remote sensing

Editorial

Editorial for the Special Issue "Advances of Remote Sensing in the Analysis of the Spatial and Temporal Variability of Land Surface"

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1. Introduction

Land systems have taken a central role in major environmental/climatic issues of the Anthropocene, as they are the result of interacting natural and anthropic processes that are crucial for life on Earth. Land provides essential resources, such as food and energy, as well as important services (e.g., pollination, carbon sequestration, environmental protection) to human society. Land-surface changes are both drivers and consequences of natural and socio-ecological processes occurring over a huge range of temporal scales. Although the spatial scales of single land systems are generally local, the aggregated effect of pervasive land changes is a main factor in global environmental change [1]. Extensive scientific literature on multiple aspects of land dynamics is testimony to the increased interest of scholars from many different research fields. However, recent progress in these studies is mainly credited to major advances in the development and use of remote sensing technologies. The availability of data from diverse sensor types (LiDAR, multispectral, hyperspectral, laser and radar altimeters, stereographic pairs of aerial photographs, etc.) and different platforms (satellite, aircraft, spacecraft, HAPS—High-Altitude Pseudo Satellites, buoy, ship, helicopter, drone, etc.) is currently fuelling land dynamics research.

The richness of spatial and temporal observational scales, the development of "big data" and machine learning methods to extract information are helping scientists to gain new insights into the complexity of land conditions, enabling ever more reliable quantifications of rates and patterns of change. Satellite sensors, in particular, are able to provide comprehensive records of global land change dynamics over long time scales [2], thereby offering precious information on the spatial and temporal variability in land surface and the interplay between different geographical areas and different scales.

The increasing demand of remote sensing and geo-spatial data has also primed the development of Earth Observation programmes, such as the Copernicus Land Monitoring Service (https://land.copernicus.eu/, last accessed on 16 November 2022), which offers free and openly accessible products on the status and evolution of the land surface, or the USGS (U.S. Geological Survey) Earth Explorer data portal (https://earthexplorer.usgs.gov/, last accessed on 16 November 2022), which enables queries to view what data types are available in specific locations. Asian repositories too are disseminating free data, including land observation remote sensing images (e.g., https://www.isro.gov.in/VedasServices.html, https://gportal.jaxa.jp/gpr/search?tab=0; last accessed on 16 November 2022). We cannot neglect to mention the Google Earth Engine Platform, which includes a repository of spatial datasets, with a specific section devoted to Land Cover data (https://developers.google.com/earth-engine/datasets/tags/landcover; last accessed on 16 November 2022), encompassing more than forty years of historical imagery and scientific datasets, which are updated and expanded daily.

In such a context, the papers published in this Special Issue represent an interesting sample of the variety of targets, application purposes, datasets and analysis tools (Table 1).

Table 1. Main features of the contributions in the Special Issue on "Advances of Remote Sensing in the Analysis of the Spatial and Temporal Variability of Land Surface".

Reference	Study Area	Data	Target	Keywords
Chu L. et al. [3]	China	Global Human Modification (GHM); MODIS 8-day Land Surface Temperature	Island land cover classes (forest; shrubland; water; grassland; wetland; bareland; cropland; impervious surface)	human modification; land surface temperature; temperature zones; coastal islands
Szabó et al. [4]	Lake Tisza (Hungary)	Landsat series surface reflectance Level 2: Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI); normalized difference vegetation index (NDVI); modified normalized difference water index (MNDWI); digital bathymetry model (Water Directorate of Central Tisza Region—KÖTIVIZIG)	Wetlands: artificial lakes sedimentation and vegetation spread.	remote sensing; sedimentation; spectral indices; time-series analyses; vegetation change; wetland monitoring
Guo et al. [5]	Altai Mountains, Karakoram Mountains, Western Himalayas, Gongga Mountains, Tian Shan, and Nyainqentanglha Mountains (China)	Landsat; Sentinel-2; Meteorological data; MOD10A; SRTM DEM	Glaciers	glaciers; SLA; temporal variation; High Mountain Asia; temperature; precipitation
Guo et al. [6]	Qilian Mountains (China)	Landsat; MOD10A; SRTM DEM; Meteorological data; Equilibrium Line Altitude Data	Glaciers	snowline altitude; equilibrium line altitude; Qilian Mountains; climate
Nie et al. [7]	Yangquan Coal Mine area, Shanxi Province (China)	Landsat series Level 1: Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI) and TIRS (Thermal Infrared Sensor); ASTER digital elevation (GDEM—Global Digital Elevation Model); Google Earth satellite images; precipitation and temperature data by the China Meteorological Data Network; raw coal production from the Shanxi Statistical Yearbook and China Coal Industry Yearbook	Coal mining areas	topographic correction; ecological environment quality; temporal and spatial evolution; driving force; coal mining area
Qian et al. [8]	Guizhou province (China)	MOD09A1: surface reflectance; MOD11A1: surface temperature and radiation rate (LST); MOD13Q1: normalized vegetation index and enhanced vegetation index (NDVI/EVI); MOD16A2: transpiration product data; MOD43A3: surface albedo (AD); and MCD12Q1: IGBP global land cover data; ASTER GDEM administrative division map of the Guizhou province; China's National Forest Continuous Inventory data (NFCI)	Karst environments	rocky desertification. supervised classification method; MODIS data; feature extraction; spatial and temporal distribution.

Table 1. *Cont.*

Reference	Study Area	Data	Target	Keywords
Liu Y. et al. [9]	South America	Meteorological Data by the Climate Research Unit (CRU) Version 4.05 (monthly average gridded daily mean Temperature, Precipitation, and Potential Evapotranspiration); Hydrological Data (Actual Evapotranspiration and changes of terrestrial water storage (TWC) from the Gravity Recovery and Climate Experiment (GRACE) and its following project GRACE-FO); surface (Qs), subsurface (Qsb), and snowmelt runoff (Qsm) simulated by the Noah model by GLDAS; MOD13C2 Version 6; Future Climate data (CMIP6).	Land cover mosaics	actual evapotranspiration; multi-source remote sensing data; boruta algorithm; support vector regression; random forest; CMIP6
Mascolo L. et al. [10]	Spain	Sentinel-1	Agricultural crops	phenology; grid-based filter; SAR; Sentinel-1
Sassu et al. [11]	North-Eastern Sardinia (Italy)	UAV: hexacopter with Canon EOS 750D, DJI Phantom 4 Pro; GNSS Leica 900 RTK receiver; Field Measurements: vineyard's height, width, and canopy volume.	Agriculture: individual and aggregate vineyard's canopy volume	precision viticulture; TRV (Tree-Row-Volume); CHM (Canopy Height Model); unmanned aerial vehicle; digital models; grapevine canopy measurement
Filipponi et al. [12]	Italy	Sentinel-2; European Vegetation Archive (EVA) dataset PhenoCam Dataset V2.0	Forests	plant phenology; phenological metrics; vegetation; EO time series analysis; temporal discriminant; forest ecosystems; land surface phenology; Sentinel-2
Yuan S. et al. [13]	Middle-High Latitudes of the Northern Hemisphere	Global Land Surface Satellite (GLASS) AVHRR albedo; GLASS—Global Land Cover (GLASS-GLC); ERA5 reanalysis products	Stable land cover types (cropland; forest; grassland; tundra; barren land; snow/ice)	blue-sky albedo; spatiotemporal variation; snow cover; soil moisture; LAI
Santarsiero et al. [14]	Municipalities of Potenza, Matera, Scanzano Jonico, Policoro, Pignola, Melfi (Basilicata—Southern Italy)	Landsat TM/OLI; Orthophotos by the Italian Military Geographic Institute (IGMI); Geo-topographic regional database (GTDB) of Regional Spatial Data Infrastructure Basilicata Region	Urban and peri-urban areas	land take; remote sensing; SVM algorithm; change detection analysis; geographic information system
Imbrenda et al. [15]	Basilicata (Southern Italy)	Landsat MT; field measurements; orthophotos (1:10,000) from AGEA (Italian Agency for the Delivery in Agriculture) and MATTM (Ministry of the Environment and Protection of Land and Sea of Italy)	Protected areas	Natura 2000; habitat conservation; controlled disturbance; landsat; NDVI; land degradation; Southern Italy
Simoniello et al. [16]	South-Eastern Sardinia (Italy)	Airborne LiDAR data (RIEGL LMS-Q560 Full-Waveform scanner); Orthophotos (Digicam H39); Google Earth satellite images	Shrublands and rocky areas	full waveform; airborne laser scanner; raw intensity data; point cloud classification; balanced accuracy; shrublands

2. Contributions of the Special Issue

Chu et al. [3] assessed the link between human modifications (derived from the Global Human Modification (GHM) dataset that provides the cumulative human modification of terrestrial lands and their estimated impacts) and changes in land-surface temperature (LST) by MODIS (Moderate-resolution Imaging Spectroradiometer) 8-day temperature products. The case study is represented by the Hainan Island in China because this place has attracted a variety of human activities in the past few decades by increasing the number of residents and tourists and a high-speed urbanization, which have been linked to thermal environmental changes. The analysis showed that there was a positive correlation between the mean temperature (from the 17-year temperature in the period 2000–2016) and the human modification index for the analyzed year; comparing human modification against the land-use categories, impervious surfaces showed the highest average human modification index, while the forest land-cover classes the lowest. These results could contribute to the development of sustainable management and coastal ecosystem conservation plans.

Szabó et al. [4] proposed a method to determine the risk of vegetation spread in lakes using satellite images. Sedimentation and vegetation diffusion in artificial and natural lakes represent a significant and worldwide problem for water storage and biodiversity conservation. The method is based on time-series monitoring of the Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Difference Water Index (MNDWI) because the presence of aquatic plants indicates sedimentation and shallow water. Deep water is not favorable for most plant species that instead require shallow water; thus, the higher the vegetation density, the higher the sedimentation. On this basis, the authors also propose the Level of Sedimentation Risk Index (LoSRI) to account for the probability of sedimentation. The approach was developed and tested on a Hungarian lake (Lake Tisza) by analyzing a 33-year (1984–2017) Landsat time series and comparing bathymetry data. The most threatened water basins were related to smaller basins or more vegetated areas (high NDVI and low percentage of open water). By identifying sedimentation areas, the proposed method can represent a useful support for water management in shallow lakes.

Guo et al. [5] used optical data at different spatial and temporal resolutions to monitor glacier SnowLine Altitude (SLA), which is a fundamental parameter to evaluate glacier equilibrium and possible links and feedbacks to climate change. It provides valuable information for improving mass balance studies useful for snowmelt runoff and hydrological models. Landsat, Sentinel-2 and MODIS data were used to derive the glacier SLA at the end of the melt season across areas of High-Mountain Asia, impacted by different wind systems (the westerlies in the northwest and the Indian monsoon in the southwest). The variety of temporal and spatial resolution of the satellite datasets helped to reliably estimate SLA and analyze its relationship with temperature and precipitation over the past ~30 years, in a region where ground-based observations and/or regional-scale constraints are rare.

The analysis results show that the Altai and Karakoram mountains experienced an average increase of up to 137 m over the past 30 years, whereas the Western Himalayas and Gongga Mountains increased by 190–282 m in the same period. The study demonstrates that summer mean temperature is the primary factor influencing the observed glacier SLA changes across High-Mountain Asia, with precipitation also playing a major role in some regions. Cloud cover, which is especially prevalent in the southeastern Tibetan imagery, is the main drawback for reliable SLA estimations and represents the main limiting factor for extending this methodology to the entire High-Mountain Asia region. In a successive study, **Guo et al**. [6] focused on the Qilian Mountains by analysing Landsat and MODIS data. The study results confirm that temperature is the main factor affecting SLA change, and precipitation has a certain mitigating effect on glacier retreat caused by temperature rise. Among the interesting results of the study, there is the influence of the water vapor content in the summer air, which was observed to also increase at high altitudes. The importance of this parameter is crucial as it significantly increases the efficiency of the melting of snow and ice, which leads to further ice losses. Thus, the authors stress the need for further studies on this topic in future research about glacier change.

Nie et al. [7] introduced a topographic correction model to optimize the remote sensing ecological index (RSEI) for the evaluation of coal-mining areas. The optimized RSEI was adopted to assess the ecological status of the largest anthracite mine in China (Yangquan Coal Mine in the Shanxi Province) by analyzing a Landsat time series (1987–2020). For the study area, the evolution of the ecological environment quality is the result of the combined effects of climate change and human factors, with human factors being the main driving force. In particular, the found ecological improvement is mainly related to past ecological-restoration activities. The effects of topography are particularly relevant for three of the four indices required for RSEI: the humidity index (WET), the normalized differential build-up and bare soil index (NDBSI) and the heat index (land-surface temperature—LST). They are less relevant for the greenness index (normalized difference vegetation index—NDVI). Thus, the authors suggest that topographic correction should be used as a necessary element in data preprocessing in areas with large terrain fluctuations, which can improve the practicability of the ecological environment quality evaluation model.

The paper by **Qian et al.** [8] focused on the building of an automatic model to extract rocky desertification areas in the region of Guizhou (China) at the aim of following their spatio-temporal evolution. The detection of degraded zones was achieved by mixing remote sensing observations and a suite of data encompassing bedrock exposure rate, temperature difference, humidity and other ancillary factors. Remote sensing data used to detect vegetation coverage relied on various MODIS time-series products, all conveniently resampled at a spatial resolution of 250 m, which is consistent with the natural scale of distribution of rocky desertification phenomena. Forest inventory data were used as the ground truth to validate the presence of rocky desertification. Three data-driven models (i.e., logistic regression; random forest—RF; and support vector machine—SVM) were developed and tested. Major results of the study are that the joint use of the SVM model, the vertical spatial structure of vegetation and the differences in seasonal phase are an effective way to improve the modeling accuracy of rocky desertification.

Liu et al. [9] developed a framework based on multiple currently popular machine learning models and multi-source remote datasets from CRU (Climate Research Unit), GLDAS (Global Land Data Assimilation System), MODIS, GRACE-FO (Gravity Recovery and Climate Experiment—Follow-On) and CMIP6 (Coupled Model Intercomparison Project), covering meteorological, vegetation and hydrological variables for Actual EvapoTransipration (AET) evaluation and prediction. Although the limitation due to the lack of substitutes on the Potential EvapoTranspiration (PET) prediction dataset from CMIP6 did not allow one to calibrate some relevant parameters for the AET prediction product, results showed that the proposed method performed well in trend assessment and related determinant factor identification at the regional scale for South America.

In **Mascolo et al. [10]**, a novel approach, based on the optimal Bayesian Filter, the Grid Based Filter (GBF), was proposed to estimate phenological stages of agricultural crops with SAR data. The optimal GBF is properly employed by considering crop phenology as a discrete variable with a finite number of stages, in accordance with the numerical scales commonly employed (e.g., Biologische Bundesanstalt, Bundessortenamt and CHemische—BBCH). Moreover, both state transitions and SAR observable evolution were properly modeled from the statistics of the (training) data, instead of relying on curve-fitting techniques and statistical assumptions. The method was applied to dual-polarization Sentinel-1 SAR time series to estimate rice crop phenology in different years and high accuracies are achieved. The results obtained confirm the soundness of the proposed approach.

Sassu et al. [11] tested the operational use of UAV Red–Green–Blue (RGB) digital camera data for canopy volume estimation in vineyards. In particular, UAV data are integrated in TRV (Tree–Row–Volume) estimations by following two approaches: one processed in ArcGIS based on the digital surface model (DSM) and digital terrain model (DTM) to derive the canopy height mode (CHM) and the second processed in MATLAB by solely analyzing the DSM. The correlations with TRV based on field measurements were performed on an experimental vineyard for three years (2016, 2017 and 2019). The empirical results obtained confirm the appropriateness of replacing or integrating field measures with UAV data. Taking into account the crucial role in determining the treatment doses appropriate for a given vineyard, the possible overestimation of TRV based on field measures can be limited with the proposed approaches, helping to reduce the use of chemicals and increase the economic performances and environmental sustainability of productive farms.

Filipponi et al. [12] focused on the fine-tuning of an automated and transferable procedure combining robust and validated statistical methodologies to exploit satellite Sentinel-2 time series. The aim of the work was to provide information about plant phenology, as a crucial discipline for supporting crop and forest management and evaluating the responses of ecosystems to global changes. In particular, multivariate statistical analysis was adopted to demonstrate the ability of the generated smoothed vegetation curve, temporal statistics and phenological metrics to serve as temporal discriminants to detect forest ecosystem responses to environmental gradients. Interestingly, the observed phenological metrics were validated adopting in situ PhenoCam data, located in the Alpine areas of Italy, with satisfactory results. This study highlights the importance of integrated data and methodologies to support vegetation recognition and monitoring activities.

Yuan et al. [13] combined Global Land-Surface Satellite (GLASS) products and ERA5 reanalysis products to investigate the spatiotemporal variation in blue-sky albedo for stable land-cover types in the middle-high latitudes of the Northern Hemisphere (30~90°N) from 1982 to 2015. The analysis is important because it shows the main drivers affecting the blue-sky albedo of different land-cover types (snow cover; soil moisture; LAI). Because, in this study, the temporal analysis is only on the interannual scale and given that there are studies pointing out the obvious seasonal differences in blue-sky albedo and the impact on blue-sky albedo due to the changing land cover type, the authors highlight the importance of carrying out further studies in the near future to explore the spatiotemporal variation in blue-sky albedo with stable and changing land-cover types on the seasonal scale.

Santarsiero et al. [14] exploited remote sensing data (Landsat TM/OLI) to extract land use/land cover (LULC) for a diachronic analysis of land-take processes in Mediterranean areas. Satellite data were classified through a supervised algorithm: the support vector machine (SVM) change detection analysis. To achieve a high level of labelling of land-take processes, satellite classification was supported by comprehensive land information (regional geo-topographic database—GTDB), integrated in a free and open-source GIS environment. The procedure allowed for a quick and cost-effective extraction of detailed land-take maps (overall accuracy greater than 90%) useful to perform effective soil monitoring and to assist land planning in a sustainable perspective.

Imbrenda et al. [15] proposed a procedure for the monitoring of protected areas through the use of satellite imagery (Landsat TM data) and GIS tools, combined in a straightforward and cost-effective methodology to assess quality conditions of terrestrial habitats belonging to the Natura 2000 network of Basilicata (Southern Italy) and detect habitat-degradation processes at an early stage. The core of the procedure was the detection of vegetation anomalies (signs of stress, cover fragmentation), by analyzing the statistical distributions of standardized NDVI (Normalized Difference Vegetation Index) for all the habitats, supported by field data to provide public administrations with indications about habitat priority areas (HPA), i.e., areas needing priority interventions and the overall habitat status (DHC—Degree of Habitat Consistency). The use of freely available satellite images and GIS tools allowed for the devised procedure to be used in the operational monitoring of protected areas to capture incoming degradation, rationalize field measurements and assess the effectiveness of the implemented measures.

Simoniello et al. [16] implemented a procedure to separate rocks and improve the accuracy of shrubland vegetation classes in low-density airborne laser scanner (ALS) acquisitions. Shrublands, such as the Mediterranean maquis, have a height and shape very similar to those of rock spikes and outcrops; thus, in low-density ASL point clouds, they are not discernable by adopting standard procedures based on height features. The procedure, based on the integration of geometric features with segmented laser intensity, was tested in a typical rural Mediterranean environment, with a mixture of maquis with shrubs, rocks and stones, providing an accurate class separation (preserved also for ALS clouds with very-low-point density, <1.5 pts/m^2). Moreover, the analysis of classification errors corroborates the relevance of adopting suitable accuracy metrics (multiclass balanced accuracy) and provides a hint for the Lambertian assumption for sclerophyllous shrubs with minimal impact for NIR-based full-waveform LiDAR acquisitions with a small footprint. The improvements in shrub-class accuracy, obtainable with the proposed procedure, can better support ecological studies for biodiversity conservation and carbon-stock estimation.

3. Concluding Remarks

The topics addressed in this Special Issue cover many of the challenges faced by research into land systems and their complexities. The fourteen research papers use a wide variety of remote data and analysis approaches to answer important questions related to land dynamics and their link to climate change, with a particular focus on vegetation cover. These studies can help to advance our understanding of how remotely sensed data can further improve knowledge on land processes at different spatial and temporal scales to support sustainability studies. We believe that readers will benefit from the insightful discussions and presentations in the Special Issue, which propose new scientific approaches towards further development. They can be a valuable support for researchers who aim to contribute to remote analyses of land cover/use, promoting ever more rapid progress.

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