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Editorial

Editorial for the Special Issue "Remote Sensing of Evapotranspiration (ET)"

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Received: 11 September 2019; Accepted: 15 September 2019; Published: 15 September 2019

Abstract: Evapotranspiration (ET) is a critical component of the water and energy balances, and the number of remote sensing-based ET products and estimation methods has increased in recent years. Various aspects of remote sensing of ET are reported in 11 papers published in this special issue. The major research topics covered by this special issue include inter-comparison and performance evaluation of widely used one- and two-source energy balance models, a new dual-source model (Soil Plant Atmosphere and Remote Sensing Evapotranspiration, SPARSE), and a process-based model (ETMonitor); assessment of multi-source (e.g., remote sensing, reanalysis, and land surface model) ET products; development or improvement of data fusion frameworks to provide continuous daily ET at a high spatial resolution (field-scale or 30 m) by fusing the advanced space-borne thermal emission reflectance radiometer (ASTER), the moderate resolution imaging spectroradiometer (MODIS), and Landsat data; and investigating uncertainties in ET estimates using an ET ensemble composed of 36 land surface models and four diagnostic datasets. The effects of the differences among ET products on water resources and ecosystem management were also investigated. More accurate ET estimates and improved understanding of remotely sensed ET products can help maximize crop productivity while minimizing water loses and management costs.

Keywords: data fusion; evapotranspiration partitioning; land surface model; process-based model; water stress

1. Introduction

Evapotranspiration (ET), a critical and major component of the water and energy balances, is a key variable for linking ecosystem functions and climate feedbacks [1], determination of crop water or irrigation requirements and crop coefficients [2], and estimation of productivity and water use efficiency of ecosystems [3,4]. Although the eddy covariance (EC) technique has been widely used for continuous measurements of ET in recent decades [5,6], it is not possible to measure ET by the EC technique at all places all the time and especially over heterogeneous landscapes. Thus, a wide range of remote sensing-based ET products at the global and regional scales has been developed in recent decades to complement the limited land surface coverage of the ground-based ET measurements [7–9]. These ET products include numerous remote sensing reanalysis-based [10–12], land surface model (LSM)-based [13,14], surface energy balance (SEB)-based [15–17], and empirical up-scaling of in situ ET observations [18,19]. The SEB-based models are gaining increased popularity because remote sensing in the thermal infrared provides information not only on the partitioning of the available energy to sensible and latent heat fluxes, but also on the predicting water stress levels [17,20]. However, a major shortcoming of SEB-based models is that they rely on available land surface temperature (LST) data from satellite observations. Consequently, SEB modeling estimates are not available for cloudy days.

Thus, the process-based ET models are gaining more acceptance to generate continuous ET estimates by utilizing a variety of biophysical parameters derived from microwave and optical remote sensing observations [21,22]. It is also recognized that there are large differences among a wide range of ET products. Validations and inter-comparisons of various ET models or ET products under diverse ecosystems and agrometeorological conditions are needed due to different levels of uncertainties and accuracies that vary over space and time [23,24].

Although several remote sensing-based ET products are available, these datasets cannot generally provide ET data at both higher spatial and temporal resolutions to derive field-scale ET estimates over heterogeneous landscapes due to satellite orbital dynamics and physical limitations of the satellite sensors. Thus, downscaling and data fusion approaches have been employed to improve the higher spatial and temporal resolutions of remote sensing-based ET products [25–28].

Accurate ET estimates are crucial to manage water resources and to assess the impacts of climate on agriculture and food security [29]. High uncertainty in ET estimates is a major obstacle to examine spatial and temporal variability in regional hydrology [30]. Thus, understanding the uncertainty of ET estimates can help to better determine water availability for agriculture and livelihoods.

This special issue compiles contributions on research related to the above-mentioned various aspects of remote sensing of ET. The major topics covered by the 11 papers in this special issue include inter-comparison and performance evaluation of several ET models or products, data fusion approach to generate higher spatial and temporal resolution ET products, model development and/or improvement, and investigating uncertainties in ET estimates. A short summary of the varied contributions to this special issue is presented in the next section.

2. Overview of Contributions

2.1. Inter-Comparison and Performance Evaluation of Several ET Models or Products

Yang et al. [31] compared three Two-Source Energy Balance (TSEB) models for estimating ET and its components (evaporation, E and transpiration, T) in semiarid climates of China. Those three TSEB models were: TSEB model with the Priestley–Taylor equation (TSEB-PT), TSEB model with the Penman–Monteith equation (TSEB-PM), and TSEB model using component temperatures derived from vegetation fractional cover and land surface temperature (VFC/LST) space (TSEB-TC-TS). The study provided valuable insights into understanding the performances of TSEB models with different temperature decomposition methods since they were responsible for the observed discrepancies in the partitioned E and T fluxes. Based on the soil wetness isoline in the VFC/LST space, the VFC/LST-based temperature decomposition method can add a further constraint on vegetation T. This could also be used as a substitution for the interactive procedure adopted in the TSEB model.

Grosso et al. [32] employed the Surface Energy Balance Algorithm for Land (SEBAL) in a salt-affected and water-stressed maize field using Landsat images to map the spatial structure of water fluxes and crop yield. The SEBAL results were compared with ET estimates of the Food and Agriculture Organization (FAO) method and three-dimensional soil–plant simulations. The study highlighted that the integration of SEBAL with field observations and soil–plant simulations could be beneficial for precision agriculture practices (e.g., precision irrigation).

Li et al. [33] evaluated four popular global ET products: Global Land Evaporation Amsterdam Model version 3.0a (GLEAM3.0a), Modern Era Retrospective-Analysis for Research and Applications-Land (MERRA-Land), Global Land Data Assimilation System version 2.0 with the Noah model (GLDAS2.0-Noah), and EartH2Observe ensemble (EartH2Observe-En) over China using a stratification method, six validation criteria, and EC measurements at 12 sites. The model performances were evaluated by biome, elevation, and climate regime as well. The study recommended the use of multi-source ET datasets since no ET product consistently performed best for the selected validation criterion.

Delogu et al. [34] assessed the model predictions of water stress and ET components for the two proposed versions (the "patch" and "layer" resistances network) of the new dual-source Soil Plant Atmosphere and Remote Sensing Evapotranspiration (SPARSE) model over 20 in situ datasets encompassing diverse vegetation and climate conditions. The SPARSE model showed good estimates of latent and sensible heat fluxes and water stress over a large range of leaf area indexes and contrasting water stress levels.

Zheng et al. [22] used ETMonitor, a process-based model, with satellite earth observation datasets as main inputs to derive daily ET by utilizing surface soil moisture from microwave remote sensing and LST from thermal remote sensing. Estimated daily ET showed good agreement with EC-measured ET in Northeastern Thailand.

Khand et al. [35] developed an automated modeling framework to construct daily time series of ET maps, addressing the challenges related to processing and gap filling of non-continuous satellite data using the moderate resolution imaging spectroradiometer (MODIS) imagery and the Surface Energy Balance System (SEBS) model. The daily ET maps generated by this modeling framework captured the spatial and temporal variations (2001–2014) of ET across Oklahoma, USA. The proposed ET modeling framework provided a pathway to construct daily time series of ET maps at a regional scale and highlighted a range of potential applications for making informed decision and policies.

Lu et al. [36] evaluated the effects of differences among five representative ET products (Australian Water Availability Project (AWAP) as a reference, ET product developed by Commonwealth Scientific and Industrial Research Organization (CSIRO), LSM-based ET product from GLDAS, remote sensing-based ET product from MODIS, and water budget-based ET product from TerraClimate) on water resources and ecosystem management in the Murrumbidgee River catchment in Australia. Large differences in ET budgets among these five ET products propagated into the estimates of mean annual runoff, soil water storage, and irrigation demands.

2.2. Data Fusion Approach to Generate Higher Spatial and Temporal Resolution ET Products

Considering the lack of concurrent higher spatial and temporal resolution ET products, Yi et al. [37] employed a data fusion framework for predicting continuous daily ET at the field-scale over heterogeneous agricultural areas of Northwest China by fusing the advanced space-borne thermal emission reflectance radiometer (ASTER) and the MODIS data. Through a combination with the linear unmixing-based method, the spatial and temporal adaptive reflectance fusion model (STARFM) was modified to generate high-resolution ET estimates over heterogeneous areas. As compared with the original STARFM, the modified STARFM showed a significant improvement in daily ET estimation, preserved more spatial details for heterogeneous agricultural fields, and provided field-to-field variability in water use.

Wang et al. [38] proposed an improved ET fusion method— the Spatio-temporal Adaptive Data Fusion Algorithm for EvapoTranspiration mapping (SADFAET)—by introducing critical surface temperature (the corresponding temperature to determine soil moisture), importing the weights of surface ET-indicative similarity (the influencing factor of ET), and modifying the spectral similarity (the differences in spectral characteristics of different spatial resolution images) for the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM). The study successfully fused daily MODIS and periodic Landsat 8 ET data in the SADFAET for producing ET at high spatial (30 m) and temporal (daily) resolutions.

2.3. Model Development and/or Improvement

Considering the knowledge gaps in differences among final ET estimates resulting from subjectivity in selecting "hot" and "cold" pixel pair, Dhungel and Barber [39] tested the assumption of low variability of surface properties by first applying an automated calibration pixel selection process for a SEB model—Mapping EvapoTranspiration at high Resolution with Internalized Calibration (METRIC). Consequently, they computed vertical near-surface temperature differences (dT) vs. surface temperature (Ts) relationships at all pixels, which could potentially be used for model calibration to explore ET variance among the outcomes from multiple calibration schemes where normalized difference vegetation index (NDVI) and Ts variability are intrinsically negligible. Significant variability in ET (ranging from 5% to 20%) and a high and statistically consistent variability in dT suggested that additional surface properties, which were not captured when using only NDVI and Ts, affected the calibration process. This approach of quantifying ET variability based on candidate pixel selection helps to quantify the biases inadvertently introduced by user subjectivity as well as to improve the model's usability and performance.

Zheng et al. [22] developed and applied a new scheme in ETMonitor, a process-based model, to take advantage of thermal remote sensing. In the improved scheme, the evaporation fraction was obtained by LST-vegetation index triangle method to estimate ET in clear days. The soil moisture stress index (SMSI) was defined to express the impact of soil moisture on ET. Clear sky SMSI, retrieved according to the estimated clear sky ET, was interpolated to cloudy days to obtain the SMSI for all sky conditions. Finally, interpolated spatio-temporal continuous SMSI was used to derive daily time-series ET.

Wang et al. [38] developed an improved ET fusion method (SADFAET) based on ESTARFM. The improvements in SADFAET were as follows: consideration of soil moisture by introducing the critical surface temperature while selecting similar pixels, use of multiple spectral bands, and introduction of the surface ET-indicative similarity to calculate the weights of similar pixels. This new method can effectively fuse ET at high and low spatial resolutions.

2.4. *Investigating Uncertainties in ET Estimates*

Jung et al. [40] investigated uncertainties in ET estimates over five different climatic regions in West Africa using an ET ensemble composed of 36 LSM experiments and four diagnostic datasets (GLEAM, ALEXI, MOD16, and FLUXNET). The LSM-based ET values had greater uncertainty estimates and larger seasonal variations than the diagnostic ET datasets. The LSM formulations and parameters had the largest impact on ET in humid regions (contributing to 90% of the ET uncertainty estimates), while precipitation contributed to the ET uncertainty primarily in arid regions. The results indicated that assimilating diagnostic ET datasets into LSMs or hydrological models could improve the accuracy of ET estimates.

3. Conclusions

The 11 papers published in this special issue highlight a variety of topics related to remote sensing of ET. This special issue provides valuable insights into understanding the performances of different ET models and products under diverse ecosystems and agrometeorological conditions. In addition, improvements on the ET models have also been proposed. Proposed ET data fusion approaches provide unique means of monitoring continuous daily ET at higher spatial resolutions (e.g., field-scale or less) over heterogeneous landscapes. More accurate ET estimates and improved understanding of remotely sensed ET products are crucial to maximize crop productivity while minimizing water losses and management costs.

Author Contributions: P.W. wrote the editorial and P.G. revised and contributed for intellectual contents.

Acknowledgments: We would like to thank all the authors who contributed to the special issue and the staff in the editorial office.

Conflicts of Interest: The authors declare no conflict of interest.

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