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Spatial distribution and changes of permafrost on the Qinghai-Tibet Plateau revealed by statistical models during the period of 1980 to 2010



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 Permafrost distribution on the QTP was simulated by two statistical models.

Logistic regression based models have advantages in permafrost simulation.
Permafrost area on the QTP is decreased

and the decreasing rate is accelerated.

HIGHLIGHTS

GRAPHICAL ABSTRACT



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ABSTRACT

The Qinghai-Tibet Plateau (QTP), where is underlain by the highest and most extensive mid-altitude permafrost, is undergoing more dramatic climatic warming than its surrounding regions. Mapping the distribution of permafrost is of great importance to assess the impacts of permafrost changes on the regional climate system. In this study, we applied logistic regression model (LRM) and multi-criteria analysis (MCA) methods to map the decadal permafrost distribution on the QTP and to assess permafrost dynamics from the 1980s to 2000s. The occurrence of permafrost and its impacting factors (i.e., climatic and topographic elements) were constructed from in-situ field investigation-derived permafrost distribution patterns in 4 selected study regions. The validation results indicate that both LRM and MCA could efficiently map the permafrost distribution on the QTP. The areas of permafrost simulated by LRM and MCA are 1.23×10^6 km² and 1.20×10^6 km², respectively, between 2008 and 2012. The LRM and MCA modeling results revealed that permafrost area has significantly decreased at a rate of 0.066 $\times 10^6$ km² decade⁻¹ over the past 30 years, and the decrease of permafrost area is accelerating. The sensitivity test results indicated that LRM did well in identifying the spatial distribution of permafrost and seasonally frozen ground, and MCA did well in reflecting permafrost dynamics. More parameters such as vegetation, soil property, and soil moisture are suggested to be integrated into the models to enhance the performance of both models. (© 2018 Published by Elsevier B.V.

1. Introduction

Permafrost is highly sensitive to climate change and is usually considered as an indicator of climate change (Romanovsky et al., 2010; Smith et al., 2010; Zhao et al., 2010). Under the scenarios of global

* Corresponding author. *E-mail address:* thuawu@lzb.ac.cn (T. Wu). warming, permafrost degradation, which generally refers to decreases in permafrost thickness and areal extent and increase in the active layer thickness (ALT) (IPCC, 2013), has been extensively reported (e.g., Anisimov and Reneva, 2006; Cheng and Wu, 2007; Guido et al., 2016; Liljedahl et al., 2016; Schuur et al., 2015; Stocker et al., 2013). Permafrost dynamics have great impacts on the local hydrological and ecological processes (Frey and McClelland, 2009; Gao et al., 2016; Nauta et al., 2014), the engineering infrastructure stability (Nelson et al., 2001), and even the global carbon balance (Crichton et al., 2016; Ding et al., 2017; Hope and Schaefer, 2015; Schuur et al., 2008; Zimov et al., 2006) and has attracted increasing attention by scientists (Oliva et al., 2018; Schuur and Abbott, 2011). The accuracy of permafrost map is of great importance to assess ecological, hydrological, especially engineering impacts of permafrost changes under the scenario of climatic warming.

Different from other cryosphere elements such as glaciers or sea ice, which can be directly measured and observed, permafrost is a largely invisible phenomenon and has high temperature sensitivity (Harris et al., 2009). Modeling, which is developed based on local-scale investigating the relationship between permafrost and related physical processes, becomes an efficient way to estimate the historical, current and future state and spatial distribution patterns of permafrost on large scale (Nan et al., 2002). Permafrost distribution models mainly can be categorized into two types: empirical-statistical models and more physically based numerical models (Harris et al., 2009; Hoelzle et al., 2001). Given that the empirical-statistical models are generally quite reliable after appropriate calibration and need only limited parameters, they are more widely used in larger-scale permafrost simulations (Boeckli et al., 2012a, 2012b; Gruber, 2012; Harris et al., 2009).

The Qinghai-Tibet Plateau (QTP) has the highest and most extensive mid-altitude permafrost on the earth. The permafrost area is approximately 1.5 million km^2 (Fig. 1), and it occupies approximately 53% of the land area on the QTP (Cheng, 1984; Wu and Zhang, 2010; Wu

et al., 2013; Zhou et al., 2000). Most of the permafrost on the QTP is warm permafrost (Luo et al., 2012; Luo et al., 2013; J. Wu et al., 2007; Wu and Zhang, 2008, 2010), which is defined as permafrost with temperatures at or higher than -2.0 °C (Cheng and Wu, 2007; IPCC, 2013). Therefore, the permafrost on the QTP are vulnerable to climate changes (Wu and Zhang, 2010; Yin et al., 2017). Over the past few decades, the QTP has experienced more dramatic warming than its surrounding region (Duan and Xiao, 2015), and permafrost degradation has been widely detected over the QTP (Cheng and Wu, 2007; Wu et al., 2013; Yang et al., 2010). Due to the significance of permafrost for climage system and human society, permafrost degradation influences on the regional hydrology processes (Wang et al., 2009; Yang et al., 2017; Zhang et al., 2003), plant phenology (Cheng and Wu, 2007; Shen et al., 2015), carbon cycles (Ding et al., 2017; Wu et al., 2018b; Zhao et al., 2018), and engineering infrastructures (Peng et al., 2015) have received more and more attention.

During the last two decades, both statistical models and numerical models have been developed and applied to investigate the current condition or future changes of permafrost on the OTP (Cheng and Wu, 2007; Zou, 2015). For example, Li and Cheng (1999) used two models, which were named the altitude model and frost number model, to simulate the distribution and changes to permafrost on the OTP under different scenarios. Nan (2003) discussed and applied the altitude model, mean annual ground temperature (MAGT) model, surface frost model, and top temperature of permafrost (TTOP) model on the QTP, and the results indicated that all four models are capable of mapping permafrost distribution. Zhang et al. (2016) used an altitude-response model to estimate future permafrost distributions under different climate change scenarios. Xu et al. (2017) statistically estimated the relationship of mean annual ground temperature (MAGT) with terrain and climate factors and quantified the distribution and changes of permafrost on the QTP over the past three decades. Zou et al. (2017) simulated the distribution of permafrost through a TTOP model that was driven by MODISderived land surface temperatures. Ran et al. (2018) quantified the



Fig. 1. Distribution of permafrost on the QTP (Li and Cheng, 1996) and the typical regions (TRs).

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