Remote Sensing of Environment 177 (2016) 184–191

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Fractional vegetation cover estimation algorithm for Chinese GF-1 wide field view data

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ARTICLE INFO

Article history:
Received 30 May 2015
Received in revised form 2 February 2016
Accepted 10 February 2016
Available online 26 February 2016

Keywords:
Fractional vegetation cover
GF-1 satellite
Wide field view data
Neural networks

ABSTRACT

Wide field view (WFV) sensor on board the Chinese GF-1, the first satellite of the China High-resolution Earth Observation System, is acquiring multi-spectral data with decametric spatial resolution, high temporal resolution and wide coverage, which are valuable data sources for environment monitoring. The objective of this study is to develop a general and reliable fractional vegetation cover (FVC) estimation algorithm for GF-1 WFV data under various land surface conditions. The algorithm is expected to estimate FVC from GF-1 WFV reflectance data with spatial resolution of 16 m and temporal resolution of four dates. The proposed algorithm is based on training back propagation neural networks (NNs) using PROSPECT + SAIL radiative transfer model simulations for GF-1 WFV canopy reflectance and corresponding FVC values. Green, red and near-infrared bands' reflectances of GF-1 WFV data are the input variables of the NNs, as well as the corresponding FVC is the output variable, and finally 842,400 simulated samples covering various land surface conditions are used for training the NNs. A case study in Weichang County of China, having abundant land cover types, was conducted to validate the performance of the proposed FVC estimation algorithm for GF-1 WFV data. The validation results showed that the proposed algorithm worked effectively and generated reasonable FVC estimates with $R^2 = 0.790$ and root mean square error of 0.073 based on the field survey data. The proposed algorithm can be operated without prior knowledge on the land cover and has the potential for routine production of high quality FVC products using GF-1 WFV surface reflectance data.

1. Introduction

Fractional vegetation cover (FVC), which refers to the fraction of green vegetation seen from the nadir, is an important parameter for characterizing the land surface vegetation conditions (Baret et al., 2013; Gitelson, Kaufman, Stark, & Rundquist, 2002; Jia, Liang, Liu, et al., 2015; Zhang, Liao, Li, & Sun, 2013). FVC is required for many weather prediction models, regional and global climate models, hydrological models and many other land surface models, and has been extensively used in applications of agriculture, soil erosion risk evaluation, drought monitoring, environmental assessment (Gutman & Ignatov, 1998; Matsui, Lakshmi, & Small, 2005; Roujean & Lacaze, 2002; Zhang et al., 2010). Therefore, accurate and timely estimation of FVC on a large scale using high spatial resolution remote sensing data is of great significance for many land surface related applications. For example, water and soil conservation assessments require high spatial and temporal resolution FVC data (Niu, Du, Wang, Zhang, & Chen, 2014), and the rapid FVC estimates from high spatial resolution remote sensing data could be valuable for such similar applications. The Chinese GF-1 is the first satellite of the Major National Science and Technology Project of China, known as the China high-resolution earth observation system. The GF-1 wide field view (WFV) cameras acquire data with high spatial resolution, wide coverage and high revisit frequency (Table 1), which are highly valuable data sources for dynamic monitoring of land surface FVC on a large scale. However, there is limited literature reporting the general algorithm for FVC estimation from GF-1 WFV data. Therefore, exploring the application potential and developing the land surface FVC monitoring methods are urgently needed.

Currently, many FVC estimation algorithms using remote sensing data have been developed, which mainly include empirical methods, pixel unmixing models, and physical model based methods (Baret et al., 2007; Bioucas-Dias et al., 2012; Guerschman et al., 2009; Jiapaer, Chen, & Bao, 2011; Liang, Li, & Wang, 2012; Xiao & Moody, 2005). The empirical methods are based on the statistical relationships between FVC and vegetation indices or reflectance of specific wavebands (Xiao & Moody, 2005). The normalized difference vegetation index (NDVI),

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http://dx.doi.org/10.1016/j.rse.2016.02.019

Table 1
Technical specification of GF-1 WFV cameras.

Payloads	Bands No.	Spectral range (μm)	Spatial resolution	Swath width (km)	Repetition cycle (day)	Local time of descending node
WFV	1	0.45–0.52	16	800 (four cameras combined)	4	10:30 AM
	2	0.52–0.59				
	3	0.63–0.69				
	4	0.77–0.89				

an index calculated from reflectance in the red and near-infrared (NIR) wavebands, is the most frequently used vegetation index for developing empirical FVC estimation models (Jiapaer et al., 2011). Moreover, some other vegetation indices calculated from visible, NIR and short-wave infrared wavebands, such as enhanced vegetation index (EVI), visible atmospherically resistant index (VARI) and modified three-band maximal gradient difference vegetation index (MTGDVI), are also proposed for FVC estimation due to the fact that NDVI may present larger uncertainties in estimating FVC for very dense canopies or open canopies with light or dark bare ground (Gitelson et al., 2002; Jiang, Huete, Didan, & Miura, 2008; Jiapaer et al., 2011). The empirical methods are computationally efficient for large remote sensing datasets and can provide as accurate estimates of FVC in comparison to deterministic or physically based models in regional scales based on the accurate parameterization of the empirical models. However, a large amount of ground measured training samples covering various vegetation types and growth conditions are required for accurately parameterizing the empirical models. In addition, one empirical model is greatly expected to estimate FVC for a specific vegetation type in the specific region, because the quantitative empirical relationship between FVC and vegetation indices or bands' reflectance is varying with vegetation types and regions. For example, Graetz's linear regression model was only suitable for sparse grassland and his nonlinear regression model was specific for degraded grassland (Graetz, Pech, Gentle, & O'Callaghan, 1986). Therefore, though there are some publically available field survey FVC records across most continents (Camacho, Cernicharo, Lacaze, Baret, & Weiss, 2013; Held, Phinn, Soto-Berelov, & Jones, 2015) that can be used to build empirical models, the amount of the records is not enough for accurately parameterizing the empirical models which need samples covering all situations encountered on the Earth's surface. Based on the actual situations, it is costly and not a good choice for developing an empirical FVC estimation algorithm of a specific sensor.

A pixel unmixing model estimates FVC at the sub-pixel level, with the assumption that each pixel is composed of several components and considering the proportion of the vegetation components as the FVC (Jiapaer et al., 2011; Jimenez-Munoz et al., 2009; Phinn, Stanford, Scarth, Murray, & Shyy, 2002). The dimidiate pixel model in the family of pixel unmixing models has been widely used for FVC estimation and has achieved many reliable results at the regional scales (Qi et al., 2000; Wu, Li, Yon, Zhou, & Yan, 2004). For example, GF-1 WFV data are evaluated to estimate FVC using dimidiate pixel model in the Beijing-Tianjin-Hebei region (Zhan et al., 2014). However, a substantial challenge in pixel unmixing model is how to determine endmembers and the spectral response of endmembers because the land surface is very complex, especially for developing the large-scale pixel unmixing model. Therefore, pixel unmixing models are also not optimal for operationally estimating FVC from GF-1 WFV data.

Physical model based methods are based on the inversion of canopy radiative transfer models, which allow to simulate the physical relationships between the vegetation canopy spectral reflectance and FVC (Jia, Liang, Liu, et al., 2015). The physical model based methods establish FVC estimation algorithms that consider more factors and elucidate the physical relationship between remote sensing signal and FVC. Thus, the physical model based methods are widely applicable for FVC estimation in large scale. However, the direct inversion of radiative transfer models is very difficult due to the complexity of the models. Usually, neural networks (NNs) and lookup table methods are the two typical alternative methods for indirect inversion of physical models, and belong to the group of physical model based FVC estimation algorithms. NNs method is based on training datasets simulated by the physical models, and become one of the most important physically based FVC estimation algorithms for their computational efficiency and good performance (Baret et al., 2006; Roujean & Lacaze, 2002). NNs trained over radiative transfer model simulations have been applied with success to estimate FVC from several sensors, leading to several operational FVC production algorithms, such as the POLDER FVC product, which uses NNs and the Kuusk model (Roujean & Lacaze, 2002) and the MERIS and CYCLOPES FVC products, which use NNs and the PROSPECT + SAIL model (Baret et al., 2007; García-Haro, Camacho, & Meliá, 2008). Therefore, based on the reality of work in the field of FVC estimation using remote sensing data, the NN inversion of physical methods is a potentially accurate choice for operationally estimating FVC from GF-1 WFV data.

The objective of this study is to develop a general and reliable FVC estimation algorithm for GF-1 WFV reflectance data under various land surface conditions. The algorithm is expected to operationally produce high quality FVC data from GF-1 WFV surface reflectance data with spatial resolution of 16 m and temporal resolution of four dates. To achieve this objective, we firstly generate a learning dataset using the PROSPECT + SAIL model with large range changes of input parameters to cover various land surface conditions, and then train the NNs for FVC estimation using GF-1 WFV reflectance data. Finally, a case study is conducted to validate the effectiveness of the proposed FVC estimation algorithm for GF-1 WFV data.

2. Methodology

The proposed FVC estimation algorithm for GF-1 WFV data was based on a radiative transfer model inversion. The neural networks approach was selected for the inversion because it was known to be computationally very efficient. Additionally, it was indicated that NNs, when trained over radiative transfer model simulations, could provide accurate surface parameters estimations because of their efficient interpolation capacity (Baret et al., 2007; Fang & Liang, 2005; Leshno, Lin, Pinkus, & Schocken, 1993). Therefore, the FVC estimation algorithm development for GF-1 WFV data consisted of generating a learning dataset using a radiative transfer model, training the NNs, and applying the NNs to estimate FVC from GF-1 WFV data.

2.1. The Chinese GF-1 WFV data

The GF-1 satellite was launched from Jiuquan Satellite Launch Centre (Gansu province, China) in April 2013, and a large amount of data have been obtained since then. GF-1 satellite is in a sun-synchronous orbit at an altitude of 645 km, and carries two panchromatic/multi-spectral (P/MS) and four wide field view (WFV) cameras. The GF-1 WFV sensor observes solar radiation reflected by the Earth in four spectral channels distributed in the visible and NIR spectral domain ranging from 450 to 890 nm. GF-1 WFV data have a spatial resolution of 16 m and swath width of 800 km with four cameras combined, as well as their high frequency revisit time of four days (Wei et al., 2015). The technical specification for GF-1 WFV cameras is shown in Table 1. The high-frequency revisit time, wide coverage ability and decametric spatial resolution of GF-1 WFV data make them highly suitable data sources for dynamic