



Editorial

Editorial for Special Issue: “New Insights into Ecosystem Monitoring Using Geospatial Techniques”

Emiliano Agrillo ^{1,*}, Nicola Alessi ¹, Jose Manuel Álvarez-Martínez ², Laura Casella ¹, Federico Filippini ¹, Bing Lu ³, Simona Niculescu ^{4,5}, Mária Šibíková ⁶ and Kathryn E. L. Smith ⁷

- ¹ Italian National Institute for Environmental Protection and Research (ISPRA), Via Vitaliano Brancati 48, 00144 Roma, Italy; nicola.alessi@isprambiente.it (N.A.); laura.casella@isprambiente.it (L.C.); federico.filippini@isprambiente.it (F.F.)
- ² IHCantabria—Instituto de Hidráulica Ambiental, Universidad de Cantabria, PCTCAN, C/Isabel Torres 15, 39011 Santander, Spain; jm.alvarez@unican.es
- ³ Department of Geography, Simon Fraser University, 8888 University Drive, Burnaby, BC V5A 1S6, Canada; bing.lu@mail.utoronto.ca
- ⁴ Laboratory LETG-Brest, Géomer, UMR 6554 CNRS, IUEM UBO, 29200 Brest, France; simona.niculescu@univ-brest.fr
- ⁵ Department of Geography, University of Western Brittany, 3 Rue des Archives, 29238 Brest, France
- ⁶ Institute of Botany, Plant Science and Biodiversity Center SAS, Dúbravská Cesta 9, 845 23 Bratislava, Slovakia; maria.sibikova@savba.sk
- ⁷ U.S. Geological Survey, St. Petersburg Coastal and Marine Science Center, Saint Petersburg, FL 33701, USA; kelsmith@usgs.gov
- * Correspondence: emiliano.agrillo@isprambiente.it



Citation: Agrillo, E.; Alessi, N.; Álvarez-Martínez, J.M.; Casella, L.; Filippini, F.; Lu, B.; Niculescu, S.; Šibíková, M.; Smith, K.E.L. Editorial for Special Issue: “New Insights into Ecosystem Monitoring Using Geospatial Techniques”. *Remote Sens.* **2022**, *14*, 2346. <https://doi.org/10.3390/rs14102346>

Received: 28 April 2022

Accepted: 6 May 2022

Published: 12 May 2022

Publisher’s Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Recent global-scale environmental issues from climate change to biodiversity loss are generating an intense social pressure on the scientific community [1]. A growing need for information on environmental topics with appropriate reliability and suitable spatial scalability (from local to global analysis and vice versa) is spreading among societies [2].

The availability of huge amounts of environmental data allows the use of advanced analytic techniques that can provide useful information from a variety of large datasets, including those observing and measuring the ecosystem processes in response to environmental drivers [3]. A multidisciplinary approach, including artificial intelligence, big data analytics, and ecological modelling, is highly recommended to interpret ecological processes and identify adequate solutions for the environmental issues of the Anthropocene [4]. However, the use of big data today generated by different sources represents a big challenge, from detailed analysis on specific topics or geographic areas to issues at wider scales and over broader timescales [5].

Earth Observation (EO) data acquired by satellite sensors offer new opportunities for the ecology sciences and are revolutionizing the methodologies applied, from experimental/theoretical to computational science [6], projecting big data from space in the mainstream of ecological analysis.

It is therefore easily foreseeable that, in the next decades, new technologies will affect the activities on ecosystem survey, mapping, and monitoring, opening a new era. The reasons are first linked to the requirements of global, continental, and national policies on the environment sustainability, such as those stated in the 2030 Agenda for Sustainable Development, that gave a new stimulus to improve ecological research in this direction [7,8]. The increasing demand from national institutions for updated information to monitor ecosystems and detect their changes in time and space plays a crucial role in demonstrating mapping products as an essential tool for biodiversity assessments [9]. Indeed, in the light of “Biological Diversity” concept (see Convention on Biological Diversity: <https://www.cbd.int/convention/text/> (accessed on 1 May 2022)), habitats are cardinal pieces for quantitative

estimations of biodiversity at local and global scales. They are basic units of ecosystems and biomes identified by abiotic environmental factors, such as climate, geomorphology, pedology, as well as by plant species composition (i.e., vegetation units) [10].

In this direction, this Special Issue aims to compile research papers dealing with both methodologies of remote sensing and implementation of research results to facilitate the environmental monitoring, using geospatial techniques, in several ecosystems (e.g., wetland, coastal, estuarine, forest, shrubland, and alpine grasslands) or for land use and land cover (LULC) changes analysis. Altogether, in this Special Issue, nine papers are published, and the results obtained are implemented along two continents, using remote sensing platforms such as Landsat (i.e., 5TM, 7ETM+ and 8OLI), Sentinel (2A/2B MSI), World-View, and SPOT 5 imageries or hyperspectral imagery from proximal sensors by airborne vehicles (i.e., helicopter). Among the methods used to process the remotely sensed data, the increasing focus on the use of machine learning algorithm models such as Random Forests (RF), Support Vector Machine (SVM), Linear Regression (LR), Convolutional Neural Network (CNN), and Deep Learning (DL) classifier is noteworthy. In Table 1, the key message of all published papers is summarized. More detailed information on each article published in this Special Issue is given below in order of the publication date.

Table 1. Topics and main findings covered in the Special Issue on “New Insights into Ecosystem Monitoring Using Geospatial Techniques”.

Reference	Study Area	Remote Sensing Data/Equipment	Target Ecosystem	Implementation on Ecosystem Monitoring
From Forest Dynamics to Wetland Siltation in Mountainous Landscapes: A RS-Based Framework for Enhancing Erosion Control. Hernández-Romero, G., et al.- https://doi.org/10.3390/rs14081864 (accessed on 1 May 2022)	Spain	Landsat TM, ETM+, OLI and Sentinel 2A/2B MSI	Natural forests in hillslopes and riparian areas	Proposed a method-ology to optimize investment for erosion prevention and wetland conservation by using only very specific areas of the landscape for habitat management (e.g., for Nature-Base Solution implementation).
Assessing the Impacts of Species Composition on the Accuracy of Mapping Chlorophyll Content in Heterogeneous Ecosystems. Lu, B., et al.- https://doi.org/10.3390/rs13224671 (accessed on 1 May 2022)	Canada	Micro-HyperSpec by Headwall Photonics Inc. (Boston, MA, USA)	Grassland	Species-specific models for estimating chlorophyll content were developed and used to generate a chlorophyll content map of a heterogeneous grassland. Impacts of species composition on the retrieval of chlorophyll content were investigated to support future chlorophyll mapping in heterogeneous ecosystems and contribute to eco-system management.

Table 1. Cont.

Reference	Study Area	Remote Sensing Data/Equipment	Target Ecosystem	Implementation on Ecosystem Monitoring
Mapping and Monitoring of Land Cover/Land Use (LCLU) Changes in the Crozon Peninsula (Brittany, France) from 2007 to 2018 by Machine Learning Algorithms (Support Vector Machine, Random Forest, and Convolutional Neural Network) and by Post-classification Comparison (PCC) Xie, G., et al.- https://doi.org/10.3390/rs13193899 (accessed on 1 May 2022)	France	SPOT-5 and Sentinel 2A/2B MSI	Coastal: cliffs, dunes, moors, peat bogs, and wetlands	Recommendations for further studies on LCLU changes: applying more vegetation indices or using hyperspectral images to differentiate between vegetation and planted croplands; exploring the potential of synthetic-aperture radar images as a supplement to the traditional optical images on cloudy seasons.
Satellite-Derived Barrier Response and Recovery Following Natural and Anthropogenic Perturbations, Northern Chandeleur Islands, Louisiana Bernier, J. C., et al.- https://doi.org/10.3390/rs13183779 (accessed on 1 May 2022)	United State	Landsat TM, ETM+ and OLI	Coastal Island and estuarine habitat	Results presented reveal along-shore-variable patterns of landscape response to both natural (storm) and anthropogenic (berm emplacement) perturbations at annual to decadal scales and provide new data that demonstrate the importance of vegetative controls on barrier shoreline change, transgression, and coastal landscape evolution. A software (NaturaSat) useful for habitat detection, at high spatial resolution that could be used in nature conservation practices, such as identifying ecosystem services, conservation value, and landscape ecology studies.
NaturaSat—A Software Tool for Identification, Monitoring and Evaluation of Habitats by Remote Sensing Techniques Mikula, K., et al.- https://doi.org/10.3390/rs13173381 (accessed on 1 May 2022)	Slovakia	Sentinel 2A/2B MSI	Habitat types sensu Habitats Directive EC 92/43	
Coastal Wetland Shoreline Change Monitoring: A Comparison of Shorelines from High-Resolution WorldView Satellite Imagery, Aerial Imagery, and Field Surveys Smith, K. E. L., et al.- https://doi.org/10.3390/rs13153030 (accessed on 1 May 2022)	United State	WorldView-2 and WorldView-3	Coastal wetland	High-resolution satellite imagery can increase the spatial scale-range of shoreline change monitoring, provide rapid response to estimate impacts of coastal erosion, and reduce cost of labor-intensive practices.

Table 1. Cont.

Reference	Study Area	Remote Sensing Data/Equipment	Target Ecosystem	Implementation on Ecosystem Monitoring
Spatiotemporal Modeling of Coniferous Forests Dynamics along the Southern Edge of Their Range in the Central Russian Plain Chernenkova, T., et al.- https://doi.org/10.3390/rs13101886 (accessed on 1 May 2022)	Russia	Landsat TM	Forest	Importance of permanent update of remote and field data for assessment of forest management regime
Earth Observation and Biodiversity Big Data for Forest Habitat Types Classification and Mapping Agrillo, E., et al.- https://doi.org/10.3390/rs13071231 (accessed on 1 May 2022)	Italy	Sentinel 2A/2B MSI	Forest	Novel approach for a spatially explicit habitat mapping in Italy, using a supervised machine learning model (SMLM), through the combination of vegetation plot database (as response variable), and both spectral and environmental predictors.
Surface Tradeoffs and Elevational Shifts at the Largest Italian Glacier: A Thirty-Years Time Series of Remotely-Sensed Images Alessi, N., et al.- https://doi.org/10.3390/rs13010134 (accessed on 1 May 2022)	Italy	Landsat TM and ETM+	Alpine ecosystems: forest, grassland, periglacial	Workflow allows to compare the geographical extension of different terrestrial ecosystems across time using a fuzzy approach. Thus, it approximates the continuous distribution of natural ecosystems, in contrast to hard or categorical classification approaches.

2. Overview of Contributions

The follow is the synthesis of results obtained in each paper published in the SI “New Insights into Ecosystem Monitoring Using Geospatial Techniques”.

G. Hernández-Romero et al. [11] introduced a study aiming at applying an RS framework useful to identify suitable locations related to the conservation and restoration of natural forests in hillslopes and riparian areas. The combination of information about LULC dynamics, wetland distribution, and erosion processes has allowed establishing an innovative spatially explicit RS-based workflow that allows addressing potential ecological and hydrological problems of wetlands in mountainous environments by using nature-based solutions related to forest ecosystems.

Mapping species-specific chlorophyll content in a heterogeneous grassland using high-spatial resolution hyperspectral images was investigated in a study by B. Lu et al. [12]. This research aimed to better retrieve vegetation chlorophyll content of different species. Overall, the utilization of species-specific models is recommended for mapping vegetation properties in heterogeneous ecosystems.

The research of G. Xie et al. [13] was aimed to study multiannual changes in LCLU in the Crozon Peninsula, an area that has mainly been marked by conversion between three types of LCLU, i.e., cropland, urban, and vegetation, in recent years, especially from 2007 to 2018. The challenge of this research was to deal with multiannual changes of a coastal area with different shapes and patterns by combining machine learning methods

with PCC. Although high classification accuracy was observed, several uncertainties and limitations persisted, such as misclassification: classifications were based on images with different spatial resolutions, cloud-free satellite images during the growing season. Hence, some recommendations can be made for further studies, such as applying more vegetation indices or using hyperspectral images and exploring the synthetic-aperture radar images.

The goal of the study of J. C. Bernier et al. [14] was to provide a comprehensive analysis of recent landscape-scale changes along the northern Chandeaur Islands using a consistent dataset and methodology to better understand temporal and spatial variability in barrier response to natural and anthropogenic disturbances over the past few decades. The results presented in this study demonstrate that automated thresholding algorithms can be applied to multiple spectral indices derived from medium-resolution Landsat satellite imagery to rapidly delineate land-cover classes and barrier-island extents at the landscape scale.

In K. Mikula et al. [15], it was presented that the NaturaSat software aims to integrate image-processing knowledge and various techniques together with vegetation science, into one multipurpose tool that is designed for performing facilities for all the requirements of habitat exploration in one place. The results obtained show that NaturaSat software implements new powerful tools, such as the semi-automatic and automatic segmentation RS imageries methods and natural numerical networks. It is robust enough for vegetation scientists and nature conservationists to accurately extract target units' borders, even at the habitat level.

With the introduction of high-resolution satellite imagery with frequent return intervals, satellite-derived wetland shoreline data could provide the same spatial and temporal detail as other sources of data, including field-based Global Positioning System (GPS) or aerial imagery-derived shoreline data, but gain greater spatial coverage and reduce the cost of shoreline monitoring by either replacing GPS field surveys or reducing the necessity of survey frequency. K. E. L. Smith et al. [16] showed the results of a semi-automated procedure to map wetland shorelines from WV imageries and compared them to contemporaneous shoreline data from GPS and digitized aerial imagery for study sites at the Grand Bay National Estuarine Research Reserve, Moss Point, MS, USA. The availability of high-resolution satellite imagery and new developments in rapid image analysis techniques can help fill the data gap and provide critical information for coastal wetland monitoring programs.

In T. Chernenkova et al. [17], the aim of the study published was to perform a vegetation mapping and to identify coniferous forests dynamics in the central Russian Plain at the edge of large metropolis influence (case study in Moscow). This study is based on both field and remote sensing data. The results obtained will contribute to the development of plans for sustainable management and conservation of forest biodiversity under different management scenarios.

A novel approach for a spatially explicit habitat mapping of forest in Italy using a supervised machine learning model and the combination of a vegetation dataset, high resolution EO data, and environmental variables was presented by E. Agrillo et al. [18]. The obtained results could be useful for monitoring the spatial patterns of ecosystems in space and time. The approach presented will allow an information technology procedure to be sped up with annual or seasonal updating, depending on the extension of the study area and the monitoring objectives. The obtained procedures could be applied on several environmental data in order to cyclically and promptly repeat spatial analysis to detect changes in space and time in support of ecosystem conservation issues, especially to evaluate the impact of illegal actions (e.g., forest harvesting) or natural hazards (e.g., destructive storms or other natural disasters) on habitat distribution.

N. Alessi et al. [19] presented a fuzzy classification of terrestrial ecosystems in a mountain environment. Using different remotely sensed indices, the authors use an unsupervised clustering to implement a temporal comparison among clustered pixels. The obtained clusters were assigned to terrestrial ecosystems based on ground observation of vegetation. The study reports an increase in the forested area to the detriment of grassland, and an

expansion of ice-free area due to the retreat of the mountain glacier. The presented approach allows monitoring terrestrial ecosystems in space and time based on their characteristic spectral signal.

All the above-mentioned studies confirm the great potential of using geospatial techniques for ecosystem monitoring. We hope that the results and findings shown here will encourage further research and the land managers of the importance and benefits of better integration of remote sensing data on operational monitoring and surveillance of ecosystems.

Author Contributions: Conceptualization, E.A.; writing—review and editing, E.A., N.A., J.M.Á.-M., L.C., F.F., B.L., S.N., M.Š. and K.E.L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Acknowledgments: As the Guest Editors, we would like to thank all the authors who accepted the challenge to share their research results and ideas in this Special Issue. Special thanks to all anonymous reviewers involved in the SI and helped the authors to improve their manuscripts. Thanks also to the editorial staff of Remote Sensing for supporting the idea of this SI. Furthermore, special thanks to Vladimir Maksimović for helping to spread the message and pressing us to publish during the COVID-19 pandemic.

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

References

1. Steffen, W.; Richardson, K.; Rockström, J.; Cornell, S.E.; Fetzer, I.; Bennett, E.M.; Biggs, R.; Carpenter, S.R.; de Vries, W.; de Wit, C.A.; et al. Planetary boundaries: Guiding human development on a changing planet. *Science* **2015**, *347*, 1259–1855. [[CrossRef](#)] [[PubMed](#)]
2. Hooper, D.U.; Adair, E.C.; Cardinale, B.J.; Byrnes, J.E.; Hungate, B.A.; Matulich, K.L.; Gonzalez, A.; Duffy, J.E.; Gamfeldt, L.; O'Connor, M.I. A global synthesis reveals biodiversity loss as a major driver of ecosystem change. *Nature* **2012**, *486*, 105–108. [[CrossRef](#)] [[PubMed](#)]
3. Hallgren, W.; Beaumont, L.; Bowness, A.; Chambers, L.; Graham, E.; Holewa, H.; Laffan, S.; Mackey, B.; Nix, H.; Price, J.; et al. The biodiversity and climate change virtual laboratory: Where ecology meets big data. *Environ. Modell. Softw.* **2016**, *76*, 182–186. [[CrossRef](#)]
4. Palmer, M.A.; Bernhardt, E.S.; Chornesky, E.A.; Collins, S.L.; Dobson, A.P.; Duke, C.S.; Gold, B.D.; Jacobson, R.B.; Kingsland, S.E.; Kranz, R.H.; et al. Ecological science and sustainability for the 21st century. *Front. Ecol. Environ.* **2015**, *3*, 4–11. [[CrossRef](#)]
5. Hampton, S.E.; Strasser, C.A.; Tewksbury, J.J.; Gram, W.K.; Budden, A.E.; Batcheller, A.L.; Duke, C.S.; Porter, J.H. Big data and the future of ecology. *Front. Ecol. Environ.* **2013**, *11*, 156–162. [[CrossRef](#)]
6. Guo, H.; Wang, L.; Liang, D. Big Earth Data from space: A new engine for Earth science. *Sci. Bull.* **2016**, *61*, 505–513. [[CrossRef](#)]
7. Pettorelli, N.; Laurance, W.F.; O'Brien, T.G.; Wegmann, M.; Nagendra, H.; Turner, W. Satellite remote sensing for applied ecologists: Opportunities and challenges. *J. Appl. Ecol.* **2014**, *51*, 839–848. [[CrossRef](#)]
8. Vihervaara, P.; Auvinen, A.P.; Mononen, L.; Törmä, M.; Ahlroth, P.; Anttila, S.; Böttcher, K.; Forsius, M.; Heino, J.; Heliölä, J.; et al. How essential biodiversity variables and remote sensing can help national biodiversity monitoring. *Glob. Ecol. Conserv.* **2017**, *10*, 43–59. [[CrossRef](#)]
9. Tuomisto, H. A consistent terminology for quantifying species diversity? Yes, it does exist. *Oecologia* **2010**, *164*, 853–860. [[CrossRef](#)] [[PubMed](#)]
10. Van der Maarel, E.; Franklin, J. (Eds.) *Vegetation Ecology*; John Wiley & Sons: Hoboken, NJ, USA, 2012.
11. Hernández-Romero, G.; Álvarez-Martínez, J.M.; Pérez-Silos, I.; Silió-Calzada, A.; Vieites, D.R.; Barquín, J. From Forest Dynamics to Wetland Siltation in Mountainous Landscapes: A RS-Based Framework for Enhancing Erosion Control. *Remote Sens.* **2022**, *14*, 1864. [[CrossRef](#)]
12. Lu, B.; He, Y. Assessing the Impacts of Species Composition on the Accuracy of Mapping Chlorophyll Content in Heterogeneous Ecosystems. *Remote Sens.* **2021**, *13*, 4671. [[CrossRef](#)]
13. Xie, G.; Niculescu, S. Mapping and Monitoring of Land Cover/Land Use (LCLU) Changes in the Crozon Peninsula (Brittany, France) from 2007 to 2018 by Machine Learning Algorithms (Support Vector Machine, Random Forest, and Convolutional Neural Network) and by Post-classification Comparison (PCC). *Remote Sens.* **2021**, *13*, 3899. [[CrossRef](#)]
14. Bernier, J.C.; Miselis, J.L.; Plant, N.G. Satellite-Derived Barrier Response and Recovery Following Natural and Anthropogenic Perturbations, Northern Chandeleur Islands, Louisiana. *Remote Sens.* **2021**, *13*, 3779. [[CrossRef](#)]

15. Mikula, K.; Šibíková, M.; Ambroz, M.; Kollár, M.; Ožvat, A.A.; Urbán, J.; Jarolímek, I.; Šibík, J. NaturaSat—A Software Tool for Identification, Monitoring and Evaluation of Habitats by Remote Sensing Techniques. *Remote Sens.* **2021**, *13*, 3381. [[CrossRef](#)]
16. Smith, K.E.L.; Terrano, J.F.; Pitchford, J.L.; Archer, M.J. Coastal Wetland Shoreline Change Monitoring: A Comparison of Shorelines from High-Resolution WorldView Satellite Imagery, Aerial Imagery, and Field Surveys. *Remote Sens.* **2021**, *13*, 3030. [[CrossRef](#)]
17. Chernenkova, T.; Kotlov, I.; Belyaeva, N.; Suslova, E. Spatiotemporal Modeling of Coniferous Forests Dynamics along the Southern Edge of Their Range in the Central Russian Plain. *Remote Sens.* **2021**, *13*, 1886. [[CrossRef](#)]
18. Agrillo, E.; Filipponi, F.; Pezzarossa, A.; Casella, L.; Smiraglia, D.; Orasi, A.; Attorre, F.; Taramelli, A. Earth Observation and Biodiversity Big Data for Forest Habitat Types Classification and Mapping. *Remote Sens.* **2021**, *13*, 1231. [[CrossRef](#)]
19. Alessi, N.; Wellstein, C.; Rocchini, D.; Midolo, G.; Oegg, K.; Zerbe, S. Surface Tradeoffs and Elevational Shifts at the Largest Italian Glacier: A Thirty-Years Time Series of Remotely-Sensed Images. *Remote Sens.* **2021**, *13*, 134. [[CrossRef](#)]