AN INTEGRATED REMOTE SENSING SYSTEM FOR LARGE SCALE ECOLOGICAL RESEARCH

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ABSTRACT: Remote sensing is the only technology that can systematically monitor physical properties of the biosphere over a vast region. However, it is still a challenge to make these measures meaningful for ecological research. Here we integrate a remote sensing pre-processing/analysis system, Eco-***i***RS, which consists of three-subsystems: An atmospheric correction model, a shadow/cloud removal model and an advanced spectral mixture analysis model (AutoMCU). We use atmospheric correction software packages (ACORN) to remove the effects of molecular and aerosol scatterings and water vapor absorption from an image, and to convert digital raw image data to surface reflectance. Contaminations (shadow and cloud cover) in an image can be removed based upon their properties in the optical and thermal spectral regions. Finally, we used AutoMCU that iteratively unmix each pixel using selected spectral endmembers based upon the rule of Monte Carlo simulation. The outcomes of Eco-***i***RS include green vegetation, non-photosynthetically active vegetation and soil fractions. These data are pivotal parameters for estimating carbon stocks and fluxes, and determining the impacts of natural and anthropogenic perturbations in terrestrial environments.

1. INTRODUCTION

Global climate change was used to be a myth that haunted human-beings implying the road to perdition in the foreseeable future. Recently, the Intergovernmental Panel on Climate Change (IPCC) has stated that the changes of biosphere are no longer suspicious after investigating more than a century of observations acquired from atmosphere, ocean and lands (IPCC, 2007). Mean surface temperature elevated about 1°C since the industrial revolution and atmosphere CO_2 concentration has increased from 280 ppm to 380 ppm; and the increase of temperature in the next century may not be linear but exponential (Hansen et al., 2006).

Limited manpower is the main constraint for frequent monitoring and assessment of ramifications of global change on ecosystems over a broad region. In most cases, million hectares of lands are managed by only a handful of staff. Therefore, an effective monitoring protocol is indeed needed. Remote sensing is the only technology that can systematically monitor physical properties of the biosphere over a vast region, and it has been heavily utilized in the recent decades (DeFries, 2008). However, it is still challenging to make these measures meaningful for terrestrial ecological research (Asner et al., 2009). Here we design a remote sensing protocol that can produce a set of derived images that are useful for monitoring the metabolism of natural settings.

2. SYSTEM REQUIREMENTS

Here we integrate a remote sensing pre-processing/analysis system termed Eco***i***RS (Ecosystem complexity observation by an ***i***ntegrated Remote Sensing system). A similar system CLAS (the Carnegie Landsat Analysis System) developed by Asner et al. (2009) was used for rapid mapping of forest cover, deforestation and disturbance over vast tropical forested regions. Eco***i***RS expands the applications to include not only other perturbations in different biomes such as drought in the temperate zone, and tropical cyclones and alien non-native species in tropical and sub-tropical regions, but the ability to quantify carbon budgets. The basic requirements for Eco***i***RS include: (*i*) Systematicity of data processing protocol, (*ii*) flexibility of satellite images and (*iii*) applicability to a high performance desktop personal computer (PC). A systematic data processing procedure is essential for effective analysis of a large volume of remotely sensed data. It would significantly reduce human error that could cause cascading effects on outcomes. In many undeveloped or developing countries in the tropical and subtropical zones, spaceborne images with public assess are the only available remotely sensed data. In additional, land surfaces of the regions are frequently covered by cloud cover, which often makes images unusable. Therefore, Eco***i***RS should be able to ingest different type of free satellite images to maximize the possibility of monitoring land surfaces. These public satellite data include the Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) on the Landsat platforms, the Moderate Resolution Imaging Spectroradiometer (MODIS) on Terra and Aqua and Hyperion on Earth Observing 1 (EO-1). Finally, with the advancement of modern technology, the performance of a personal computer with a 64-bit Windows operating system (e.g., Windows XP 64-bit, Windows 7) is not far away from high performance Linux computer cluster (Asner et al., 2008) when dealing with a certain size (e.g., 1 gigabyte) of remotely sensed images but at much lower cost. Therefore, it is pivotal to design Eco***i***RS to be compatible with a personal computer that would make it as a feasible tool for research institutes with limited funding sources and facility.

3. MODEL DESCRIPTION

Eco***i***RS consists of three main functions: (*i*) Atmospheric correction to reduce atmospheric effects obscuring land surface reflective properties such as molecular and aerosol scatterings and water vapor absorption; (*ii*) cloud and shadow removal to mask out thick cloud cover and shadow generated by terrain and cloud; (*iii*) spectral mixture analysis to extract sub-pixel information of abundance of photosynthetically active vegetation (PV), non-photosynthetically active vegetation (NPV) and soil substrate cover fractions (Figure 1). Selection of analytical tools to accomplish each task was based upon the principles of simplicity, automation and accuracy.

3.1. Atmospheric correction

The software used for Eco***i***RS to minimize the effects of atmospheric effects within an image is the Atmospheric COrrection Now (ACORN, ImSpec, Palmdale, California, USA) version 6b. ACORN is a MODTRAN4 (MODerate spectral resolution atmospheric TRANSsmittance algorithm and computer model version 4) based atmospheric correction tool (Berk et al., 1999) to produce high quality surface reflectance without ground measurements. ACORN provides two main modules for reducing atmospheric effects in multispectral and hyperspectral images within the spectral range of 350-2500 nm. Eco***i***RS switches between multispectral and hyperspectral modes when processing Landsat TM/ETM+ and Hyperion images, respectively. Note that Eco***i***RS currently also accepts the MODIS 8-Day 500 m surface reflectance product (MOD09A1), but the system would bypass atmospheric correction since these images have been atmospherically corrected before data acquisition.

ACORN requires input images to be converted as 16-bit radiance (W $m^{-2}\mu m^{-1}sr^{-1}$) before further processes. Landsat images obtained from Internet (e.g., the USGS Global Visualization Viewer [GLOVIS]: http://glovis.usgs.gov/) are usually in the form of a digital number (DN) and it needs to be converted to radiance by referring to coefficients provided by the official website (http://landsathandbook.gsfc.nasa.gov/). On the other hand, Hyperion downloaded from GLOVIS are at the level of 1GST (radiometrically and geometrically corrected data) can be directly used without conversion since the default form of 1GST data is in radiance. Most information required for performing atmospheric correction can be found in the metadata except for atmospheric water vapor and atmosphere visibility. For the multispectral mode, only one value of each parameter can be assigned for each image. According to the ACORN user manual (ACORN, 2008), a typical water vapor amount for an arid region would be 15 mm and 25 mm for a humid area; and an average visibility is about 100 km and 20 km for a hazy condition. Therefore, values within these ranges should be provided by users. In many cases, users can refer to an international network of precipitable water vapor estimation for setting up proper parameters (SuomiNet, http://www.suominet.ucar.edu/). For the hyperspectral mode, water vapor is retrieved from the image on a pixel-by-pixel basis using the water vapor absorption bands at 940 and/or 1150 nm and Eco***i***RS arbitrarily selects both bands for the process. Per pixel visibility is estimated from the Hyperion data using nonlinear least-squares spectral fitting between their radiance spectra and MODTRAN modeled radiance with the aerosol optical depth as the primary fitting parameter. Detailed information of the characteristics and computation algorithms of ACORN can be found in Kruse (2004).

3.2. Cloud and shadow removal

Cloud and shadow are main “noises” for remote sensing land surface research that are commonly observed in the tropical/subtropical zones and mountainous regions, respectively. Eco***i***RS implements a modified version of Irish et al. (2006) to remove cloud cover from Landsat images. Reflectance of cloud cover is relatively high in the visible region (400-700 nm) especially in the red region (about 600-700 nm). In addition, the temperature is relatively lower comparing with other land objects, which can be retrieved by utilizing conversion coefficients provided by the Landsat official website. Therefore, we label a Landsat cloud pixel if it reflects more than 35% of energy in band 3 (630-690 nm) with image temperature greater than 290 ºK (Irish et al. 2006). Since the majority of monitored natural areas are highly vegetated, an additional threshold of greenness the Normalized Difference Vegetation Index (NDVI) less than 0.5 was set to enhance the algorithm since NDVI is very sensitive to cloud cover. For MODIS and Hyperion, only the range of cloud endmembers in the optical region (350-2500 nm) for each band was used (n > 1000) to map cloud cover (Table 1) since there are lacking of spatially corresponding in sync thermal data available. The criterion of for setting values is to subtract one standard deviation from the mean by referring to endmember values for each band. Overall, results are satisfactory based upon visual assessment.

Shadow can suppress reflectance of land surfaces and introduces uncertainty to the analysis. More than 1000 shadow endmembers were selected from Landsat TM and ETM+ (n = 20), and Hyperion (n = 35) images. Values below the one standard deviation above the mean for each band are defined as shadow pixels. Note that no shadow mask was applied to MODIS images since shaded areas are usually not discernible at the spatial resolution of 500 m.

3.3. Spectral mixture analysis

The core of Eco***i***RS is AutoMCU (an Automated Monte Carlo Unmixing), which is an advanced spectral mixture analysis model. Spectral mixture analysis is a mathematical approach often used to derive sub-pixel cover fractions of land surface materials acquired from remotely sensed data (Adams et al., 1993). This method is ideal for use in natural settings where sub-pixel cover variation is high. Each endmember component contributes to the pixel-level spectral reflectance (ρ_{pixel}) as the linear combination of endmember (e) spectra:

$$\rho_{\mathrm{pixel}} = \Sigma[\rho_{\mathrm{e}} \bullet C_{\mathrm{e}}] + \varepsilon$$

$$= [\rho_{\mathrm{PV}} \bullet C_{\mathrm{PV}} + \rho_{\mathrm{NPV}} \bullet C_{\mathrm{NPV}} + \rho_{\mathrm{soil}} \bullet C_{\mathrm{soil}}] + \varepsilon \quad (1)$$

$$\Sigma[C_{\mathrm{e}}] = 1.0 \quad (2)$$

where ρ and C are the reflectance and cover fraction of each endmember (photosynthetically active vegetation [PV], non-photosynthetically active vegetation [NPV] and soil), respectively, and ε is the error term (eq. 1). Eq. 2 indicates that the endmembers sum to unity. Asner et al. (2000) suggested that there were a number of endmember combinations that can produce a particular spectral signal, so a wide range of numerically acceptable unmixing results for any image pixel were possible. Hence, Automated Monte Carlo Unmixing (AutoMCU), a probabilistic spectral mixture analysis technique (Asner and Lobell, 2000; Asner and Heidebrecht, 2002) was implemented to account for this natural variability (Asner, 1998) through iterative random selection of endmember reflectance from 'bundles' (Bateson et al., 2000). Endmember bundles for NPV and soils can be directly acquired using a field spectroradiometer at a 1 nm spectral resolution (Huang et al., 2007). There are two approaches to acquire PV endmembers. In some cases, top-layer canopy sunlit leaves can be collected by a tree climber or using a shotgun (Martin et al., 2008). Hemispheric leaf spectra were generated by an integrating sphere and were also collected using a field spectroradiometer (Asner and Martin, 2008); these were converted to canopy reflectance using canopy radiative transfer (Li and Strahler, 1992). However, in most cases, it is very difficult to collect PV spectra from field due to the high stature of vegetation canopy (e.g., tropical rainforest). Therefore, we extracted PV endmembers from atmospherically corrected Hyperion images acquired in these settings with extremely high canopy closure. High resolution spectra were convolved to match with the spectral profiles of selected images (TM/ETM+, MODIS, Hyperion).

There are two options available for AutoMCU: Multispectral and hyperspectral modes. In the multispectral mode, original spectral profiles are used to estimate proportions of PV, NPV and soil cover in each pixel. According to Asner et al. (2003) and Huang et al. (2007), 250 times of repetition for each pixel should be sufficient. Histograms of PV, NPV and should be in the shape of normal distribution with high kurtosis (a measure of peakedness), or AutoMCU will reject the process and request another round of unmixing. In the hyperspectral mode (for Hyperion only), AutoMCU uses the tied-shortwave infrared spectra technique. The difference of spectral signatures among PV, NPV and soils is most distinguishable within a part of shortwave infrared region (2000-2400 nm), and it can be further amplified by 'tying' these spectra at 2022 nm (Asner and Lobell, 2000). Repetition of 250 times of unmixing was also applied for each Hyperion pixel.

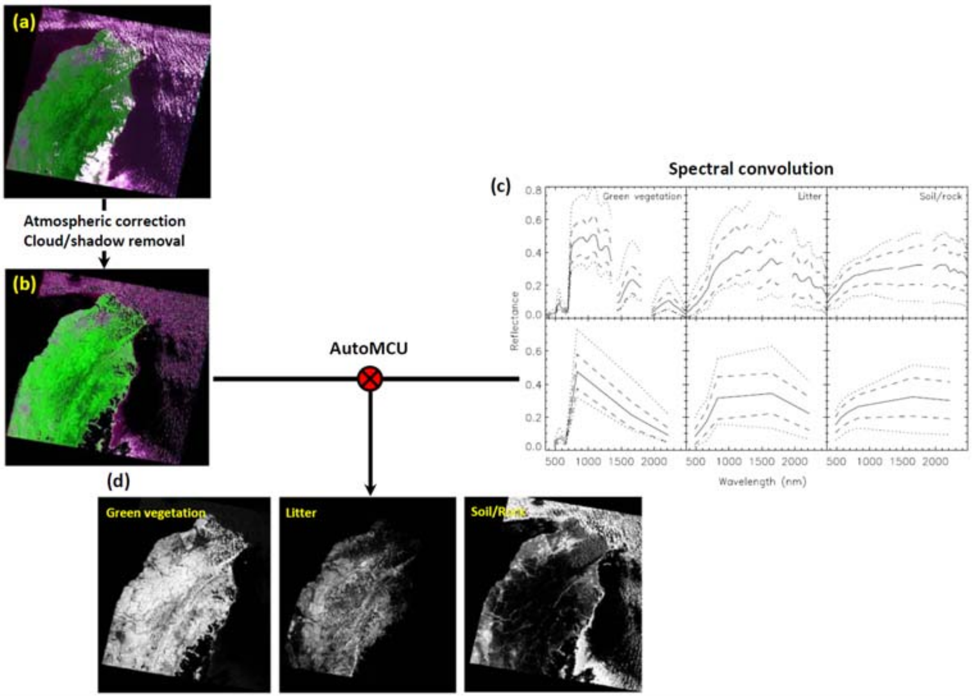

Figure 1. A conceptual model for Eco***i***RS. The brighter pixels in (d) indicate higher values.

3. MODEL APPLICATIONS

The main outcomes Eco***i***RS include PV, NPV and soil cover fractions. These data are crucial parameters for estimating carbon stocks (Huang et al., 2007; Huang et al., 2009) and fluxes (Huang et al., 2008; Huang and Asner, 2010) in terrestrial environments, and may be useful for determining the impacts of natural (e.g., tropical cyclones) and anthropogenic perturbations (Asner et al., 2009).

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