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Intercomparison of Landsat albedo retrieval techniques and evaluation against in situ measurements across the US SURFRAD network

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ABSTRACT

Surface albedo is an essential parameter not only for developing climate models, but also for most energy balance studies. While climate models are usually applied at coarse resolution, the energy balance studies, which are mainly focused on agricultural applications, require a high spatial resolution. In this context Landsat is one of the most used remote sensing sensors.

The albedo, estimated through the angular integration of the Bidirectional Reflectance Distribution Function (BRDF), requires an appropriate angular sampling of the surface. However, Landsat sampling characteristics, with nearly constant observation geometry and low illumination variation, prevent from deriving a surface albedo product.

In this paper we present an algorithm to derive a Landsat surface albedo based on the BRDF parameters estimated from the MODerate Resolution Imaging Spectroradiometer (MODIS) Climate Modeling Grid (CMG) surface reflectance product (M{O,Y}D09) using the VJB method (Vermote, Justice, & Bréon, 2009). We base our method on Landsat unsupervised classification to disaggregate the BRDF parameters to the Landsat spatial resolution. We tested the proposed algorithm over five different sites of the US Surface Radiation (SURFRAD) network and inter-compare our results with Shuai, Masek, Gao, and Schaaf (2011) method, which also provides Landsat albedo. The results show that with the proposed method we can derive the surface albedo with a Root Mean Square Error (RMSE) of 0.015 (7%). This result supposes an improvement of 5% in the RMSE compared to Shuai et al.'s (2011) method (with a RMSE of 0.024, 12%) that is mainly determined by the correction of the negative bias (lower retrieved albedo than in situ data).

1. Introduction

Surface albedo is a key radiation parameter required for modeling the earth's energy budget and the land-atmosphere radiative interactions. It is a crucial parameter in determining the magnitude of energy fluxes in the soil–plant–atmosphere continuum (Bonan, 2008; Chapin, Randerson, McGuire, Foley, & Field, 2008), affecting surface temperature, evaporation and transpiration, cloud formation and precipitation, thus ultimately impacting gross primary productivity (Dickinson, 1983; Lawrence & Slingo, 2004; Ollinger et al., 2008; Sellers et al., 1997).

Detailed knowledge of land surface fluxes, especially latent and sensible components, is important for monitoring the climate of land surface, for evaluating parameterization schemes in weather and climate models used to predict fluxes exchanges between the surface and the lower atmosphere, and for agricultural applications such as irrigation scheduling (Courault, Seguin, & Olioso, 2005). It has been well recognized that surface albedo is among the main radiative uncertainties in current climate modeling (GCOS, 2011). An accuracy requirement of 5% is suggested by the Global Climate Observing System (GCOS, 2011) for albedo characterization at spatial and temporal scales compatible with climate studies. In fact, a sensitivity analysis estimating the albedo uncertainties impact on climate modeling showed that absolute albedo accuracy between ± 0.02 and ± 0.03, equivalent to an uncertainty of ± 10 W m^{-2} of the net radiation, results in significant changes in regional climate simulations (Nobre, Sellers, & Shukla, 1991; Sellers et al., 1995).

Albedo is highly variable in space and time, both as a result of changes in surface properties (e.g. snow deposition or sea-ice growth and melting, changes in soil moisture and vegetation cover) and as a function of changes in the illumination conditions (solar angular position, atmospheric and cloud properties). The increasing spatial resolution of modern climate models and the high spatial resolution required by most energy balance studies (<100 m) makes it necessary to examine spatial features of global surface albedo. The surface albedo is estimated at in situ level either with albedometers or through several directional surface reflectance measurements using a goniometric system (Liang,

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Li, & Wang, 2012). These measurements, though, demand a high logistical requirement and only few surfaces can be characterized and measured. In this context, and in order to account a wide range surface cover types, remote sensing fulfills an important role in accurate retrievals of surface albedo. Consequently, there are several albedo products derived from different satellite sensor data, such as the MODerate Resolution Imaging Spectroradiometer (MODIS, Schaaf et al., 2002), the Advanced Very High Resolution Radiometer (AVHRR, Csiszar & Gutman, 1999), the Polarization and Directionality of the Earth Reflectance (POLDER, Maignan, Breon, & Lacaze, 2004) and the Meteosat Second Generation (MSG, Carrer, Roujean, & Meurey, 2010). However, in some cases the estimation of surface albedo from remotely sensed data is a challenging problem due to the low angular sampling of the sensor considered. This is the case of Landsat satellite series, which has the potential to provide medium resolution (30 m) images. As a consequence, some energy balance studies that need the surface albedo as input parameter consider the surface reflectance as an equivalent to the surface albedo, while this approximation just applies to Lambertian surfaces (Nicodemus, Richmond, Hsia, Ginsberg, & Limperis, 1977). Recently, Mattar et al. (2014) presented a study about the impact of this approach concluding that it can lead to significant errors not only on the fluxes but also on the evapotranspiration product.

Shuai, Masek, Gao, and Schaaf (2011) presented a methodology to generate a Landsat surface albedo product based on the MODIS Bidirectional Reflectance Distribution Function (BRDF) MDC43 product at 500 m (Schaaf et al., 2002). By using an unsupervised Landsat classification, they select for each class those MODIS pixels that are homogeneous at Landsat resolution. Then, they derive directly the surface albedo from the spectral Albedo-to-Nadir Reflectance ratios for each class and estimate the broadband albedo using the narrow to broadband equation proposed by Liang (2000). This method presents a Root Mean Square Error (RMSE) generally less than 0.03, but it is mostly determined by a negative bias (lower retrieved albedo than in situ data). Román et al. (2013) evaluated this Landsat albedo product by using field and airborne measurements. Their results also show a negative bias in the order of 0.03. The authors discussed that the bias could be consequence of some systematic and random errors on the Landsat albedo processing chain. Among the possible sources they suggested are the following: errors due to slight overcorrection in the reflectance retrieval, small differences in the Relative Spectral Response (RSR) or the assumption of spatial/temporal uniformity at the Landsat (30 m) pixel scale.

The objective of this paper is to present a method that improves upon the Shuai et al. (2011) albedo product, hereafter referred as the standard Landsat albedo. The algorithm presented is based on the disaggregation of the BRDF parameters from MODIS to Landsat spatial resolution by matrix inversion and exploiting the information from all the pixels along the scene. The inputs of the method are the unsupervised Landsat classification and the MODIS Climate Modelling Grid (CMG) BRDF. Thus, the method proposed has three main differences compared to the original Landsat albedo. First, we avoid the selection of homogeneous MODIS pixels at Landsat spatial resolution, which is based on a threshold to define the purest pixels and assumes the spatial uniformity at Landsat pixel scale. Román et al. (2013) pointed out that this assumption could be a possible source of errors by including heterogeneous patterns of the surface into the same class at Landsat scale. Second, we derive the BRDF from MODIS CMG surface reflectance instead of working on 500 m spatial resolution. Working with a coarser resolution compared to higher resolution may introduce some errors in the disaggregation of CMG pixels since it decreases the amount of MODIS pixels through each Landsat scene and, therefore, the information available for the matrix inversion. However, the 500 m surface reflectance product presents a shift in its grid that increases with the view zenith angle and results in a weak relation between the location of the grid cells and their observations (Tan et al., 2006). Consequently, this may introduce some noise in the BRDF inversion, which requires several observation geometries. Thus, working with aggregated MODIS data (such as the CMG product) can minimize this effect (Tan et al., 2006). Of course, CMG resolution may be coarse and this error can also be minimized with a better spatial resolution by using the 1 km aggregated product.

Third, the last difference with Shuai et al. (2011) method is that we use a different BRDF inversion algorithm instead of the official MDC43 product. The method used in this paper was presented by Vermote, Justice, and Bréon (2009) (hereafter referred as VJB method). Compared to the official product, it permits more accurate tracking of vegetation phenology and retains the highest temporal resolution (daily, cloud cover permitting) without the noise generated by the day-to-day changes in observation geometry. Bréon and Vermote (2012) compared this method with the MCD43 MODIS product for the correction of the surface reflectance time series. Their results showed that the performances of the two approaches are very similar, demonstrating that a simple four-parameter NDVI-scaled model performs as well as a more complex model with many more degrees of freedom. Abelleyra and Verón (2014) supported recently these conclusions at higher spatial resolution by comparing (at 250 m spatial resolution) the surface reflectance corrected for the BRDF using the VJB method to the BRDF correction using the MCD43 product. Additionally, the VJB method has been also applied satisfactorily to estimate BRDF-adjusted surface reflectance (Claverie et al., 2013).

2. Methodology

2.1. BRDF model

Following Vermote et al. (2009) notation the surface reflectance (ρ) is written as:

$$\rho(\theta_s, \theta_v, \phi) = k_0\left[1 + \frac{k_1}{k_0}F_1(\theta_s, \theta_v, \phi) + \frac{k_2}{k_0}F_2(\theta_s, \theta_v, \phi)\right] \quad (1)$$

where θ_s is the sun zenith angle, θ_v is the view zenith angle, ϕ is the relative azimuth angle, F_1 is the volume scattering kernel, based on the Rossthick function derived by Roujean, Leroy, and Deschamps (1992) and F_2 is the geometric kernel, based on the Li-sparse model (Li & Strahler, 1986) but considering the reciprocal form given by Lucht (1998). Although these are the models used in the MCD43 product, in order to derive the BRDF with the VJB method, we consider the same models but corrected for the Hot-Spot process proposed by Maignan et al. (2004). F_1 and F_2 are fixed functions of the observation geometry, but k_0, k_1, and k_2 are free parameters. Following this notation, we use V as k_1/k_0 and R for k_2/k_0.

For view-illumination geometries typical of medium-resolution sensors such as MODIS, in order to obtain enough bidirectional observations to retrieve the BRDF free parameters, a period of sequential measurement is usually needed to accumulate sufficient observations. During this temporal window the model parameters are assumed to be constant. This method is currently used to derive the MCD43 product, which combines registered, multidate, multiband, atmospherically corrected surface reflectance data from Terra and Aqua data to fit a BRDF in seven spectral bands over a composite period of 16 days when the target is supposed to be stable. This product is produced every eight days, although it is based on the data acquired during the 16 day composite period after the date specified.

2.2. VJB method

Looking for an improvement in the albedo temporal resolution that mitigated the assumption of a stable target, Vermote et al. (2009) presented the VJB method that assumes that the BRDF shape variations throughout a year are limited and linked to the Normalized Difference Vegetation Index (NDVI). This method accounts for the fact that the