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Validation of Global LAnd Surface Satellite (GLASS) fractional vegetation cover product from MODIS data in an agricultural region

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ABSTRACT

Fractional vegetation cover (FVC) is an important parameter for describing the land surface vegetation conditions and widely used for land surface process simulations and global change studies. Global FVC products are mainly derived from satellite data and several global FVC products have been generated. Validation of the satellite FVC products is important before they can be applied. The objective of this study is to validate the newly generated Global LAnd Surface Satellite (GLASS) FVC product based on the time series of field FVC measurements in an agriculture region in the Heihe Basin of Northwest China. The high spatial resolution remotely sensed Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Compact Airborne Imaging Spectrometer (CASI) data were used to upscale the ground FVC measurements to validate the GLASS FVC product at 0.5 km spatial resolution. The results indicated that the GLASS FVC was highly accurate with the coefficient of determination (R^2) of 0.86 and root-mean-square error (RMSE) of 0.087. Furthermore, the time series FVC profiles were consistent with the crop growing characteristics. It can be a reliable FVC product for agricultural applications.

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1. Introduction

Vegetation is the basic component of terrestrial ecosystem and plays an important role in biogeochemical cycling, energy exchange and hydrological cycling processes on the earth surface (Zhang et al. 2013; Baret et al. 2007). Fractional vegetation cover (FVC), defined as the fraction of green vegetation as seen from the nadir of the total statistical area, is an important parameter for describing land surface vegetation conditions which is also required for many land surface process models, weather prediction models,

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regional and global climate models, hydrological models and global change studies (Baret et al. 2013; Gitelson et al. 2002; Zhang et al. 2013; Gutman and Ignatov 1998; Matsui, Lakshmi, and Small 2005). Therefore, accurate and timely estimation of long-term FVC on the global scale is of great significance for many land surface processes and climate change studies as well as for its extensive applications in agriculture, forestry, environment management, ecological monitoring, disaster risk monitoring, and drought monitoring (Zeng et al. 2000; Roujean and Lacaze 2002; Godinez-Alvarez et al. 2009; Jia et al. 2015).

Remote sensing provides the only feasible way to generate FVC products at the global scale because of its ability to quickly provide broad, periodic and easily available observation data on the land surface (Jiapaer, Chen, and Bao 2011; Zeng et al. 2000). Currently, several large scale FVC products have been produced using remote sensing data, such as the POLarization and Directionality of the Earth's Reflectances (POLDER) FVC product (Roujean and Lacaze 2002), the Envisat MEdium Resolution Imaging Spectrometer (MERIS) FVC product (Baret et al. 2006), the Spinning Enhanced Visible and Infrared Imager (SEVIRI) FVC product (García-Haro, Camacho, and Meliá 2008), the Change in Land Observational Products from an Ensemble of Satellites (CYCLOPES) FVC product (Baret et al. 2007), and the Geoland-2/BioPar version 1 (GEOV1) FVC product (Baret et al. 2013). Before the FVC products can be applied, the quality and accuracy of these products must be initially verified. Therefore, many studies have been implemented to validate the existing FVC products (Fillol et al. 2006; García-Haro, Camacho, and Meliá 2008; Mu et al. 2015). However, it can be found that the accuracy validation results of these existing FVC products are unsatisfactory. For example, the FVC products of SEVIRI and MERIS sensors have good spatial consistency, but the MERIS FVC product presents systematically underestimate the FVC values approximately 0.1–0.2 (García-Haro, Camacho, and Meliá 2008); The CYCLOPES FVC product is higher than the SEVIRI FVC product by approximately 0.15, and the values of SEVIRI FVC product lies between those of the MERIS and CYCLOPES FVC products, but the validation reports note that the values of the CYCLOPES FVC product are lower than those values of spatial aggregation from high spatial resolution Satellite Pour l'Observation de la Terre (SPOT) data, thus the FVC products of SEVIRI, MERIS and CYCLOPES all underestimate FVC in some extent. The GEOV1 FVC product is generated by correcting the systematic underestimation of the CYCLOPES FVC product and considered being closer to the ground FVC estimates (Camacho et al. 2013). However, the validation of GEOV1 FVC product in an agriculture region indicates that it overestimates FVC by up to 0.2 in this cropland (Mu et al. 2015). Therefore, the extensive accuracy assessment of FVC products is of great significant for accurately application of remote sensing data derived FVC products.

The Global LAnd Surface Satellite (GLASS) FVC product is a newly generated global FVC product from Moderate Resolution Imaging Spectroradiometer (MODIS) data using machine learning methods based on the training samples generated from global distributed high spatial resolution satellite data (Jia et al. 2015; Yang et al. 2016). The initial validation of GLASS FVC product using global distributed 44 reference data from validation of land European remote sensing instruments (VALERI, accessed at: http://w3.avignon.inra.fr/valeri) sites indicates that the GLASS FVC product has comparable accuracy with GEOV1 FVC product (Jia et al. 2015). Furthermore, the spatial and temporal comparisons between GLASS and GEOV1 FVC products show that the GLASS FVC product has much better spatial and temporal continuities. Thus, the GLASS FVC product is also a reliable long-term global FVC product for related applications. Extensive assessment of GLASS FVC product based on more ground data is very important for in-depth understanding of this new generated global FVC product. Therefore, this study aims to validate the GLASS FVC product based on time series ground FVC measurements covering the whole growth periods of the major crop type in an agriculture region, whereas the agriculture monitoring is one of the major application fields of FVC data.

2. Materials and methods

Validation of these coarse spatial resolution FVC products is usually difficult to achieve because ground point FVC measurements are not suitable for direct comparisons due to the surface heterogeneity (Morisette et al. 2006; Jia et al. 2015). Using high spatial resolution remote sensing data to scale the ground FVC measurements up to coarse spatial resolution pixels for evaluating is always a suitable choice (Liang et al. 2002). Therefore, the strategy for validating the GLASS FVC product in the agricultural region is based on the high spatial resolution FVC data upscaled from the ground FVC measurements. The ground FVC measurements and high spatial resolution remote sensing data including the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and airborne Compact Airborne Imaging Spectrometer (CASI) data are acquired during the Heihe Watershed Allied Telemetry Experimental Research (HiWATER) project in an oasis agriculture region of Heihe River Basin, China (Li et al. 2013; Mu et al. 2015). The ASTER and CASI data upscale the time series field FVC measurements covering the whole crop growth season using a statistical model. The GLASS FVC product is temporally interpolated and re-projected to match the ASTER and CASI FVC reference data, and then FVC values from each pixel of the GLASS FVC product are directly compared with the averaged FVC value from their spatial matched ASTER and CASI FVC pixels. Finally, the accuracy indicators including root-mean-square error (RMSE) and coefficient of determination (R^2) are used to evaluate the performance of the GLASS FVC product.

2.1. *GLASS FVC product from MODIS data*

The GLASS FVC product is supported by the China's National High Technology Research and Development Program which aims to generate long term global land surface parameters. The algorithm for GLASS FVC product from MODIS data is firstly generated using general regression neural networks (GRNNs) method with training samples derived from global sampled Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) data (Jia et al. 2015). However, in the process of generating long term global GLASS FVC product, it is found that the computational efficiency of GRNNs method is not satisfactory. Therefore, four machine learning methods including back-propagation neural networks (BPNNs), GRNNs, support vector regression (SVR), and multivariate adaptive regression splines (MARS), are evaluated using the same training samples to find out an suitable algorithm for generating GLASS FVC product that has both accuracy comparable to the GRNNs method and satisfactory computational efficiency (Yang et al. 2016). Finally, the MARS method is found to be a suitable algorithm for generating the long term GLASS FVC product (Yang et al. 2016).

The temporal and spatial resolutions of GLASS FVC product from MODIS data are 8 days and 0.5 km with a sinusoidal grid projection. The initial validation results of this FVC product present a comparable estimation accuracy with the GEOV1 FVC product, whereas the temporal and spatial continuities are much better than it (Yang et al. 2016; Jia et al. 2015). Therefore, comprehensive evaluation of the GLASS FVC product in typical vegetation regions is more helpful to further understand the performance of the newly generated global FVC product.

2.2. *Study area*

The study area is selected in the middle reaches of Heihe River Basin located in the Northwest China (Mu et al. 2015; Li et al. 2013). The central geographical coordinates of the study area is approximately latitude 38°52′N and longitude 100°22′E, covering an area of approximately 36 km^2 (Figure 1). The study area is part of an oasis region with annual mean temperature and precipitation approximately 7 ~ 10°C and 140 mm, respectively. The major part of the oasis is used as cropland and the dominated crop type is corn, which is planted in May and harvested in September. Small patches of orchards, vegetables and wheat are also found in the agriculture region.

2.3. *Field FVC measurements*

The field FVC measurements were conducted from 30 May to 3 September in 2012, covering the whole growing season of corn. The field survey frequency was initially 5 days before late July and increased to 10 days afterward. Twenty-two sampling sites were selected throughout the study area, in which sixteen sites were located in corn fields. The size of each site was approximately 10 m × 10 m for the low vegetation types

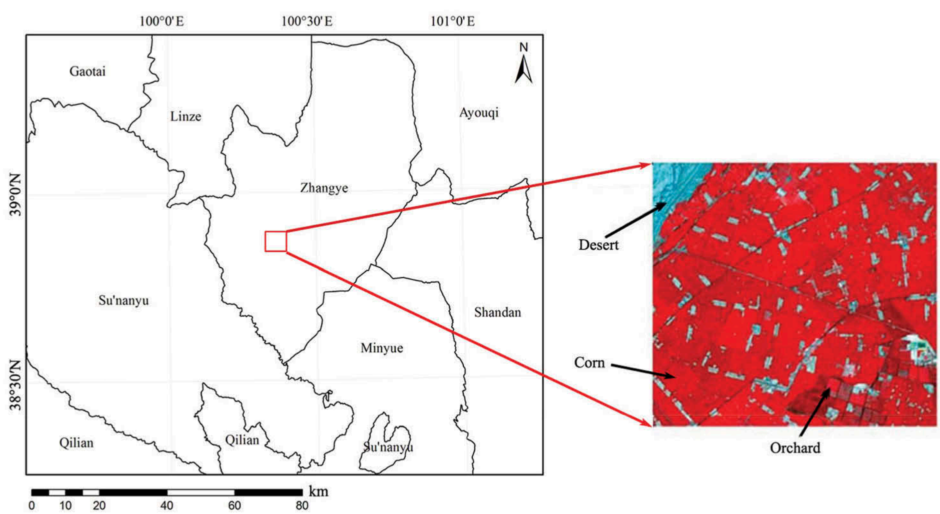

Figure 1. The geographical location of the study area.

such as corn and 30 m × 30 m for tall vegetation types such as orchards (Mu et al. 2015). Land surface for cropland and orchards was homogeneous in the study area, such that the sampling site significantly represented an ASTER pixel scale and ground measurements at sampling sites were considered as ground truth FVC of high spatial resolution pixels for upscaling.

The field FVC data were quantitatively measured using digital photography. The photographs of low vegetation types were acquired from the nadir with a long stick equipped with a camera at the end. For the tall trees in the orchard, a top-down direction was used to take photographs of low vegetation under the tree crown, whereas a bottom-up direction was used to capture the tree crown. In addition, when taking the photographs on the cropland sites, the camera was fixed vertically downward at a certain height to guarantee that at least two rows existed in one photograph and the center of the photograph was located at the center of the interrow between the crop rows (Ren et al. 2013). This strategy improved the representativeness of the field FVC measurements at the patch scale. Nine photographs were taken along with the two diagonals of the squared sampling site in each site, and the FVC estimates from the nine photographs were averaged to estimate the FVC for the sampling site of low vegetation types (Mu et al. 2015). As for the sampling sites of tall vegetation types, the FVC was calculated using the following equation that accounted for the FVC of tree and understory vegetation viewed at the nadir direction between tree gaps:

$$\mathrm{FVC} = \mathrm{FVC}_{\mathrm{up}} + \left(1 - \mathrm{FVC}_{\mathrm{up}}\right) \times \mathrm{FVC}_{\mathrm{down}} \tag{1}$$

where $\mathrm{FVC}_{\mathrm{up}}$ and $\mathrm{FVC}_{\mathrm{down}}$ were FVC values extracted from the photographs captured by the bottom-up and top-down directions, respectively.

The FVC of a digital photograph was defined as the percentage of vegetation pixel number to the total pixel number. Firstly, the photograph edges were removed to eliminate the perspective effect and the distortion of the image, which could cause a systematic error of FVC estimation (Zhao et al. 2012). Then, the FVC of each photograph was estimated using a Gaussian simulation and segmentation method in the Commission Internationale de L'Eclairage (CIE) L*a*b color space (Liu et al. 2012; Song et al. 2015). This method separated green vegetation and non-vegetation pixels through histogram clustering which supported that green vegetation and background distribution of greenness in the color space were Gaussian, and then computed the FVC of a single photograph (Liu et al. 2012). The visual observations of the FVC estimation results showed that the FVC estimates from each digital photographs were acceptable.

2.4. *FVC reference maps derived from ASTER and CASI data*

The ASTER L1B and CASI data were selected for upscaling ground FVC measurements to validate the GLASS FVC product. The spatial and temporal resolutions of ASTER data were 15 meters and 15 days, respectively. The ASTER data included nine images which were acquired on 30 May, 15 June, 24 June, 10 July, 2 August, 11 August, 18 August, 27 August and 3 September, 2012. CASI data with spectral range from 380 to 1050 nm and spatial resolution of 1 m were acquired on 29 June and 7 July, 2012.

The CASI data covered an area of 30 km × 30 km in the middle reaches of the Heihe River. The pre-processing of ASTER and CASI data included geometric correction, radiometric calibration, and atmospheric correction using synchronous measurements, and then the land surface reflectance data were generated.

The ASTER and CASI reflectance data were processed into FVC reference data through an empirical transfer function which was based on the statistical relationship between Normalized Difference Vegetation Index (NDVI) and field FVC measurements (Mu et al. 2015). Linear and nonlinear regressions usually achieved good FVC estimation result using NDVI. Therefore, the statistical model combined linear and nonlinear conditions was used for FVC data generation using NDVI from ASTER and CASI data (Mu et al. 2015):

$$FVC = (a \times NDVI + b)^k \tag{2}$$

where *a, b* and *k* are the model coefficients, which are determined based on the field survey FVC data and the corresponding ASTER NDVI, and used to estimate FVC from ASTER and CASI NDVI data. The FVC maps generated from each ASTER and CASI data at their original spatial resolution would be used as the reference FVC data to validate the GLASS FVC product. The GLASS FVC data were temporally interpolated using cubic spline interpolation method to obtain the FVC values at the acquiring dates of the ASTER and CASI data, and then FVC values from each pixel of the GLASS FVC product were compared with the averaged FVC value from their spatial matched ASTER and CASI FVC pixels.

3. Results and discussion

A randomly selected pixel to compare the temporal variation of GLASS FVC product and FVC reference data was shown in Figure 2. It could be clearly seen that most of the FVC

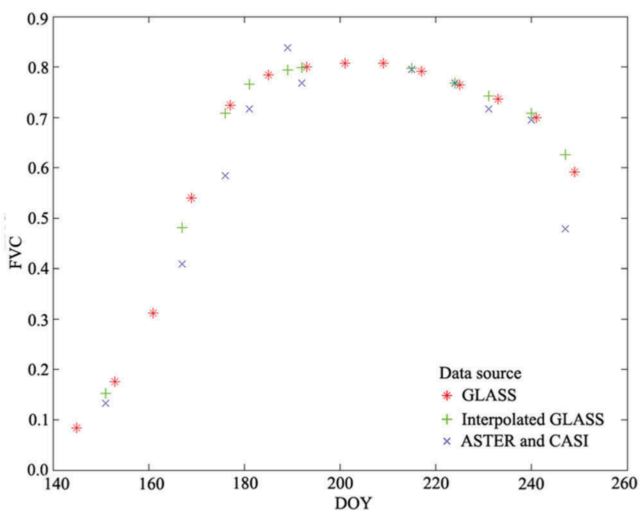

Figure 2. Time series of GLASS FVC, interpolated GLASS FVC, aggregated ASTER and CASI FVC data of a randomly selected pixel.

values from GLASS FVC product were very close to the FVC reference values. There were also some larger differences between GLASS FVC and ASTER FVC on 15 June (Day of Year, DOY 167), 24 June (DOY 176), and 3 September (DOY 247). The GLASS FVC values on these three days were higher than the ASTER FVC by about 0.1. The main reason might be that GLASS FVC was re-projected and temporally interpolated to match with the ASTER FVC data, which could brought larger uncertainties especially for the temporal interpolation, because corn was in the rapid growth period on 15 June and 24 June, and in the decline period on 3 September, which caused rapid FVC variations in these periods. In addition, the statistical model built from the field FVC measurements and high spatial resolution NDVI data to transfer field measurements to high spatial resolution FVC maps also exhibited residual errors, though the aggregating high spatial resolution FVC might reduce these errors.

Furthermore, the GLASS FVC values showed a clearly smooth curve reflecting the crop growing characteristics throughout the corn growing season and well captured the seasonal FVC variations of corn. The FVC began to increase in late May and rapidly reached to a peak value in early July along with the rapid growth of corn, then the FVC kept a high value and decreased from late August to the middle of September. It could be also found that there were small uncertainties for the ASTER and CASI FVC, for example the CASI FVC on 29 June and 7 July were clearly presented slight deviation from the smooth corn growing curve. Therefore, these results preliminarily indicated that the GLASS FVC product could effectively capture the seasonal FVC variations of corn and close to the ground FVC observations.

The scatter points of the GLASS FVC values and the corresponding FVC reference values at the eleven time phases were presented in Figure 3. Qualitatively, it was found that most of the scatter points were aggregated near or on the reference line (y = x) which indicated a

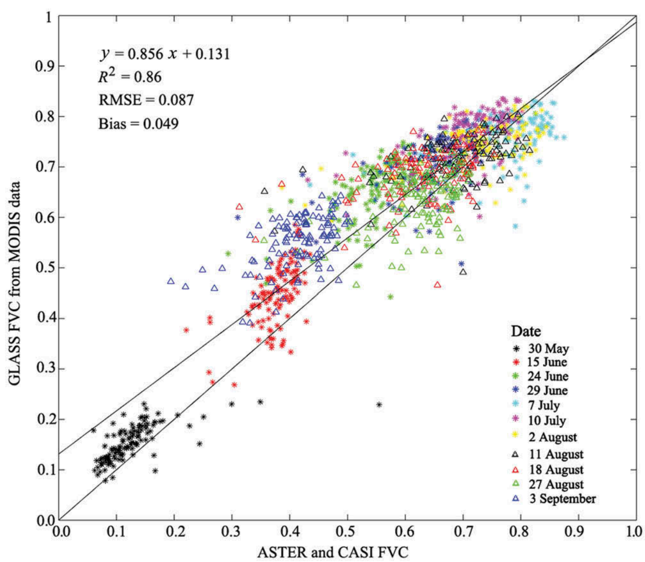

Figure 3. GLASS FVC from MODIS data versus the corresponding aggregated FVC from ASTER and CASI FVC.

satisfactory performance of the GLASS FVC product. Furthermore, most of the scatter points with moderate FVC values were just above the reference line which indicated the GLASS FVC were slightly higher than the reference FVC. These FVC points were mostly from 15 June, 24 June and 3 September, which were in the corn growth periods with rapid FVC variations. These results were consistent with the findings in the analysis of the temporal FVC variation aforementioned. The main reason might be the uncertainties from temporally interpolated GLASS FVC in the periods of rapid FVC variation and the residual errors of the statistical model to transfer the field FVC measurements to high spatial resolution FVC maps. Considering these uncertainties, the deviation of the GLASS FVC in the rapid FVC variation periods of corn was acceptable. Quantitatively, the performance of the GLASS FVC (R^2 = 0.86, RMSE = 0.087, Bias = 0.0149) in the agriculture region was satisfactory. The accuracy performance of the GLASS FVC product in the same region was also better than that of the GEOV1 FVC product (R^2 = 0.71, RMSE = 0.193) using the same reference FVC maps, and the GEOV1 FVC presented even higher overestimation of FVC with moderate values (Mu et al. 2015). These results further indicated the satisfactory performance and reliability of the GLASS FVC product in the agriculture region.

4. Conclusion

The GLASS FVC product generated from MODIS data was validated in an agriculture region based on time series field FVC measurements covering the whole crop growing season in 2012. The validation results showed that the time series GLASS FVC profiles were consistent with the crop growing characteristics and the overall performance of GLASS FVC product was satisfactory with R^2 equal to 0.86 and RMSE equal to 0.087, which was better than the performance of GEOV1 FVC product in the same region using the same reference FVC data. Therefore, it could be concluded that the GLASS FVC product achieved acceptable performance over agriculture region and would be a reliable FVC data source for agriculture monitoring related applications. Further work should focus on extensive assessments of the GLASS FVC product using more ground data over other vegetation types.

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Conflicts of Interest

The authors declare no conflict of interest.

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