A Multilayer Soil Texture Dataset for Permafrost Modeling over Qinghai–Tibetan Plateau

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Abstract

As a sensitive indicator to climate change, permafrost is extensively distributed over the Qinghai-Tibetan Plateau (QTP). The physical process-based models (PPM) are more capable of simulating the hydrothermal processes of permafrost than often-used statistical empirical models. The application of any permafrost PPM to QTP, however, is challenged by the availability of soil profile data, which are usually absent in deep layers. In the paper, a 1km resolution multiple-layer soil texture dataset (MSTD) with eighteen layers, beyond the depth of zero annual amplitude (DZAA) of soil temperature, has been developed for supporting permafrost modeling over QTP. It revealed that loam, sand and gravel are mainly distributed over the study area, and more loams occur in the east and in top layers while more gravels in the west and in deep layers. Further efforts will be placed to improve the dataset accuracy by collecting more soil survey profiles from other sources.

1. Introduction

The global average temperature has increased by approximately 0.85 °C over the past 100 years, with the prominent periods of warming from 1976 onwards. Widespread permafrost degradation due to climate warming during the last several decades has already induced many feedbacks in the global climate system and can significantly impact local hydrology, energy and moisture balances on land surface, carbon exchange between land and atmosphere, as well as engineering infrastructure[1-4]. Therefore, more and more attentions have been paid to understanding, assessing, and predicting the changes of permafrost in recent years [3, 5-8].

Modelling is an essential method to evaluate characteristics of thermal state, moisture/ice content and spatial distribution of permafrost [9-11]. It is especially useful in projecting the responses of permafrost to climate change and assessing hazards induced by permafrost degradation [3, 12-14].The Qinghai-Tibetan Plateau (QTP) is the largest geomorphological unit on the Eurasian continent, and the largest permafrost region in low and middle latitudes. The mean elevation is more than 4000 m above sea level, less influenced by anthropological activities, thus making itself an ideal place for inspecting ecosystem response and its sensitivity to climate warming [6, 15]. Modelling and mapping of the general distribution of permafrost on the QTP have been divided into statistical empirical models (SEM) and physical process-based models (PPM). PPMs have advantages in temporal and spatial modelling with their regionally adaptable process options and parameterization schemes [16, 17], and it was easy to couple with global climate model (GCM). Some permafrost state indicators, such as the mean annual ground temperature (MAGT) at the depth of zero annual amplitude(DZAA), active layer thickness (ALT) and ground ice content can also be obtained through PPMs. Few works have focused on the simulation of permafrost related processes on the QTP using PPMs, because the shortage of the continuous area forcing data, especially the soil data, to drive the model[18].Consequently, the complete picture of permafrost changes over the QTP thus cannot be concluded. But, modelling of the ongoing changes permafrost distribution and characteristics driving by continuous area soil in the QTP is imperative, and thus the motivation for this study.

Recently, Shang guan et al. [2013] created a composited China soil properties dataset (CSPD) with more detailed information on physical and chemical properties at eight soil layers to a depth of 2.3 m. The database are much reliable [19] compared with previous datasets (e.g., The Harmonized World Soil Database). But, it remains indispensable to be updated in west region of the QTP owing to it was produced by limited sample data in that region. Furthermore, the depth of CSPD cannot meet the DZAA needs of permafrost research in QTP. The deeper soil boreholes are, however, generally only available for small areas because obtaining these boreholes is time consuming and expensive. A major requirement of permafrost PPMs research in QTP, therefore, is an understanding of the nature soil texture, especially deeper soil texture. Unfortunately, a lack of information concerning deeper soil texture dataset has impeded the permafrost research in QTP.

This paper describes the development of a multilayer soil texture dataset (MSTD), which including top layer MSTD is updated from China soil properties dataset(CSPD) by recently surveyed samples and deep layer MSTD were predicted by an optimal model for application PPMs research permafrost over QTP. The MSTD is prepared at 1km resolution with eighteen layers exceeding the depth of zero annual amplitude (DZAA) of permafrost.

2. Methodology

The top layer MSTD is updated from CSPD by detailed soil survey profiles where location on west and north QTP. The region to be updated was first selected through the simple intersection between soil sample and china SOTER unit. Then, it is need to obtaining a representative value of soil sample for each standard layers in all selected SOTER unit. The medians for the sand, silt and clay contents of the linked soil sample were calculated for each sample layer. The update value of sand, silt and clay content were replacement by using the median value for each selected SOTER unit so the influence of extreme values is partially ignored compared to a mean value. Finally, the all PSD of CSPD, which including update and no update data, were converted to the USDA soil texture class by using USDA soil textural triangle, which it has been widely used to transfer PSD data into soil texture associated soil hydraulic and thermal properties. However, gravel is common in top layer soil profiles on the QTP. Those USDA coarse-grained soil (e.g., sand class) need subdivided into gravel class if the fractions of gravel is more than sand.

The deep layer MSTD was designed based on prediction model using the direct soil texture data of boreholes. One of the key areas of prediction deep layer MSTD is the choice of models which have been introduced to link soil texture and environmental variables. Various modelling techniques have been used for the digital mapping of soil texture. The most commonly used models include artificial neural network (ANN), decision tree (DT), K-nearest neighbor (KNN), random forest (RF), multiple linear regression (MLR) ,regression tree (RT), naive Bayes (NB) and support vector machine (SVM). The other key areas is the choice of environmental factor, which one is important predictor factor for deep layer MSTD in all soil environmental factors. Based on the theory of soil forming factors and soil-landscape modeling [20, 21], we screened climate (frozen soil type), neighbor layer, soil parent material (quaternary geology), and topography, as the governing environmental factors for consideration in this study. Potential nine variables, in which topographical factors can be split into six variables, are listed in Table 1. Therefore, the available combinations of soil environmental factors include T, T+C, T+P, T+C+P, T+N, T+C+N, T+P+N, and T+C+P+N (T,C,P and N are alias show in Table 1). These candidate models input is soil environmental factor related combination.

Table 1. Potential variables for use deep soil texture.

Factors	Variables	Alias
Climate	Frozen soil type	C
Parent material	Quaternary geology	P
	Altitude	
	Slope	
Topography	Aspect	T
	Plane curvature	
	Profile curvature	
	Topographic wetness index	
Neighbor layer	Soil Texture	N

Since eight models and eight combinations to be used in deep soil MSTD prediction, there will be 64 result for each deeper soil layers. It is crucial to screen the optimal model and the combination as the final choice to predicted deep layer MSTD. Therefore, those models and combinations need to be evaluation using field investigation data. A 10-fold cross-validation was used in all model and combinations. Those models and combinations are evaluated by the calculation overall accuracy (OA). The bigger the OA value, the better is the prediction quality. Finally, the optimal model and predictor combinations are to be used predicted deep layer MSTD.

3. Results

A 10-fold cross-validation was used chose optimal model and predictor. Fig 1 shown goodness-of-model 10 fold cross-validation OA of for different predictor model with each deep soil layer. In this figure, there is no universal method applicable for all layer. But, the worse model is MLR in almost all layer since the relationship between soil and the predictor is not a simple linear. Usually, tree models (C50, RT, and RF), no matter classification and regression, shows the best performance for each layer. So, to ensure the accuracy of OA value above 0.65 in all layers, The C50 is the optimal selected for predict deep layer MSTD.

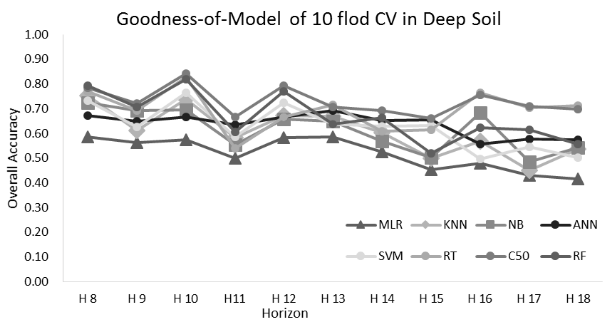

Fig 1. Goodness-of-model of 10 fold cross-validation in deep MSTD

Similar to the optimal model selection, goodness-of-environmental 10 fold cross-validation OA with different environmental predictor combination for deep soil layer shown in Fig 2. In the hierarchical analysis of environmental correlation, applications neighbor layer appeared the better techniques (Fig 2). In order to ensure the accuracy of the all layers are above 0.65, the T+C+P+N environmental predictors combination is the best selected for predict deep layer MSTD.

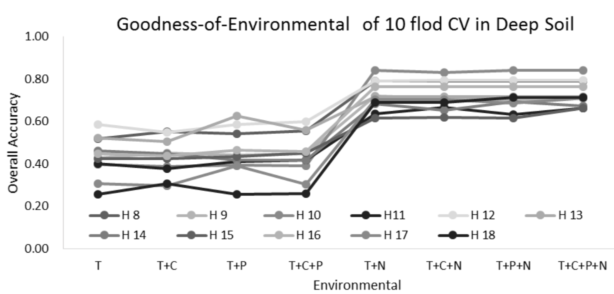

Fig 2. Goodness-of-environmental of 10 fold cross-validation in deep MSTD

The relative to each layer highest accuracy C50 model, T+C+P+N environmental factors combination have been used in deep soil MSTD prediction and it is eventually aggregated by china SOTER using the largest area proportion of soil texture classes to represent whole SOTER unit. It is necessary to evaluate this aggregated MSTD result using available field investigation data.

A comprehensive spatially detailed MSTD was produced for each layer. The accuracy of overall MSTD as shown in Table 2. The KAPPA and OA of original CSPD and overall MSTD were separately calculated with field investigation samples. Mainly due to there are rarely available samples in north QTP for original CSPD, the accuracy of original CSPD is some low, but the improvement is obvious for all layers in top layer MSTD. In all, the OA accuracy of the final aggregated MSTD are all above 0.55.

Table 2. soil texture accuracy of overall MSTD

H	CSPD		MSTD		H	MSTD	
	KAPPA	OA	KAPPA	OA		KAPPA	OA
H1	0.24	0.33	0.61	0.68	H10	0.54	0.62
H2	0.28	0.28	0.60	0.67	H11	0.51	0.57
H3	0.24	0.36	0.59	0.65	H12	0.53	0.59
H4	0.22	0.28	0.63	0.71	H13	0.49	0.57
H5	0.21	0.33	0.57	0.65	H14	0.48	0.56
H6	0.27	0.26	0.58	0.66	H15	0.65	0.67
H7	0.25	0.22	0.64	0.75	H16	0.68	0.71
H8			0.57	0.59	H17	0.67	0.69
H9			0.55	0.65	H18	0.66	0.68

The spatially detailed MSTD was shown in Fig 3. It could be seen that the QTP contains mainly loam, sand and gravel, which cover different for each layer and more than 70% of the total area, respectively. The soil particle size of deep layer soil is larger than top layer soil. Loam percentage is significant reduction and sand and gravel percentage is significant increase with increasing depth of soil profile. In addition, soil texture regional characteristics, with a clear variation from east to west, being more loam in the east while more gravel in the west (Fig 3).

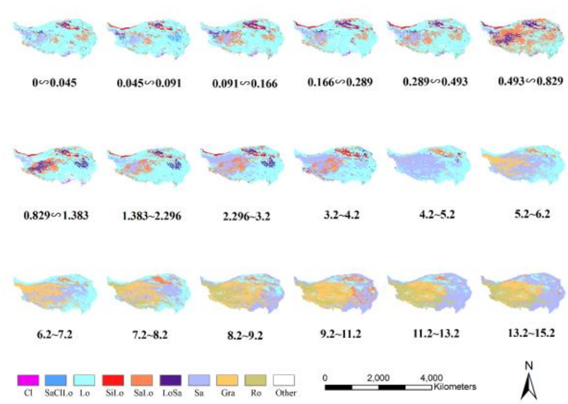

Fig 3. The result of MSTD

4. Conclusion

As a sensitive indicator to climate change, permafrost is extensively distributed over the QTP. Modelling of the ongoing changes permafrost distribution and characteristics drive by soil in QTP is imperative. This paper describes the development of a MSTD for use in regional and continental-scale permafrost PPMs research over QTP. The MSTD with eighteen layers to a DAZZ of QTP, at 1km resolution, has become available to permafrost researchers. The following conclusions can be drawn:

The QTP contains mainly loam, sand and gravel. Soil texture distribution characteristics is with a clear variation from east to west and top to deep. More loam in the east and top while more gravel in the west and deep over QTP.

The C50 model shows the best performance for each deep layer. It could be recommended as the spatial prediction models of QTP, which is an area of limited human exploration that has little or no data available.

Neighbor layer is important predictor factor for each deep layer in all relevant soil environmental factors. In addition, it is almost widespread more input environmental variables result in a favorable model fit.

The MSTD provide crucial data support for the hydrothermal process of permafrost research. Efforts will be made to improve the soil texture accuracy by using additional sources of soil survey and characterization information.

5. References

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