# Response to Reviewer #1

## 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. 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:**

**This work employed geographically and temporally weighted neural network (GTWNN) model to construct the daily snow density grid products in China, with the support of satellite, ground, and reanalysis data, which is useful for estimating water resources and predicting natural disasters. However, some important issues need to be addressed. The details are as follows.**

**1.In terms of abstract, the content needs to be specified and well organized. For instance, in Line 6 of this section, the detailed results supporting that the GTWNN model can improve the estimation of snow density should be given; and in Line 10, the specific models should be listed.**

***Response from Authors:***

Thank you very much for this comment. According to the advice, we revised the abstract accordingly and added the detailed results comparing with other regression models and snow density product. The revised Abstract is as follows.

***Abstract.***

Snow density plays a critical role in estimating water resources and predicting natural disasters such as floods, avalanches, and snowstorms. However, gridded products for snow density are lacking for understanding its spatiotemporal patterns. In this study, considering the strong spatiotemporal heterogeneity of snow density, as well as the weak and nonlinear relationship between snow density and the meteorological, snow, topographic, and vegetation variables, the geographically and temporally weighted neural network (GTWNN) model is constructed for estimating daily snow density in China from 2013 to 2020, with the support of satellite, ground, and reanalysis data. The leaf area index of high vegetation, total precipitation, snow depth, and topographic variables are closely related to snow density among the 20 influencing variables. The 10-fold cross-validation results show that the GTWNN model achieves the $R^2$ of 0.531 and RMSE of 0.043 g/cm$^3$, outperforming the geographically and temporally weighted regression model ($R^2$ = 0.271), geographically weighted neural network model ($R^2$ = 0.124), and reanalysis snow density product ($R^2$ = 0.095), which demonstrates the superiority of the GTWNN model by capturing the spatiotemporal heterogeneity of snow density and the nonlinear relationship to the influencing variables. The performance of the GTWNN model is closely related to the state and amount of snow, in which more stable and plentiful snow would result in higher snow density estimation accuracy. With the benefit of the daily snow density map, we are able to obtain knowledge of the spatiotemporal pattern and heterogeneity of snow density in China. The proposed GTWNN model holds the potential for large-scale daily snow density mapping, which will be beneficial for snow parameter estimation and water resource management.

**2.In the introduction, it is not clear why satellite, ground, and reanalysis data are used.**

***Response from Authors:***

Thanks for your question. To achieve daily snow density mapping and understand the relationship between snow density and its influencing variables, 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 revised the Introduction (seventh paragraph) to illustrate the reasons why satellite, ground, and reanalysis data are used, and the revisions are shown as below.

***1 Introduction***

Geographically weighted regression (GWR) is a model that considers spatial heterogeneity by using local multiple linear regression technology (Fotheringham et al., 1998). To further incorporate temporal dependency, geographically and temporally weighted regression (GTWR) model has been introduced for many disciplines, such as meteorology, hydrology, and social economics (Chen et al., 2017; He and Huang, 2018; Huang et al., 2010). The machine learning approaches such as Random Forests (RF) (Breiman, 2001) and General Regression Neural Network (GRNN) (Specht, 1991) have become popular to fit nonlinear relationships, and it is in the initial stage for estimating snow density (Broxton et al., 2019). We can incorporate geographical and temporal weights into a neural network model to capture the spatiotemporally various and nonlinear relationship between snow density and its influencing variables. In addition, considering the impact of different influencing variables, the satellite data can provide information of the snow-related and topography-related variables, and the reanalysis data can provide information of the meteorology-related variables for estimating snow density based on the true value provided by ground observations. Consequently, to achieve large-scale snow density mapping, we can develop a geographically and temporally weighted neural network (GTWNN) model by considering the multiple influencing variables with the support of satellite, ground, and reanalysis data, which not only considers the spatiotemporal heterogeneity for snow density, but also explains the nonlinear relationship between snow density and different influencing variables.

**3.In the end of Section 2.1, the snow season is divided into three periods. Considering the climate and environment show great spatial heterogeneity in snow cover areas in China, this division of snow season should be expounded.**

***Response from Authors:***

Thanks for the constructive suggestion. The division of different snow periods is used for analyzing the snow density estimation results. We greatly agree with that the different snow cover regions show great spatial heterogeneity in terms of climate and environment in China. For example, Xinjiang has less precipitation than Northeast China-Inner Mongolia, and the environment and climate in Tibetan Plateau are distinct due to the high elevation. In addition, the snow density is affected by many influencing variables, such as meteorological variables (e.g., temperature, wind), snow variables (e.g., snow depth), topographic variables (e.g., elevation, slope), and latitude, etc., which are also various among different snow cover regions. However, to ensure the results analysis is comparable, the division of snow periods should be the same in different snow cover regions. Accordingly, we roughly divide the different snow periods according to the seasons in China.

Specifically, the hydrological year is defined as the time period from 1 September to 31 August of the next year in China, in which September, October, and November are treated as the autumn season, December, January, and February as the winter season, March, April, and May as the spring season (Ke et al., 2016; Sun et al., 2020). The three snow periods (snow accumulation period, snow stable period, and snowmelt period) are divided according to the autumn, winter, and spring seasons.

We added the reason for the division of snow season in the revised manuscript, which is shown as follows.

***2.1 In Situ Snow Density***

Therefore, the study focuses on estimating snow density in the snow season from September to May of the next year. To further analyze the estimation results, the snow season is roughly divided into the snow accumulation period (September –November, autumn), the snow stable period (December–February of the next year, winter), and the snowmelt period (March–May, spring) according to the division of season (Ke et al., 2016).

**4.In terms of Equation 2, not all the variables are explained in detail.**

***Response from Authors:***

Thanks for the comment on details. We swapped the position of Equation 2 and Equation 3, and corrected the problems you pointed out, which makes the introduction of GTWNN model more reasonable. The revisions are shown as below.

***3.1 GTWNN Model***

$$d_{ST}^{i} = \sqrt{\left[\left(j_p - j_s^i\right)^2 + \left(k_p - k_s^i\right)^2\right] + \varphi(t_p - t_s^i)^2}\ , \qquad (2)$$

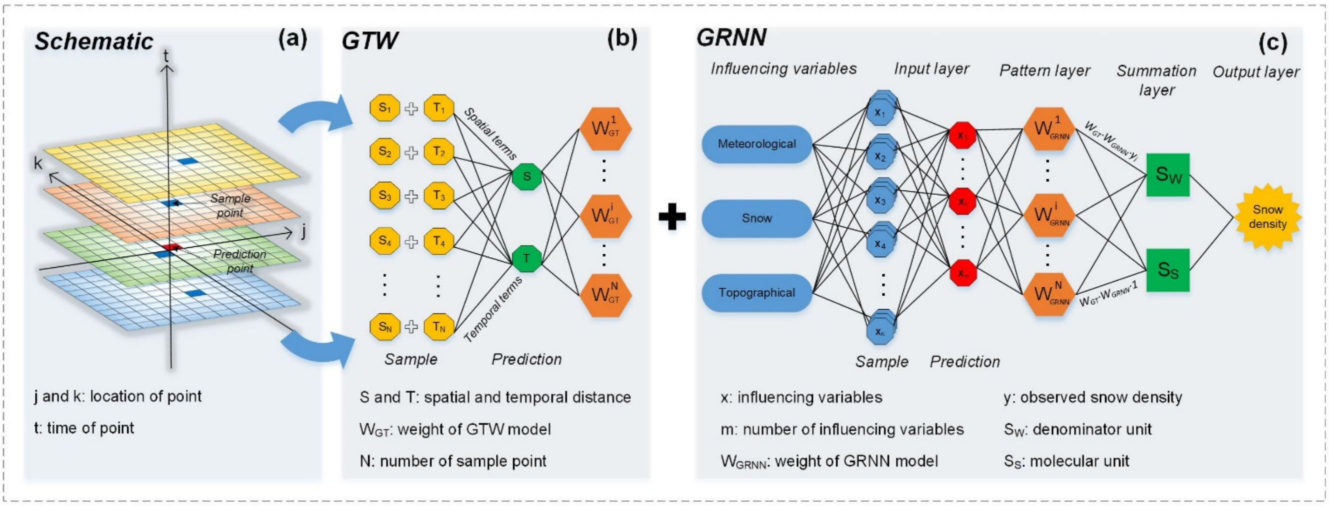
$$W_{GT}^{i} = \begin{cases} [1 - \left(\frac{d_{ST}^{i}}{h_{ST}}\right)^2]^2, & d_{ST}^{i} < h_{ST} \\ 0, & d_{ST}^{i} \geq h_{ST} \end{cases}\ , \qquad (3)$$

where $d_{ST}^{i}$ denotes the spatial and temporal distance between the $i_{th}$ ($i$=1, 2, …, N) sample point ($s$) and the prediction point ($p$), in which $j$ and $k$ represent the location of point, and $t$ represents the time, as shown in Figure 2a. $W_{GT}^{i}$ indicates the weight of the sample point in the GTW model.

**5.The variables in Figure 2 should be explained in or below this picture.**

***Response from Authors:***

Thanks for your careful review for our manuscript. According to the suggestion, we revised Figure 2 by explaining all the important variables for each module. The revised Figure 2 is shown as below. Hope our efforts have addressed the concern.




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

**6.How each kinds of data are used specifically is not given in Section 2 or 3.**

***Response from Authors:***

Thank you very much for this question. Totally, three kinds of data are used in our study, including ground observation data, satellite data, and reanalysis data, respectively. As answered in Question 2, the ground observation data serves as the true value of snow density. The satellite data is used to provide information of the snow-related influencing variables, and the reanalysis data is used to provide information of the meteorology-related influencing variables for estimating snow density.

To clarify how the different data are used, we rewrote Subsection 2.3 Data Integration to clarify how to preprocess and to use each kind of data. In addition, we revised Subsection 3.1 to further explain the role of each data in the GTWNN model. The revisions are shown as below.

***2.3 Data Integration***

Three kinds of data are used, including ground observation data, satellite data, and reanalysis data, where the ground observation data is used to provide the true value of snow density, and the satellite and reanalysis data are used to provide information of different influencing variables of snow density. 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. Accordingly, the ground observations of snow density measured at multiple sites are averaged for each 25 km grid cell. In addition, the min-max normalization method is applied to normalize different influencing variables. After that, we collect 16935 samples for model establishment and validation, where a sample refers to a grid cell with ground observations of snow density and its influencing variables.

***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.

**7.In Section 3.2, the title of this section is not appropriate for the content. In addition, how to evaluate the GTWNN model (such as the metrics to evaluate the performance) should be described.**

***Response from Authors:***

Thanks for this constructive suggestion. We revised Subsection 3.2 and added the metrics to evaluate the model performance. We agree with that the title of Subsection 3.2 (Model Evaluation) is not appropriate for the content, because in addition to the validation methods (such as the 10-fold cross-validation technique and metrics), we also described methods for selecting the influencing variables and the parameters of the GTWNN model. Hence, we modified the title of this subsection to be 3.2 Parameter Selection and Model Evaluation Method. The revisions are presented as below. Hope our efforts have addressed the major concerns.

***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 $\varphi$ 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, 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. Finally, a scale factor $\varphi$ 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.

**8.In table 2, the details about each model are deficient.**

***Response from Authors:***

The authors greatly thank for the comment. The aim of comparison with other regression models is to demonstrate the superiority of the GTWNN model on capturing the spatiotemporal heterogeneity of snow density and non-linear relationship between influencing variables and snow density. We added the details about each model for comparison, including the differences among 6 models and the corresponding comparison results (See revised 4.3.1 Comparison with Other Regression Models). In addition, we revised the caption of Table 2 to clarify the meaning of each model. The revisions are shown as below.

***4.3.1 Comparison with Other Regression Models***

The GTWNN model is compared with five other regression models to demonstrate its advantages for snow density estimation by capturing the spatiotemporal heterogeneity of snow density and its non-linear relationship to influencing variables, as shown in Table 2. The models involved for comparison include the multiple linear regression (R) model, geographically weighted regression (GWR) model, geographically and temporally weighted regression (GTWR) model, general regression neural network (GRNN) model, and geographically weighted neural network (GWNN) model. It is noted that the original R and GRNN models are global regression models established on all samples, regardless of the geographical and temporal weights. The R model captures the linear relationship between snow density and its influencing variables, and the GRNN has strong nonlinear mapping ability (Specht, 1991). Meanwhile, the GWR (Fotheringham et al., 1998) and GWNN models are local models improved from the R and GRNN models by incorporating spatial dependencies, in which the sample points have different weights ($W_G$) according to the spatial distance ($d_S$). The GTWR and GTWNN models further incorporate temporal dependencies, which adds a new scale factor $\varphi$ to balance the different weights of the spatial and temporal distances. The optimal parameters of the compared models are determined by the 10-fold cross validation strategy as that for the GTWNN model.

**Table 2. Accuracies of various models for estimating daily snow density, where R refers to the multiple linear regression model, GWR refers to the geographically weighted regression model, GTWR refers to the geographically and temporally weighted regression model, GRNN refers to the general regression neural network model, GWNN refers to the geographically weighted neural network model, and GTWNN refers to the geographically and temporally weighted neural network model.**

| Model | Slope | $R^2$ | RMSE | MAE |
|---|---|---|---|---|
| R | 0.783 | 0.015 | 0.060 | 0.044 |
| GWR | 0.069 | 0.022 | 0.143 | 0.091 |
| GTWR | 0.398 | 0.271 | 0.070 | 0.043 |
| GRNN | 2.394 | 0.033 | 0.062 | 0.046 |
| GWNN | 0.489 | 0.124 | 0.062 | 0.043 |
| GTWNN | 0.906 | 0.531 | 0.043 | 0.028 |

**9.The text and logic in the manuscript needs improved, particularly in the Results Section. For example, what's the relationship between Section 4.1 (Descriptive Statistics of Ground Observations) and other results? The position of Section 4.2.3 (Importance of the Influencing Variables for Snow Density Estimation) needs consideration.**

***Response from Authors:***

Thanks for your comments. According to the suggestions, we reviewed all the text and logic in the manuscript and made revisions accordingly, especially in the Results Section.

Firstly, in Subsection 4.1 Descriptive Statistics of Ground Observations, the aim of the descriptive statistics of the snow density in different years, months, and snow cover regions is to show the spatiotemporal distribution of snow density in China, based on the observed values at the stations, which can be used to verify the results of snow density mapping (as described in 4.4 Mapping of Snow Density). In addition, the snow density box plots (as shown in Figure 3), including the mean, median, upper and lower quartile value (25%~75%), and upper and lower whisker range (1%~99%), show the dispersion and variation fluctuations in snow density, together with the number of ground observations in different times and areas, which may be the reasons for the accuracy performance of the GTWNN model estimation in different snow cover regions and months (as describe in 4.2.2 Accuracy of GTWNN Model in Different Regions). We add the aim of Subsection 4.1 and the relationships to other results, as below.

***4.1 Descriptive Statistics of Ground Observations***

Snow density has strong spatiotemporal heterogeneity, and we calculated statistics of the ground observations of the 16935 generated samples in terms of the snow density and the number of observations in different years, months, and snow cover regions, as shown in Figure 3, which show the dispersion and variation fluctuations in snow density and can be used to verify the results of snow density mapping.

***4.2.2 Accuracy of GTWNN Model in Different Regions***

The Tibetan Plateau has the lowest $R^2$ of 0.517 and the highest RMSE and MAE, which is mainly caused by the high variation fluctuations of snow density and sparse meteorological stations, as indicated in Figure 3c.

***4.4.2 Temporal Change***

In addition, the monthly mean snow density from the estimated daily snow density map in Figure 9f shows a similar pattern with that from the ground observations in Figure 3b, which further demonstrates the effectiveness of the proposed GTWNN model for snow density estimation.

Secondly, we reorganized the content and logic of the Result Section and adjusted the position of original Subsection 4.2.3, and now the content of Section 4.2 includes 4.2.1 Relationship between Influencing Variables and Snow Density, 4.2.2 Accuracy of GTWNN Model in Different Regions, and 4.2.3 Accuracy of GTWNN Model in Different Months.

As a whole, in Section 4, the first part introduces the descriptive statistics of ground observations, which is the basis to explore the spatiotemporal distribution snow density in China based on the ground observations. The second part is model validation, which is presented in order from input influencing variables to output results in different snow cover regions and snow periods. Next, to highlight the superiority of the GTWNN model, the third part is model comparison, which includes the comparison with other regression models and reanalysis snow density product. Finally, the estimated results are mapped to reveal the spatiotemporal distribution of now density.

**10.Snow density and its CV in different snow cover regions vary apparently, as well as the monthly changes of snow density. While, the explications about these phenomena are limited in the present manuscript.**

***Response from Authors:***

Thank you very much for providing the professional suggestion. We added the content about the mean snow density and CV in different snow cover regions and periods in Figure 8, and briefly explained the reasons for these phenomena in Subsection 4.4. The revisions are presented as below.

***4.4.1 Spatial Distribution***

The spatial distribution of snow density in different snow periods and the entire snow season in China are mapped and shown in Figure 8a–d by calculating the average of the daily snow density estimated by the GTWNN model from 2013 to 2020. It is noted that the estimated daily snow density maps are masked by the daily snow cover product to remove the nonsnow pixels (Hao et al., 2021b). In addition, to understand the spatiotemporal heterogeneity of snow density, we also calculate the mean snow density and CV in different snow periods and regions, as shown in Figure 8e and f.

In the snow accumulation period, the mean snow density is generally lower than 0.13 g/cm$^3$, and the difference of mean snow density in different snow cover regions is small (Figure 8e), except for the Northeast Plain and North China Plain (Figure 8a), in which the liquid water content within snow is much higher than that in other areas (Dai and Che, 2011). In the snow stable period, the mean snow density of China increases to 0.145 g/cm$^3$, especially Xinjiang and Tibetan Plateaus are above average in China (Figure 8e). The highest snow density occurs in the western Tibetan Plateau and South China (Figure 8b), which has abundant precipitation and snow density values are above 0.2 g/cm$^3$. In the snowmelt period, the mean snow density continues to increase to 0.153 g/cm$^3$, especially increasing to 0.178 g/cm$^3$ in northern Xinjiang (Figure 8e) and over 0.16 g/cm$^3$ in Changbai Mountain of Northeast China (Figure 8c). For the mean snow density of the entire snow season shown in Figure 8d and e, the mean snow density is 0.138 g/cm$^3$, 0.151 g/cm$^3$, and 0.156 g/cm$^3$, in Northeast China-Inner Mongolia, Xinjiang, and Tibetan Plateaus respectively. As shown in Figure 8d, the northern Xinjiang, the northwest Tibetan Plateau, and Northeast China have relatively higher snow density than Inner Mongolia and the southeast Tibetan Plateau in the three major snow cover regions, which may be related to latitude, elevation, surface type (Zhong et al., 2014, 2021b).

The mean CV of snow density generally increases across China from snow accumulation period (0.170) to snowmelt period (0.192), as shown in Figure 8f. However, the CV in different snow cover regions varies apparently. It continuously decreases in Xinjiang and Tibetan Plateau from snow accumulation period to snowmelt period. However, the CV of Northeast China-Inner Mongolia achieves the lowest in the snow stable period, but that of the other area reaches the highest in the snow stable period, which may be related to the different snow classes, and the surface type, elevation, and altitude will also affect the volatility of the snow density. Totally in the whole snow season, Xinjiang shows the lowest CV and Northeast China-Inner Mongolia has the largest CV among the three snow cover regions.

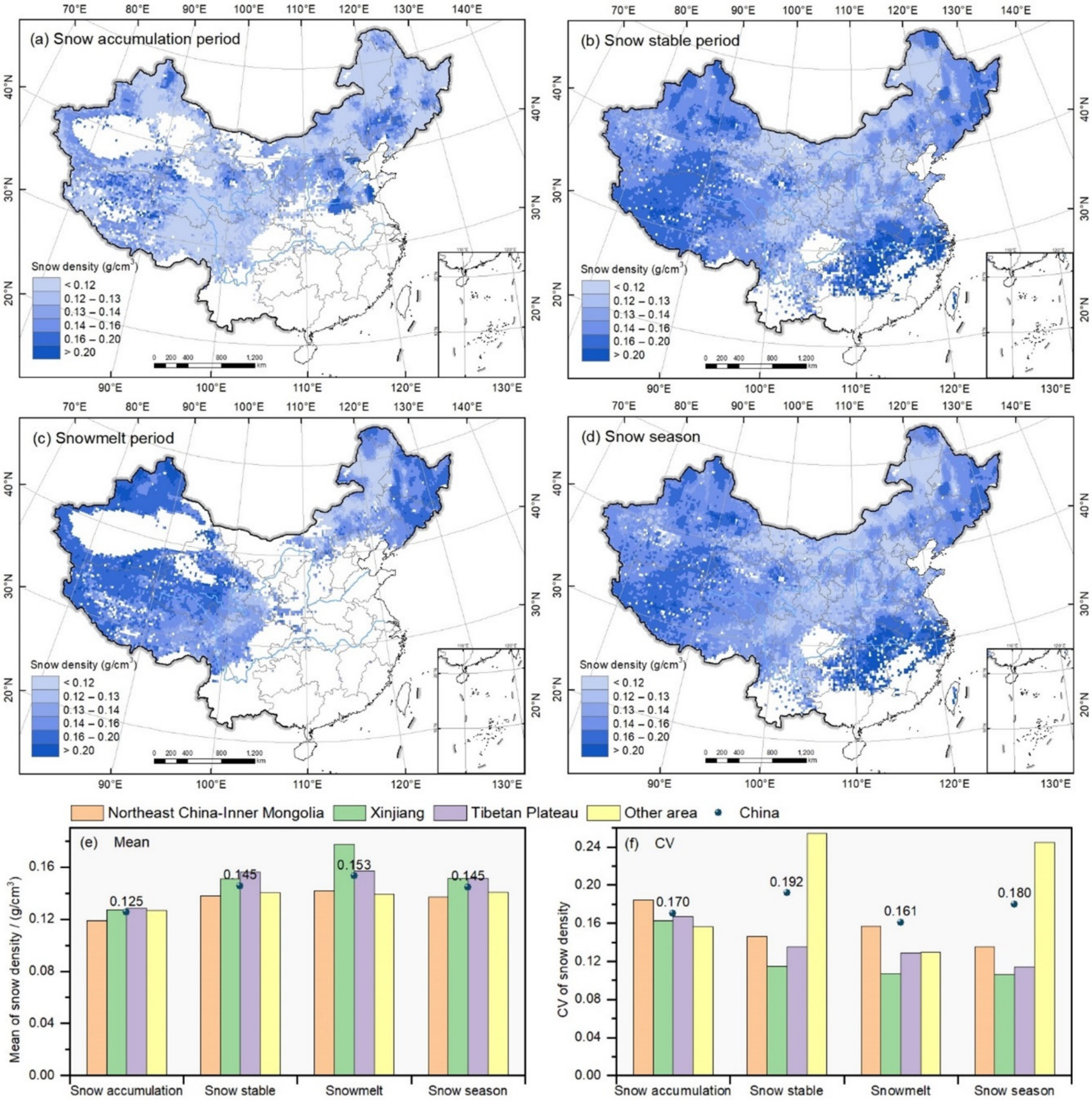



**Figure 8. Spatial distribution of mean snow density in different snow periods in China from 2013 to 2020, including the snow accumulation period (a), snow stable period (b), snowmelt period (c), and entire snow season (d), as well as the mean snow density (e) and CV (f) in different snow periods and snow cover regions.**

### *4.4.2 Temporal Change*

To reflect the monthly change in snow density in different snow cover regions, we calculate the mean snow density in each month of the snow season from January 2013 to December 2020, as shown in Figure 9a–e, as well as the monthly mean snow density of the 8 years, as shown in Figure 9f.

Figure 9a–e shows that the snow density in different regions as well as the entire study area tends to increase from the start of snow accumulation to the peak and then decrease until the late snowmelt period in each year. In the snow accumulation and stable periods, snow density increases with the snow accumulation and mechanical compaction. In the early snowmelt period, snow surface melt decreases snow depth while increasing snow density via meltwater percolation, and then, most of the snow melts into water and the snow density decreases (McCreight and Small, 2014).

However, the snow density fluctuations appear different over time. Specifically, the months with the maximum and minimum snow density are various in different regions, which may be related to the climate conditions in different periods and regions. The monthly changes of Xinjiang and the Tibetan Plateau are similar and apparently different from those of Northeast China-Inner Mongolia, which is because the temperature and gradient between the snow and the atmosphere is small in the Northeast China (Ebner et al., 2016), with low air temperature and vapor pressure in the snow stable period (Ji et al., 2017), in addition, snow cover is relatively shallow, the metamorphism caused by the compaction is not significant (Yang et al., 2020), which allow the snow density of Northeast China-Inner Mongolia to fluctuate less during the seasonal changes. However, in Xinjiang and the Tibetan Plateau, the seasonal evolution of snow density is obvious at the high altitudes and elevation areas, which may be caused by the relatively high water vapor (Ji et al., 2017) and the temperature cycling between day and night may accelerate snow metamorphism (Ebner et al., 2016).

In addition, the monthly mean snow density from the estimated daily snow density map in Figure 9f shows a similar pattern with that from the ground observations in Figure 3b, which further demonstrates the effectiveness of the proposed GTWNN model for snow density estimation.

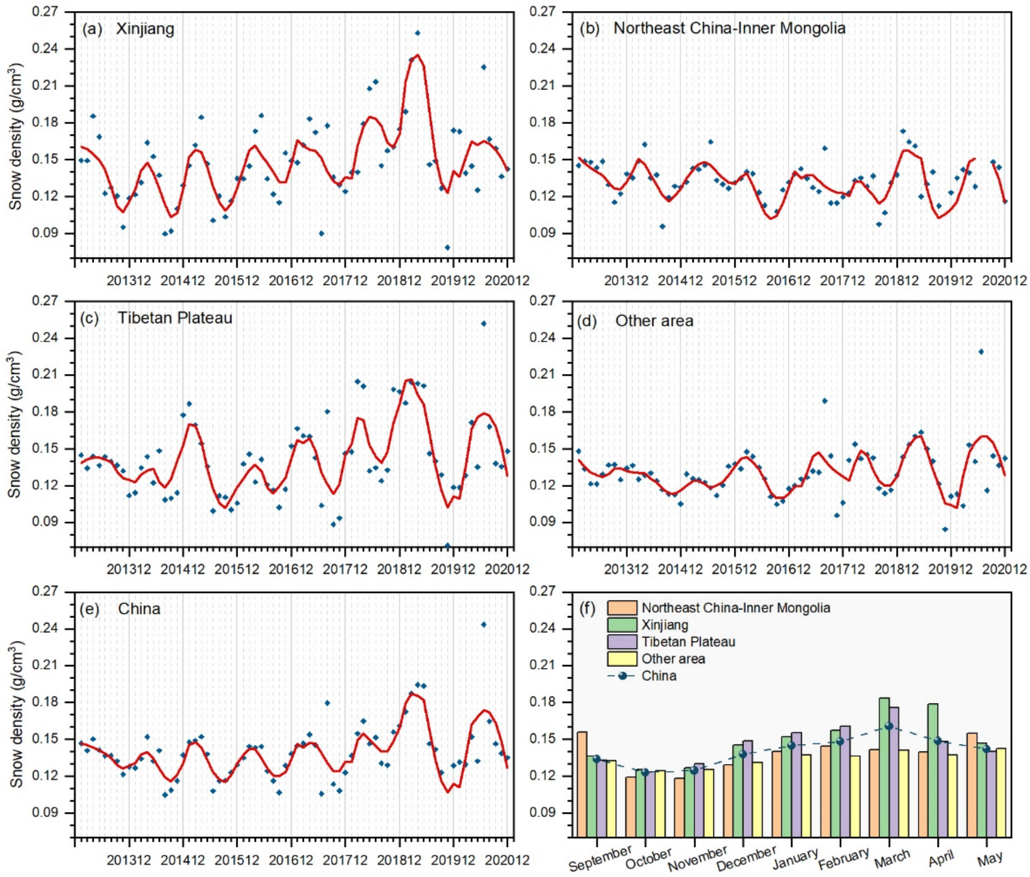



**Figure 9. Mean snow density in each month of the snow season from January 2013 to December 2020 in different snow cover regions, including Xinjiang (a), Northeast China-Inner Mongolia (b), Tibetan Plateau (c), other area (d), and the entire study area (e), and the monthly mean (f) snow density of the 8 years.**

## References


Breiman, L.: Random forests, Mach. Learn. 45, 5–32, https://doi.org/10.1023/A:1010933404324, 2001.

Broxton, P. D., van Leeuwen, W. J. D., and Biederman, J. A.: Improving Snow Water Equivalent Maps with Machine Learning of Snow Survey and Lidar Measurements, Water Resources Research, 55, 3739–3757, https://doi.org/10.1029/2018WR024146, 2019.

Dai, L. and Che, T.: Spatiotemporal distributions and influences on snow density in China from 1999 to 2008, Sciences in Cold and Arid Regions, 3, 325–331, https://doi.org/10.3724/SP.J.1226.2011.00325, 2011.

Essery, R., Pomeroy, J., Ellis, C., Link, T.: Modelling longwave radiation to snow beneath forest canopies using hemispherical photography or linear regression. Hydrological Processes 22, 2788–2800. https://doi.org/10.1002/hyp.6930, 2008.

Fotheringham, A., Brunsdon, C., and Charlton, M.: Geographically Weighted Regression: The Analysis of Spatially Varying Relationships, Geographical Analysis, 35, 272–275, https://doi.org/10.1111/j.1538-4632.2003.tb01114.x, 2003.

Fotheringham, A. S., Charlton, M. E., and Brunsdon, C.: Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis, Environment and Planning, 30, 1905–1927, https://doi.org/10.1068/a301905, 1998.

Hao, X., Huang, G., Che, T., Ji, W., Sun, X., Zhao, Q., Zhao, H., Wang, J., Li, H., and Yang, Q.: The NIEER AVHRR snow cover extent product over China – a long-term daily snow record for regional climate research, Earth System Science Data, 13, 4711–4726, https://doi.org/10.5194/essd-13-4711-2021, 2021b.

Ji, D., Shi, J., Xiong, C., Wang, T., and Zhang, Y.: A total precipitable water retrieval method over land using the combination of passive microwave and optical remote sensing. Remote Sensing of Environment, 191, 313-327. https://doi.org/10.1016/j.rse.2017.01.028, 2017.

Ke, C. Q., Li, X. C., Xie, H., Ma, D. H., Liu, X., and Kou, C.: Variability in snow cover phenology in China from 1952 to 2010. Hydrology and Earth System Sciences, 12(4), 4471-4506, https://doi.org/10.5194/hess-20-755-2016, 2016.

McCreight, J. L. and Small, E. E.: Modeling bulk density and snow water equivalent using daily snow depth observations, The Cryosphere, 8, 521–536, https://doi.org/10.5194/tc-8-521-2014, 2014.

Rodriguez, J. D., Perez, A., and Lozano, J. A.: Sensitivity Analysis of k-Fold Cross Validation in Prediction Error Estimation, IEEE Transactions on Pattern Analysis and Machine Intelligence, 32, 569–575, https://doi.org/10.1109/TPAMI.2009.187, 2010.

Specht, D. F.: A general regression neural network, 2, 568–576, https://doi.org/10.1109/72.97934, 1991.

Sun, Y., Zhang, T., Liu, Y., Zhao, W., and Huang, X.: Assessing Snow Phenology over the Large Part of Eurasia Using Satellite Observations from 2000 to 2016. Remote Sensing, 12(12), 2060, https://doi.org/10.3390/rs12122060, 2020.

Yang, J. W., Jiang, L. M., Lemmetyinen, J., Luojus, K., Takala, M., Wu, S. L., and Pan, J. M.: Validation of remotely sensed estimates of snow water equivalent using multiple reference datasets from the middle and high latitudes of China, Journal of Hydrology, 590, 125499, https://doi.org/10.1016/j.jhydrol.2020.125499, 2020.

Zhong, X., Zhang, T., and Wang, K.: Snow density climatology across the former USSR, The Cryosphere, 8, 785–799, https://doi.org/10.5194/tc-8-785-2014, 2014.

Zhong, X., Zhang, T., Kang, S., and Wang, J.: Spatiotemporal variability of snow cover timing and duration over the Eurasian continent during 1966–2012, Science of The Total Environment, 750, 141670, https://doi.org/10.1016/j.scitotenv.2020.141670, 2021b.

**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!**