Response to reviewer

May 3rd, 2022

Tc-2022-45 “Towards Large-Scale Daily Snow Density Mapping with Spatiotemporally Aware Model and Multi-Source Data”

We would like to thank the reviewer for your constructive comments, which helped to substantially improve the manuscript. Below we will address each concern in a point-by-point answer:

- **Bold: comments of the reviewer**
- Regular: answer of the authors
- *Italics or red words: changes to the initial manuscript*

Comments by reviewer:

Snow density plays a critical role in estimating water resources and predicting natural disasters such as floods, avalanches, and snowstorms. A GTWNN model was constructed for snow density estimation and achieved daily snow density mapping from 2013 to 2020 in China with the support of remote sensing, ground observation, and reanalysis data. This study provides important spatiotemporal parameters for snow cover hydrology and other aspects. The main suggestions and opinions are as follows:

1. L115, “Based on the SCA data, the snow cover duration (SCD) is calculated to account for the impact of gravity on snow density”, How to understand that snow density is affected by gravity, and what does it have to do with SCD?

Response from Authors:

The authors greatly thank for the question. The aim of calculating the snow cover duration (SCD) is to account for the impact of snow duration on snow density rather than the gravity. Several models considered the effect of inputting time series on snow density, for example for seasonal (Sturm et al., 2010) and biweekly (Jonas et al., 2009) timescales, which indicates that the accumulated snow cover days cannot be ignored. We made changes in Subsection 2.2 Satellite and Reanalysis Data.

Revised subsection 2.2 Satellite and Reanalysis Data

“Based on the SCA data, the snow cover duration (SCD) is calculated to account for the impact of snow duration on snow density.”

2. "Spatiotemporally Aware Model" in the title is not mentioned in the manuscript and should be explained.

Response from Authors:

Thanks for the comment on details. The spatiotemporally aware model represents the geographically and temporally weighted neural network (GTWNN) model, which consists of geographically and temporally weighted (GTW) model to capture spatiotemporal heterogeneity and a generalized regression neural network (GRNN) to deal with the weak and nonlinear relationships between snow density and its influencing variables. We explained it in the revised manuscript.

Revised subsection 3.1 GTWNN Model

The schematic of the GTWNN model is shown in Figure 2, which is a spatiotemporally aware model composed of a geographically and temporally weighted (GTW) model to capture spatiotemporal heterogeneity and a generalized regression neural network (GRNN) to deal with the weak and nonlinear relationships between snow density and its influencing variables

3. Whether the lack of observation data in 2019-2020 is related to the epidemic, making it impossible to conduct

a large number of observations.

Response from Authors:

Thank you very much for this comment. The smaller numbers of observation data in 2019–2020 is because of the lack of snow pressure data recorded by the meteorological stations. According to the regulations, a lot of stations only observed snow depth and did not observe snow pressure, which makes it impossible to calculate snow density and the number of observations is significantly reduced in 2019–2020.

4. The verification result in Fig.4 is that all the data as a whole is added to the training model, or is the training divided by region and month? Is it the 10-fold validation result of the trained model? Please explain further

Response from Authors:

Thank you very much for the question. All data are divided into 8 parts by year from 2013 to 2020, and each part is used for training by the 10-fold validation, which means all the samples (each year) are divided into 10 equal folds randomly, nine folds are exploited for the model fitting, and the one remaining fold is used for the validation, the above step is repeated 10 times. Finally, we built the models of each year and obtain the estimated snow density of all data, which are compared with the observed snow density to verity the model accuracy. We added the explanation in the revised manuscript.

The reason for training by year is on the consideration of the spatiotemporal heterogeneity of snow density and the different importance of influencing variables in different years. Accordingly, the stepwise regression analysis method is used to select significant variables for the GTWNN model in each year. Motivated by the raised question, we also tried to train the GTWNN models by region and by month with the 10-fold validation, as shown in Table S1. Comparing the models trained by month, region, and year, the former two models achieve relatively higher R^2 than the model by year, but the RMSE and MAE remain unchanged. Hope our efforts have addressed the major concerns.

Table S1. Accuracies of various methods for estimating daily snow density.

Method	Slope	R^2	RMSE	MAE
Month	0.988	0.521	0.043	0.028
Region	0.983	0.518	0.043	0.028
Year	0.986	0.515	0.043	0.028

Revised subsection 3.2 Model Evaluation

The GTWNN model is constructed separately for each year with the consideration of the snow variety in different years. The stepwise regression analysis method is used to filter the influencing variables by performing the F test ($\alpha < 0.05$) and T test ($\alpha < 0.1$) to select significant variables for the GTWNN model in each year. There are three essential parameters in each GTWNN model, including the spatiotemporal bandwidth h_{ST} and the scale factor φ of the GTW model and the $spread$ of GRNN model. The 10-fold cross-validation technique is adopted for determining the optimal parameters (Fotheringham et al., 2003; Rodriguez et al., 2010); that is, all the collected samples are randomly divided into 10 folds, nine folds are exploited for the model fitting, and one fold is used for the validation. Finally, a scale factor φ of 0.01, $spread$ of 0.5, and an adaptive bandwidth regime h_{ST} of 8 with the same best model performance are obtained in different year.

5. L200, Does the reason for the lower accuracies in Northeast China-Inner Mongolia consider the effect of different underlying surfaces on snow density? Forests and farmland in the Northeast, and grasslands in Inner Mongolia may have very different effects on snow density.

Response from Authors:

The authors greatly agree with this suggestion that the different underlying surface will affect the estimation of snow density. Actually, we have considered the influence of underlying surfaces by using the leaf area index of high vegetation (LAI_HV), which is the one-half of the total green leaf area per unit horizontal ground surface area for high vegetation type. The variable LAI_HV has the largest average correlation coefficient among all the variables and is selected for modeling in most of the years, except for 2019, as shown in Figure 6.

Moreover, according to the advice, we downloaded the MODIS land vegetation classification product (MCD12Q1_V6) with a spatial resolution of 500 m and resample them to 25 km to further explore the influence of different land cover on snow density.

Based on the stepwise regression analysis method, the MCD12Q1 is selected as the significant variables only in 2013 and 2017, and the Pearson correlation coefficients between snow density and MCD12Q1 are 0.0446 and -0.0556, respectively. The correlation relationship is relatively weak compared with other influencing variables, as shown in Figure 6. We calculated the accuracy of GTWNN model after inputting the MCD12Q1 into the models as an influencing variable, which is slightly improved in comparison with the original GTWNN model without inputting MCD12Q1, with R^2 0.521, RMSE 0.043 g/cm^3, and MAE 0.028 g/cm^3, as shown in Table S2. In addition, it is noted that the accuracy improvement by inputting MCD12Q1 in Northeast China-Inner Mongolia and Tibetan Plateau is higher than that in Xinjiang.

Therefore, both the high correlation value of the LAI_HV variable and the improvement by inputting MCD12Q1 demonstrate the importance of underlying surfaces for estimating snow density, especially for the Northeast China-Inner Mongolia. Accordingly, the lower accuracies in Northeast China-Inner Mongolia would mainly be caused by the more forest cover and less stable snow cover in Northeast China-Inner Mongolia than in Xinjiang (See revised subsection 4.2.1 Accuracy of GTWNN Model in Different Regions). Hope our efforts have addressed the major concerns.

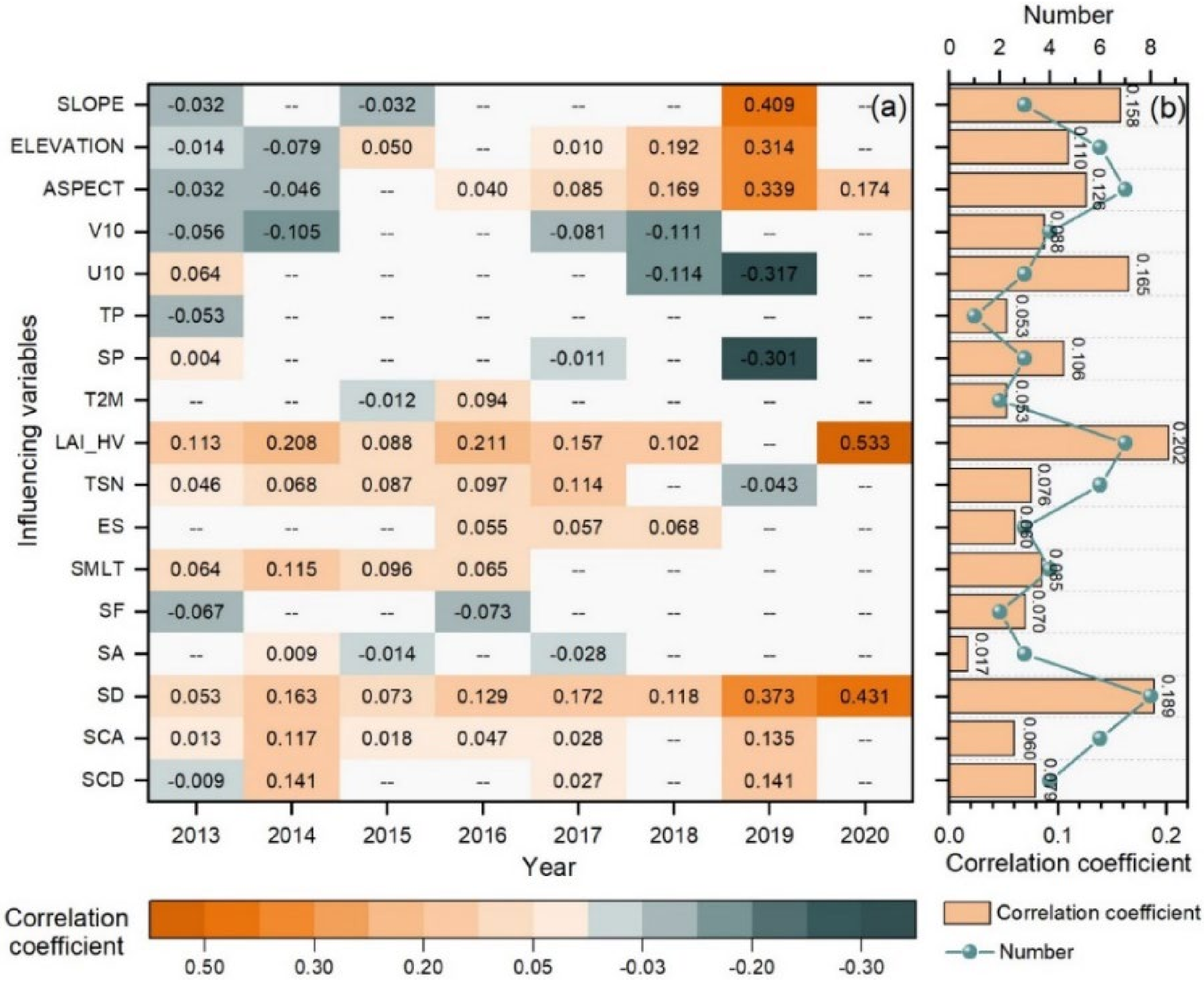

Figure 6. Correlation coefficient between snow density and its influencing variables selected by the stepwise regression method in each year (a), and the average of the absolute value of the correlation coefficient and the number of selections within these years (b).

Table S2. Impact of MCD12Q1 on accuracies of estimated snow density.

Model	Region	Slope	R^2	RMSE	MAE
Original GTWNN model	China	0.986	0.515	0.043	0.028
	Xinjiang	1.016	0.632	0.038	0.025
	Northeast China-Inner Mongolia	1.018	0.564	0.040	0.025
	Tibetan Plateau	0.926	0.483	0.056	0.040
	Other areas	0.793	0.182	0.054	0.038
GTWNN model with the input of MCD12Q1	China	0.968	0.521	0.043	0.028
	Xinjiang	1.011	0.634	0.038	0.025
	Northeast China-Inner Mongolia	0.997	0.575	0.039	0.024
	Tibetan Plateau	0.934	0.497	0.055	0.040
	Other areas	0.740	0.180	0.054	0.038

6. The reasons for the slightly lower accuracy in the snow melting and accumulation periods are not only the rapid changes in the snow density itself, and insufficient sampling in observation time and space, but also because the snow accumulation in the early stage of snow accumulation is less, and the water content when the snow melts Therefore, the observation is more difficult, and the observation error is relatively large.

Response from Authors:

Thanks for providing the professional suggestion. These comments consider the snow characteristics during the snow accumulation and melt periods, which lead to increased observation difficulty and measurement error, and thus can more comprehensively explain the reason for the slightly lower accuracy in these periods. We added the reason in our revised manuscript.

Revised subsection 4.2.2 Accuracy of GTWNN Model in Different Months

It is noted that the observation error is also cannot be ignored, which may be caused by the less snow in the early stage of snow accumulation period, or the large water content when the snowmelt period, making the observation more difficult.

Revised subsection 5.1 Essential Issues of Constructing and Applying GTWNN Model

In contrast, if the snow changes rapidly, distributes sparsely, or the observation difficulty increases, such as in the early snow accumulation period and the late snowmelt period, the estimated snow density would be less credible and need to be used with caution.

7. The verification result of the snow density of ERA5 is worse than that of the model in this paper, but many parameters of ERA5 are used in the machine learning model of this paper, so the accuracy of these parameters, if there is also a large error, will not affect the final model accuracy?

Response from Authors:

Thanks for this comment. The reason for choosing the ERA-5 data is that the high spatiotemporal resolution and rich variables compared to other reanalysis data, with a spatial resolution of 0.1° and a temporal resolution of one hour. The near-surface meteorological state and flux fields, including the air temperature, wind speed, surface pressure, and total precipitation, are corrected for the altitude differences and have improved quality (Muñoz-Sabater et al., 2021). The reanalysis can provide an estimation of the meteorological gridded dataset by assimilating various observations into the forecast model system (Dee et al., 2014). The ECMWF ERA-5 land hourly dataset, as any other simulation, provides estimates which have some degree of uncertainty.

To verify whether the accuracy of the influencing variables affect the final model accuracy, we downloaded the instantaneous near surface (2 m) air temperature and precipitation from the China meteorological forcing dataset (CMFD), with a spatial resolution of 0.1° for comparison. CMFD is the high spatial-temporal resolution gridded near-surface meteorological dataset in China, which was made through fusion of remote sensing products, reanalysis datasets and in-situ station data (He et al., 2020). Since CMFD only provides data until 2018, we use CMFD data to replace the temperature and precipitation data of ERA-5, and the accuracies of the models with different influencing variables from 2013 to 2017 are shown in Table S3.

The accuracies of new model with CMFD are slightly higher than those of original model indicated by R^2, but the RMSE and MAE remain the same, which indicates that the accuracy of the influencing variables will affect the model accuracy, but the temperature and precipitation data of ERA-5 are comparable to that of CMFD for driving our model. It is also noted that the differences of influencing variables will affect the stepwise regression analysis results, making the significant variables and the correlation coefficient between snow density and the selected influencing variables changed each year, which may also affect the final model accuracy.

According to the above results, we can conclude that the accuracy of influencing variables would affect the final model accuracy. Even though the accuracy of ERA-5 snow density worse than ours, the temperature and precipitation data of ERA-5 achieve comparable performance with CMFD data for driving our model. In addition, considering the high spatiotemporal resolution and rich variables, especially the temporal coverage of ERA-5 data (1950–), we finally choose the ERA-5 data in this study.

We added discussion about the impact of low accuracy of influencing variables on snow density estimation in the revised manuscript. Hope our efforts have addressed the major concerns.

Revised subsection 5.1 Essential Issues of Constructing and Applying GTWNN Model

In addition, the accuracy of influencing variables would also affect the GTWNN model estimation accuracy.

Table S3. Accuracy of estimated snow density with different influencing variables.

Year	Original model			New model (CMFD)		
	R^2	RMSE	MAE	R^2	RMSE	MAE
2013	0.477	0.042	0.027	0.497	0.041	0.027
2014	0.483	0.041	0.026	0.483	0.041	0.026
2015	0.448	0.043	0.029	0.442	0.043	0.028
2016	0.531	0.039	0.025	0.535	0.039	0.025
2017	0.533	0.042	0.026	0.546	0.042	0.026
Overall	0.497	0.041	0.027	0.503	0.041	0.027

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Our authors greatly appreciate the advices and suggestions from the reviewer, and we tried to further improve our work accordingly, hope the revisions could successfully address the raised concerns. Many thanks again!