Response to Reviewer #2

June 21st, 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. However, to explain our revisions more effectively, we modified the order of these questions, but the number is not change. 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 the estimation of snow water equivalent (SWE). Predicting a temporally and spatially variant snow density is not trivial and is usually assume constant for SWE estimates. This study presents a geographically and temporally weighted neural network (GTWNN) model to predict daily snow density across China. This work relies on empirical relations with influencing variables and machine learning algorithm, to predict density over time and space. This work proposes a great way to map snow density over China, but further clarifications are needed before publications.

In general, no physical understanding of snow density with influencing variable was explored or used in the modelling. This method relies purely on empirical relations. Not those empirical relations cannot be used but perhaps adding a bit more physical understanding in the variables selection or using a physical model at the regional scale could improve this work.

Response from Authors:

Thank you very much for the suggestion. The suggestion about adding physical understanding in the variables selection or using a physical model at the regional scale will be responded in detail in specific comment 9.

Specific comments:

1. L52-56 This paragraph needs more on how topography and vegetation influence snow density. It might also be also useful to define the scale at which these processes operate relative to this work.

Response from Authors:

Thank you very much for this comment. Accordingly, we revised the Introduction part on how topography and vegetation influence snow density in detail, and the revisions are shown as below.

1 Introduction

The terrain and surface types also play an important role in snow density (Clark et al., 2011; Judson and Doesken, 2000). For example, snow density was found to be lower at higher elevations, and even decreased by approximately 0.006 g/cm^3 with each 100 m increase in elevation (Zhong et al., 2014), which is indirectly affected by energy balance, temperature decreases with elevation in general (Elder et al., 1998). The indirectly effect of slope on snow density includes two ways, one is redistribution of snow via avalanching and wind transport, another is the amount of radiation received, which results in changes in snow grain size, porosity, and density. In addition, the aspect also affects the snow density through radiation, because sunny-facing slopes that experience high radiation inputs will be more likely to have snow melt, introducing liquid water into the snow, which also increase snow density by filling the pore space with liquid water (Wetlaufer et al., 2016). The average snow density in forest areas was 8%–13% less than that in open areas (Zhong et al., 2014), and these observed density differences are attributed to either mass, delivery, wind, or radiation effects (Bonner et al., 2022). Mass effect is a reduction in the snow mass due to canopy interception loss, with lower compaction rates and snow density. Delivery effect is that snow is trapped by the canopy and then delivered to the underlying snowpack, either as unloaded snow or draining melt water. Wind effect occurs when wind speed is reduced by forest obstruction, resulting in a higher snow density relative to open areas because of wind packing. Radiation effect can control snow layer temperature, and melt-refreeze cycles to change snow density (Essery et al., 2008; Storck et al., 2002; Winstral and Marks, 2014).

2. L71 This is true but maybe used them at the regional scale to add a physical basis of energy exchange in the snowpack.

Response from Authors:

Thanks for your question. We agree with that. To make it more rigorous, we revised this sentence as follows.

1 Introduction

One method to explain the spatial and temporal variations in snow density is to use a physical model, such as the coupled energy and mass-balance model ISNOBAL (Hedrick et al., 2018; Marks et al., 1999), which can explicitly simulate a number of snowpack properties including snow density and SWE at the regional scale, and add a physical basis of energy exchange in the snowpack. However, snow density physical models are complex and cannot achieve large-scale spatialization of snow density (Raleigh and Small, 2017).

3. L120 More is needed here on how the topographic parameters were estimated. Was the mean of all pixels at 30m resolution used to estimate the elevation? Could the standard deviation or other statistical parameters of sub pixel variability be used?

Response from Authors:

Thanks for the comment in detail. Accordingly, we added the details on how to estimate the topographic parameters. The slope and aspect are firstly calculated by elevation at 30 m resolution, and they are resampled to 25 km to get the mean values. In addition, according to the suggestion, we tried to calculate the standard deviation of elevation and slope (ELEVATION_STD and SLOPE_STD), which reflect the topographic relief within the range of 25 km, and to explore the effectiveness of the two statistical parameters for snow density estimation. The performance of the new GTWNN model with additional input of ELEVATION_STD and SLOPE_STD are shown in Table S1 as below.

As shown in Table S1, the R^2 of new models are higher than that of original model in 5 of 9 years, and the overall accuracy is slightly improved from 0.515 to 0.516. Although the standard deviation of elevation and slope cannot apparently improve the GTWNN model accuracy, it is still an influencing variable closely related to the snow density. Therefore, we added the ELEVATION_STD and SLOPE_STD in our new model and updated all the related results in the revised manuscript.

Table S1. Accuracy of estimated snow density with different influencing variables.

Year	Original model			New model		
	R^2	RMSE	MAE	R^2	RMSE	MAE
2013	0.484	0.041	0.027	0.485	0.041	0.027
2014	0.470	0.041	0.026	0.504	0.040	0.026
2015	0.439	0.043	0.029	0.466	0.042	0.028
2016	0.526	0.039	0.025	0.516	0.040	0.026
2017	0.526	0.043	0.027	0.528	0.042	0.027
2018	0.518	0.050	0.033	0.493	0.051	0.035
2019	0.620	0.049	0.033	0.606	0.050	0.033
2020	0.508	0.045	0.026	0.525	0.044	0.025
Overall	0.515	0.043	0.028	0.516	0.043	0.028

The revisions are shown as below.

2.2 Satellite and Reanalysis Data

The topographical variables of elevation are obtained from the Shuttle Radar Topography Mission (SRTM) digital elevation model with a spatial resolution of 30 m, and then slope and aspect are derived based on the elevation.

2.3 Data Integration

Before the model development, data pre-processing is conducted. Firstly, since the spatial resolution varies among the different satellite data and reanalysis data, they are resampled to 25 km for snow density mapping using different resampling methods depending on the data type. The spatial resolution of 25 km is determined to match that of most SD and SWE products by passive microwave remote sensing. However, not only the mean of elevation and slope are obtained at 30 m resolution using the resampling method, but also the standard deviation of elevation (ELEVATION_STD) and slope (SLOPE_STD) are calculated to reflect the topographic relief within the range of 25 km.

4. Section 3.2 It is not clear how the model is evaluated… against ground observations? It says in the objectives that daily snow density mapping is achieve by integrating satellite, ground and reanalysis data. One or two sentences are needed here to clarify which is used for what and how the model is trained and validated.

Response from Authors:

Thanks for your careful review for our manuscript. Firstly, we revised the title of Subsection 3.2 to Parameter Selection and Model Evaluation Method, in which the metrics to evaluate the model performance is added, and the methods for selecting the optimal parameters of the GTWNN model and validation methods also are revised in detail.

Secondly, we agree with that some sentences about how each kinds of data are used and how the model is trained and validated need to be added. Generally, we input the multi-source data into the GTWNN model, including the satellite, ground and reanalysis data. Among the three kinds of data, ground observation data has high accuracy but limited numbers because of the sparsity of stations, serving as the true value of snow density. Satellite data is used to provide information of the snow-related influencing variables, and reanalysis data is used to provide information of the meteorology-related influencing variables for estimating snow density. We finally collect 16935 samples after data preprocessing, where a sample refers to a grid cell with ground observations of snow density and its influencing variables. All samples are used the 10-fold cross-validation technique to evaluate the model performance and determine the optimal parameters, 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, and then the above step is repeated 10 times so as to evaluate the model performance on each fold of the validation samples, therefore, all samples are both training and validation dataset.

Accordingly, we revised Section 2.3 to illustrate how each kind of data is used in this study, and also revised Section 3.2 to illustrate 10-fold model validation method.

2.3 Data Integration

Three kinds of data are used, including ground observation data, satellite data, and reanalysis data, where the ground data is used to provide the observed snow density, and the satellite and reanalysis data are used to provide information of different influencing variables.

3.2 Parameter Selection and Model Evaluation Method

There are three essential parameters in GTWNN model, including the spatiotemporal bandwidth h_{ST} and the scale factor φ of the GTW model, and the $spread$ of GRNN model. To evaluate the model performance as well as to determine the optimal parameters, the 10-fold cross-validation technique is adopted (Fotheringham et al., 2003; Rodriguez et al., 2010); that is, 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, and then the above step is repeated 10 times so as to evaluate the model performance on each fold of the validation samples. Finally, a scale factor φ of 0.01, $spread$ of 0.5, and an adaptive bandwidth regime h_{ST} of 8 are obtained, which can achieve the best performance.

In addition, to assess the performance of the GTWNN model, the coefficient of determination (R^2, unitless), the mean absolute prediction error (MAE, g/cm^3), and the root mean squared prediction error (RMSE, g/cm^3) are adopted.

5. Figure 4 Again, how was it trained and validated. Can you define the dataset percentage used for training and validation? Was it trained on some years and evaluated on the remaining years and same for the region?

Response from Authors:

Thank you very much for this question. Originally, we built the models for each year from 2013 to 2020. The models are trained and validated using the 10-fold cross-validation technique, as answered in Question 4. For each year, 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, and then the above step is repeated 10 times so as to evaluate the model performance on each fold of the validation samples. Hence, we finally obtain the estimated snow density of all data, which are compared with the observed snow density to validate the model accuracy in different periods and snow cover regions.

In fact, the GTWNN model is a spatiotemporal interpolation model based on the ground observation snow density, and is constructed separately for each year with the consideration of the snow variety in different years, which cannot be trained on some years and evaluated on the remaining years. We revised the introduction of GTWNN Model to clarify this, and the revisions are shown as below.

5.2 Advantages and Limitations

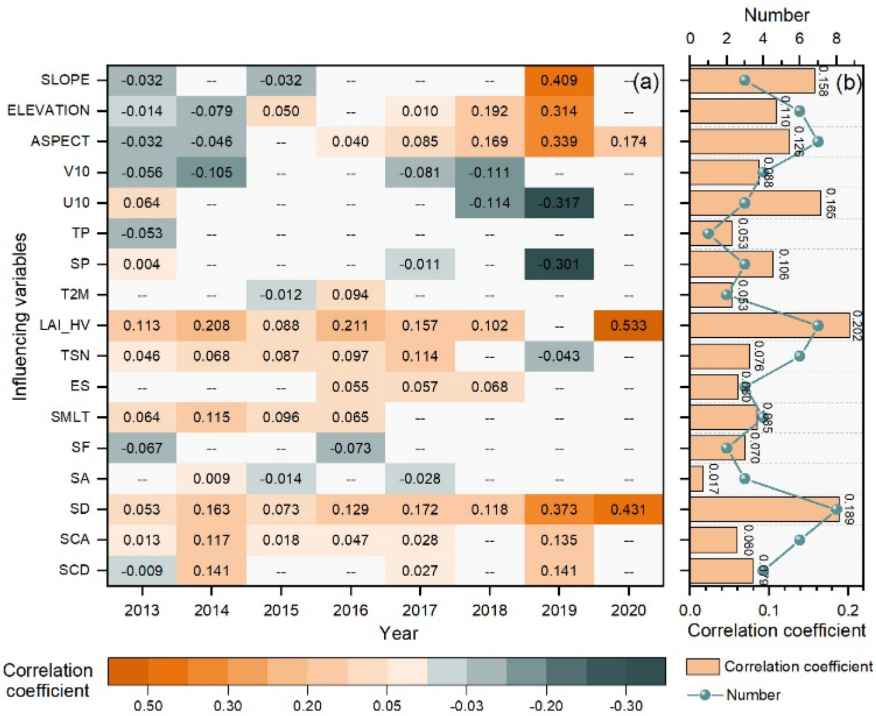
It is noted that the GTWNN model is a spatiotemporal interpolation model based on the ground observation snow density, and the confidence of the snow density map produced by the GTWNN model is still constrained by the distribution of the observation stations

6. Section 4.2.3 Other methods than Pearson correlation factor can be used to investigate the importance of influencing variables. This only indicates a correlation. I would suggest using a permutation importance-based method or an impurity importance from a tree classifier. Maybe it would give better insight on the variables.

Response from Authors:

Thanks for this constructive suggestion. Accordingly, we tried the permutation importance-based method to investigate the importance of influencing variables. According to our understanding, the process of permutation importance-based method is as follow: (1) put all influencing variables into the GTWNN model and get the baseline metric, defined by R^2; (2) scramble each variable column in turn, and input into the model to evaluate the metric again; (3) calculate the differences between the baseline metric and metric by permutating the variables column, reflecting the importance of different influencing variables. However, since the influencing variables are weak for snow density, the results of the scrambled influencing variables are random, and the corresponding 10-fold cross-validation results are also random. Hence, we repeat the permutation importance-based method many times and filter out different influencing variables. Finally, we calculate the mean of differences between the baseline metric and metric by permutating the different variables column, and the results are shown in Figure S1.

Compared with original Figure 4, more influencing variables are selected by the permutation importance-based method in different years than the stepwise regression method, especially after 2016. However, the importance of different influencing variables indicated by the permutation importance-based method is similar with each other, and the most important variables are ES, SF, SCA, SCD. It is noted that the LAI_HV and topographic variables are still important. In addition, we can find that the difference values of different influencing variables are so small and most of the values are below 0.01, which indicates that the input of GTWNN model has little effect on the model accuracy.



Original Figure 4. 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).

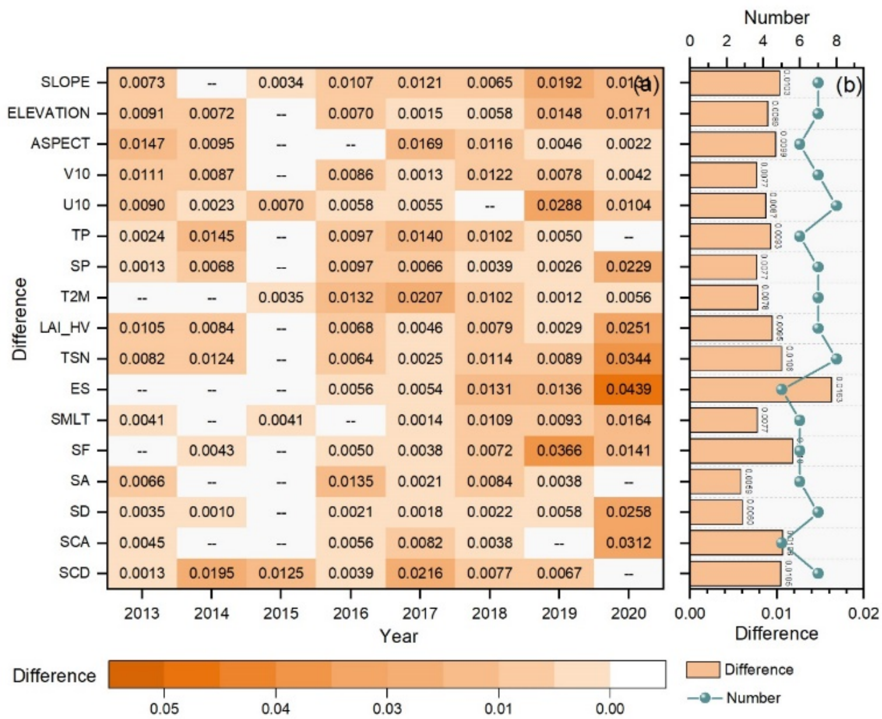


Figure S1. Differences between the baseline metric and metric by permutating the different influencing variables column in each year (a), and the average of the absolute value of the correlation coefficient and the number of selections within these years (b).

We further compare the effect of different variable selection methods on the performance of GTWNN model. The selected influencing variables involved for comparison include all the variables, variables selected by the permutation importance-based method, variables with the top 30% selected by the permutation importance-based method, and variables selected by the stepwise regression method, and the model accuracies are shown in Table S2. The permutation importance-based method is effective for improving the R^2 of the GTWNN model, in comparison with the stepwise regression method. Surprisingly, if we input all influencing variables into GTWNN model, the R^2 is higher than the other models.

Table S2. Accuracies of various methods for investigate the importance of influencing variables.

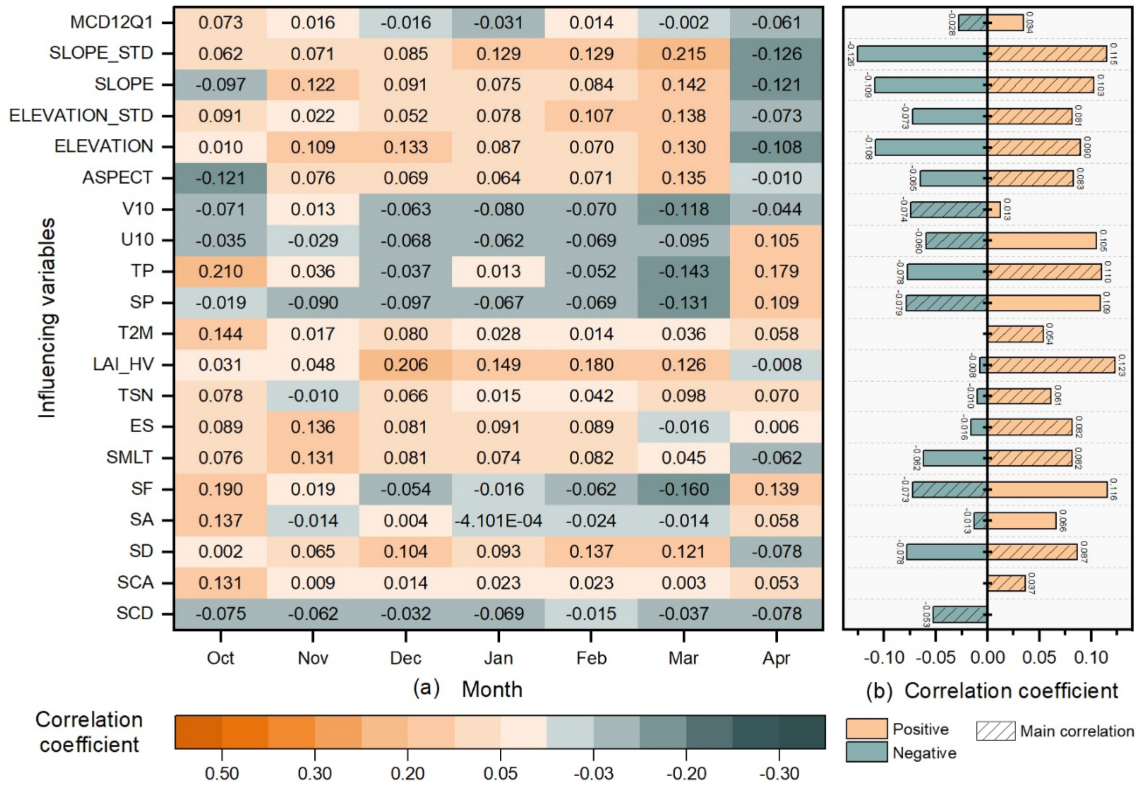
Influencing variables	Slope	R^2	RMSE	MAE
All variables	0.978	0.519	0.043	0.028
Permutation importance	0.984	0.518	0.043	0.028
Permutation importance with 30%	0.997	0.512	0.043	0.028
Stepwise regression	0.986	0.515	0.043	0.028

Finally, we choose to input all influencing variables into the GTWNN model in our revised manuscript, and to calculate the Pearson correlation coefficient between snow density and all the influencing variables in different months rather than in each year, to better understand the relationship between snow density and different influencing variables, as shown in the revised Subsection 4.2.1 Relationship between Influencing Variables and Snow Density. Hope our efforts have addressed the major concerns.

4.2.1 Relationship between Influencing Variables and Snow Density

The Pearson correlation coefficient between snow density and the influencing variables is calculated to indicate the importance of the variables in each month, as shown in Figure 4a, where September and May are not involved because of the small number of ground observations. The influencing variables and the corresponding correlation coefficient values are various in different months because of the heterogeneity of snow. In addition, we calculate the average value from October to April for the positive and negative correlation coefficients, respectively, to indicate the importance of each influencing variable for snow density. We also count the number of months with positive or negative correlations and mark the correlations that appear in more months as "main correlation", to clearly show the relationship between snow density and different influencing variables, as shown in Figure 4b. In general, the correlations between snow density and all influencing variables are very weak, with the maximum average correlation coefficient of only 0.123, which indicates the great difficulty for the estimation task of snow density.

For the 8 snow variables, SD shows apparently higher importance because it has the larger average correlation coefficient of 0.087, followed by ES and SMLT with average correlation coefficient of 0.082. It is noted that the snow density is mainly negatively correlated with SF, SA, and SCD, and positively correlated with other snow variables, indicating that the less new snowfall, more snowmelt, and deeper snow depth tend to result in higher snow density. Among the 5 meteorological variables, TP has the highest average correlation coefficient of 0.110, indicating that higher precipitation can increase snow density. All five topographical variables show highly positive correlation, with average correlation coefficient values of approximately 0.1. Surprisingly, the variable LAI_HV has the largest positive correlation coefficient among all the variables, indicating the importance of vegetation for snow density estimation. In summary, LAI_HV has the strongest correlation with snow density, followed by the TP, SD, and topographic variables among the 20 variables.



Revised Figure 4. Correlation coefficient between snow density and its influencing variables in each month (a), and the average value of the positive and negative correlation coefficients, respectively, where the main correlation marked as shade refers to the positive or the negative correlation that occurs in more month than the other (b).

7. L90 It is stated "to understand how the influencing variables affect snow density estimation". How was this address in the study?

Response from Authors:

Thanks for the constructive suggestion. As answered in Question 6, to understand the relationship between snow density and its influencing variables, we calculated the Pearson correlation coefficient between snow density and all the influencing variables in different months, which is a simply statistical analysis without a physical basis. Therefore, this sentence "to understand how the influencing variables affect snow density estimation" is imprecise, we revised it as "to understand the relationship between snow density and its influencing variables". Hope our efforts have addressed your concern.

1 Introduction

to validate the effectiveness of the proposed model in various situations and to understand the relationship between snow density and its influencing variables.

8. Section 4.3.2 What does this section adds to the manuscript. Does it relate to the objectives? Also, most of the influencing variables come from the ERA-5 reanalysis dataset. Does it affect the results?

Response from Authors:

The authors greatly thank for the comment. According to previous studies, the large-scale daily snow density mapping is currently rare. The reanalysis product ERA-5 can provide the large-scale daily snow density grid dataset, which is produced by comprehensively considering various influencing variables, such as snow pressure, viscosity, near surface air temperature, and wind speed (Muñoz-Sabater, 2019). In addition to highlighting the superiority of the GTWNN model by comparing with other regression models by Section 4.3.1, we want to demonstrate the high accuracy of estimated snow density product by comparing with other large-scale daily snow density products by Section 4.3.2.

In addition, 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.

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

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

9. Line 363 It is stated that weak correlations exist between snow density and the influencing variables chosen for the predictive model. Could a physical snowpack model (ISNOBAL, CROCUS or SNOWPACK) be used for the 4 different regions (not all pixel) to try to add a physical base to the prediction that is mostly empirical through weak correlations at the moment?

Response from Authors:

Thanks for your professional comments. According to our understanding about the physical snowpack models (ISNOBAL, CROCUS, and SNOWPACK), ISNOBAL (Marks et al., 1999) is a distributed, physically based energy and mass balance snow model that explicitly solves for a number of snowpack properties including snow depth, density, and SWE, CROCUS is the first model to simulate the metamorphism and layering of the snowpack (Brun et al., 1992), which made possible the first real-time distributed simulation of the snowpack over an alpine region for operational avalanche forecasting (Durand et al., 1999), and SNOWPACK is a multi-purpose snow and land-surface model that focuses on a detailed description of the mass and energy exchange between the snow, the atmosphere and optionally with the vegetation cover and the soil. It also includes a detailed treatment of mass and energy fluxes within these media (Lehning et al., 2002a; Lehning et al., 2002b). However, these models were mostly used in a small scale area, the spatial scales of various studies range from 0.015 km^2 over a 2.5 m grid (Kormos et al., 2014), 1180 km^2 over a 50 m grid (Hedrick et al., 2018), 460 km^2 over a 75 m grid (Marks et al., 1999), and 2150 km^2 over a 250 m grid (Garen and Marks, 2005), which all have the high spatial resolution at the regional scale. In our study, the estimation task is performed at the resolution of 25 km, which is much coarser than before. Accordingly, we only have the ground observation data about snow parameters, which is sparsely distributed in China. In addition, the meteorological data of the highest spatial resolution is the ERA-5 reanalysis product with the resolution of 0.1°. Even though the snow density physical models can help us understand the relationship between snow density and different influencing variables from a physical mechanism perspective, the above limitations may prevent snow density physical models, even at small regional scales. Hope our efforts have addressed the major concerns.

10. Line 389 The GTWNN can deal with spatiotemporal heterogeneity but how about temporal and spatial transferability of the model in the training/validation?

Response from Authors:

Thank you very much for the question. The GTWNN model could be simply expressed as $snow\ \ density = f_{(S,T)}(x, y)$, where $snow\ \ density$ is the estimated snow density in each cell, (S, T) presents the spatial and temporal distance between the sample point and the prediction point, which is used to select the suitable sample point, and the model input includes x and y, x refer to the influencing variable of snow density, y refers to the ground observation data, as shown in Figure 2. As answered in Question 5, the GTWNN model cannot achieve the spatial and temporal transferability. We revised Section 3.1 to further clarify the function of GTWN as below.

3.1 GTWNN Model

The GTWNN model 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, including the meteorological variables, snow variables, topographical variables, and vegetation variables, which could be expressed as shown in Eq. (1), and its schematic is shown in Figure 2.

$$snow\ \ density = f_{(S,T)}(x, y)\ , \qquad (1)$$

where $snow\ \ density$ is the estimated snow density in each cell, (S, T) presents the spatial and temporal distance between the sample point and the prediction point, and x refers to the influencing variables of snow density, y refers to the ground observation data.

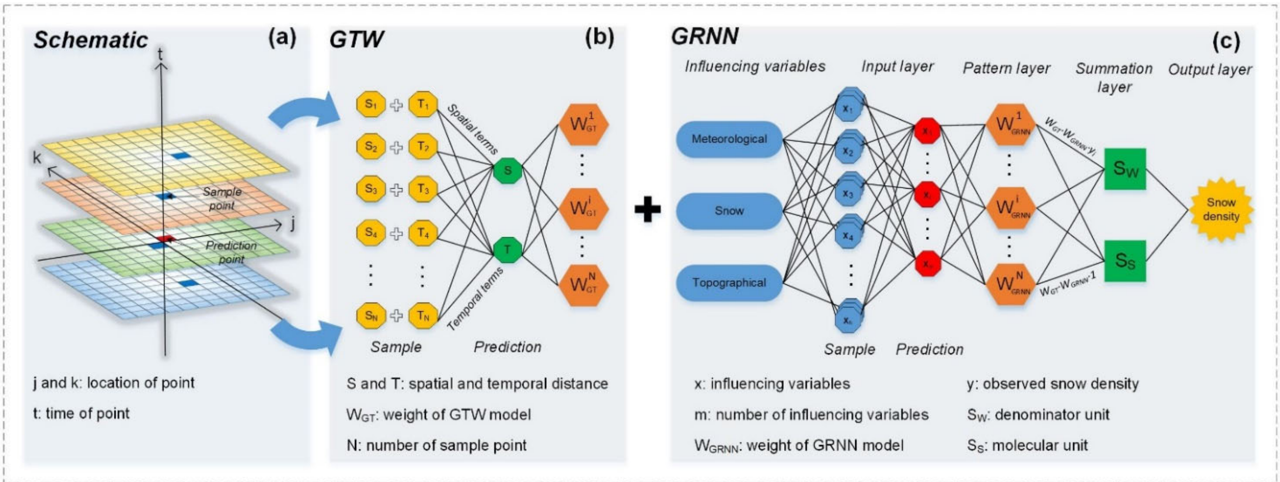


Figure 2. Schematic of the GTWNN model for the estimation of snow density.

11. Line 402 How would that be achieved? Using a physical model?

Response from Authors:

Thank you very much for your comment. Since GTWNN model cannot achieve the spatial and temporal transferability, we expect to further develop a snow density prediction model without the dependence of observed snow density for model inference. Intuitively, we think about developing advanced machine learning methods with spatiotemporal awareness, such as the Geographically Weighted Regression analysis combined with Bayesian Maximum Entropy theory (BME-GWR) (Xiao et al., 2018), space-time random forest (STRF) model (Wei et al., 2019), and space-time support vector regression (STSVR) model (Yang et al., 2018), which can not only consider the spatiotemporal heterogeneity of snow density, but also achieve snow density prediction without ground observation. Of course, if the collected data and the scale are allowed to run a physical model, it would be better to combine the physical model and the machine learning models. Hope our efforts have addressed your concern.

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