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Editorial

Advances in Land–Ocean Heat Fluxes Using Remote Sensing

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Abstract: Advanced remote sensing technology has provided spatially distributed variables for estimating land–ocean heat fluxes, allowing for practical applications in drought monitoring, water resources management, and climate assessment. This Special Issue includes several research studies using state-of-the-art algorithms for estimating downward longwave radiation, surface net radiation, latent heat flux, columnar atmospheric water vapor, fractional vegetation cover, and grassland aboveground biomass. This Special Issue intends to help scientists involved in global change research and practices better comprehend the strengths and disadvantages of the application of remote sensing for monitoring surface energy, water, and carbon budgets. The studies published in this Special Issue can be applied by natural resource management communities to enhance the characterization and assessment of land–ocean biophysical variables, as well as for more accurately partitioning heat flux into soil and vegetation based on the existing and forthcoming remote sensing data.

Keywords: land–ocean heat flux; downward longwave radiation; latent heat flux; fractional vegetation cover; remote sensing

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1. Introduction

The world is currently confronted with historically unprecedented climate challenges, particularly those related to land–ocean heat fluxes. To understand the exchanges between energy, water, and carbon among the atmosphere, land and ocean remote sensing has provided many observations, algorithms, and products to estimate and obtain energy and biophysical variables at a large scale [1–4]. Although these algorithms and products are widely applied to estimate regional or global heat fluxes, estimation results may differ greatly due to differences in these algorithms and the forcing inputs [5–7].

Currently, an increasing number of advanced remote sensing algorithms and strategies have been applied to estimate land–ocean variables, including downward shortwave radiation [8–10], longwave radiation [11–13], surface net radiation [14–16], latent heat flux [17–20], vegetation leaf area index [21–23], fractional vegetation cover [24–26], gross primary productivity [27–29], and soil moisture [30–32]. For example, Yao et al. [17] proposed a Bayesian model averaging (BMA) framework to integrate five traditional latent heat flux algorithms, including the Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm, the revised remote sensing-based Penman–Monteith algorithm, the Priestley–Taylor-based algorithm, the modified satellite-based Priestley–Taylor algorithm, and the semi-empirical Penman algorithm for improving global land surface latent heat flux estimation. Subsequently, Jia et al. [24] developed a fractional vegetation cover algorithm that is based on backpropagation neural networks (NNs) from PROSPECT + SAIL radiative transfer model simulations for GaoFen-1 (GF-1) satellite canopy reflectance and the corresponding fractional vegetation cover values. Additionally, Zhang et al. [10] introduced an improved thin-plate smoothing spline algorithm to locally "calibrate" the downward shortwave radiation product based on the reconstructed downward shortwave radiation data from surface meteorological observations. Recently, Xu et al. [14] designed a downscaling scheme to produce a long-term (2002–2013) high-spatial-resolution (0.05°) daily ocean surface net radiation from J-OFURO3 (the third-generation Japanese Ocean Flux Data Sets with Use of Remote Sensing Observations) data sets at 0.25° using Advanced Very-High-Resolution Radiometer (AVHRR) top-of-atmosphere (TOA) observations and other ancillary data. All in all, these novel remote sensing algorithms represent attractive and efficient approaches for estimating land–ocean biophysical variables of interest on all scales from different regional and global sites.

This Special Issue highlights the recent advances in land–ocean heat fluxes using remote sensing. As guest editors, our objective is to encourage leading scientists to focus on their research topics, using state-of-the science research methods in order to provide high-quality peer-reviewed articles for this Special Issue of *Remote Sensing*. We have accepted peer-reviewed manuscripts that focus on the retrieval and application of various land–ocean heat fluxes variables. The theme of this Special Issue includes the total ocean columnar atmospheric water vapor construction from microwave remote sensing data; Indian ocean dipole (IOD) index prediction from a convLSTM deep learning method; downscaling an evapotranspiration product using a deep learning method; the application of energy and water cycle key parameters; satellite-based estimation of land surface longwave radiation and latent heat flux; ocean surface net radiation estimation using satellite products; and land surface fractional vegetation cover and grassland aboveground biomass estimation from the optical remote sensing.

2. Overview of Contributions

The studies of this Special Issue cover a wide range of themes, from land surface energy variables estimation to terrestrial biophysical parameters retrieval, to ocean surface energy variables simulation. Here, we summarize the individual articles in the chronological order of acceptance.

First, Feng et al. [33] produced a daily global land-surface downward longwave radiation product with a 0.05 degree spatial resolution from 2000 to 2018 using the gradient boosting regression tree (GBRT) algorithm driven by air temperature, relative humidity, total column water vapor, downward shortwave radiation, and elevation. Compared with other global land surface radiation products, the generated land surface downward longwave radiation product performed better than the CERES-SYN (clouds and Earth's radiant energy system synoptic version 4.1) data set and ERA5 reanalysis product. The generated land surface downward longwave radiation product has a higher spatial resolution and accuracy than the existing radiation data sets.

Second, Liu et al. [34] developed a fractional vegetation cover estimation algorithm for Fengyun-3 (FY-3) reflectance data. For this algorithm, the PROSAIL model was selected to simulate high-quality training samples, including the simulated red and near-infrared (NIR) reflectance data and the corresponding fractional vegetation cover values. Then, a random forest (RF) regression algorithm for the fractional vegetation cover estimation was built from the samples. Thus, the fractional vegetation cover in 2015 was estimated using the developed RF regression algorithm. The validation showed that the proposed algorithm had a satisfactory performance based on the Earth Observation LABoratory (EOLAB) reference fractional vegetation cover data, which illustrated that FY-3 reflectance data were capable of estimating reliable fractional vegetation cover.

Third, Sun et al. [35] employed an optimal interpolation (OI) algorithm to generate a high-spatial-resolution global ocean columnar atmospheric water vapor product at 0.25 degree by fusing multiple microwave radiometer observations, including SSMIS (Special Sensor Microwave Imager Sounder), WindSat, AMSR-E (Advanced Microwave Scanning Radiometer for Earth Observing System sensor), AMSR2 (Advanced Microwave Scanning Radiometer 2), and HY-2A microwave radiometer. The validation results showed that the fusion products generated by merging AMSR2 and HY-2A microwave radiometer data have higher accuracy when compared with the water-vapor fusion products from AMSR-E data. Therefore, AMSR-E data can be replaced with AMSR2 and HY-2A microwave radiometer data.

Fourth, Chen et al. [36] evaluated the performance of the J-OFURO3 (the Japanese Ocean Flux Data Sets with Use of Remote Sensing Observations, version3) sea-surface net-radiation data set using buoy observations from 55 sites. The validation results showed that the overall accuracy of J-OFURO3 sea-surface net radiation was satisfactory, but an inconsistency issue occurred in long-term sea-surface net radiation variations. To overcome this issue, a simple but effective correction algorithm was proposed to correct the inconsistency of long-term sea-surface net-radiation variations. The results demonstrated that the corrected J-OFURO3 sea surface net radiation product variations were more reasonable, and its daily accuracy significantly improved.

Fifth, Yu et al. [37] estimated aboveground grassland biomass (AGB) using AVHRR, MODIS, meteorological data, ancillary information, and 75 AGB ground-observations from 1982 to 2018 in the Three-River Headwaters Region (TRHR) of China. To improve the spatial representativeness of point-based observations, the GBRT algorithm was used to upscale grassland AGB from point-based observations to a 1 km spatial resolution using MODIS, meteorological, and other ancillary data. Then, a GBRT algorithm was also used to upscale grassland AGB from a 1 km to 5 km spatial resolution using AVHRR and meteorological and other ancillary data. The model produced validation results that presented reasonable accuracy. This study also found that the annual variation in grassland AGB in the TRHR increased significantly from 1982 to 2018, and this might be attributed to increased precipitation and vegetation greening. A reliable long-term grassland AGB product in the TRHR during 1982–2018 was generated using the proposed GBRT algorithm.

Sixth, Zhang et al. [38] proposed a data-fusion framework based on an extremely randomized tree-fusion model (ERTFM) to produce high spatiotemporal resolution reflectance data by fusing the Chinese GaoFen-1 (GF-1) and MODIS reflectance data. Then, based on the fused high-spatiotemporal-resolution reflectance data, a modified-satellite Priestley–Taylor (MS–PT) model was used to estimate terrestrial latent heat fluxes. The validation results demonstrated that the fused reflectance data using ERTFM presented close similarity to the validated GF-1 images. Compared with other fusion methods, ERTFM had a better performance in predicting surface reflectance. Importantly, ERTFM can be applied to improve latent heat flux estimation with high spatiotemporal resolution and has shown a great potential to promote agricultural development and water resources management.

Seventh, Peng et al. [39] developed an empirical scheme that included two conditional algorithms: (1) Case 1 (when the length ratio of daytime (LRD) was greater than 0.4) using downward shortwave radiation as inputs and (2) Case 2 (LRD $\leq$ 0.4) using downward longwave radiation as inputs for ocean surface net radiation estimation. The validation results showed that the performance of the proposed empirical scheme was satisfactory for estimating ocean surface net radiation. However, because there were a limited number of samples, the performances of the proposed algorithms were poor in high-latitude areas, and the algorithms did not work in the case of LRD < 0.3.

Eighth, Li et al. [40] applied a convolutional LSTM (convLSTM) neural network to calculate the long-term Indian Ocean Dipole (IOD) index by predicting the sea surface temperature (SST) in the next seven months. Based on the analysis of complex temporal and spatial relationships among marine atmospheric data, the wind field signal information of the physical ocean was proposed to predict the IOD phenomenon from the combination of prior knowledge of the physical ocean with the deep learning method. The experimental results illustrated that the convLSTM could predict the anomaly of IOD better, and the IOD index could generally fit the real IOD index variation trend well, which had an important impact on the IOD phenomenon.

Ninth, Long and Cui [41] introduced a deep neural network-based global evapotranspiration product downscaling algorithm driven by satellite and meteorological data.

This downscaling algorithm was successfully used to downscale Global Land Evaporation Amsterdam Model (GLEAM) evapotranspiration product. The downscaled evapotranspiration was found to have a high spatial resolution but to be consistent with the original GLEAM evapotranspiration product. The validation at the Heihe River basin demonstrated that the downscaled GLEAM evapotranspiration had high accuracy compared to ground observations. The proposed downscaling algorithm bridges the gaps between the coarse evapotranspiration product and the required finer product for local users.

Tenth, He et al. [42] investigated the mechanism of drought over the Mongolian Plateau (MP) using MODIS, Himawari 8, and ERA5 reanalysis data sets. The aridity index (ADI) (the ratio of potential evapotranspiration to precipitation) is used to detect the variations in drought. The results illustrated that the annual average of ADI increased noticeably during 1979–2020. However, the temperature continued to increase from August to December during 2016–2020, which might lead to an increase in potential evapotranspiration and a decrease in soil moisture from August through December of the previous year. This study demonstrated that global warming, land degradation, and increased surface net radiation increase potential evapotranspiration and reduce soil moisture, leading to drought.

Eleventh, Jin et al. [43] documented that significant errors occurred when diurnal data were used to replace diurnal–nocturnal data to estimate the daily sea-air CO_2 flux (F). Considering that the errors were mainly controlled with the partial pressure of CO_2 in seawater (pCO_{2w}) and the sea surface temperature (SST) in the control experiment, pCO_{2w} and SST equations of the nocturnal effect of the CO_2 flux were established. The nocturnal effect reduces the errors associated with using diurnal data to estimate the CO_2 flux. The mean global daily CO_2 flux estimated from the nocturnal effect and the sub-regional pCO_{2w} algorithm (cor_F_{com}) was smaller by 0.75 mol m^{-2} y^{-1} than that based solely on the sub-regional pCO_{2w} algorithm (day_F_{com}).

More importantly, the above information illustrates how the unprecedented record length of earth observations from space-borne remote sensors, along with technological advances in observations, modelling and simulation, and advances in artificial intelligence (AI) techniques, enable new and transformative ways to undertake Earth System Science research and applications in general, including the separation, detection, and analysis of Land–Ocean fluxes. Combining those observations and methods, additional algorithms to monitor and predict significant climate events could and have been developed. For example, Geiss and Levy [44] developed algorithms to automate the detection of features (e.g., structure and phases of the Inter-Tropical Convergence Zone (ITCZ) and the Asian and Indian Monsoon) in climate data. Those automated and user-trained algorithms can spatially and temporally analyze data and detect the presence of features using multi-resolution analysis (MRA) via wavelet transform (WT), as well as fuzzy set theory (e.g., Bede [45]) rule/classification operators. They can search all locations in an image rather than a specific latitude band, and they can be applied to different data sets and locations without modification; moreover, the MRA makes it unnecessary to define a feature using preset quantitative criteria. Levy [46], Geiss et al. [47], and Levy et al. [48] applied those methods to 30-year record of daily TOA observations and other satellite ancillary data, including different satellite data analyzed by Kumar et al. [49] and latent and sensible heat flux over the global oceans retrieved from remote sensors and evaluated by Bentamy et al. [50], showing some skills in predicting breaks in the monsoon associated with intra-seasonal drought conditions, as defined by a monsoon break index developed from precipitation data by Kumar and Dessai [51].

3. Conclusions

Advanced remote sensing algorithms for estimating land and ocean heat fluxes variables are a challenging scientific topic that will remain of great interest for many scientists for upcoming decades. This Special Issue is aimed at summarizing the recent advances in land–ocean heat fluxes using remote sensing. In general, remote sensing can improve land–ocean heat flux estimations from three aspects, including algorithms development (empirical algorithms, physical algorithms, and hybrid algorithms), product generation (vegetation and carbon variables, water variables, and energy variables), and data applications (e.g., drought monitoring, El Nino and Southern Oscillation, Monsoon Intra-seasonal Oscillation, CO_2 flux analysis, and changing climate due to global warming). The manuscripts in this Special Issue represent some important and meaningful progress in estimating land and ocean heat fluxes variables using state-of-the-art satellite technology. Further work in this research area is required to develop hybrid algorithms by combining physical process and empirical parameters to better characterize land and ocean biophysical variables [52–55].

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