

Dear editor,

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

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

1) We added the Fig. 12 that described the snow cover mapping results comparison between random forest SCA and Grody's algorithm SCA;

10 2) We added another example of the comparison between MODIS and the estimated fractional snow cover (Figure S-8 in the Appendix) on January 10th, 2017 (2017010).

3) We added another two years data (2008-2009) to validate the snow cover mapping capability in Section 4.4.

4) The figures (Fig. 2 and Fig. 9) were updated.

15 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

Response to Reviewer #2

20 Overview and General Comments:

The revised manuscript is much improved in terms of its organization, explanations of the results and English writing, grammar and syntax. The authors have addressed sufficiently many of the reviewers' original comments and suggestions, however, there are a few areas that may require additional attention and a couple of concerns that were not fully addressed.

25 The authors have conducted a comprehensive study in considering the inputs and characteristics associated with passive microwave retrievals and algorithms to estimate snow cover fraction. However, it focuses still on only two winter months and is limited by the number of years used in the training, testing and validation, using the period from 2008-2017 (in relation to SSMI/S sensor F-16). Selecting just the mid-winter months of January and February to demonstrate the application of the random forest regression approach as to determine snow cover fraction does limit the study to mostly dry snow events, and ignores the ablation and accumulation seasons, which are understandably harder to train and estimate and may require more  
30 time to address. If it is not too costly (as based on their computational timing estimates shown in the paper), could the authors include a couple of other months, at least for the random forest regression and Grody SCA algorithm methods, to see how they perform? For example, include December (reflecting more accumulation phase) and March (more ablation phase processes) to see how well the algorithms perform for different conditions and intermediate snow levels, especially the March case.

Response: Thanks for your comment and constructive suggestion to enhance our manuscript.

Although we have finished searching the theory and method in fractional snow cover retrieval from passive microwave brightness temperature, the presentation of retrieval results in other months following this study's method are hard to finished in such limited time. As you said, snow properties between snow accumulation phase and snow ablation phase exhibit great differences. If you want to generate fractional snow cover results for other months, you need to respectively rebuild a new model suitable for the snow ablation phase or other snow cover phases. For example, to establish fractional snow cover model for snow ablation phase, the daily MODIS and passive microwave data downloading, data preprocessing, information extracting, model establishing, and results analyzing would take at least 4 months.

As an explorative experimental study, this study needs to explore and demonstrate the feasibility of using passive microwave data to estimate fractional snow cover, because we did not know whether the passive microwave data can be used to retrieve the sub-pixel snow cover area of passive microwave data. In addition, this study has emphasized why we only used the data in January and February *"To explore the feasibility of estimating fractional snow cover using passive microwave data, this study only selected January and February of 2008 – 2017 as the study period in here"* in page 4 lines 21-23.

In addition, we have discussed the disadvantage of the study period only limited in January and February in Section 5.1 *"Therefore, it is necessary for future studies to increase the number 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)."*

During the long review of this manuscript, we have further explored other issues in fractional snow cover retrieval from passive microwave data (Xiao et al., 2020). It should be pointed out that the data and methods used in our recently completed study are quite different from those in this study. Our latest research also explored the different performance of fractional snow cover retrieval from passive microwave data in different months (September to May). The results, which could answer your question, found that the best prediction performance of retrieving fractional snow cover is in January, the worst is in May, and the accuracy of the estimated fractional snow cover is varying with snowpack properties (Xiao et al., 2020).

Reference:

Xiao, X., He, T., Liang, S.: Retrieval of fractional snow cover from passive microwave data coupled with microwave radiation transfer model and machining learning method, in preparation, 2020.

Though the authors point out (page 18-L11, page 21-L12, and page 23-L7) that the amount of intermediate fractional snow cover values is much lower, since they focus on peak winter months, the question arises then -- does their random forest regression snow cover retrieval approach, that was trained and tested for this study, adequately predict intermediate snow cover fraction values?

Response: Thanks for your comment. At the beginning of this study, we only using the data during 2014 - 2016 to provide training sample selection dataset. Due to the study time focus in winter with more cloud contamination in optical remote

sensing image, we found the amount of intermediate fractional snow cover values in the training sample is not enough and also doubted the robustness of the established retrieval models. Then, we increased the number of intermediate values in the training sample data set by extending the study period to 2011. In order to make the training samples more representative, we associated with the stratified sampling method to randomly select enough training sample from the expanding datasets. As a result, we can find that the fractional snow cover values have a relatively good distribution in Fig. 7A - 7D and have a reliable predictive capability in fractional snow cover (Fig. 6 and 7). In addition, the verification experiments with in-situ measurement show that our proposed fractional snow cover retrieval method has high ability in snow cover mapping with high overall accuracy (OA = 0.85; Fig 11)

When looking at Fig. 6, which compares the reference (MODIS) with the random forest (RF) passive-microwave snow cover estimates for forest land type, the reader sees some of the intermediate snow cover fraction values captured across the RF-based estimates. However, when one looks at the Supplemental Figs. 4-6, for the other three land types (prairie, shrub and bare soil), most of all the values congregate either between 0.8 and 1.0 or near 0.2, for the RF estimated values, with only a few points near 0. With not knowing the distribution of land cover types, it is hard to know how many “intermediate” values are captured mainly due to vegetation canopy presence. For the other land cover types, intermediate values are not well captured, possibly reflecting mostly dry snow winter conditions, thus not making the approach tested a truly “fractional” snow cover product.

Response: Thanks for your comment. As you seen, the distribution of fractional snow cover values shows great varieties over different land cover types. Due to cloud contamination and rigorous filter rules, not so much number of intermediate fractional snow cover values were obtained for our further analysis. One important fact should be pointed that the presentation of evaluation results of predicted values in this paper heavily is dependent on the number of reference MODIS fractional snow cover values. When compared to the other three methods, the random forest-based algorithm has the best performance in fractional snow cover estimation. From this explorative experiment, we have demonstrated that it is feasible using passive microwave remote sensing data to estimate fractional snow cover.

To generate more robust and high accuracy fractional snow cover products, there are many issues that need to pay more attention to solve and investigate in future work, e.g., 1) the application of the proposed method in other study periods (seasons or months); 2) the different sensitivity to snow cover extent for optical and passive microwave satellite sensor in coarse resolution; 3) the different responses of optical and passive microwave satellite sensors to snow cover interception by forest or other vegetation (Lv and Pomeroy, 2019); 4) the effect of different land cover types in sub-pixel (Salminen et al., 2018); 5) filling data gaps of passive microwave data for generating full coverage fractional snow cover products, etc.

Reference:

Lv, Z., & Pomeroy, J. W.: Detecting intercepted snow on mountain needleleaf forest canopies using satellite remote sensing. *Remote Sensing of Environment*, 231, 111222, 2019.

Salminen, M., Pulliainen, J., Metsmki, S., Ikonen, J., Heinil, K., & Luojus, K.: Determination of uncertainty characteristics for the satellite data-based estimation of fractional snow cover. *Remote Sensing of Environment*, 212, 103-113, 2018.

The authors stated in their introduction section that “there is an urgent need to acquire snow cover area within a sub-pixel to provide accurate snow cover information”, as a main motivation for performing this study. I feel the authors do try to capture

the fractional nature of snow cover with their algorithm and passive microwave estimates. However, not many spatial map examples are provided to show how well the overall the passive microwave fractional snow cover estimates perform for the mid-winter months (Jan-Feb) against the MODIS-based fractional estimates to demonstrate this. It would be helpful if there was at least one other date provided and shown (e.g., besides Feb 27, 2017, in Fig 8) and perhaps a date that the MODIS product had less cloud coverage and more intermediate snow present.

Response: Thanks for your suggestion. The reference MODIS fractional snow cover data could not provide snow cover area information in most cases due to cloud contamination while the passive microwave-based fractional snow cover data can offer the users and researchers continue snow cover area information in continental scale (Fig. 8 and Figure S-7 in the Supplements). Following your suggestion, we added a spatial map example of reference MODIS fractional snow cover with relative much mediate values and the estimated fractional snow cover on January 10th, 2017 (2017010) in Supplement (Figure S-8).

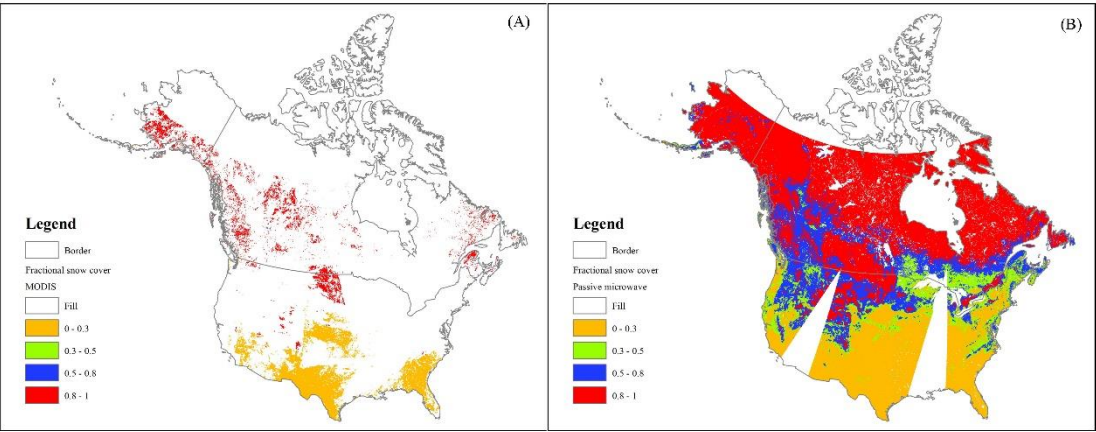


Figure S-8. Comparison of the reference MODIS fractional snow cover (A) with our estimated fractional snow cover (B) at 6.25-km spatial resolution on January 10th, 2017 (2017010)

Thank you for addressing and explaining further the reason for the “binary” nature of the aggregated (15x15) MODIS snow cover gridcells compared (Figure 8B panel), due to the “rigorous” screening of only including snow or non-snow pixels within the 15x15 aggregate. Also, the side analysis (not included in the paper) is helpful to see if you were to relax that constraint by allowing a 5% amount of pixels to be factored in (that are cloud or inland water), and how that translated into more “intermediate” valued gridcells, ranging from 0.3 and 0.8. With the original rigorous screening process still applied in the paper, at least shown in Fig. 8, the MODIS snow cover reference acts more as a “binary” snow cover, which does not seem to reflect fractional snow cover here. By selecting such thresholds (e.g.,  $\leq 0.3$  cutoff as no-snow) and rigorous constraints, this may eliminate many pixels that could be used in the training process, even though the design is to utilize the most accurate input data values to establish the regression parameters.

Response: Thanks for your constructive suggestions. In the following study, we will design several experiments to analyze this idea.

In addition, the Supplemental Figure, S-7B, shows the authors’ passive-microwave based fractional snow cover estimates on a “continuous” scale, from 0 to 100% coverage (per pixel), related to Fig. 8. Based on this image, areas showing low snow cover values, e.g.,  $< 0.2$ , seem to be appearing in areas like southern Florida (e.g., color-graduation near values of 0.2) and desert regions in the Southwestern U.S., which typically do not see much or no snow at all. In this case, the MODIS-based

“non-snow” areas (in dark blue) look correct, and the lower estimated snow cover fraction values in the passive microwave product seem to overestimate the “low or no snow” fraction values, which is definitely shown in their Figs. 6 and 7.

Response: Thanks. We not only found a significant overestimation in the low reference fractional snow cover value (or snow-free) in this study, but also found this similar results in our latest study (Xiao et al., 2020). And also, the minimum estimate of fractional snow cover in this study approximately 0.01. We defined the problem you proposed as snow cover misclassification from passive microwave satellite data. There are four possible reasons that can explain this snow cover misclassification from passive microwave satellite data:

1) The main source of snow cover misclassification in this study may be the heterogeneity of the land surface. Specifically, the attenuation and scattering of passive microwave radiation are not only caused by the snowpack, but also by other non-snow scatterer (e.g., desert, arid land, cold land) (Grody and Basist 1996; Dai et al., 2017). At the 6.25-km spatial resolution, there may be great various kinds of land cover except snow cover in winter. In low fractional snow cover pixel, however, most area of the mixed pixel is covered by non-snow type (more than 80%). Then, in this pixel, the scattering contribution from non-snow scatterer is more likely to mistakenly considered to be due to more snow cover area or more snowpack amount (Dai et al., 2017). For this reason, Grody’s algorithm designed to develop a series rules to filter out these snow-free surfaces for decreasing snow cover overestimation (Grody and Basist, 1996). From another aspect to understand the radiation scattering contribution of non-snow scatterer, shallow snow depth (~ 0 cm) is seriously overestimated in some cases up to 20 or 50 cm (Che et al., 2016; Xiao et al., 2018) and the shallow snow always occur with low fractional snow cover. Based on this explanation, we knew that the snow cover area is likely to be overestimated in low snow cover condition.

2) The second error source may be the inversion method used in this study. According to the introduction of random forest method in Section 3.4.4, we knew that random forest predictor (classification or regression) is an ensemble predictor that produces multiple decision trees. The final predicted output by the random forest predictor is determined by averaging all the results of the established sub decision trees (Breiman, 2001; Belgiu and Drăguț, 2016). This may result in the final predicted result would be greater than 0 when the true value is close to 0. These overestimation results near 0 also can be found in other studies applying random forest method (Wei et al., 2019). Under the condition of low snow cover, some sub decision trees may overestimate the snow area in sub-pixel, and then average with other sub decision trees, the final output will be greater than 0 or greater.

3) The third error source of snow cover misclassification may be explained by the principle difference between optical and passive microwave satellite sensors in observing land surface snow cover. Optical sensor is based on snow have high reflectance in the visible band while passive microwave sensor is based on that microwave radiation signal can be scattered by ice crystal particles in snowpack (Grody and Basist 1996). The sensitivity of the optical sensor to detect snow cover is always higher than that of the passive microwave sensor in low snow cover area. This area always is covered by shallow snow, which means that the optical sensor is relatively easy to identify snow cover from other land cover types.

4) In addition to the above three explanations, the occurrence of cold precipitation also can be an error source for snow cover area overestimation. Our recent study (Xiao et al., 2020), in which we analyzed the relationship between the estimated results and climatic factors at several meteorological stations, found the occurrence of cold precipitation can contribute to the overestimation of snow cover area when ground is snow-free (or low fractional snow cover) condition, as described in Section 4.4 this study “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 72.6% of total misclassification records (CE = 0.17), of which 64.3% comes from precipitation, 7.0% from cold desert, and 0.9% from frozen ground”

We revised the explanation statements in section 4.3: “*For the snow cover area overestimation, one possible error source is the used inversion method, of which the final predicted outputs are obtained by averaging all results of the established sub decision trees (see Section 3.4.4) (Breiman, 2001; Belgiu and Drăguț, 2016) and this overestimation can be found in other study applying random forest study (Wei et al., 2019). Additionally, the attenuation and scattering of passive microwave radiation are not only caused by the snowpack. The non-snow scatterer (e.g., precipitation, cold desert, frozen ground) may be the majority error source potentially contributing to the overestimation of snow cover area as these scatters were easily misclassified as snow cover in less snow cover conditions (Grody and Basist, 1996; Dai et al., 2017). A detailed analysis on the misclassification due to non-snow scatterer is provided in Section 4.4.*” in page 19 lines 8-16.

#### References:

1) Belgiu, M., and Drăguț, L.: Random forest in remote sensing: A review of applications and future directions, ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24-31, 10.1016/j.isprsjprs.2016.01.011, 2016.

2) Breiman, L.: Random Forests, Machine Learning, 45, 5-32, 10.1023/a:1010933404324, 2001.

3) Che, T., Dai, L., Zheng, X., Li, X., and Zhao, K.: Estimation of snow depth from passive microwave brightness temperature data in forest regions of northeast China, Remote Sensing of Environment, 183, 334-349, 2016.

4) Dai, L., Che, T., Ding, Y., and Hao, X.: Evaluation of snow cover and snow depth on the Qinghai–Tibetan Plateau derived from passive microwave remote sensing, The Cryosphere, 11, 1933-1948, 10.5194/tc-11-1933-2017, 2017.

5) Grody, N. C., and Basist, A. N.: Global identification of snow cover using SSM/I measurements, IEEE Transactions on geoscience and remote sensing, 34, 237-249, 1996.

6) Xiao, X., Zhang, T., Zhong, X., Shao, W., and Li, X.: Support vector regression snow-depth retrieval algorithm using passive microwave remote sensing data, Remote Sensing of Environment, 210, 48–64, 2018.

7) Xiao, X., He, T., Liang, S.: Retrieval of fractional snow cover from passive microwave data coupled with microwave radiation transfer model and machining learning method, In preparation, 2020

8) Wei, J., Huang, W., Li, Z., Xue, W., & Cribb, M.: Estimating 1-km-resolution pm2.5 concentrations across china using the space-time random forest approach. Remote Sensing of Environment, 231, 111221, 2019.

What would be helpful in relation to Figs. 8 and S-7, would be to see an example of the same panels, e.g., like with respect to Fig. 8, but a case where MODIS has less cloud presence to show spatially the similarities and differences between the passive microwave product to the optical based sensor.

Response: Thanks for your suggestion. The purpose of Figure S-7 is to present a continues value comparison of MODIS and the PM-based estimated fractional snow cover as a reference of Fig. 8. As we described in this study, the rigorous filter rules make it is really hard to access more intermediate fractional values. Specially, according to our analysis, the numbers of values of MODIS ranging 0.2 ~ 0.8 are no more than 1500 pixels within a day in most cases. From several MODIS fractional snow cover images at 6.25 km, we found the intermediate value is always around the 100% and 0% snow cover area. But we think

this suggestion can be applied in future study when comparing different fractional snow cover products.

In addition to these issues, the motivation and methods described are disconnected at times in the paper, and the authors should want to present aspects of their study in a more coherent way. For example, the Section 3.1 Overview section is very helpful to provide readers a “roadmap” as to what is to come and expected in the study, but even the purpose of exploring the four different methods in relation to introducing the fourth method as an hypothesized better approach is simply stated, but those connections seem to be lacking in the Introduction and Section 3.1. I would recommend stating more directly in the Introduction section as to why the random forest regression was selected and provide a short description as what are its advantages, relative to other methods previously applied. I feel the first paragraph in your Section 3.4.4 subsection (on page 12) should be given earlier on in the paper, like in the Introduction section, as to why it is being pursued as an application and how it contributes to your overall hypothesis.

Response: Thanks for your suggestions and comments. We removed the description of random forest from Section 3.4.4 to Section 3.1 as following:

*“Random forest is an ensemble learning method, gaining the attention of many researchers because it is more efficient and robust than the single method (Breiman, 2001). As a classifier, random forest has been successfully employed 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 successfully estimate land surface temperature (Zhao et al., 2019), biomass (Mutanga et al., 2012), and soil moisture (Qu et al., 2019). In this study, random forest regression (described in Section 3.4.4) was selected as the retrieval method to mine the relationship between passive microwave brightness temperature and fractional snow cover. We also compared random forest with other three methods (linear regression, MARS and ANN) widely used in fractional snow cover retrieval from optical remote sensing data in model performance. Fig. 2 provides an overview of the workflow that consists of four parts”* in page 7 lines 7-15.

#### Specific Comments

How were the specific years available for the SSMI/S PM dataset selected originally for: 1) training, 2) testing and 3) evaluation? For example, was 2010 simply selected randomly for the testing year of the four different snow cover retrieval algorithms? If you performed all your algorithm testing and training for the datasets used for different sets of years, do you think you would obtain the same level of results and validation, even though samples are drawn randomly? For example, if you had chosen 2008-2014 for training, 2015 for testing and 2016-2017 for validation, would you expect your table values (e.g., Table 5) and plots to look similar in nature (e.g., Fig. 7) as currently shown? Why or why not?

Response: Thanks for your comments. One thing needs to be emphasized and clarified again is that the selection of experimental data is random. Here, we provide details of the process of experimental design changes. At the beginning, the designed experiment was only using 2014 - 2016 data for training and 2017 for testing and evaluation, but we found the intermediate value in the training data is not enough, and then we updated the experiment design by extending the study period to 2011 for training sample. Moreover, in order to ensure that the evaluation and analysis in different parts independent, we added the data of 2010 used in Section 4.3 for testing the performance of different methods. Up to now, we added another two years data in 2008 and 2009 in evaluation and validation stage following your suggestions.



From the data selection aspect, the year of data used in the training, testing, or evaluation phases does not affect the final experimental conclusion. The most important thing is to ensure enough representative training data sets for establishing the retrieval model. The purpose of the data used in the evaluation stage and testing stage is to evaluate the performance of established retrieval models. Specifically, in our latest study (Xiao et al., 2020), we only used two years data set to provide the training samples because there is less cloud and provide more MODIS reference data in other two seasons (autumn and spring). And the results showed a same level of accuracy in January and February. Moreover, the widely used random forest method is robust because it is based on ensemble learning strategy and has high generalization ability.

In my opinion, if you can give more representative and enough number of training samples, the experimental design as you suggested can also obtain the same level results.

Reference:

Xiao, X., He, T., Liang, S.: Retrieval of fractional snow cover from passive microwave data coupled with microwave radiation transfer model and machining learning method, In preparation, 2020

If you used more years (e.g., 20+ years) of overlapping satellite passive microwave sensor datasets, e.g., different SSM/I versions, could you apply the random forest regression approach separately for each month (and more months) and by region (e.g., U.S. Rocky Mountains, Upper Great Plains), since each of these categories would have distinct snow characteristics, like differences in snow densities (e.g., coastal mountains vs. continental plains regions, or accumulation vs. ablation periods), which can affect brightness temperature signals?

Response: It's a valuable suggestion and comment. Thank you very much. Because of high heterogeneity in coarse resolution of passive microwave data, it is necessary to consider more influential factors to improve the fractional snow cover retrieval from passive microwave data.

As factors you mentioned above, all of these would affect the brightness temperature by different ways and means. For example, in mountainous areas, the complex mountainous terrain will affect the distribution of snow cover, as well as the climatic factors, and then affect the snow property in the local area, thus affecting the scattering of microwave radiation signal observed by satellite sensor. When the study area is relatively small, e.g., U.S. Rocky Mountains, or Upper Great Plains, the method could be applied into different seasons associate with the effect of different forest cover fraction and climate conditions (wind speed, air temperature, soil temperature, etc.). From our recent experiments, we found the time variation and weather conditions play an important role in fractional snow cover estimation from passive microwave data.

Abstract: The authors state around line 14: "under all-weather conditions", which I feel is not representative to summarize in the abstract. The authors can say that they applied the random forest regression technique, along with three other retrieval algorithms, for "dry snow conditions in peak Northern Hemisphere winter months (January and February)."

Response: Thank you. We revised this statement to "... to estimate fractional snow cover over North America in winter months (January and February)" in lines 14-15

Abstract (around lines 19-20): The authors mention that they obtain "with higher accuracy and no out-of-range estimated values" associated with the random forest regression technique. They may also want to note that this algorithm tends to



underestimate upper fractional snow cover values and especially overestimates when no to little snow fraction is present, in comparison to the reference snow cover dataset.

Response: Thanks for your comment. The description was changed to “*Although over- and under-estimation around two extreme values of fractional snow cover, the proposed retrieval algorithm out-performed the other three approaches (linear regression, artificial neural networks, and multivariate adaptive regression splines), using independent test data for all land cover classes, with higher accuracy and no out-of-range estimated values*” in lines 18-21.

Page 4, Lines 26-27: The authors state here that they used “bilinear interpolation” to “aggregate the 3.125 km spatial resolution data to 6.25 km”. Typically, bilinear interpolation is used for downscaling coarser grid datasets to finer grids. How was such an interpolation used here for “aggregation”? Please provide additional background on why this was selected, versus an averaging or mode-based scheme.

Response: Thank you. We revised “... bilinear interpolation was used to aggregate the 3.125 km spatial resolution data to 6.25 km” to “... we aggregated the 3.125 km spatial resolution data to 6.25 km by averaging the surrounding 4 pixels” in page 4 lines 27-28.

Page 5, lines 7-8: Authors state that GHCN-D data from 50,000 sites across Canada and US were collected and included in this study. Actually, this number is higher than what is available for the sites with actual snow depth measurements taken (e.g., may be closer to 10,000 stations for the year of interest, e.g., 2017). The authors may want to mention here how many stations are exactly included in their ground station analysis.

Response: Thanks. We revised the statements to “*More than 50 000 measurement sites across Canada and United States were collected, and all available records applied in validation stage are from 18000 sites*” in page 5 lines 9-11.

Pages 6-7, Section 3.1: I would recommend, early on in this section, mentioning that you compare your application of random forest regression as a new retrieval method against the other three known methods (linear regression, MARS and ANN), and specifically mention them in the first paragraph of this section. The reason is that these other methods have been applied before and you are demonstrating the application of this fourth method. If it has never been applied in such an application related to passive microwave snow cover estimates, you will want to highlight that as both novel and part of your hypothesis that you are testing in deriving snow cover estimates from passive microwave brightness temperatures.

Response: Thanks for your suggestion. We add the description “*We also compared random forest with other three methods (linear regression, MARS and ANN) widely used in fractional snow cover retrieval from optical remote sensing data in model performance*” in the first paragraph of Section 3.1 (page 7 lines 13-15)

Page 13, lines 6-7: The authors state here that “As several attempts to optimize the parameters of random forest structure had failed, all parameters used were the default values.” Can you further describe here then what default values you began with, and one of the approaches you applied to optimize the parameters?

Response: Thanks. When you go into the software WEKA and select random forest method, all parameters are list in the panel: batch size (100), max. depth (unlimited), number of Features ( $\log_2(\text{predictors}) + 1$ ), number of iterations (100) and other 12 parameters. In the parameter optimization experiments, we mainly changed above 4 parameters: batch size, max. depth, number of Features, number of iterations.

Pages 17-18: Please expound here on why the shrub and bare land types may be experiencing more “binary” type extremes (“more distributed at two polar ends”) for snow cover presence (shown in Figs. 7B,b, and D,d) than the other two land types.

Response: Thanks for your comments. We just randomly selected the dataset following the description “*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 Section 4.3. The selected datasets are presented in Fig. 7. We do not control MODIS data selection except that using the rigorous cloud filter rules. As to why more cloud cover during this period, this is beyond the scope of this study.

Page 18, near lines 10-15: “This means that the pixel was identified as snow cover when fractional snow cover value was less than 0.3.” In this last sentence here, did you mean to that “the pixel was identified as snow cover when fractional snow cover value was greater than 0.3”? The authors may want to check what they reported here.

Response: Thank you very much. We revised the sentence to “*This means that the pixel was identified as snow cover when fractional snow cover value was greater than 0.3*” in page 18 lines 27-28.

Page 19, lines 1-2: What is meant by “overestimated (~0) and underestimated (~0)”? Did you mean to make the “0” with “overestimated” a “1”? Please clarify what is meant here for the two cases.

Response: Thank you very much. We revised to “... *were overestimated (~0) and underestimated (~1)*” in page 19 line 18.

Section 4.4: For the snow depth evaluation of the random forest approach (in Section 4.4) vs. the Grody SCA algorithm (also using passive microwave retrievals), I believe only two months total of data were used for the validation (Jan-Feb, 2017). Since the GHCN station snow-depth measurements are not used in the training stage, would it be more representative of this part of the validation to use more years, e.g., 2008-2010 and 2017? Two months only of evaluation does not seem sufficient for this validation.

Response: Thanks for your comments. Following your suggestion, we added another two years data in 2008 and 2009 which is same as used in Section 4.3 to validate the snow cover mapping results for the proposed algorithm and Grody SCA algorithm. In this section, we collect more than 18000 meteorological stations. And more than 900 000 records are gathered to validate the capability of snow cover map for these two methods. We updated the presentation of Figure 11. Correspondingly, we modified the description of the statistics in Section 4.4.

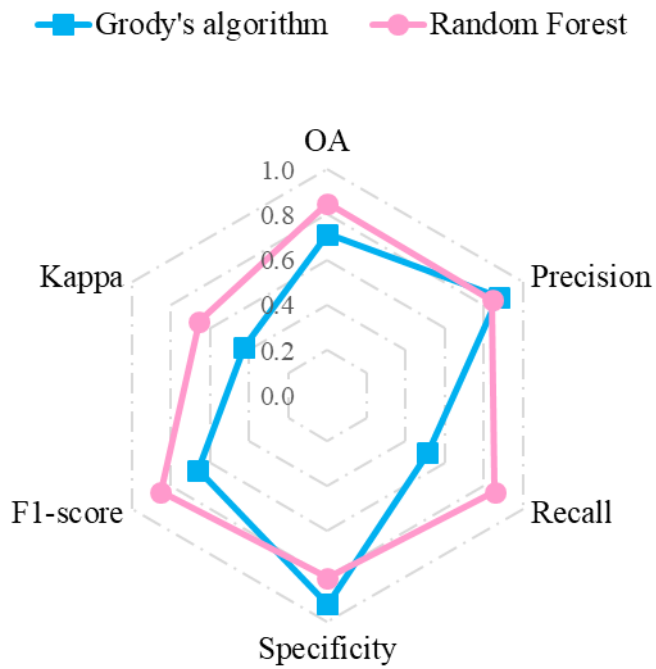


Fig. 11. The accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) of snow cover detection from two algorithm (Grody' algorithm; Random forest).

Page 22, line 20: The authors mention that passive microwave based satellites work “around the clock”, which is partly true. Most microwave measurements (unless they are from geosynchronous satellites) may have a repeat time over the same location every 2 to 3 days, producing gaps in available data and not continuous (e.g., per day) in time (hence why you see the non-overlapping swaths of “missing” or “filled” areas in panel C of Fig. 8). It might be better to simply remove that phrase here.

Response: Thank you for your suggestion. We removed “around the clock” in page 23 line 6.

Figure 8: Why are the legend categories for Figure 8B and C distributed unevenly and alternating in range values (e.g., 0-0.3, 0.3-0.5, 0.5-0.8, 0.8-1.0)? It seems more appropriate to apply “quarters” and have four equal category ranges (e.g., 0-0.25, 0.25-0.50, 0.5-0.75, 0.75-1.0). Please provide explanation as to how these ranges were selected within the main text.

Response: Thanks for your comment. Each threshold used here has its specific meaning and purpose. This threshold 0.3 was selected through a series of experiments described in Section 4.4. Then this study used 0.3 as a threshold to define snow-covered or snow-free. Typically, 0.5 was chosen as a threshold to define snow-covered and snow-free in fractional snow cover study using optical remote sensing data. Therefore, the using of 0.3 and 0.5 can make other readers or researchers easily compare the capability of snow cover mapping of our proposed method with other methods.

To reduce misunderstandings, I modified the threshold selection description: “Thus, Fig. 8B and 8C used the threshold 0.3 to define snow-covered and snow-free area, and this threshold was adopted through a series of experiments in Section 4.4. The threshold 0.5 was selected according to previous optical remote sensing study on fractional snow cover (Arsenault et al., 2014; Gascoin et al., 2019)” in page 18 lines 25-28.

## Technical Corrections

Page 8, line 3: Recommend changing “no-forest” to “non-forest”.

Response: We changed “no-forest” to “*non-forest*” in page 8 line 13.

Page 8, lines 20-21: The superscripts used to define snow cover for Terra and Aqua MODIS sensors, e.g., “S<sup>Aqua</sup>”, seem to be reversed for the given satellite. I believe you meant to use “Terra” for the Terra satellite snow cover ground status, “S”. “Whether a pixel in Terra (S<sup>Aqua</sup>)”... should be: “Whether a pixel in Terra (S<sup>Terra</sup>)”, and then the same for the Aqua snow cover term following that.

Response: Thanks. We revised it in page 8 line 31.

Page 17, lines 27-28: You may want to clarify within the sentence that starts as “Fig. 7A and 7a show ...”, that this corresponds to the forest land type.

Response: Thanks. We added “*For forest type, Fig. 7A and 7a show that ...*” in page 18 line 5.

Page 17, line 30: Within the phrase, “best performance on the evaluation data”, change “on” to “for”.

Response: Thanks. We changed “on” to “*for*” in page 18 line 8.

Page 18, line 3: Remove “can” from “we can found that ...”

Response: we removed “can” in page 18 line 12.

Page 18, lines 27-28: You may want to update this sentence to include the additional years you drew randomly from for snow cover validation – 2008 and 2009.

Response: Thanks. We modified this sentence to “... *on independent datasets from 2008 – 2010 and 2017 on each land cover type*” in page 19 line 7.

Description for Fig. 8 on Page 18 should mention the date of the images sooner in the paragraph - February 27th, 2017.

Response: Thanks. We add the date information “*on February 27th 2017*” in page 18 line 17.

Page 19, line 10: Add “be” to “may easily be neglected”.

Response: Thanks. We revised the sentence to “... *may easily be neglected* ...” in page 19 line 28.

Page 19, line 30: Change “In additional” to “In addition”.

Response: we changed “In additional” to “*In addition*” in page 20 line 17.

Page 20, line 6: Change: “goo agreement” to “good agreement”.

Response: we changed “goo agreement” to “*good agreement*” in page 20 line 24.

Page 20, lines 12-14: Authors accidentally copied or repeated similar information here from Section 4.3, describing the results from Fig. 8, and not related to what is described in this paragraph related to Fig. 11. I recommend them removing these last two sentences in this paragraph.

Response: Thanks. We removed these two sentences in page 20.

Page 21, line 10: The authors may simply want to list the datasets used, such as: “The estimation results of the random forest model [for the training, testing and evaluation] datasets ...”

Response: Thank you. we modified the sentence to “*The estimation results of the random forest model (for the training, testing and evaluation datasets; Sections 4.2 and 4.3) showed that ...*” in page 22 lines 5 - 6.

Page 21, line 14: Change “this” to “these” in the phrase, “Even in [this] cases ...”

Response: Thanks. We changed “this” to “these” in page 22 line 10.

Page 22, line 10: Typically, the terms used here, “under-forested and over-forested” in terms of snow cover are more often referred to as: “under or above forest canopy”. I would recommend updating this paragraph to reflect the use of these terms.

Response: Thanks. We changed the description “under-forested and over-forested” to “*under or above forest canopy*” in page 23 lines 4-9.

Table 5 caption: Change “brackets” to “parentheses”. Brackets are different from what is used in the table.

Response: we changed “brackets” to “*parentheses*” in Table 5 caption.

Table 7: This table and its caption are hard to follow, especially what the percentages are being reported on the right. Please further note what is meant in the caption and what are indicated by the percentages.

Response: We added the data in 2008-2009 in validation stage in section 4.4 and Table 7 was removed.

Figure 2: The diagram still shows for the fractional snow cover “evaluation” dataset – just 2017. I believe the authors added 2008-2009 to the validation dataset. Is this correct? If so, authors may want to update this diagram to reflect the total years used in the validation period.

Response: Thanks. We updated Figure 2.

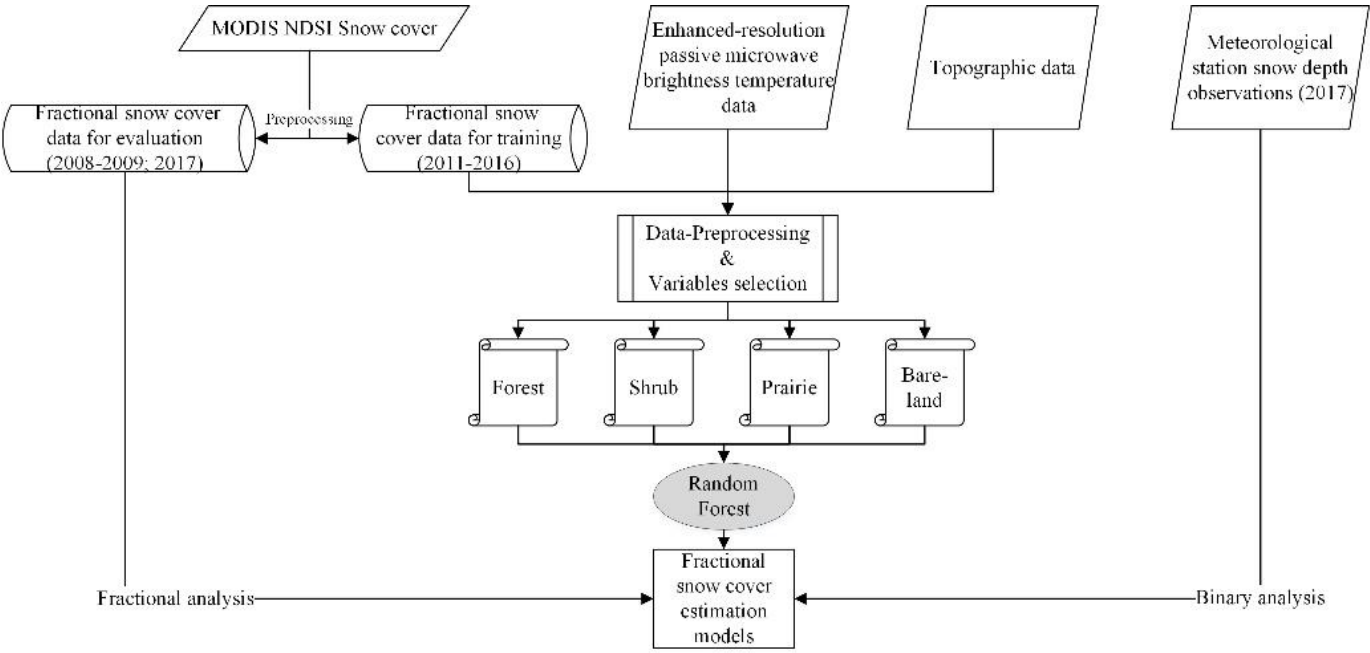
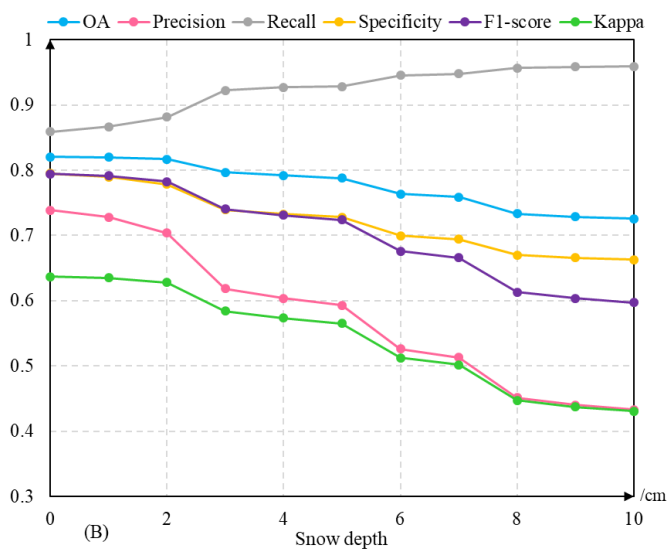
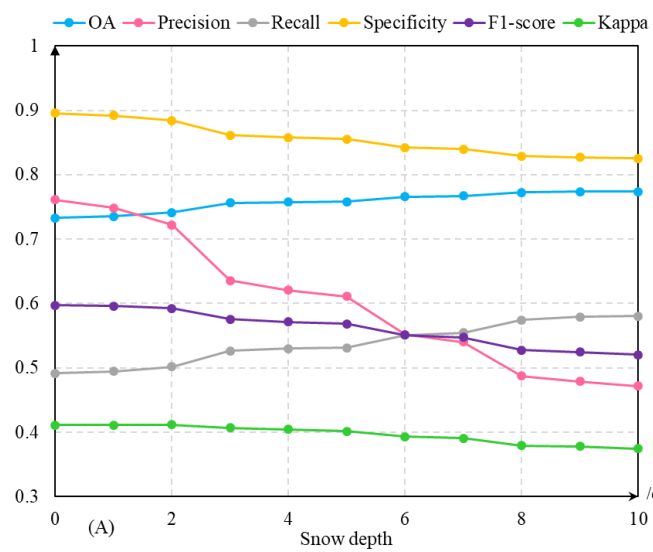


Figure 9 B: X-axis label is misspelled – change: “Snow detph” to “Snow depth”.

Response: Thanks. We updated Figure 9



# 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. Optical satellite remote sensing has proven to be an effective tool for monitoring global and regional variations of snow cover. However, accurately capturing the characteristics of snow dynamics at a finer spatiotemporal resolution continues to be problematic as observations from optical satellite sensors are greatly impacted by clouds and solar illumination. Traditional methods of mapping snow cover from passive microwave data only provide binary information at a spatial resolution of 25 km. This innovative study applies the random forest regression technique to enhanced-resolution passive microwave brightness temperature data (6.25 km) to estimate fractional snow cover over North America [in winter months \(January and February\)](#) ~~under all weather conditions~~. Many influent factors, including land cover, topography, and location information, were incorporated into the retrieval models. Moderate Resolution Imaging Spectroradiometer (MODIS) snow cover products between 2008 and 2017 were used to create the reference fractional snow cover data as the "true" observations in this study. [Although over- and under-estimation around two extreme values of fractional snow cover,](#) ~~t~~The proposed retrieval algorithm out-performed the other three approaches (linear regression, artificial neural networks, and multivariate adaptive regression splines), using independent test data for all land cover classes, with higher accuracy and no out-of-range estimated values. The method enabled the evaluation of the estimated fractional snow cover using independent datasets, where the root-mean-square error of evaluation results ranged from 0.189 to 0.221. The snow cover detection capability of the proposed algorithm was validated using meteorological station observations with greater than 310 000 records. We found that binary snow cover obtained from the estimated fractional snow cover was in good agreement with ground measurements (kappa: 0.67). 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. The experimental results show that passive microwave brightness temperature data may potentially be used to estimate fractional snow cover directly, where this retrieval strategy offers a competitive advantage in snow cover detection.



## 1. Introduction

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

Snow cover data is typically obtained from meteorological stations or in-situ manual measurements, which is spatially discontinuous and labor intensive. Remote sensing has become an attractive alternative tool to ground-based measurements as it is able to cover a wide area and is capable of high frequency observations. 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; snow-covered or snow-free. However, snow cover often varies within a limited scale area, characterized by high spatial heterogeneity, especially in alpine terrain areas. Dobрева and Klein (2011) demonstrated that the use of binary snow cover classification in snow cover area estimation may produce considerable uncertainties. Binary snow cover lacking fractional features hinders accurate characterization of the spatial distribution of snow cover and cannot accurately capture variations in seasonal snow cover dynamics. In terms of the energy budget perspective, binary snow cover introduces significant uncertainties into the global energy budget estimation because of the large surface albedo differences 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 provide accurate snow cover information. Fractional snow cover allow for the derivation of snow cover area at the sub-pixel level; this is a better option compared to binary snow cover (Salomonson and Appel, 2004).

Fractional snow cover maps derived from optical imagery have been produced for over 40 years. Optical satellite observations have been recognized for their suitability in estimating fractional snow cover because of their high spatial resolution. Moderate- to high- resolution optical observations have been popular in previous snow cover studies, for example 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 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 relationship between satellite observations and fractional snow cover. As such, non-linear approaches

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 that the estimated fractional snow cover using MARS method was in good agreement with the reference fractional snow cover, with the average correlation coefficient being  $R = 0.93$  (Kuter et al., 2018). However, polar regions contend with clouds and limited solar illumination, which are the greatest challenges for snow cover detection using optical satellite data. This has resulted in snow cover maps with incomplete spatial coverage, at times with gaps of up to 70% (Parajka and Blöschl, 2008). Although there have been constant efforts 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 information on snow cover (Dong and Menzel, 2016; Gafurov and Bárdossy, 2009), most studies have focused on binary snow cover.

When there are consecutive cloudy days, the use of data fusion technology introduces significant uncertainties in detecting snow cover from optical imagery. Passive microwave sensors are largely advantageous because they have capacity to measure microwave radiation emitted from the ground under the clouds and in darkness. Compared with active microwave sensors, passive sensors, have a large swathe width and generate a massive amount of daily observations that extends for several decades (Cohen et al., 2015). To date, passive microwave brightness temperature data 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 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 studies on snow cover area were limited to binary information. 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). All these algorithms utilize different thresholds for 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 to identify global binary snow cover.

As the effect of environmental factors (e.g., vegetation, topography, and wind) on snow cover distribution produces great 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). Despite the coarse resolution of passive microwave sensors, its ability to detect snow cover in the presence of clouds demonstrates its effectiveness as a snow cover monitoring tool. There is an urgent need for daily time-series and full space-

covered sub-pixel snow cover area data 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 Section 2.1 below), which has high spatial resolution (3.125 and 6.25 km) depending on frequency (Brodzik et al., 2018a; Long and Brodzik, 2016). This passive microwave data with enhanced resolution 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 daily fractional snow cover at a 6.25 km resolution. The datasets used in this study are described in Section 2, including the enhanced-resolution passive microwave data, ground-based measurements, MODIS snow cover and land cover products, and topographic data. Section 3 details the proposed retrieval algorithm using the random forest method as a retrieval function. Section 4 presents the results from the methods comparison, evaluation, and validation experiments. Finally, Section 5 discusses the possible factors that impact on 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 a new version of passive microwave brightness temperature data known as the Calibrated Enhanced-Resolution Passive Microwave Daily EASE-Grid 2.0 Brightness Temperature. This passive microwave gridded data spans from 1978 to mid-2017, using the Level-2 satellite records from multiple passive microwave sensors (Brodzik et al., 2018b; Brodzik et al., 2016, Updated 2018.). This enhanced-resolution data 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 – 2017 to~~ To explore the feasibility of estimating fractional snow cover using passive microwave data, this study only selected January and February of 2008 – 2017 as the study period in here. The Special Sensor Microwave/Imager (SSMIS) sensor (F-16) used in this 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 to avoid the effects of wet snow as much as possible (Derksen et al., 2000). To achieve a common resolution, ~~bilinear interpolation was used to~~ we aggregated the 3.125 km spatial resolution data to 6.25 km by averaging the surrounding 4 pixels.

## 2.2 Ground measurements

Although ground measurements of snow cover have limited spatial representation in passive microwave coarse spatial resolution, in-situ measurements continue to be the most authentic and reliable data source for snow depth estimation or snow cover detection (Chen et al., 2018; Sturm et al., 2010). 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 was provided by the National Climatic Data Center (available in <http://doi.org/10.7289/V5D21VHZ>), and integrates daily observations from approximately 30 different data sources. The new version data was updated on June 13, 2018, and contained measurements from over 100 000 stations worldwide. These stations record various aspects of meteorological observations, including snow depth and snowfall (Menne et al., 2012b). ~~Data for M~~more than 50 000 measurement sites across Canada and United States were collected, and all available records applied in validation stage are from ~~these~~ approximate 18000 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 because of 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). The accuracy of the version 6 MODIS snow cover products has 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 binary snow covered area (SCA) datasets are 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 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 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 study used both MOD10A1 and MYD10A1 NDSI snow cover products to generate reference fractional snow cover for North America. The NDSI snow cover data was initially converted to binary snow cover for aggregation into fractional snow cover data at 6.25 km spatial resolution (see Section 3.2).

### 2.3.2 Land cover product

Generally, the retrieval accuracy of snow cover parameters is strongly dependent on the land cover type (Xiao et al., 2018; Kuter et al., 2018; Dobрева and Klein, 2011; Huang et al., 2018). We 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 – 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 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 study, MCD12Q1 data was resampled into the 6.25 km grid using a simple majority method, then integrated into five classes; forest, shrub, prairie, bare land, and water (refer to Xiao et al. (2018)). Fractional snow cover retrieval models were established for four of these land cover types, excluding 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 has a 1 arc-min spatial resolution and was developed by the National Geophysical Data Center of the National Oceanic and Atmospheric Administration (NOAA) (Amante and Eakins, 2009). This study also considered elevation, slope, and aspect factors. Elevation was directly acquired from ETOPO1, which was re-projected and resampled into the grid at the 6.25 km spatial resolution. The slope and aspect data were obtained from ETOPO1 data by ArcGIS 10.5 (Buckley, 2019). Fig. 1 shows the elevation pattern for 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 snow pack attenuates the upward microwave radiation (Chang et al., 1987). This microwave radiation attenuation was mainly dominated by volume scatter relying on properties of the snow cover. Previous studies have demonstrated that there is great heterogeneity in snow properties and the distribution of snow cover, both of which may be influenced by many factors (Xiao et al., 2020), including, 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 (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

To develop a fractional snow cover prototype retrieval method combined with optical and passive microwave data, we only used the January and February datasets, as snow cover areas are at a maximum and snowpack properties are relatively stable during this period (Xiao et al., 2018). The influential factors on snow cover, including topography factor, land cover, location and time, were indirectly or directly considered during retrieval of the fractional snow cover. To date, many researchers have applied machine learning techniques for the retrieval of snow cover parameters to explore the relationship between passive microwave signals and snow properties (Xiao et al., 2018; Tedesco et al., 2004). Random forest is an ensemble learning method, gaining the attention of many researchers because it is more efficient and robust than the single method (Breiman, 2001). As a classifier, random forest has been successfully used employed 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 successfully estimate land surface temperature (Zhao et al., 2019), biomass (Mutanga et al., 2012), and soil moisture (Qu et al., 2019). In this study, random forest regression (described in Section 3.4.4) was selected as the retrieval method to mine the relationship between passive microwave brightness temperature and fractional snow cover. We also compared random forest with other three methods (linear regression, MARS and ANN) widely used in fractional snow cover retrieval from optical remote sensing data in model performance. Fig. 2 provides an overview of the workflow that consists of four parts:

First, a ground “truth” observation was necessary to produce snow cover areas in sub-pixel. Under clear-sky conditions, the reference fraction of snow cover was generated within a 6.25 km pixel cell by applying the aggregation method to the MODIS binary snow map (see Section 3.2). To make the experiment to be fully independently, the 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 2017 data, used in the evaluation stage.

Second, to the best of our knowledge, there are few attempts to directly develop fractional snow cover from passive microwave brightness temperature data. This meant a series of sensitivity experiments of input variables selection were required. Input parameters were selected based on a series of tests described in Section 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 found that the separate estimation of fractional snow cover (Dobrev and Klein, 2011) and snow depth (Xiao et al., 2018) on different land cover types produced better results than those obtained from the combined retrieval model. As such, the random forest models were developed separately for the four land cover types.

Fourth, the last stage consisted of evaluation and validation of the established model. Data from 2010 was used to assess the performance of four different approaches (linear regression, MARS, ANN, and random forest) for estimating fractional snow cover. Additionally, the independent datasets in 2008 – 2009 and 2017 were used to evaluate the performance of the random forest-based retrieval algorithm for the four land cover types. Independent validations of snow cover detection

capability were conducted using the 2017 retrieval results and station snow depth measurements across North America. There were 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 the reference fractional snow cover data obtained from the interpretation of MODIS snow cover products. The highest priority was 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 studies 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 pixels with very low visible reflectance) 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 more reasonable than 0.4 for snow cover identification in no-forest regions, whereas, forest-covered regions insufficient station measurements for a reliable and complete evaluation. MODIS snow cover performance is better for non-forest landscapes than forest-covered counterparts, where it is less accurate for snow cover identification (Hall and Riggs, 2007; Parajka et al., 2012).

This study selected conservative NDSI thresholds of 0.1 and 0.4 for no-forest-covered areas and for forest-covered areas, respectively (Riggs and Hall, 2016) to determine “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 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 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 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 cover more than 40% of MODIS snow cover data, in some cases exceeding 60% (Dong and Menzel, 2016; Yu et al., 2016; Parajka and Blöschl, 2006). As such, cloud removal processing is essential to mitigate the cloud obstruction of MODIS products. This study adopted the cloud removal method combining the MOD10A1 and MYD10A1 snow cover products, as proposed by Gafurov and Bárdossy (2009). This method consists of two main filters as shown in Fig. 3:

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 ( $S_t^{AquaTerra}$ ) or Aqua ( $S_t^{TerraAqua}$ ) 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).

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

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

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 areas should be a larger footprint area than the pixel resolution to avoid MODIS geolocation uncertainties (Wolfe et al., 2002; Dobрева and Klein, 2011). In this study, a window of 15\*15 pixels of MODIS binary snow cover data (MCTD10A1; 500 m) was used to calculate the fraction of snow cover in a 6.25 km pixel. We adopted the most rigorous pixel filtering rule, by which one clouded pixel cannot be allowed within a 15\*15 pixel window. This is 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, selecting the fewest number of variables to establish 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 is unrealistic. Therefore, we conducted six scenarios to evaluate and finally screen input variables. 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) (listed in Table 1). The 22 GHz channel was excluded because it is sensitive to water vapor.

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].

### 3.3.2 Determining sample size

Although the random forest method can avoid overfitting (Breiman, 2001), it is important to evaluate 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 (Dobrevă and Klein, 2011). Good quality training samples indicate that the sample data is not biased towards a certain value. The distribution of the fractional snow cover value from our dataset shows that more than 70% of values were near 0 and 1. 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 reducing the accuracy of the estimation. To address this, we adopted stratified random sampling as a sample selection strategy (Xiao et al., 2018; Dobrevă and Klein, 2011), where stratification was performed on the fractional snow cover at 0.01 increments.

From previous studies, the sample size, approximately 0.25% of the total study area, was adopted by Colditz (2015) when using the random forest method. This value has also been evaluated in optical and active remote sensing studies (Nguyen et al., 2018; Du et al., 2015). In this study, we generated the training sample datasets separately from 0.15% to 0.35% of the total cover area for each land cover class (in 0.05% increments). Then, sensitivity tests were carried out for the four land cover types. This means the training dataset would represent the values of fractional snow cover categories for each land cover type (see Section 4.1.2). All 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. Note that the four methods input the same variables selected by the sensitivity test, including 12 characteristic variables and one target variable (see 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 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. This method was undertaken in WEKA 3.8.3 and did not use any attribute selection method. In the Appendix, we present 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 widely applied in remote sensing studies. Tedesco et al (2004) developed an SWE and snow depth retrieval algorithm based on an ANN technique using passive microwave brightness temperature. Xiao et al. (2018) also used ANN to derive snow depth, and Kuter et al. (2018) and Czyzowska-Wisniewski et al. (2015) used ANN 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 multilayer perceptron can easily handle the nonlinear relationship between the input and output without any prior knowledge (Haykin, 2009). The inputs of each neuron were multiplied and summed by the connection weight. The output results were subsequently computed 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.

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

### 3.4.3 MARS

The MARS technique has been applied in a number of studies and in many fields, such as 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 a MARS technique that organizes a simple model for the complex and high-dimensional relationship between input variables and the target by smoothly connecting piecewise linear polynomials (known as basis functions (BFs)). The ranges of the input variables were cut into a series of sub-ranges by knots; these were the connection points for two pieces of BFs. A simple BFs format of MARS is expressed in Eq. 3, where  $\max(\cdot)$  indicates that only positive parts were take; otherwise, it was assigned a zero; and  $\tau$  is a univariate knot.

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

The MARS method involves two phrases to establish a regression model; forward phase and backward phase. In the forward phase, BFs were generated using a stepwise search of all univariate candidate knots and all variables interactions. These adopted knots and 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, resulting in an over-fitted and complicated model. In the backward phase, the redundant BFs that least contribute to model prediction 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 maximum number of basis functions (max\_BFs), and the maximum degree of interactions among 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 the performance of the MARS model. We conducted several tests to optimize the structure of MARS and found that more complex structures had a longer modeling time, however, did not significantly improve model performance. Specifically, the modeling time of the complex structure (max\_BFs = 100, max\_INT = 2) was four times greater than the simple structure (max\_BFs = 40, max\_INT = 2) based on our analysis experiments. As such, the simple structure was chosen, as per Kuter et al. (2018). 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 many researchers 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 successfully estimate land surface temperature (Zhao et al., 2019), biomass (Mutanga et al., 2012), and soil moisture (Qu et al., 2019).~~

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

### 3.5 Snow cover identification

The microwave radiation characteristics of precipitation, cold deserts and, frozen ground are similar to those of snow cover (Grody and Basist, 1996), and as such, snow cover area is likely to be overestimated. Grody and Basist (1996) proposed a snow cover identification algorithm, distinguishing snow cover from precipitation, cold desert, and frozen ground. 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 on the assessment of different passive microwave snow cover detection algorithms and 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) as the highest frequency in this study was 91 GHz instead of 81 GHz in Special Sensor Microwave Images/Sounder (SSMIS) sensors (Che et al., 2008).

There were two main objectives for using the revised Grody's algorithm (hereafter referred to Grody's algorithm) in this study. The first was to compare the snow cover identification capability of the proposed fractional snow cover estimation algorithm with respect to ground snow depth measurements (see Section 4.4). The second purpose was to assess the effect of non-snow scatterer in estimating fractional snow cover, due to this algorithm's special ability to distinguish the non-snow scatterer (i.e., precipitation, cold desert, and frozen ground). In both optical and microwave remote sensing research, capability

assessment of snow-free detection has been regularly neglected in most snow cover detection studies.

### 3.6 Validation of snow cover identification

When using the in-situ snow depth (or SWE) measurements to quantitatively validate the accuracy of snow cover area data, converting snow depth into binary snow cover using an appropriate threshold is the first challenge. Many different depth thresholds have been suggested in 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 5 cm for 25 km spatial resolution (Liu et al., 2018); and 2 cm for 0.75° grid resolution (Brown and Derksen, 2013). Due to these significant disagreements in the depth thresholds, Gascoin et al. (2019) conducted a sensitivity experiment that tested the agreement between in-situ measurements and optical snow cover area products. The sensitivity of passive microwave snow cover identification results to snow depth at 6.25 km spatial resolution was also tested by computing the accuracy metrics with snow depth increasing from 0 to 10 cm.

Then, we needed to determine the threshold for converting fractional snow cover to binary snow cover. To date, few studies exist on fractional snow cover from the passive microwave pixel-level. Dai et al. (2017) considered snow cover on the grid if fractional snow cover (25 km) was larger than 10%. If the fraction of snow cover was less than 0.25, the SWE was set to 0 mm to correct the snow cover area in the daily SWE product based on Luoju et al. (2018). However, optic remote sensing studies often adopted 0.5 as the threshold of fractional snow cover (Hall and Riggs, 2007). Sensitivity experiments of fractional snow cover similar to snow depth were conducted to obtain the optimum conversion threshold. Both sensitivity experiments were carried out using 2017 bare land type datasets in Section 4.4.

### 3.7 Performance accuracy assessment

When evaluating the estimation performance of fractional snow cover in Section 4.1-4.3, we used conventional accuracy metrics; correlation coefficient ( $R$ ; Eq. 4), mean absolute error (MAE; Eq. 5) and root mean square 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.

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

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

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

We evaluated the predicted accuracy of fractional snow cover and assessed snow cover identification performance (see

Section 4.4). 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). 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 to measure the accuracy of binary classification. Cohen's kappa coefficient measures the agreement between snow cover products and ground measurements. All these indices were 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) to better understand which input variables have a good relationship with fractional snow cover and the combination of the variables that can improve retrieval model performance. The data used for variable sensitivity tests in this part spanned only two years (2014 – 2015) as the 91 GHz H polarization data was missing over the area south of 50° N for 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 the bare land type datasets.

The variable selection tests were used to identify a better combination of different variables (Table 4). Scenario -3, which only involves V polarization data, yielded 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 six scenarios, which may be due to the lack of further available information from input variables that could be fully exploited (Xiao et al., 2018). Scenario -2, only containing passive microwave brightness temperature data similar to the variables used in Xu et al.(2016), had the second poorest performance. This shows that 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, 6 and Scenario -2 and 3 (Table 1) was whether or not considering the basic input variables (location information and topographic factors). The comparison results (i.e., Scenarios -1, 4, 5, 6 vs. Scenarios -2 and 3) indicate that the effect of location



information and topography need to be considered to estimate snow parameters. 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. Scenarios -1, 4 and 5, generated better results; there were no significant differences in R, MAE and RMSE for the tests on the four land cover types (Table 4; Tables S4 and S5 in Appendix). 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. Although the selection methods of Scenario -4 and 5 performed well (in terms of modeling time and accuracy of predicted target), only one scenario was selected; the other may be used as an alternative in future. 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 sensitivity to training sample size where the accuracy metrics used were the same as Section 4.1.1. As the values and variation trends of the accuracy metrics of the OOB error and 10-fold cross validation error were almost equivalent, only the OOB error is shown in Fig. 4 and Figs. S-1, 2, 3 (in the Appendix). 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 R and a slight decrease in MAE and RMSE when the training sample size increased from 0.15% to 0.25% on the shrub type, whilst there was a significant increase in modeling time. As the sample size increase from 0.25% to 0.35%, the model consistently estimates fractional snow cover accurately (higher R and 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 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 modeling time. 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. The reasons underpinning 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. We 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). A comparison of the modeling time for the four methods (Table 5) showed that linear regression had the shortest time, with less than 1 s for the four land cover types, followed by ANN with approximately 51 s (forest), 22 s (shrub), 156 s (prairie) and 35 s (bare land). Random

forest modeling times were very close to ANN modeling times for each land cover type. In contrast, MARS was the most time consuming, with the longest time (approximately 6.5 h) for the prairie type and the shortest (19 min) for the shrub type. The absolute value of modeling time would vary under different computing capabilities.

Table 5 and Fig. 5 present the results of the four retrieval methods for the four land cover types. The retrieval models of the shrub type predominantly have the lowest RMSE in contrast with the other three land cover types using the four methods (Table 5; cf. Fig. 5 and Figs. S-4, 5, 6 in the Appendix). The random forest model had the highest R (0.916), lowest MAE (0.202) and RMSE (0.245), and no out-of-range records for the forest type (Table 5; Fig. 5 and 6). The distribution and variation of MAE and RMSE for the four methods were similar under different land cover types, with the exception of the shrub type (Table 5; Fig. 5). With the exception of ANN, the ranking of the three algorithms based on the accuracy of results (MAE and RMSE) for the shrub test data was also the same as under other land cover types (i.e., Random forest > MARS > linear regression). Random forest had the greatest R value, followed by ANN, then MARS, and for most of the land cover types the smallest R value was from the linear regression. Fig. 6 illustrates that the random forest (Fig. 6D) produced a relatively small number of overestimated ( $\sim 0$ ) and underestimated ( $\sim 1$ ) values compared with the other three models (Fig. 6A – 6C). The MAE (0.315) and RMSE (0.401) of ANN were greater than MARS (MAE = 0.208, RMSE = 0.254). The number of out-of-range estimated values of ANN (36.62%; 161260) was also greater than MARS (2.65%; 11667), which may be attributed to a major underestimation of the fractional snow cover using the ANN method. The maximum and minimum of ANN and MARS on the forest type were 0.949 (-0.52) and 2.132 (-0.122), respectively. For the other three land cover types, the number of out-of-range pixels of the four methods were almost in the same order (random forest < ANN < MARS < linear regression).

The random forest-based models had the best performance with the highest R, and lowest MAE and RMSE (Table 5). Previous studies have generally neglected the analysis and evaluation of whether the estimated value is out-of-range (Liang et al., 2017; Wang et al., 2017; Hao et al., 2019; Masson et al., 2018). Table 5 show that the random forest models for the four land cover types produced reasonable fractional snow cover values ranging 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 less than MARS (16.39%), both numbers exceed 0.5 million. Kuter et al. (2018) estimated fractional snow cover using MARS and ANN techniques, also yielded similar out-of-range values. The linear regression method had the poorest performance in estimating fractional snow cover from passive microwave data, with the lowest R and the largest number of out-of-range records. These results indicate that nonlinear methods should first be used. Xiao et al. (2018) demonstrated the nonlinear relationship between passive microwave brightness and snow depth. De Lannoy et al. (2012) provided an exponential function for converting SWE to fractional snow cover. Thus, it is reasonable that a non-linear-relationship exists between

fractional snow cover and passive microwave brightness temperature.

### 4.3 Evaluation of fractional snow cover

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). [For forest type](#), 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 [for](#) 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.

Apart from the scatter plots and statistical analysis, Fig. 8 shows the distribution pattern of snow cover from a spatial perspective [on February 27th, 2017](#), 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 ~~0.3 of fractional snow cover~~ to define snow-covered and snow-free area, and this [threshold](#) was adopted through ~~the a series of~~ experiments in Section 4.4. [The threshold 0.5 was selected according to previous optical remote sensing study on fractional snow cover](#) (Arsenault et al., 2014; Gascoin et al., 2019). This means that the pixel was identified as snow cover when fractional snow cover value was ~~less~~ [greater](#) 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. [We also provide another date comparison for MODIS and the estimated fractional snow cover on January 10th, 2017 in the Appendix.](#) 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).

Thus far, we have evaluated the performance of random forest-based models on independent datasets from 2008 – 2010 and 2017 on each land cover type. The results from the random forest (Table 5; Fig. 6D; Figs. S-4 – 6; Fig. 7) show that the minimum estimates were higher than 0 and approximately 0.01. ~~This~~ [For the snow cover area overestimation, one possible error source is](#) ~~may be because the used inversion method, of which the final predicted outputs random forest uses a results output principle where the regression output results~~ are obtained by averaging [all results of the established sub decision trees from multiple trees](#) (see Section 3.4.4) (Breiman, 2001; Belgiu and Drăguț, 2016) [and this overestimation can be found in other study applying random forest study](#) (Wei et al., 2019). [Additionally, the attenuation and scattering of passive microwave radiation are not only caused by the snowpack. Other](#) [The non-snow scatterers \(i.e., precipitation, cold desert, frozen ground\) may be the majority error source potentially contributing to the overestimation of snow cover area as these scatters were easily misclassified as snow cover in less snow cover conditions](#) (Grody and Basist, 1996; Dai et al., 2017). [A detailed analysis on the misclassification due to non-snow scatterer is provided in Section 4.4.](#) Although MODIS snow cover products are highly accurate in snow cover identification (Tran et al., 2019), the estimated results indicate that a large number of fractional snow cover values were overestimated ( $\sim 0$ ) and underestimated ( $\sim 1$ ). Some fractional snow cover estimates, at the individual pixel level, show a large discrete distribution near the 1:1 line (Fig. 7). These misestimates are not confined to the results of the random forest model, but also appear in results of the other three methods (Fig. 6; Fig. S-4 – 6 in the Appendix). ~~Other non-snow scatterers (i.e., precipitation, cold desert, frozen ground) may potentially contribute to the overestimation of snow cover area as these scatters were easily misclassified as snow cover in less snow cover conditions (Grody and Basist, 1996). A detailed analysis on the misclassification is provided in Section 4.4.~~ Satellite sensors may provide completely different snow cover information because of different satellite overpass time. 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, the error caused by the differences in the satellite overpass time may easily [be](#) neglected when using multi-sensor observations for data fusion.

#### 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 the implementation of the cloud removal and filling process for MODIS snow cover data. When applying the rigorous

pixel filters (see Section 3.2), there was 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 in the absence of reference MODIS fractional snow cover we conducted further analysis on snow cover detection capability. 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 fractional snow cover derived from random forest. We collected all available meteorological station snow depth measurements of [2008-2009 and 2017](#) (January and February) over North America, obtaining more than ~~900344~~ 000 pairs of records. This includes the snow depth measurements, snow cover area converted from the estimated fractional snow cover (hereafter referred to 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 [using data in 2017](#). Fig. 9 shows that the accuracy metrics vary with increasing snow depth, whereby the metrics change significantly when snow depth exceeds 2 c, and reach a relative optimum when snow depth is equal to 2 cm. Che et al. (2008) stated that snow cover may be detected by passive microwave sensors when snow depth is greater than 2 cm. 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. We also conducted a series of sensitivity experiments 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 variation trends; the F1-score is up to the maximum value when FSC = 0.3. In addition, ~~at~~ the other two indicators (OA, kappa) also reached their maximum when the FSC value were ranging between 0.3 and 0.4. As expected, 0.3 was 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 SCA against ground snow depth measurements [in 2008-2009 and 2017](#) (Fig. 11 and Fig. ~~S-8S-9~~). Fig. 11 illustrates that the overall accuracy of snow cover identification had significantly improved by ~~2018~~%, from 0.71 for Grody's algorithm SCA to 0.8~~54~~ for random forest SCA, indicating that the latter's results were in good agreement with ground snow cover measurements (kappa = 0.~~6765~~). For the random forest SCA, precision (0.8~~43~~) was lower than the recall (0.8~~67~~), which means that snow cover area was more likely to be overestimated (CE = 0.1~~67~~) than underestimated (OE = 0.1~~43~~), with respect to in-situ measurements. In contrast, for Grody's algorithm SCA, precision (0.87) was larger than the recall (0.5~~12~~). By utilizing the proposed method, the OE of snow cover identification had reduced by 71% compared to the OE for Grody's algorithm SCA. The snow cover identification accuracy for the four land cover types are illustrated in Fig. ~~S-8S-9~~ (in the Appendix) by radar charts. ~~Additionally, Fig. 8 presents a simple example of the snow cover identification results of the random forest SCA (Fig. 8C) compared with MODIS composite binary snow cover products (Fig.~~

8A) on February 27th, 2017. Fig. 8 shows that the cloud-free area (snow-cover and snow-free area) in MODIS was almost captured by our estimated results.

We subsequently explored the influence of non-snow scatterers in estimating fractional snow cover. The CE of Grody's algorithm (CE = 0.13) was lower than random forest SCA (CE = 0.4716). Fig. 11 shows that the overall snow-free identification capability of Grody's algorithm SCA (specificity = 0.9293) was significantly superior to the random forest SCA (specificity = 0.81), which was also apparent for the four land cover types (Fig. S-8S-9). This may possibly be due to Grody's algorithm filtering out non-snow scatter signature (precipitation, cold desert, and frozen ground) (Grody and Basist, 1996). We counted the number of records in which a pixel had been detected as snow-free by the station and Grody's algorithm, however, was considered snow-covered by random forest SCA. 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 7072.64% of total misclassification records (CE = 0.4716), of which 6364.39% comes from precipitation, 67.04% from cold desert, and 0.97% from frozen ground. For forest, shrub, prairie and, bare land types, this misclassification proportion because of the non-snow scatters were 767.07%, 9392.35%, 7068.6% and 6765.43%, 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 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). For different results of these two snow cover mapping algorithms, an example is given to illustrate the inconsistency and consistency of snow cover mapping between the random forest SCA and Grody's algorithm SCA (Fig. 12). For the comparison results in snow cover mapping, Fig 12 shows that the most areas of North America have consistent snow cover mapping results: Code A (cyan) and B (green) regions. Referring to the continue fractional snow cover image (Fig. S-7b in the Appendix), the inconsistent in monitoring snow cover extent always occur in mid-latitude regions with the value of fractional snow cover around 0.5. According to our experimental results analysis, the mid-value of fractional snow cover regions is one source of the omit error for Grody's algorithm SCA.

## 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 (Dobrev and Klein, 2011; Kuter et al., 2018; Nguyen et al., 2018; Belgiu and Drăguț, 2016). Previous studies 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 improves the accuracy of estimates, we found that a training sample dataset covering about 0.3% of the total study area 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 taking modeling time as an index in this study.

The estimation results of the random forest model ~~on~~ (for the training, testing and evaluation ~~(test)~~ datasets; ~~—~~(Sections 4.2 and 4.3) showed that generally, the prediction performance of the random forest model was closely related to the quality of training sample. 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 (Dobrevva 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 ~~these~~ 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 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. Therefore, it is necessary for future studies to increase the ~~amount~~ number 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).

## 5.2 Effects of vegetation

Snow cover detection can be partially or completely obscured (or intercepted) by dense vegetation canopies. This introduces major uncertainties in accurate detection of snow cover (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 fractional snow cover retrievals typically have the least accuracy under the forest type in comparison to other land cover types (Table 5; Figs. 6 and 7). There are two reasons that may be attribute to this error; 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 found in forest covered areas and complex terrain (Hall and Riggs, 2007; Tran et al., 2019; Coll and Li, 2018). 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 term of the NDSI threshold in forested areas (Section 3.2), we used 0.4 as a conservative threshold. According to previous studies, our operation (merely using NDSI as the criterion) in forest-covered areas would produce greater commission errors compared with using the Normalized Difference Vegetation Index (NDVI) as



auxiliary information (Hall and Riggs, 2007). The retrieval results indicated that the NDSI threshold in forested areas needs optimization using numerous data (Riggs et al., 2017; Xin et al., 2012). In addition to the influence of forests on MODIS data, forests also hamper the upwelling microwave radiation emitted from the ground. Snow cover in forested areas may be divided into under ~~\_forested~~ and ~~above\_ever\_forested~~ canopy snow cover (Xin et al., 2012). This apparently distinguishes the interference effects of evergreen forests and deciduous forests on snow cover (Gascoin et al., 2019; Romanov and Tarpley, 2007). Additionally, there are major differences in the observation means for optical and passive microwave sensors in forested areas. The capacity for optical sensors to observe ~~above\_ever\_forested~~ canopy snow cover is mainly dependent on the vegetation canopy density (Kuter et al., 2018), while microwave sensor may obtain information on snow cover under vegetation canopy (under-~~\_forested~~ canopy snow cover) (Che et al., 2016; Cohen et al., 2015). Overall, the combination of these two effects may produce low estimation accuracy for fractional snow cover.

## 6. Conclusions

Many previous studies have focused on estimating fractional snow cover utilizing optical remote sensing imagery, which suffers from cloud contamination during data acquisition. In contrast, microwave sensors offer attractive advantages of working under all weather conditions ~~and around the clock~~. In this study, we attempted to develop an algorithm for 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. Using the reference fractional snow cover stem from MODIS snow cover products as the “true” observation, we established 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 proposed algorithm accounted for a series of influential factors including topography, land cover, and location information. Compared with the other three methods (linear regression, ANN and 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 results of the evaluation using the reference fractional snow cover data in 2017 showed that our proposed algorithm had good retrieval performance in estimating fractional snow cover, with RMSEs ranging from 0.167 to 0.198. Moreover, in-situ snow depth measurements were used to validate the accuracy of the proposed fractional snow cover estimation algorithm in snow cover mapping. Snow cover detection capability of the random forest-based method was 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. Although the random forest-based models achieved an acceptable accuracy, the fractional snow cover was more likely to be overestimated (CE = 0.17) than underestimated (OE = 0.13). In addition, 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 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 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. Furthermore, to reduce some of the limitations (e.g., forest effects) (Cohen et al., 2015) and deficiencies (overestimation and underestimation) identified in this study, future studies should pay greater attention to the prediction of the fractional snow cover using passive microwave data. To the best of our knowledge, this study may represent the first attempt to establish a relationship between microwave brightness temperature and the reference “true” fractional snow cover using machine learning methods. 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).

**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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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.

I	Elements	Scenario-1	Scenario-2	Scenario-3 [3]	Scenario-4	Scenario-5	Scenario-6 [9]
D		[18]	[13]		[11]	[12]	
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 is Kelvin (K).

Scattering Materials	Description
Scattering signature	$(Tb_{19V} - Tb_{37V}) > 0 \text{ K}$
Precipitation	$(Tb_{22V} \geq 259 \text{ K})$ or $(254 \text{ K} \leq Tb_{22V} \leq 258 \text{ K and } (Tb_{19V} - Tb_{37V}) \leq 2 \text{ K})$
Cold desert	$(Tb_{19V} - Tb_{19H}) \geq 18 \text{ K and } (Tb_{19V} - Tb_{37V}) \leq 10 \text{ K}$
Frozen ground	$(Tb_{19V} - Tb_{19H}) \geq 8 \text{ K and } (Tb_{19V} - Tb_{37V}) \leq 2 \text{ K}$

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.

	Prediction	Ground observation (true)	
		snow-covered (Positive)	snow-free (Negative)
	snow-covered (Positive)	TP (true positive)	FP (false positive)
	snow-free (Negative)	FN (false negative)	TN (true negative)
$OA = (TP + TN)/(TP + TN + FN + FP)$			
$OE = FN/(TP + FN)$			
$CE = FP/(TP + FP)$			
$Precision = TP/(TP + FP) = 1 - CE$			
$Recall = TP/(TP + FN) = 1 - OE$			
$Specificity = TN/(TN + FP)$			
$F1 = (2 * Precision * Recall)/(Precision + Recall)$			

5 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~~-parentheses 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)

5 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

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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 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%

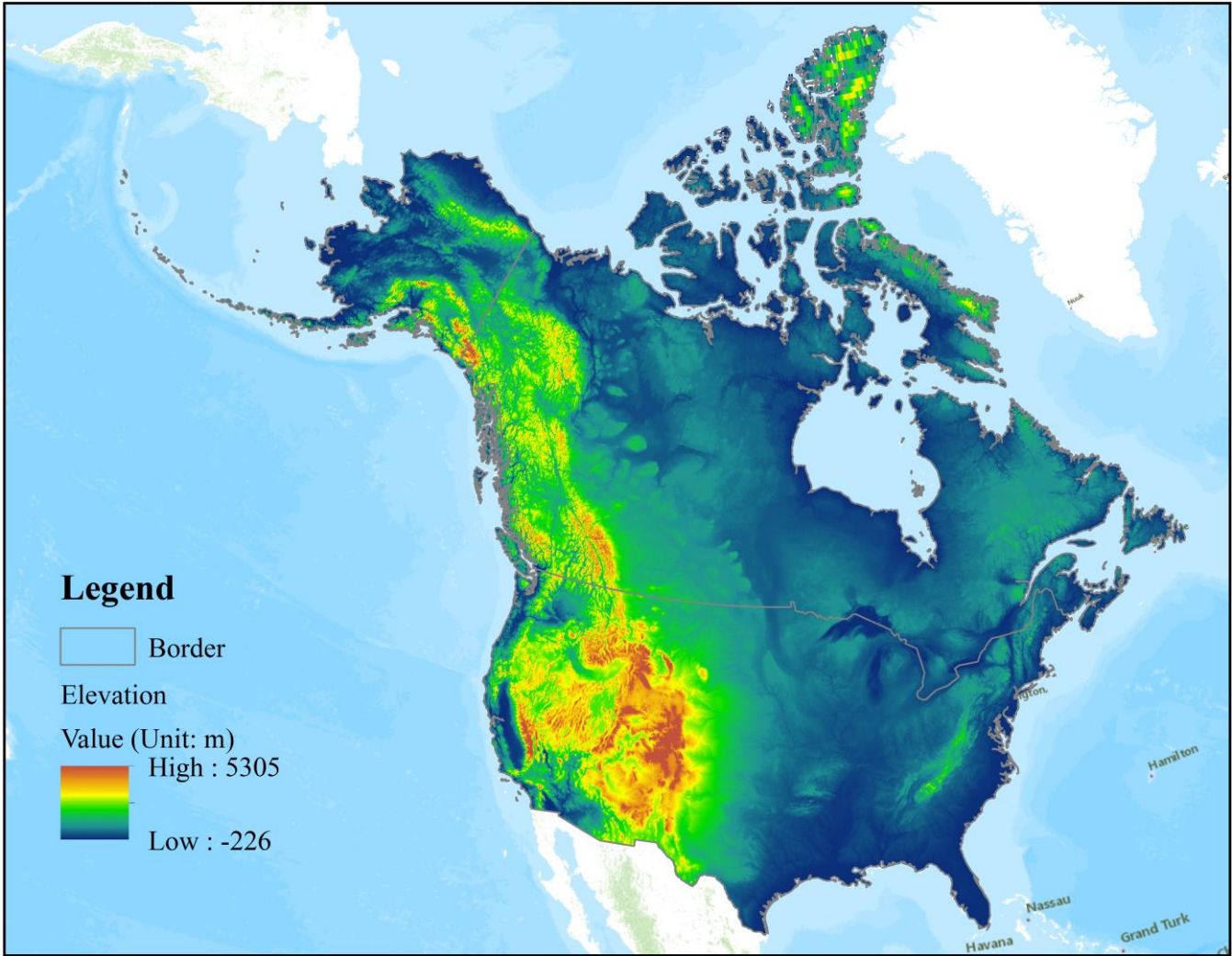


Fig. 1 Topographic map of North America.

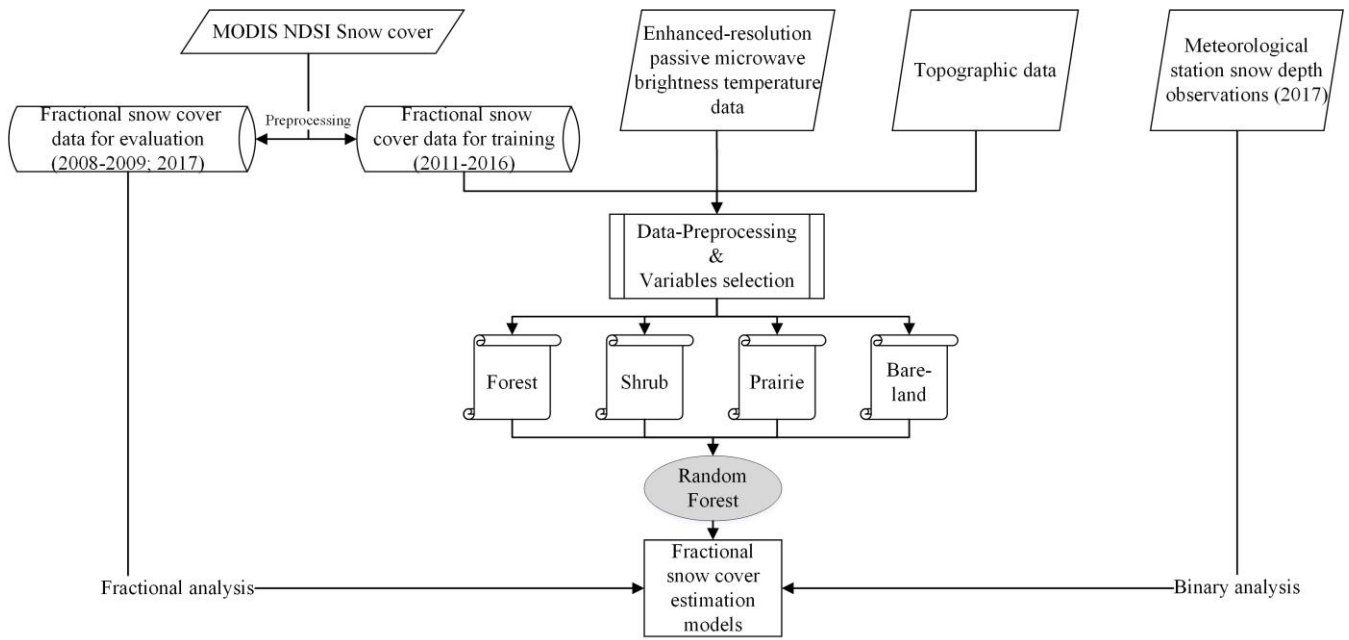


Fig. 2. Workflow diagram illustrating the processing of fractional snow cover retrieval.

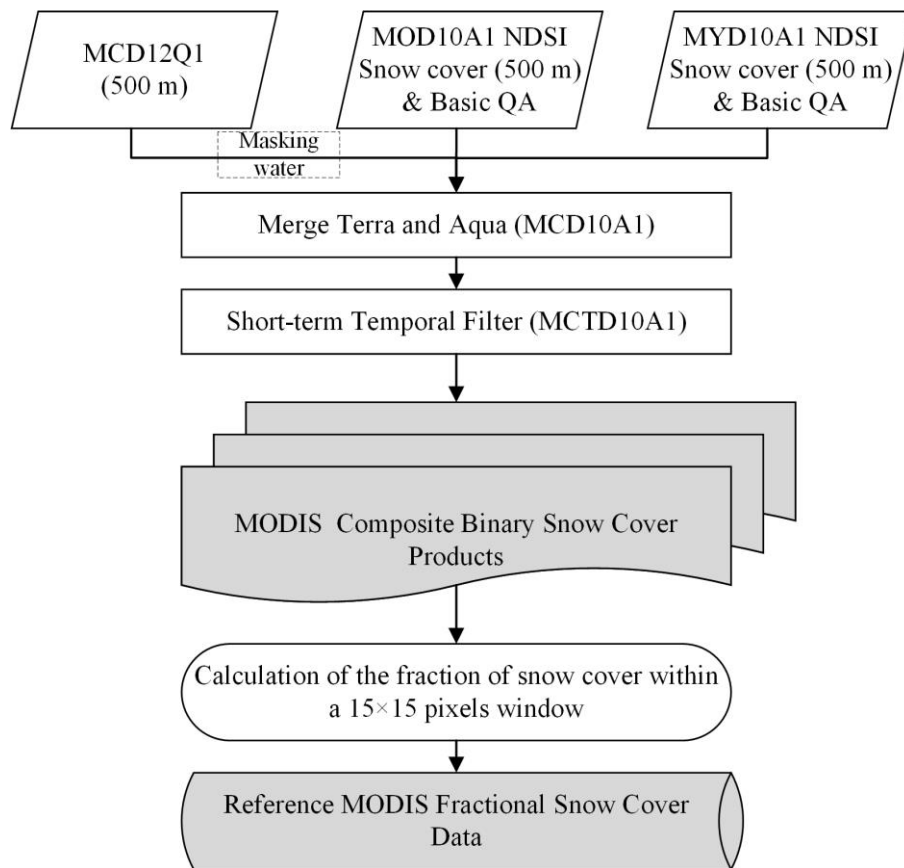


Fig. 3. The generation of MODIS fractional snow cover



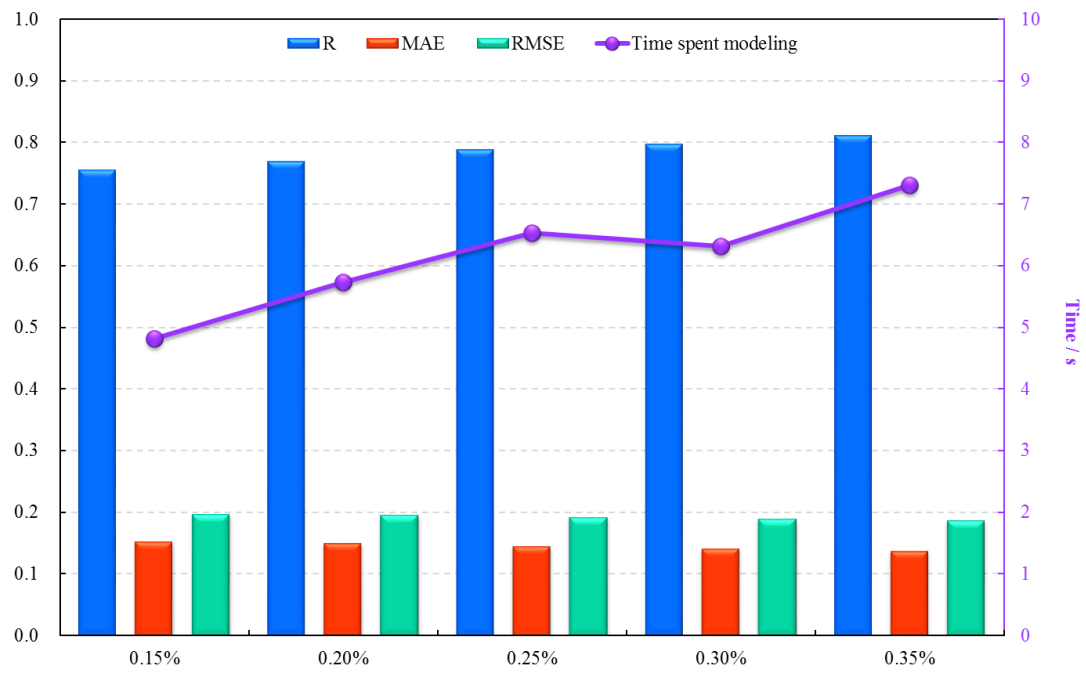
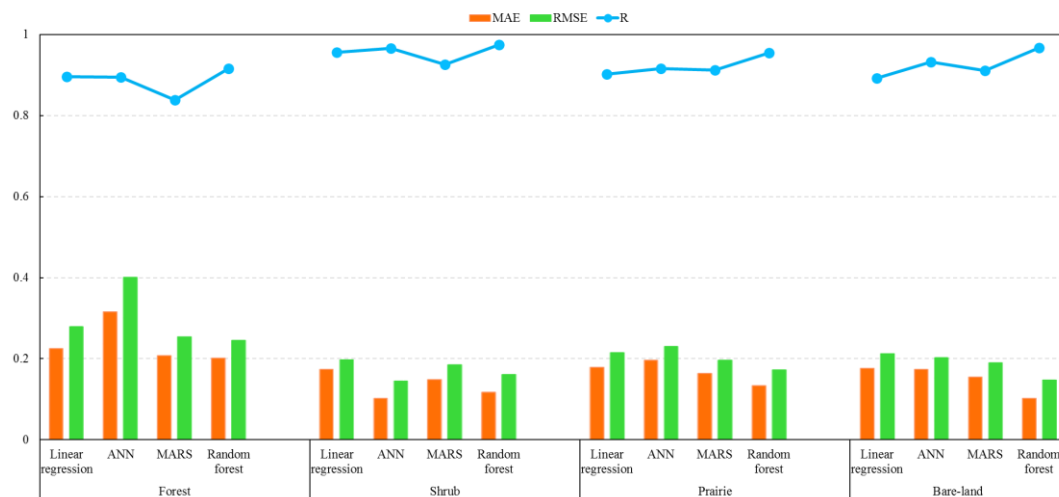


Fig. 4. The performance of random forest models with increasing the size of training sample for shrub type



5 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.

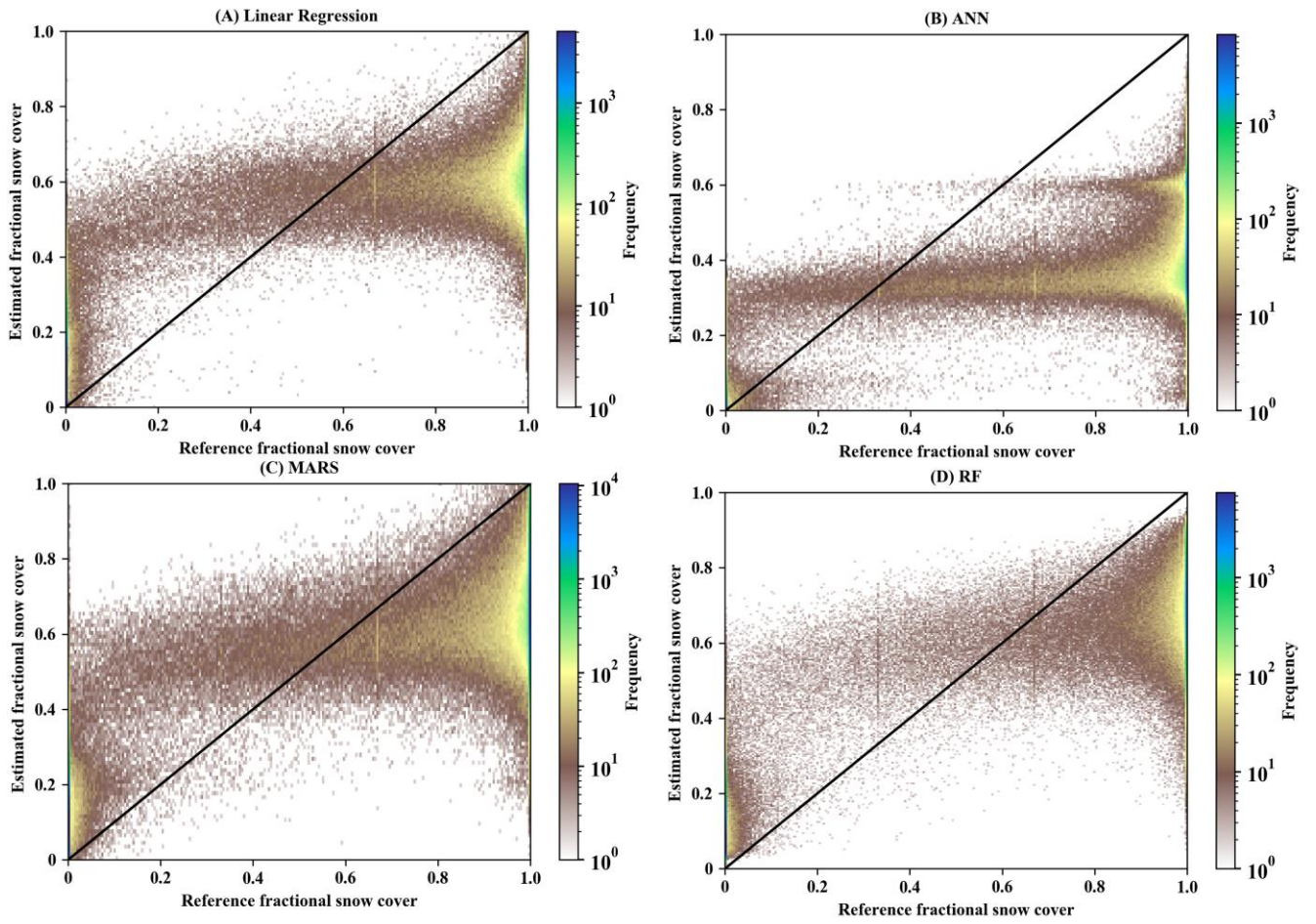


Fig. 6. The color-density scatter plots between the estimated fractional snow cover and MODIS-derived fractional snow cover for four algorithms (linear regression, ANN, MARS, and random forest) for forest type. The accuracy metric refer to Table 5. [Note: out-of-range fractional snow cover values of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

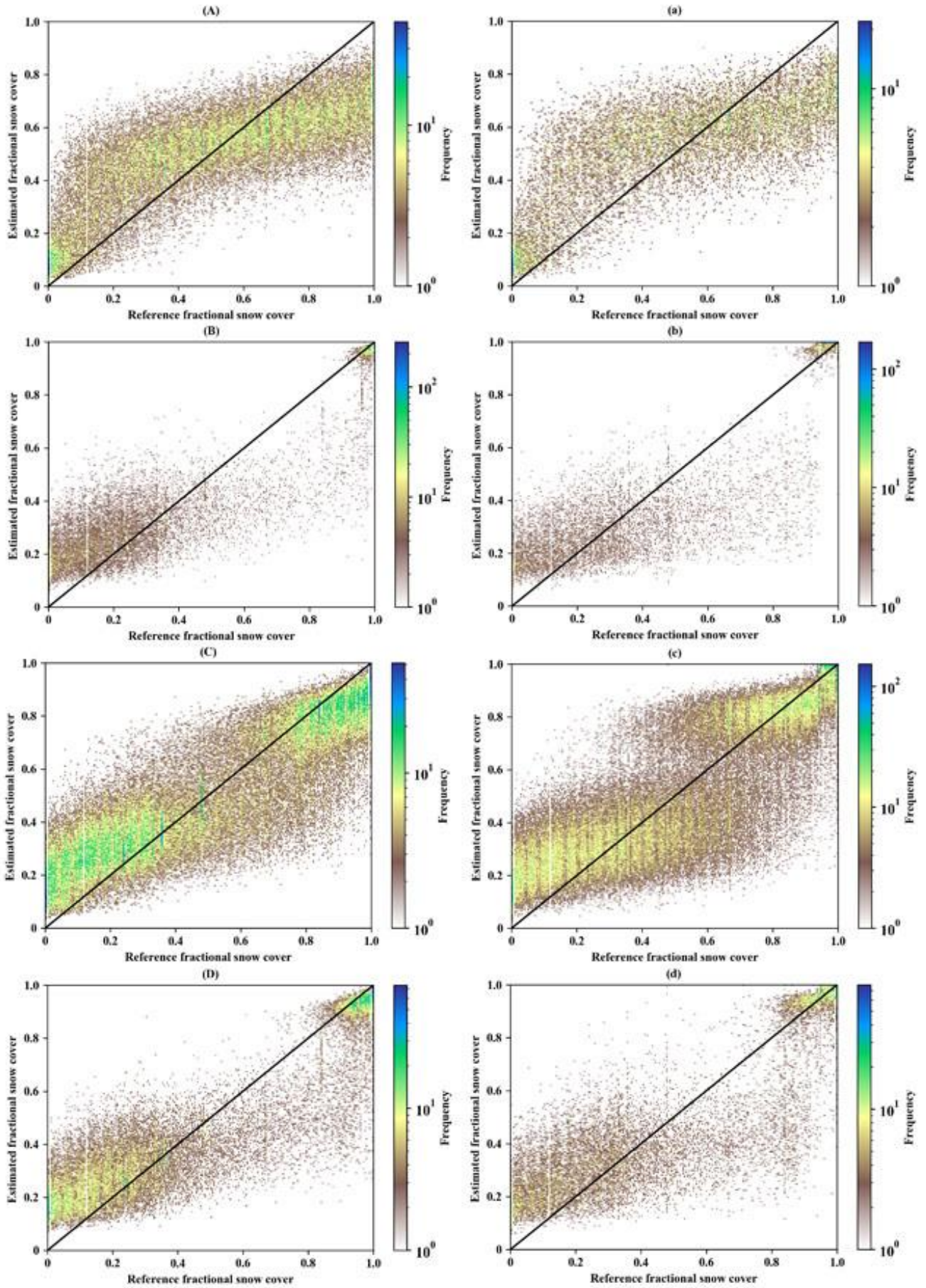


Fig. 7. The color-density scatter plots between the estimated fractional snow cover and MODIS-derived fractional snow cover for four land cover types (forest: A, a; shrub: B, b; prairie: C, c; bare land: D, d). Left column with capital letters is the



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

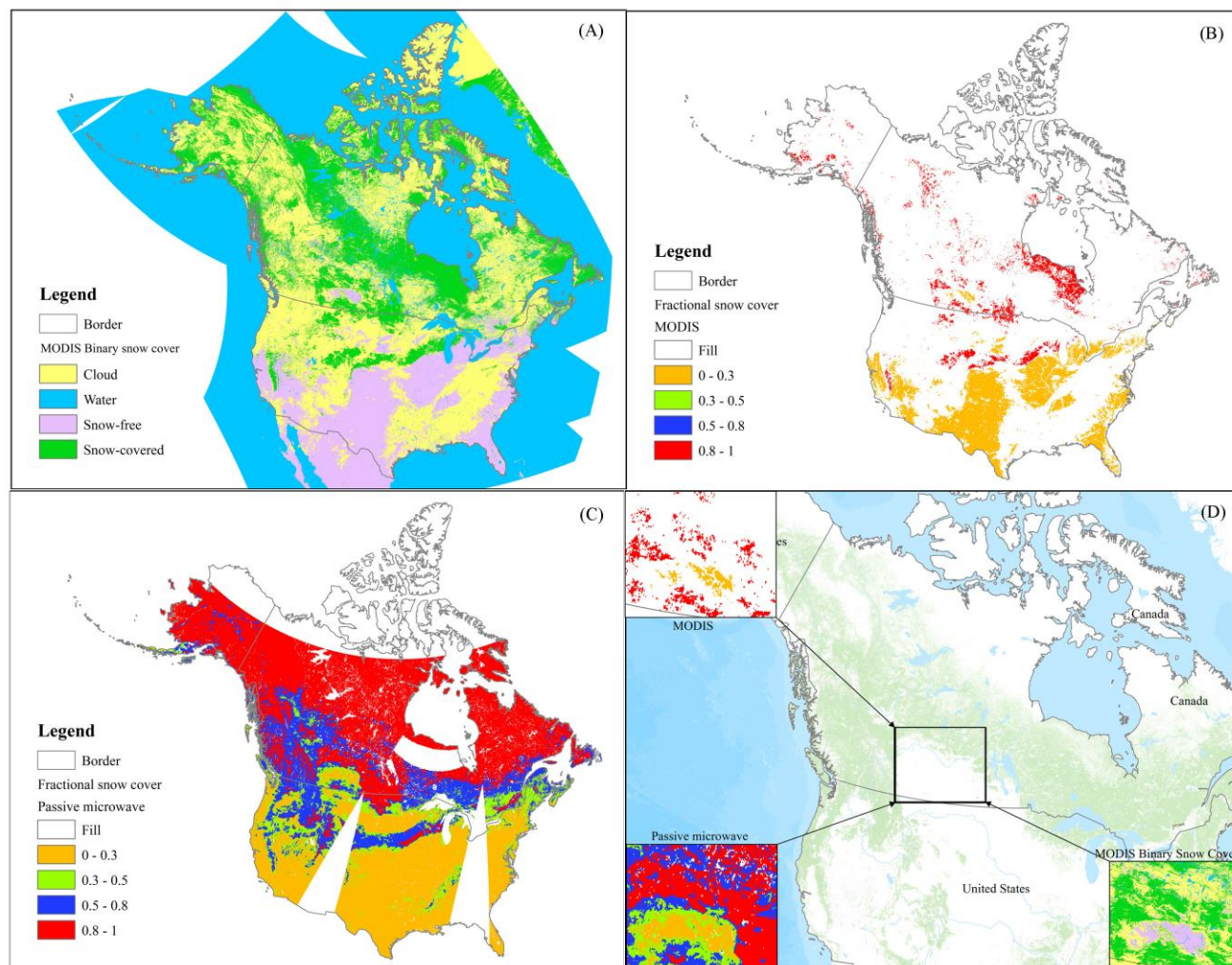


Fig. 8. Comparison of our estimated fractional snow cover (C, 6.25-km) with the reference MODIS fractional snow cover (B, 6.25-km) with respect to the MODIS composite binary snow cover products (A, 500-m); and a comparison example in the Central Canada area (D) on February 27th, 2017 (2017058). [Cf.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

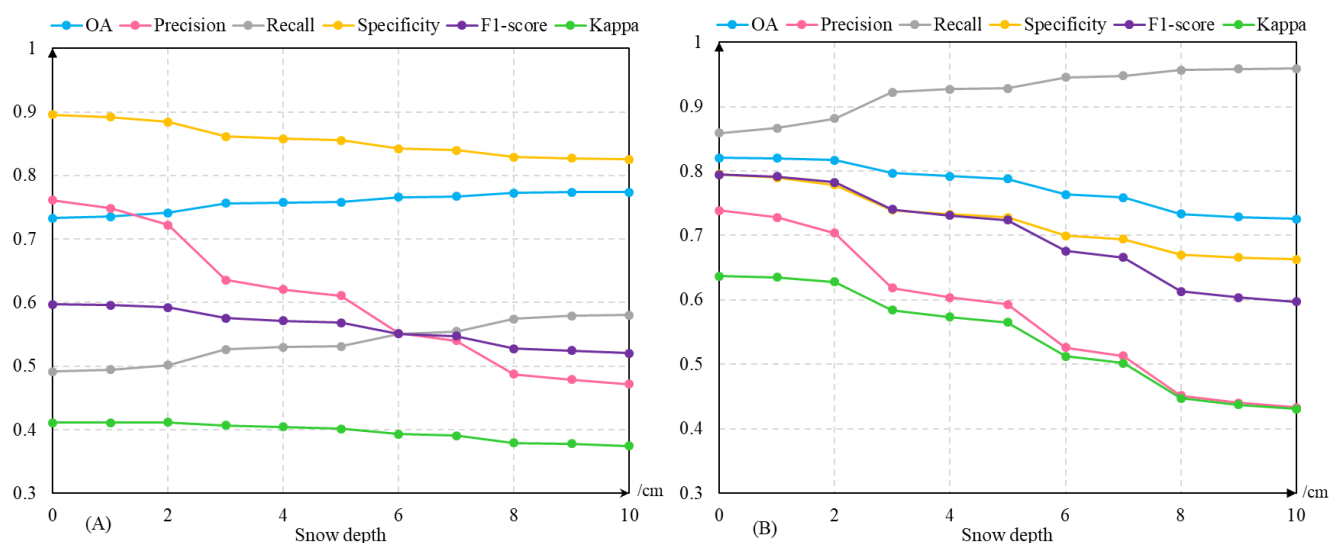


Fig. 9. The changes of accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) for snow cover detection results of two algorithm (A: Grody's algorithm; B: Random forest) with increasing in situ snow depth value.

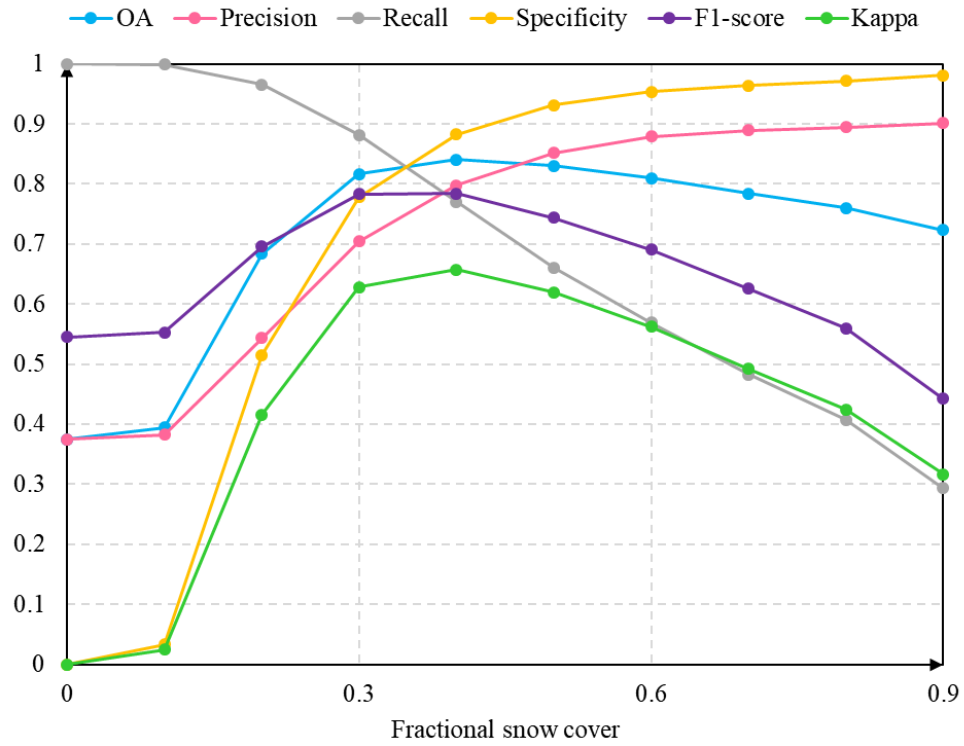


Fig. 10. The changes of accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) for snow cover detection results with increasing fractional snow cover value (FSC).

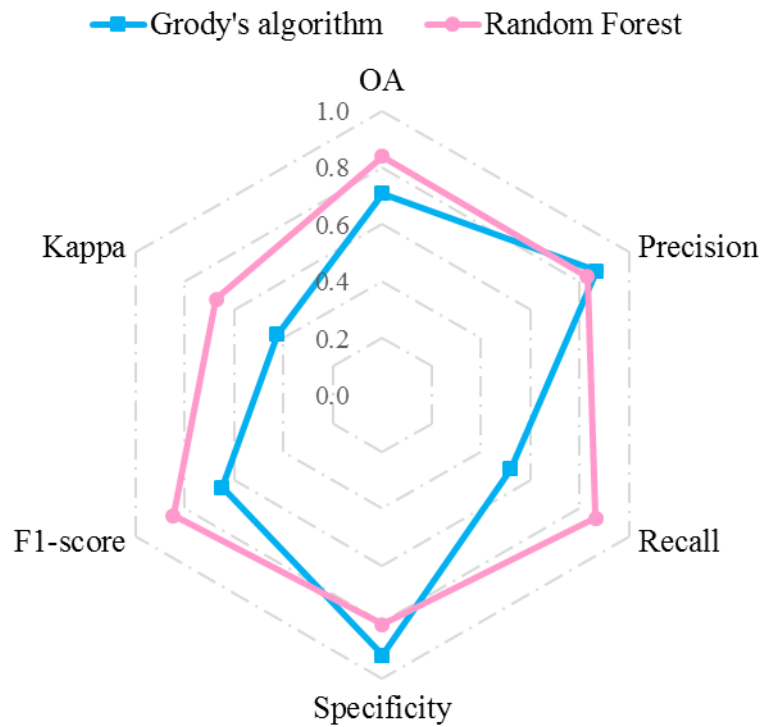


Fig. 11. The accuracy indicators (OA, precision, recall, specificity, F1-score, kappa) of snow cover detection from two algorithm (Grody' algorithm; Random forest).

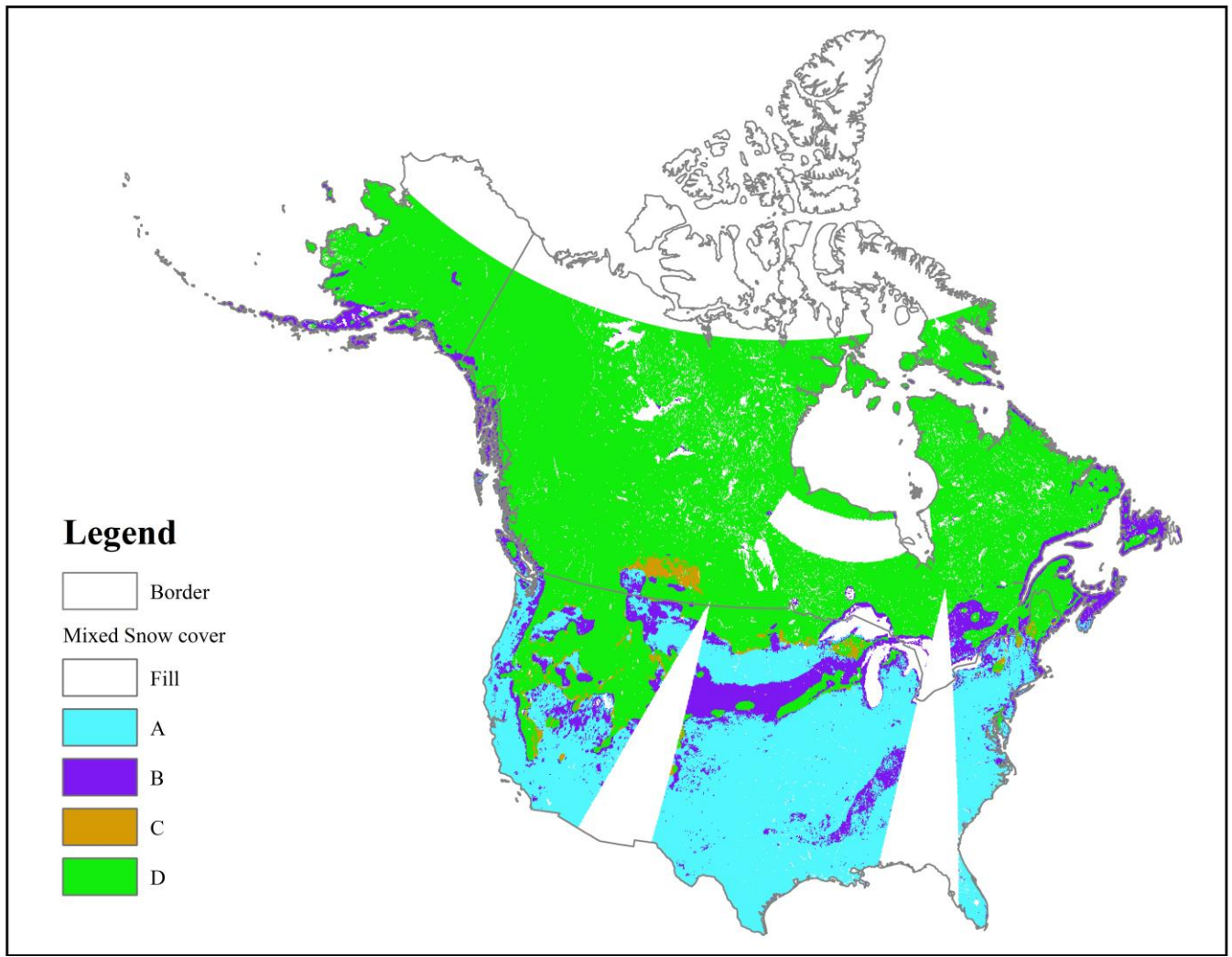


Fig. 12. The mixed snow cover detection map for different condition combinations of Random forest SCA and Grody's algorithm SCA on February 27th, 2017 (2017058). A:  $SC_{Grody} = 0$  &  $FSC \leq 0.3$ ; B:  $SC_{Grody} = 0$  &  $FSC > 0.3$ ; C:  $SC_{Grody} = 1$  &  $FSC \leq 0.3$ ; D:  $SC_{Grody} = 1$  &  $FSC > 0.3$ ;  $SC_{Grody} = 0$  denotes snow-free (precipitation, cold desert and frozen ground) determined by Grody's algorithm SCA, otherwise it is snow-covered;  $FSC \leq 0.3$  denotes snow-free cover detected by random forest SCA, otherwise, it is snow-covered.

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