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Editorial

Quantitative Remote Sensing of Land Surface Variables: Progress and Perspective

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1. Introduction

The land is of particular importance to the human being, not only because it is our, as well as terrestrial biomes', habitat, but the land surface also plays a unique role in the Earth system. For example, it regulates the climate through exchange of matter, energy, and momentum with the atmosphere [1]. Data on the status and dynamics of the land surface variables are essential for understanding the land surface processes and entangling interactions between the land and other Earth system components. Since the emergence of remote sensing, the land surface is among its key study domains.

The quantitative remote sensing system does not directly measure land surface parameters of interest. Instead, the signature remote sensors receive is electromagnetic radiation reflected, scattered, and emitted from both the surface and the atmosphere. The inversion algorithm is needed to obtain land surface parameters from remotely sensed data. It is not a trivia task to reliably retrieve land surface parameters since the remote sensing signature is a function of not only the variable of interest but also many other atmosphere and surface characteristics. Multifaceted aspects of the remote sensing data, such as the temporal, spectral, spatial, polarized information, as well as ancillary and prior knowledge, are typically used in a synthetic way to improve the quality of land parameter retrievals [2].

Numerous parameters regarding the land surface properties can now be estimated with the help of remote sensing, to name a few, surface cover type, snow cover and amount, surface altitude, surface radiative fluxes, biophysical parameters, biochemical variables, vegetation structure, and many other variables. With the maturity of the retrieval algorithms, many products of land surface variables have been generated from remotely sensed data by various agencies. For example, the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) land team produces 16 different products of land parameters [3]. The Global Land Surface Satellite (GLASS) Product suite includes 12 land variables [4]. The Satellite Application Facility on Climate Monitoring (CM SAF) develops dozens of real-time operational products and long-term climate data records of surface radiation, energy, and water fluxes [5]. The increased availability and improved quality of remote sensing land products have promoted their applications in various modeling and analytical studies and advanced our knowledge on global environmental changes as a unique source of observational evidence from the space-based perspective.

With the availability of more advanced remote sensing data from various types of instruments with different spectral characteristics and temporal and spatial resolutions, the field of quantitative land remote sensing is advancing at an unprecedented rate. Considerable effort has been devoted to the study of land remote sensing theory and methodology; development of retrieval algorithms to estimate land surface variables from remote sensing data; assessment of land remote sensing data and products by comparing them with in situ measurements, modeling results or other remote sensing products; and application of remote sensing data and products in answering various scientific problems. This special issue collected 11 papers on several areas of quantitative land remote sensing, which will be briefly summarized in the following section.

2. Contributions of the Special Issue

2.1. Algorithm Development

Algorithm development is still one of the most active research directions of quantitative land remote sensing. Six papers from this special issue focus on efforts to develop improved algorithms to estimate various key land parameters, thus advancing the applications of remote sensing to new areas or investigating the capability of emerging remote sensing technologies.

Satellite mapping of crop residue plays an important role in agricultural conservation as it is vital for preserving soil moisture, reducing erosion, and carbon sequestration. Hively et al. [6] mapped crop residue of farmlands with plow-till to continuous no-till management located in the Eastern Shore of Chesapeake Bay (Maryland, USA) using Worldview-3 shortwave infrared (SWIR) data. Statistical analysis between percent residue cover and SWIR spectral indices was developed using both polynomial and linear least squares regressions. Hively et al. [6] demonstrated that SWIR indices including the Shortwave Infrared Normalized Difference Residue Index (SINDRI) and the Lignin Cellulose Absorption Index (LCA) were most deterministic spectral indices for monitoring crop residue.

Harmful algal blooms (HAB) have become a major water quality issue in many parts of the world, especially in coastal waters where recreational use of water is severely affected by algal outbreaks. Using historical algal outbreaks paired with MODIS data, Karki et al. [7] developed data-driven prediction models for Charlotte County, in southwestern Florida, to predict the onset of algal blooms. Karki et al. [7] presented a prototype of an early warning system which is capable of providing two to three days advance warning of impending outbreaks. The developed system automatically downloads MODIS data over a study area, uses a multivariate regression model, and produces a spatial map of potential outbreaks. The model predictions were 90% for same-day mapping and 65%, 72%, and 71% for the one-, two-, and three-day advance warnings, providing effective tools for large scale, automated bloom monitoring.

Peterson et al. [8] utilized remote sensing, machine learning, and statistical modeling for improved in-land water resources management. In this study, the researchers developed a feature fusion approach based on canonical correlation analysis to extract pertinent spectral information, and then trained a predictive reflectance–suspended sediment concentration (SSC) model using a feed-forward neural network (FFNN), a cascade forward neural network (CFNN), and an extreme learning machine (ELM). These models were then used to predict SSC using Landsat images, providing sediment mapping, and management tools to improve sediment transport and monitoring along large fluvial systems.

With the recent advances in unmanned aerial vehicles (UAVs) and the proliferation of thermal infrared cameras, there is a need to review technical capabilities and efficacy of most popular thermal cameras. Sagan et al. [9] employed test sites located in Midwestern and Western parts of the United States representing temperate and arid ecosystems to evaluate three commercially available UAV thermal cameras, including ICI 8640 P-series, FLIR Vue Pro R 640, and thermoMap for their potential for forest monitoring, vegetation stress detection, and plant phenotyping. The authors used a suite of statistical analysis including analysis of variance (ANOVA), correlation analysis between camera temperature and plant biophysical and biochemical traits, and heritability in order to examine the sensitivity and utility of the cameras against selected plant phenotypic traits and in the detection of plant water stress. Additionally, a new method to evaluate image quality in terms of blur and focus at different scales, a non-reference image quality evaluator, was developed. The paper provided a first comprehensive review of these popular UAV thermal cameras for vegetation monitoring.

Because of the parallax effect, cloud coverage observed by the remote sensors may be inconsistent with the actual cloud conditions on the ground. Such solar-cloud-sensor geometry will lead to errors in retrieving land surface parameters directly from the remote sensing images. Wang et al. [10] investigated its impacts on downward shortwave radiation (DSR) and presented a geometry-based correction approach. The pixels affected by the parallax effect were first identified using the cloud geometry information. DSR was then calculated according to the actual cloud coverage conditions. Experiments with the MODIS data demonstrated the cloud parallax effect could cause discrepancy in DSR up to 80%.

Zhou et al. [11] presented a Data-Based Mechanistic (DBM) model to estimate LAI profile from MODIS time series data. The DBM model was trained with historical data of LAI and surface reflectance. The ensemble Kalman filter was then used to sequentially assimilate surface bidirectional reflectance observations with the DBM and canopy radiative transfer model to generate updated LAI estimates in an optimal way. The validation against field LAI measurements and high resolution LAI reference maps suggested the proposed approach improve accuracy of LAI retrievals and was able to generate a gap-free LAI time series.

2.2. Product Validation

Users of satellite products put a high priority on the accuracy of the satellite-generated products—and a product will be used only if it is reliable and therefore fully validated. The objective of validation efforts is to characterize product uncertainties and evaluate the performance of new retrieval algorithms. Multiple validation methods and activities are usually necessary to assess new satellite products compliance with specifications. For most of the standard land products, two methods have been widely used to validate and determine the uncertainties in retrievals derived from satellite measurements: The comparison with ground-based measurements and satellite products inter-comparison. This special issue collected three papers on product validation.

Campos-Taberner et al. [12] employed a multi-scale validation framework proposed by Committee on Earth Observation Satellites (CEOS) Land Product Validation (LPV) to comprehensively assess three coarse resolution LAI products over rice cropland, including MODIS (MOD15A2), Copernicus PROBA-V (GEOV1), and EUMETSAT Polar System (EPS) LAI products. High resolution LAI reference maps were first generated from Landsat-7/8 and Sentinel-2A and validated with in situ LAI collected over multiple sites during three rice seasons. All three LAI products are able to capture the rice phenology and agree well with the LAI reference maps with various levels of uncertainties.

Gallo et al. [13] presented the Land Product Characterization System (LPCS), a web-based validation framework developed by the National Oceanic and Atmospheric Administration (NOAA) and the U.S. Geological Survey (USGS) to provide ground-based and satellite-derived data products to the community and facilitate validation efforts. LPCS provides functionalities to search, access, and analyze various in situ and satellite data products, and perform co-registration and statistical comparison of products from different data sources through a single interface. LPCS includes standard products available from Landsat four to eight, MODIS onboard Terra and Aqua satellites, Suomi National Polar-Orbiting Partnership (S-NPP)/Joint Polar Satellite System (JPSS) Visible Infrared Imaging Radiometer Suite (VIIRS), the Geostationary Operational Environmental Satellite (GOES)-16 Advanced Baseline Imager (ABI), and some of the European Space Agency (ESA) Sentinel series. To illustrate the capabilities of LPCS, Gallo et al. [13] compared surface reflectance products derived from Landsat and MODIS in their paper.

The Landsat Burned Area Essential Climate Variable (BAECV) product is a 30 m resolution burned area product over the conterminous United States (CONUS) generated by the U.S. Geological Survey. Vanderhoof et al. [14] assessed the BAECV with burned area reference maps derived from high-resolution satellite images. A maximum likelihood supervised classifier trained with manually created burned data was used to generate the reference maps. This study supplemented the earlier validations of the BAECV where the independent Landsat data were used and avoided the errors induced by the data source itself. This study reported commission and omission errors at the pixel level as well as the landscape metrics at the patch level.

2.3. Soil Spectroscopy

Soil properties such as organic matter, available nutrients, heavy metals, clay content, water availability, and electrical conductivity, directly affect the soil coupled water, energy, carbon, and nutrient cycles. The assessment of soil properties is important to characterize the overall soil quality and improve soil management to address key challenges including food security, climate variability and change, environmental impacts, land degradation, and biodiversity. Two papers in this special issue presented nondestructive and cost-effective approaches to derive soil properties using soil spectroscopy measurements (from the visible to the short-wave infrared spectral domains) and quantitative mathematical models.

Liu et al. [15] used soil characteristics and hyperspectral measurements of cropland, grassland, and woodland topsoil samples collected across Europe from the European Commission Land Use/Land Cover Area Frame Survey (LUCAS) to evaluate the potential of Partial Least Squares (PLS) regression as a dimension reduction tool for soil spectra and the performance of the gradient-boosted decision tree (GBDT) method to assess soil properties. Results showed that the combined PLS-GBDT approach had better performance than PLS or GBDT alone and was able to retrieve soil organic carbon, total nitrogen content, and clay fraction with coefficients of determination varying from 0.658–0.679, 0.687–0.719, and 0.739–0.812, respectively.

Qi et al. [16] collected and analyzed soil spectra and soil samples from four watersheds in Israel and compared the relative performances of the linear multi-task learning (LMTL) algorithm and the partial least squares regression (PLS-R) single-task learning algorithm to derive different soil properties. The authors found that the multi-task algorithm had a slightly higher retrieval capability and was able to assess the organic matter with a good accuracy and a ratio of performance to deviation (RPD) higher than 2, the Ph, amount of nitrogen, phosphorus, and water content with a moderate accuracy (RPD between 1.4 and 2), and the amount of potassium and the electrical conductivity with a lower accuracy (RPD lower than 1.4).

Using field and laboratory-based spectroscopy, Liu et al. [15] and Qi et al. [16] demonstrated the potential of airborne and satellite hyperspectral measurements for large-scale soil property monitoring and mapping.

3. Conclusions

The application of remotely sensed data for land surface variables has been a major research focus for the remote sensing community since remote sensing data become available. The information derived from remote sensing of land surface variables continues to expand. The quantity and quality of land surface variables estimated from remote sensing data have significantly improved over more than half a century of development. Remote sensing data and products are playing an increasingly essential role in our understanding and modeling of land dynamics and processes. This special issue has collected 11 papers on this active research area. We thank the authors for their contributions and hope this collection will be of benefit to the remote sensing community as well as other interested readers.

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