~it would be~~presents itself as an interesting research direction for the development of the studies on fractional snow cover estimation ~~as an extension of the present fractional snow cover study~~. Furthermore, t~~T~~o reduce some of the limitations (e.g., forest effects) (Cohen et al., 2015) and deficiencies (overestimation and underestimation) ~~faced~~ identified in this study, ~~the~~ future ~~works~~ studies should pay greater ~~more~~ attention to the prediction of the fractional snow cover using passive microwave data. To the best of our knowledge, this study ~~is~~ may represent the first attempt to establish a relationship between ~~the~~ microwave brightness temperature and the reference "true" fractional snow cover using machine learning methods. However, it ~~presents~~ also contains significant ~~strong~~ limitations in ~~the~~ understanding ~~of~~the physic~~sal~~ that relates fractional snow cover to the signature of passive microwave brightness temperature ~~mechanism~~ (Cohen et al., 2015; Che et al., 2016). ~~Thereby, F~~future studies need ~~work will try~~ to use physical snowpack models and radiation transfer theory to explore the physical mechanis~~ticm~~ relationships between microwave brightness temperature and fractional snow cover (Pan et al., 2014).

Competing interests: We declare that we have no competing interests.

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Appendix

Supplementary material for this article is available in supplement.

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List of Tables and Figures

Table 1. The input variables list. Line means this variable is not selected; asterisk indicated the variable is selected. The numbers in square brackets denote the number of variables. T19H is the brightness temperature (T) in 19-GHz channel with H polarization; T_19V_19H denotes the difference of brightness temperature between 19V and 19H channel; others are similar.

ID	Elements	Scenario-1 [18]	Scenario-2 [13]	Scenario-3 [3]	Scenario-4 [11]	Scenario-5 [12]	Scenario-6 [9]
1	Latitude	*	-	-	*	*	*
2	Longitude	*	-	-	*	*	-
3	DEM	*	-	-	*	*	-
4	Slope	*	-	-	*	*	-
5	Aspect	*	-	-	*	*	-
6	T19H	*	*	-	*	-	-
7	T19V	*	*	*	*	-	-
8	T37H	*	*	-	*	-	*
9	T37V	*	*	*	*	-	*
10	T91H	*	*	-	*	-	*
11	T91V	*	*	*	*	-	*
12	T_19V_19H	*	*	-	-	*	-
13	T_19V_37V	*	*	-	-	*	*
14	T_19H_37H	*	*	-	-	*	-
15	T_22V_19V	*	*	-	-	*	*
16	T_22V_91V	*	*	-	-	*	*
17	T_37V_37H	*	*	-	-	*	-
18	T_37V_91V	*	*	-	-	*	*
References		(Liu et al., 2018)	(Xu et al., 2016)	(Kim et al., 2018)	(Xiao et al., 2018)		(Nguyen et al., 2018)

Table 2. The description of the revised Grody's algorithm. The unit~~e~~ is Kelvin (K).

Scattering Materials	Description
Scattering signature	$(Tb19V - Tb37V) > 0$ K
Precipitation	$(Tb22V \geq 259\ K)$ or $(254\ K \leq Tb22V \leq 258\ K\ and\ (Tb19V - Tb37V) \leq 2\ K)$
Col~~e~~d desert	$(Tb19V - Tb19H) \geq 18\ K$ and $(Tb19V - Tb37V) \leq 10\ K$
Frozen ground	$(Tb19V - Tb19H) \geq 8\ K$ and $(Tb19V - Tb37V) \leq 2\ K$

Table 3. Confusion matrix defining the accuracy of the predicted snow cover map reference to the in-situ snow cover observation. The characters (TP, FP, FN, TN) represent the number of records of snow-covered or snow-free in a particular conditions.

		Ground observation (true)	
		snow-covered (Positive)	snow-free (Negative)
Prediction	snow-covered (Positive)	TP (true positive)	FP (false positive)
	snow-free (Negative)	FN (false negative)	TN (true negative)

$OA = (TP + TN)/(TP + TN + FN + FP)$

$OE = FN/(TP + FN)$

$\mathrm{CE} = FP/(TP + FP)$

$Pecision = TP/(TP + FP) = 1 - CE$

$Recall = TP/(TP + FN) = 1 - OE$

$Specificity \ = TN/(TN + FP)$

$F1 = (2 * Precision * Recall)/(Precision + Recall)$

Table 4. Variable selection tests in 6 scenarios on bare land type data for random forest method. The accuracy indexes of the estimation are calculated using OOB error estimates and 10-fold cross validation (CV).

	Indexes	Scenario-1	Scenario-2	Scenario-3	Scenario-4	Scenario-5	Scenario-6
OOB-error	R	0.776	0.679	0.590	0.778	0.774	0.708
	MAE	0.152	0.178	0.197	0.150	0.152	0.170
	RMSE	0.194	0.224	0.248	0.193	0.194	0.216
10-fold CV	R	0.777	0.682	0.596	0.778	0.775	0.710
	MAE	0.152	0.178	0.197	0.151	0.153	0.170
	RMSE	0.193	0.223	0.246	0.193	0.194	0.215
Time spent modeling / s		7.37	5.57	3.46	5.43	5.26	5.27

Table 5. Performance of linear regression, ANN, MARS and random forest model using test datasets from 2010 for four land cover types. FSC indicate fractional snow cover. The number outside brackets indicate the number of pixels; The number inside brackets indicate their percentage.

Method	Land cover type	Time spent modeling/s	R	MAE	RMSE	Max. /Min.	FSC < 0 (%)	FSC > 1 (%)
Linear regression	Forest	0.37	0.896	0.225	0.279	1.204 (-0.183)	44978 (10.21)	554 (0.13)
	Shrub	0.24	0.956	0.174	0.198	1.605/-0.382	335 (0.06)	125589 (24.17)
	Prairie	0.49	0.902	0.179	0.215	1.524 /-0.331	23604 (0.87)	632417 (23.22)
	Bare land	0.29	0.892	0.177	0.213	1.647 /-0.087	912 (0.10)	30208 (3.32)
ANN	Forest	51.09	0.895	0.315	0.401	0.949 / -0.520	161260 (36.62)	0 (0)
	Shrub	21.73	0.966	0.103	0.146	1.251 / -0.327	15267 (2.94)	38207 (7.35)
	Prairie	156.29	0.916	0.197	0.23	1.527 / -0.166	743 (0.03)	310285 (11.39)
	Bare land	35.31	0.932	0.174	0.203	1.730 / 0.173	0 (0)	39491 (4.34)
MARS	Forest	2518.10	0.838	0.208	0.254	2.132 / -0.122	8844 (2.01)	2823 (0.64)
	Shrub	1127.24	0.926	0.149	0.185	2.053 / -0.239	2977 (0.57)	121693 (23.42)
	Prairie	23406.76	0.912	0.164	0.197	1.764 / -0.733	4371 (0.16)	469416 (17.24)
	Bare land	2518.10	0.911	0.156	0.191	2.253 / -0.844	469 (0.05)	142155 (15.62)
Random Forest	Forest	52.16	0.916	0.202	0.245	0.960 / 0.011	0 (0)	0 (0)
	Shrub	16.76	0.975	0.118	0.162	0.999 /0.023	0 (0)	0 (0)
	Prairie	214.06	0.955	0.134	0.173	1.000 / 0.011	0 (0)	0 (0)
	Bare land	38.73	0.967	0.103	0.148	0.998 / 0.027	0 (0)	0 (0)

Table 6. The performance of random forest models on training and validation data under four land cover types.

Land cover type	Training			Validation		
	R	MAE	RMSE	R	MAE	RMSE
Forest	0.702	0.166	0.207	0.636~~0.932~~	0.180~~54~~	0.221~~193~~
Shrub	0.772	0.146	0.191	0.712~~971~~	0.160~~42~~	0.212~~199~~
Prairie	0.807	0.142	0.182	0.752~~946~~	0.148~~63~~	0.189~~67~~
Bare land	0.807	0.144	0.190	0.719~~950~~	0.165~~52~~	0.216~~198~~

Table 7. The effect of precipitation, cold desert and frozen ground in snow cover misclassification. FP is false positive that means it is the number of pixels that are misclassified as snow cover by ~~Random forest FSC~~Random forest SCA. $SD_{obs} = 0$ denotes snow-free measured in station; $SC_{Grody} = 0$ denotes snow-free (precipitation, cold desert and frozen ground) determined by Grody's algorithm; $FSC > 0.3$ denotes snow cover detected by our method.

Land cover types	FP	$SC_{obs} = 0$ & $SC_{Grody} = 0$ & $FSC > 0.3$	Percentage
Overall	28638	20063	70.06%
Forest	1966	1528	77.72%
Shrub	519	485	93.45%
Prairie	13530	9554	70.61%
Bare land	12623	8496	67.31%

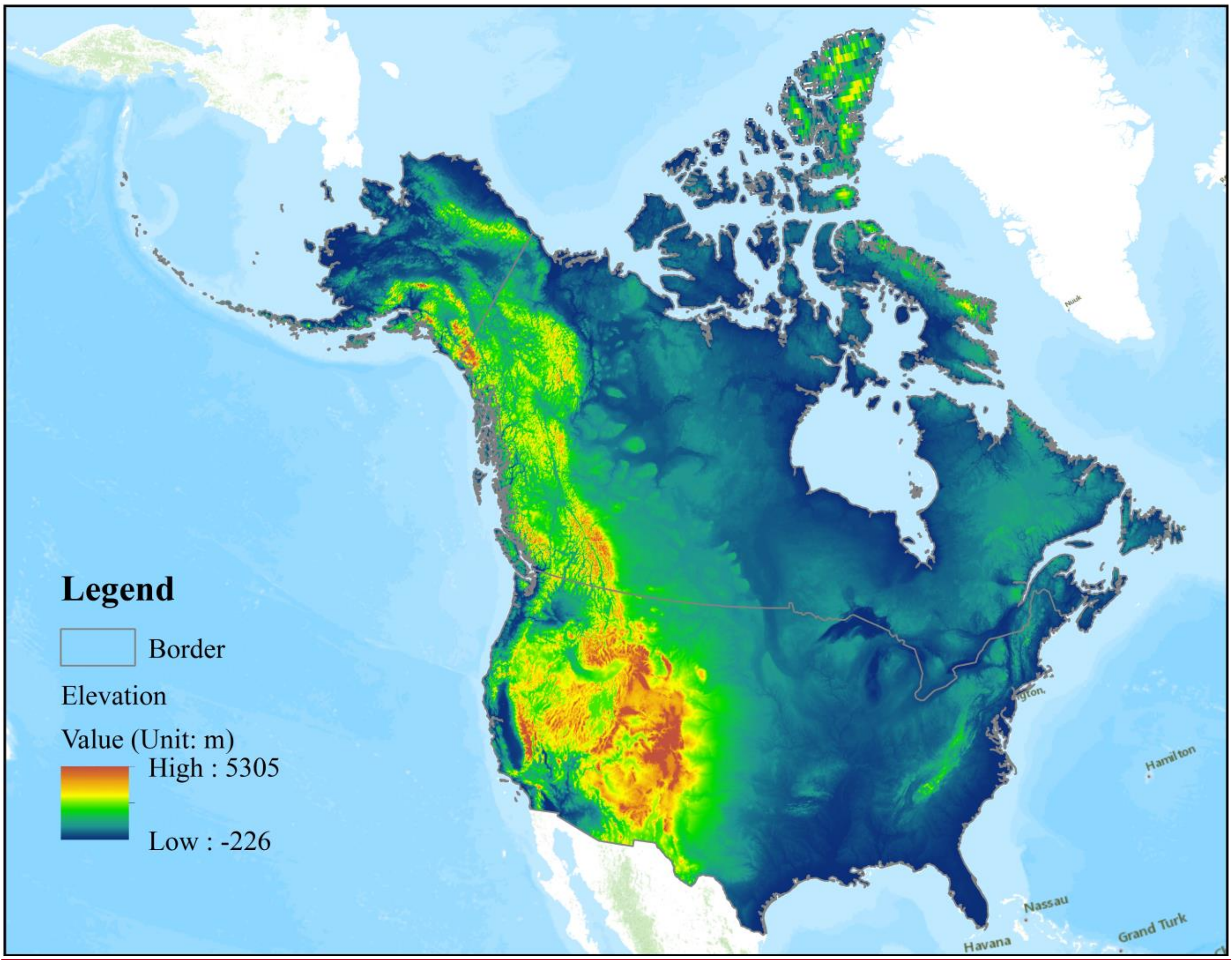


Fig. 1 Topographic map of North America.

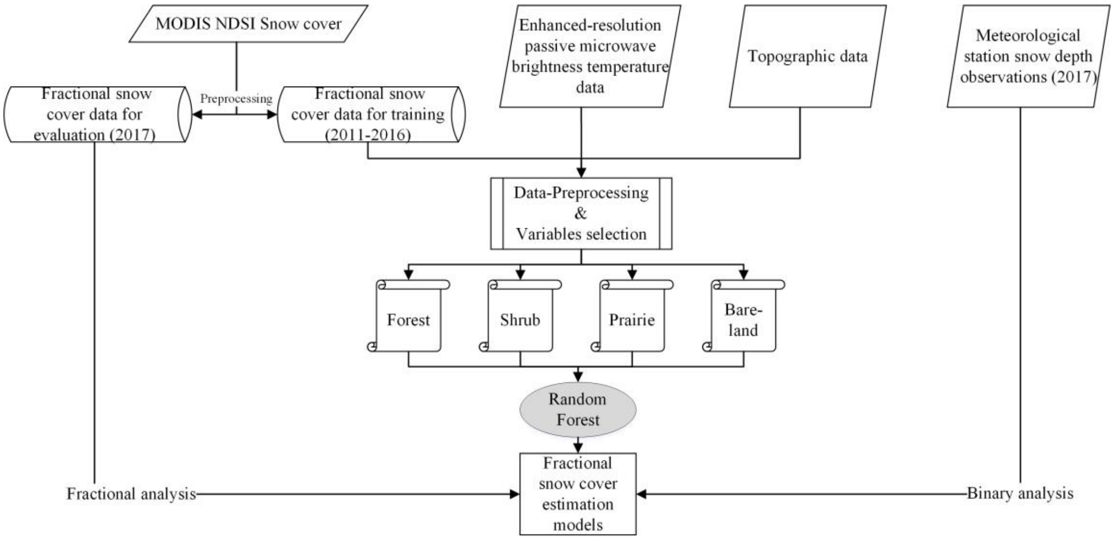
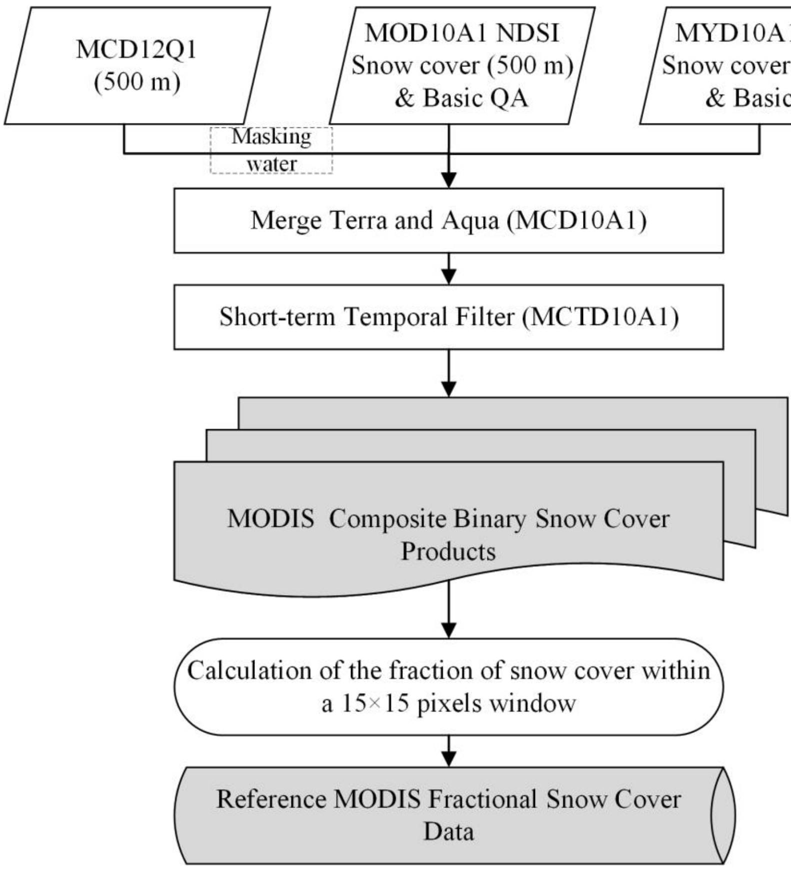


Fig. 2. Workflow diagram illustrating the processing of fractional snow cover retrieval.



5 Fig. 3. The generation of MODIS fractional snow cover

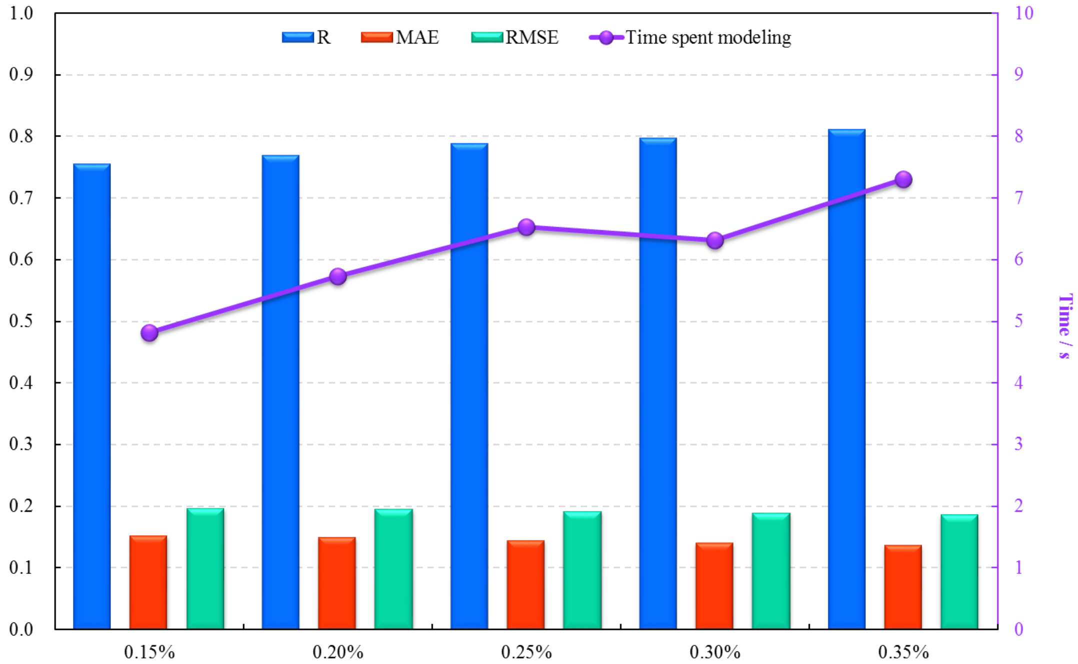


Fig. 4. ~~Using OOB error estimates to evaluate~~ T~~t~~he performance of random forest models with increasing the size of training sample ~~size~~ for shrub type

Fig. 5. The variation of the accuracy indexes (MAE, RMSE and R) on four algorithms (linear regression, ANN, MARS and Random forest) for four land cover.

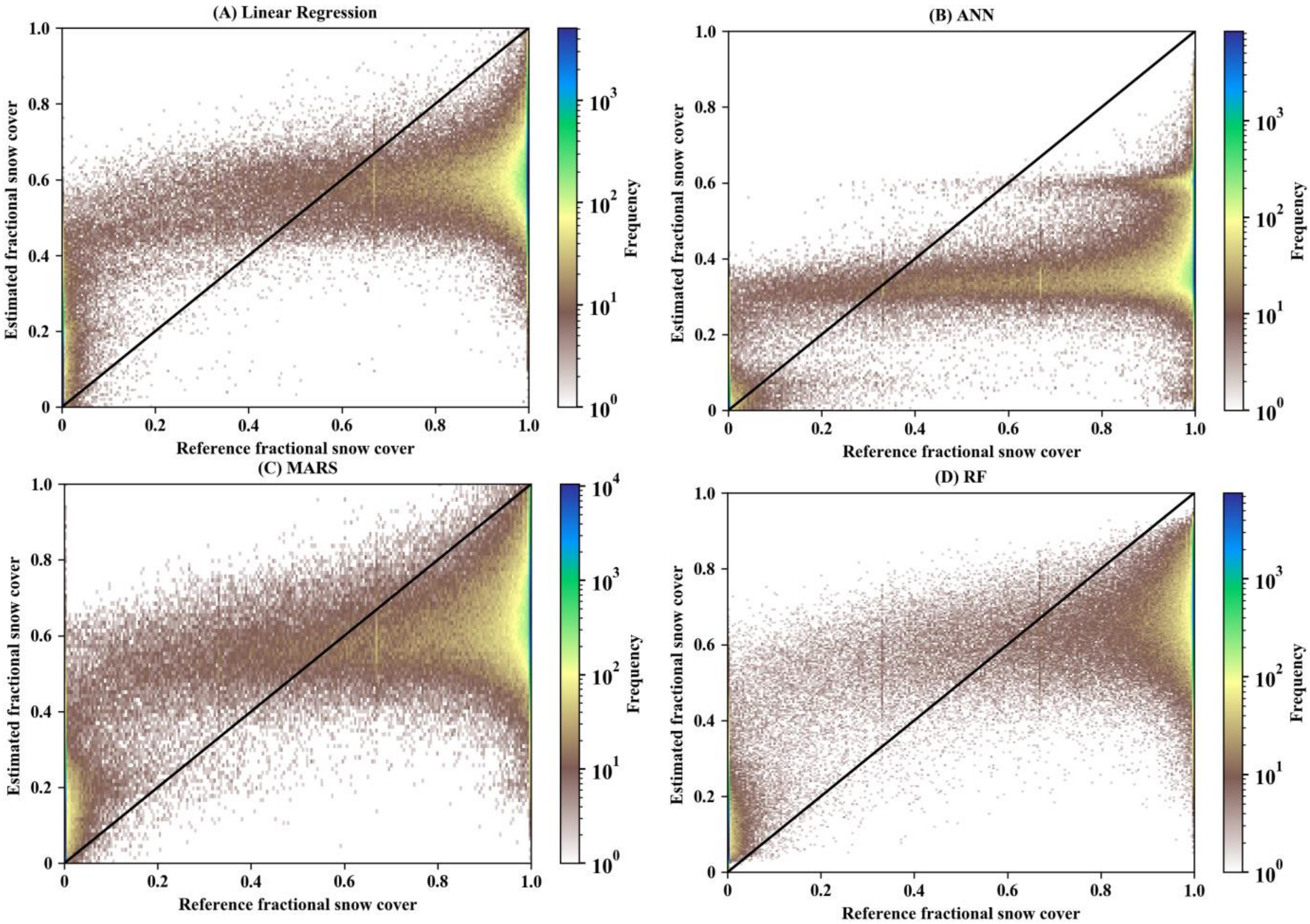


Fig. 6. The color-density scatter plots between the estimated fractional snow cover and MODIS-derived fractional snow cover for four algorithms (linear regression, ANN, MARS, and random forest) for forest type. The accuracy metric refer to Table 5. [Note: out-of-range fractional snow cover values of linear regression, ANN and MARS were truncated on 0 and 1]

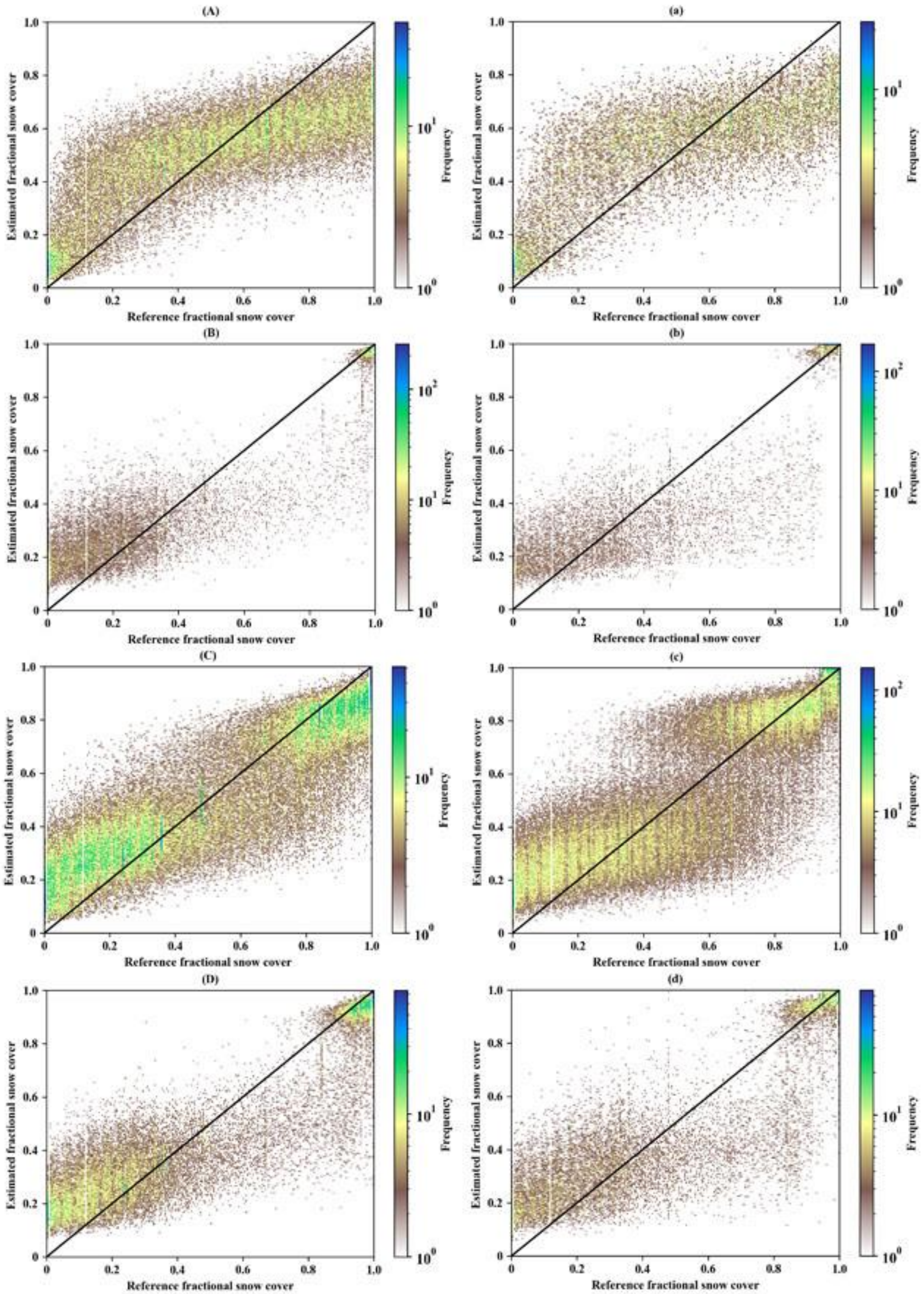


Fig. 7. The color-density scatter plots between the estimated fractional snow cover and MODIS-derived fractional snow cover for four land cover types (forest: A, a; shrub: B, b; prairie: C, c; bare land: D, d). Left column with capital letters ~~are~~ is

the results in the training stage (A-D); right column with lowercase letters ~~are~~ is the results in the evaluation stage (a-d).

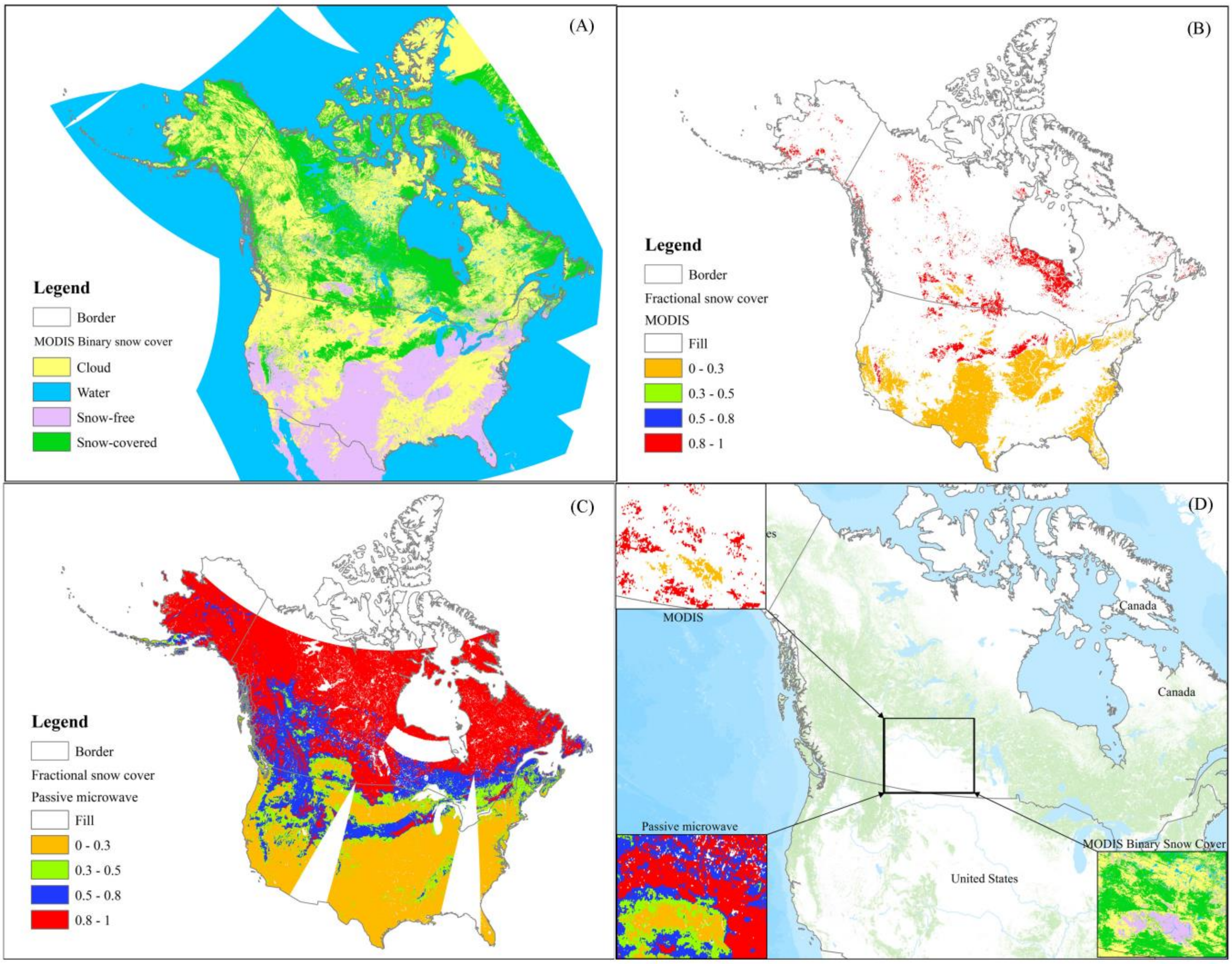


Fig. 8. Comparison of our estimated fractional snow cover (C, 6.25-km) with the reference MODIS fractional snow cover (B, 6.25-km) with respect to the MODIS composite binary snow cover products (A, 500-m); and a comparison example in the Central Canada area (D) on February 27th, 2017 (2017058). [Cf. the results in continuous value (Fig. ~~ure~~ S-7 in the Appendix)]

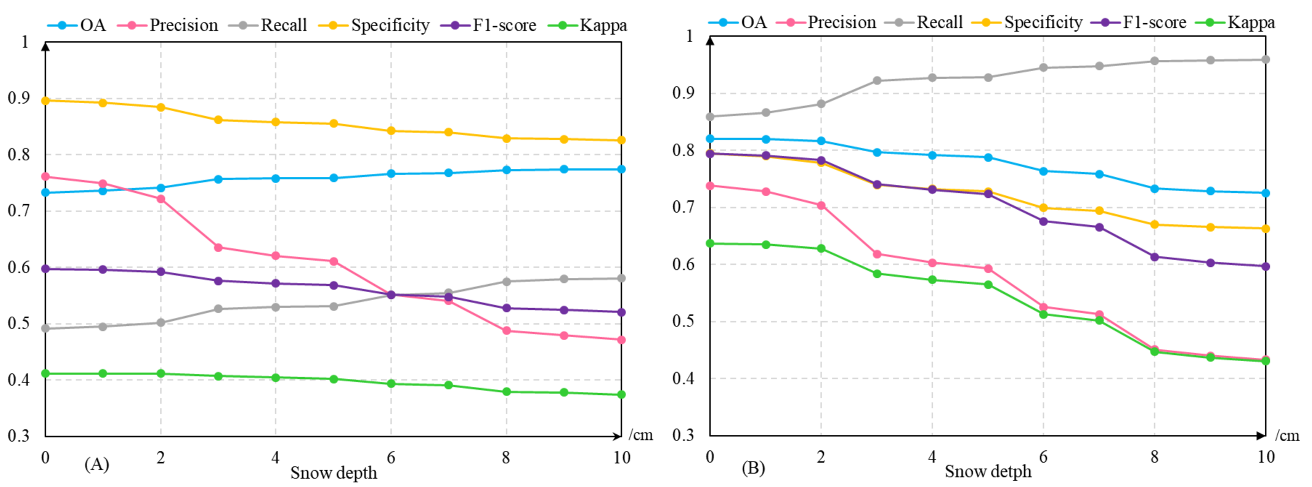


Fig. 9. The changes of accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) for snow cover detection results of two algorithm (A: Grody' algorithm; B: Random forest) with increasing in situ snow depth value.

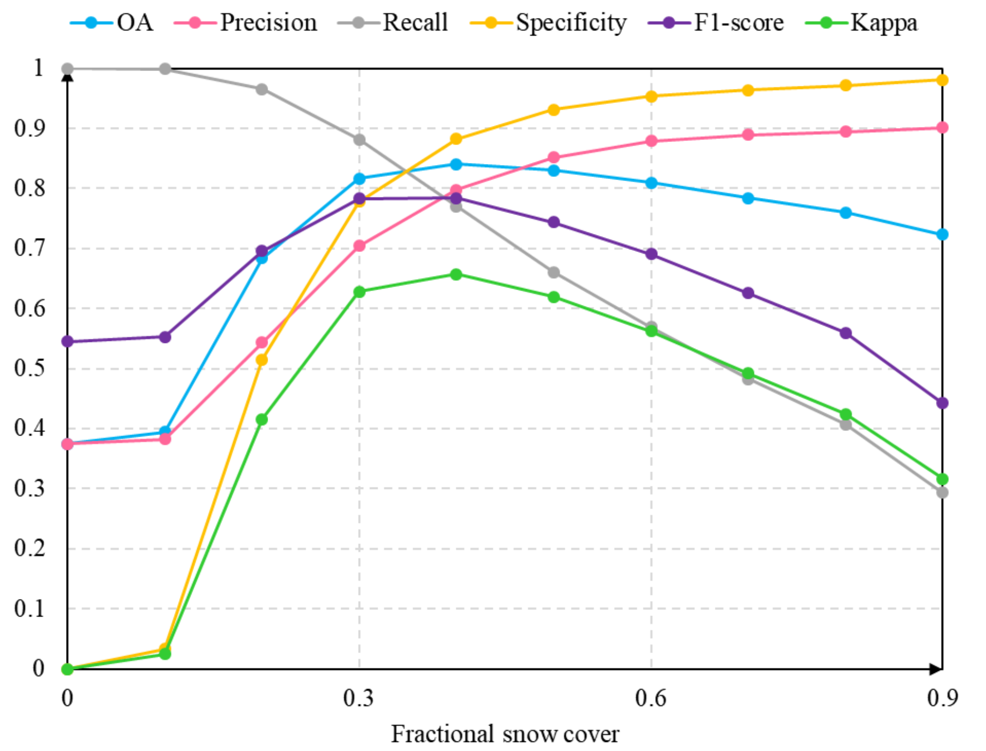


Fig. 10. The changes of accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) for snow cover detection results with increasing fractional snow cover value (FSC).

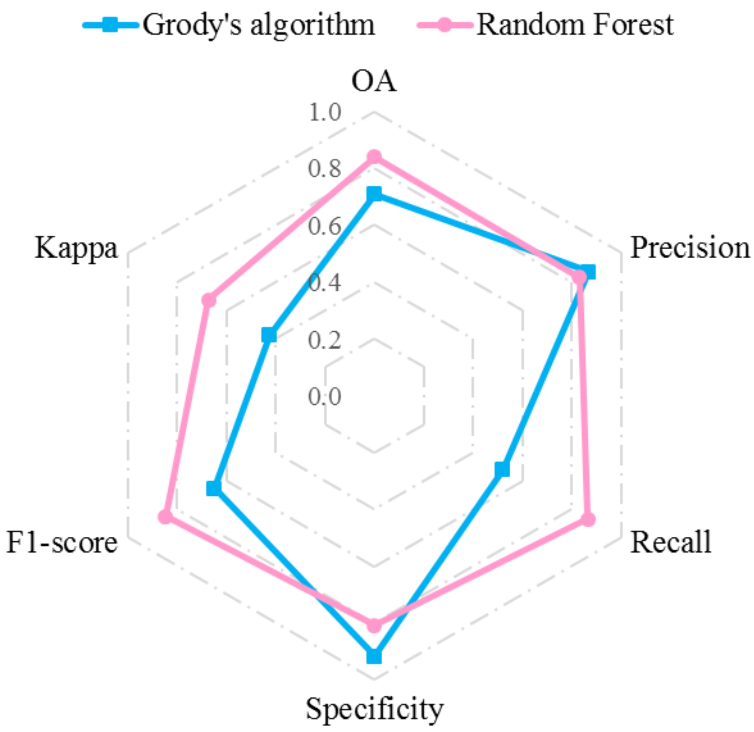


Fig. 11. The accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) of snow cover detection from two algorithm (Grody' algorithm; Random forest).