Snow Depth Estimation in Xilingol Based on Reflectance and Brightness Temperature: Postprint

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Abstract

Snow cover constitutes a critical water resource in the arid and semi-arid regions of northwestern China and represents one of the key factors influencing global climate change. Currently, optical image reflectance and radar brightness temperature data serve as the primary data sources in snow cover remote sensing. This study, for the first time, integrates these two types of remote sensing data to estimate snow depth, and compares the performance of partial least squares regression and machine learning algorithms (artificial neural networks, support vector machines, and random forest algorithms) in snow depth estimation. Using snow depth data from Xilingol League during 2012–2015 as a case study, the results demonstrate that snow depth estimation based on the combination of reflectance and brightness temperature data achieves superior accuracy compared to single-source data, with the random forest algorithm exhibiting the best performance (root mean square error of 2.93 cm), which meets the requirements for practical applications. The findings hold significant importance for research on water resource distribution and ecological environment assessment in northwestern China.

Full Text

Estimation of Snow Depth Based on Reflectance and Brightness Temperature in Xilin Gol League

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Abstract

Snow is a crucial water resource in the arid and semi-arid regions of northwestern China and represents a significant factor influencing global climate change. Currently, optical imagery reflectance and radar brightness temperature data constitute the primary remote sensing datasets for snow monitoring. This study, for the first time, combines these two types of remote sensing data to estimate snow depth and compares the performance of partial least squares regression and machine learning algorithms (artificial neural networks, support vector machines, and random forest) in snow depth estimation. Using snow depth data from Xilin Gol League during 2012–2015 as an example, the results demonstrate that snow depth estimation based on combined reflectance and brightness temperature data achieves higher accuracy than using single data sources alone, with the random forest algorithm delivering the best performance (RMSE = 2.93–3.92 cm), meeting the requirements for practical applications. These findings hold significant importance for research on water resource distribution and ecological environment assessment in northwestern China.

Keywords: snow depth; MODIS; MWRI; machine learning

Introduction

Snow constitutes one of the most important factors affecting global climate change, and its impact on the radiation balance of the land-atmosphere system has been well documented by scientists worldwide. Snow is also an extremely vital water resource in the arid and semi-arid regions of northwestern China, playing a critical role in regional water balance and maintaining close relationships with agricultural and pastoral production. Thick winter snow cover provides thermal insulation and moisture preservation for crops and forage grasses, offering favorable water resource security for spring agricultural production. Consequently, snow has long been a focal point in climate change research, and macroscopic, scientific assessment of snow resources is essential for studies on water resource cycling and global energy exchange. As one of the key parameters in snow resource assessment, accurate estimation of snow depth has remained a central objective in snow remote sensing research.

Currently, remote sensing data for snow depth estimation can be categorized into optical remote sensing data and passive microwave remote sensing data. In the optical remote sensing domain, previous studies have established statistical relationships between snow depth and AVHRR reflectance in the Qilian Mountains and southern Qinghai Plateau. More recently, MODIS data with higher spatial and spectral resolution has been increasingly applied to snow depth estimation. In the passive microwave domain, Chang et al. developed a statistical method linking snow depth to brightness temperature differences between 19 GHz and 37 GHz horizontal polarization based on radiative transfer and Mie scattering theory. Jiang Lingmei et al. and Wang Gongxue et al. systematically explored the potential of Chinese MWRI microwave radiation data for snow depth estimation, achieving favorable results. Through continuous development and improvement, brightness temperature-based methods have become one of the most widely used algorithms for passive microwave remote sensing of snow depth.

However, optical remote sensing cannot penetrate the snow surface to obtain internal snow information, and reflectance in certain bands becomes saturated when snow depth exceeds a certain range, limiting estimation accuracy. In contrast, passive microwave remote sensing offers inherent advantages in penetration capability and all-weather operation, making it more suitable for snow depth estimation. Nevertheless, its spatial resolution is relatively coarse, typically ranging from 25 km to 100 km, which fails to meet the requirements of local-scale research. While some studies have integrated optical and passive microwave remote sensing data for snow identification, comprehensive monitoring of snow depth using both data types has not been reported. Therefore, the primary objective of this study is to evaluate the potential of combining optical and passive microwave remote sensing data for snow depth estimation.

Given the complexity of snow depth estimation, simple linear models may introduce substantial uncertainties. Partial least squares regression can overcome multicollinearity among independent variables and has important applications in remote sensing. Additionally, machine learning algorithms such as artificial neural networks, support vector machines, and random forest have attracted considerable attention from remote sensing scholars. Neural networks can handle complex mapping relationships, support vector machines can transform low-dimensional data into high-dimensional space for regression, and random forest algorithms offer fast learning and strong robustness. Consequently, the second objective of this study is to compare the snow depth estimation accuracy of these four methods to provide a theoretical reference for remote sensing-based snow depth estimation in northern China.

1. Study Area Overview

Xilin Gol League (112°–120°E, 42.5°–46.7°N) is located in central Inner Mongolia Autonomous Region, with an elevation ranging from 900 to 1,300 m. The region belongs to the temperate arid and semi-arid continental climate zone, characterized by cold winters and relatively hot summers. The snow cover period is concentrated from November to March of the following year across most of the league.

2.1 Snow Depth Data

The snow depth data used in this study were obtained from field observations at meteorological stations in Xilin Gol League, covering the period from 2012 to 2015. The maximum observed snow depth was 37 cm. According to land cover classification maps, the underlying surfaces at these meteorological stations are all grassland.

2.2 MODIS Reflectance Data

MODIS/Terra surface reflectance data corresponding to the snow depth observation period were downloaded. This dataset maximally removes cloud contamination and retains high-quality reflectance data. The Normalized Difference Snow Index (NDSI) was calculated to distinguish snow from non-snow targets by leveraging snow' s high reflectance in visible bands and strong absorption in shortwave infrared bands. NDSI is one of the most widely used indices in snow remote sensing and is calculated as follows:

NDSI = (Reflectance_{visible} - Reflectance_{SWIR}) / (Reflectance_{visible} + Reflectance_{SWIR})

2.3 FY-3B Brightness Temperature Data

The FY-3B satellite, China' s second-generation polar-orbiting meteorological satellite, carries the Microwave Radiation Imager (MWRI), which provides brightness temperature data at five center frequencies (10.65, 18.7, 23.8, 36.5, and 89.0 GHz) in both horizontal and vertical polarizations. The dataset includes ascending (daytime) and descending passes, with the daytime ascending orbit data (approximately 14:00 local time) used in this study.

2.4 Data Processing Workflow

First, reflectance and brightness temperature data were extracted based on the geographic coordinates of meteorological observation stations corresponding to snow depth observation times. Second, NDSI was calculated and only data with NDSI $>$ 0.1 were retained. Finally, reflectance and brightness temperature data served as independent variables, with snow depth as the dependent variable in regression models. During validation, a cross-validation approach was employed to evaluate model performance.

3.1 Snow Data Overview

A total of 1,000 snow depth samples from multiple meteorological stations were used in this study. The frequency histogram (Fig. 2) shows that snow depth observations do not follow a normal distribution, failing to meet the requirements of simple linear regression and demonstrating that simple linear models are unsuitable for snow depth retrieval. Frequency decreases with increasing snow depth, with most observations concentrated in the 1–20 cm range, accounting for 85% of total samples.

3.2 Inversion Accuracy Comparison

The inversion accuracy of four regression methods using optical remote sensing data, passive microwave remote sensing data, and their combination is presented in Table 1. For partial least squares regression, the number of principal components must be determined, while random forest requires pre-determination of the number of variables per decision tree. To avoid impacts from variable selection, Table 1 shows average accuracy across all possible variable combinations to enable better comparison between methods and data sources.

When using only reflectance data, random forest achieved the best accuracy (RMSE = 3.65 cm), followed by neural networks and support vector machines. When using only brightness temperature data, random forest still performed best (RMSE = 3.12 cm), though the difference with artificial neural networks was not significant. Partial least squares consistently showed the poorest performance. Notably, for all four methods, brightness temperature data yielded higher accuracy than reflectance data, likely because reflectance data easily saturates.

When combining reflectance and brightness temperature data, random forest again achieved the best performance, though accuracy differences among the three machine learning algorithms were minimal (RMSE = 2.93–3.92 cm), substantially lower than partial least squares (RMSE = 7.12 cm). Although partial least squares can eliminate variable collinearity, its performance in snow depth estimation is poor, possibly due to its difficulty in adapting to complex snow conditions.

The 1:1 plots of measured versus predicted snow depth (Fig. 3) reveal that partial least squares systematically underestimates snow depth, with all predicted values < 20 cm, indicating poor accuracy. Neural network predictions generally fall near the 1:1 line but are relatively scattered. For support vector machines, most data points cluster around the 1:1 line, though some outliers reduce accuracy due to the complexity of snow depth estimation. Random forest shows the best performance, with data points compactly distributed around the 1:1 line. Notably, all methods exhibit overestimation at low snow depths and underestimation at high snow depths.

For random forest, using brightness temperature data alone versus combined data shows only a 0.19 cm difference in RMSE, indicating that brightness temperature data alone can achieve good accuracy. Typically, passive microwave data have coarse spatial resolution but high accuracy, while optical remote sensing data have high spatial resolution. Fusing both data types promises to yield snow depth distribution maps with both high spatial resolution and high accuracy.

3.3 Snow Depth Spatial Distribution Map

A clear-sky MODIS image from January 15, 2013, with minimal cloud cover, was selected for Xilin Gol League. The 500 m resolution true-color composite shows most of the league covered by snow, with NDSI values approaching 1 in most areas. Fig. 6 presents the snow depth spatial distribution map generated by fusing reflectance and brightness temperature data using the random forest algorithm (results from other algorithms are not shown). Snowfall in northeastern Xilin Gol League (East Ujimqin Banner and Wulagai) exceeds that in western regions (Erenhot, West Ujimqin Banner, and Zurihe), consistent with the spatial distribution pattern in Fig. 6. The maximum snow depth (21 cm) occurs in East Ujimqin Banner.

4. Discussion and Conclusion

This study demonstrates that combining optical and passive microwave remote sensing data improves snow depth estimation accuracy by integrating surface optical information from reflectance data with internal snow information from brightness temperature data. Machine learning algorithms (artificial neural networks, support vector machines, and random forest) can achieve satisfactory snow depth estimation accuracy, with random forest performing best. Although partial least squares can eliminate variable collinearity, its poor performance in snow depth estimation may stem from its inability to handle complex snow conditions.

The proposed method leverages the advantages of both optical and microwave remote sensing, enabling the generation of high-accuracy, high-spatial-resolution snow depth distribution maps through machine learning algorithms. This approach holds significant importance for snow depth monitoring research in northwestern China.

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Note: Figure translations are in progress. See original paper for figures.