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*Editorial*

# Integrating Remote Sensing and Geospatial Big Data for Land Cover and Land Use Mapping and Monitoring

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## 1. Introduction

The last few decades have seen an explosion in the availability of remotely sensed and geospatial big data, which are defined by the 3 Vs: a large volume of data; a variety of different forms of data; and the rapid velocity of data arrival [1]. The term big data is particularly applicable to remote sensing. The opening of the Landsat archive [2], the spatially and temporally rich data now available from the Sentinel satellites [3], and the proliferation of small satellites photographing the Earth [4] all provide new opportunities for characterizing and monitoring the Earth's surface.

New sources of geospatial big data (as well as regular geospatial data) can also benefit the mapping and monitoring of land cover and land use. These include data from authoritative sources, e.g., data from official censuses and surveys, as well as data generated by citizens, both actively and passively. Citizen science [5] and volunteered geographic information [6] can provide data on land cover and use through initiatives such as OpenStreetMap (OSM) [7], Geo-Wiki [8], and many other projects that involve volunteers monitoring the environment or landscape features. Mobile phones and low-cost sensors can provide new streams of information through mobile apps that facilitate data collection [9] or that collect information in the background [10], as well as a variety of different sensors that are being used for environmental monitoring [11,12]. Data from social media, including geotagged photographs from sites such as Flickr or street-level photographs from providers such as Google Street View and Mapillary, can be processed using computer vision and segmentation to extract information related to land cover and land use [13,14].

The logical progression of this field of study is the integration of remote sensing with these different sources of geospatial data using various machine learning and data fusion approaches to create new data sets on land cover and land use. Much of the previous integration work in this area has focused on urban areas because of the large number of geospatial data sets available for cities [15]. Yet, there is considerable potential for creating better data sets in other domains as well. One example is the mapping of land use intensities, which involved integrating Corine land cover and other remotely sensed data sets with statistical and other geospatial data sources [16] to produce a map for Europe with a 1 km resolution. Another example is the recently produced global map of forest management [17], which used data crowdsourced via the Geo-Wiki platform to train a classifier with satellite imagery to produce a wall-to-wall map of forest management at a 100 m resolution.

The purpose of this Special Issue is to bring together the latest papers on methods and applications that integrate remote sensing with geospatial data in the mapping and monitoring of land cover and land use. This includes applications that span different types



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of land cover and land use as well as those that focus on change detection. The next section summarizes the papers included in this Issue.

## 2. Overview of Papers in the Special Issue

This Special Issue contains nine papers, with the list of authors spanning four different continents. These papers have been grouped based on three main themes. The first is urban applications, which is a theme already documented in the literature [15]. The second is monitoring and understanding changes over time, while the third theme covers other types of land cover and land use applications.

### *2.1. Urban Applications*

Two papers cover this theme. In the first paper by Zheng et al. (List of Contributors, 1), the authors used remote sensing in combination with other geospatial data, including OSM and Points of Interest (POIs), to map urban land use for the year 2018 in Zhengzhou City, Henan Province, China. Rather than adopting a more traditional pixel-based approach, the city was first delineated into parcels using a combination of the OSM road network and data on impervious surfaces. The POI data were then used to determine the land use type in each parcel using a majority voting approach. This was followed by the use of a random forest classifier to train a land use prediction model based on features from Sentinel 2 imagery, OSM data, and the land use types derived from the POI database. The authors achieved overall accuracies that varied between 78 and 85% for the detailed and less detailed urban land use classes, respectively, representing improvements in accuracy over other previously used methods.

A quite different urban application can be found in the paper by Kenyon et al. (List of Contributions, 2), who focused on the use of satellite imagery for delineating housing sub-markets in the city of Madrid. Normally, clustering algorithms are applied to individual housing data, but this requires large amounts of data that are not always available or are costly to purchase. Hence, this paper tested whether satellite imagery alone could be used for this task. Using the MOSAIKs model to extract features from different-sized patches of Sentinel 2 imagery (representing different-sized neighborhoods), the k-means clustering algorithm was used to produce clusters of sub-markets. Then, using data on house listings available from the Idealista website for more than 75,000 properties, the clusters were assessed for homogeneity (in terms of cost, age, size, etc.) and compared across different scales. The results showed that more homogeneous clusters were produced for larger neighborhoods, indicating the need to consider a larger urban context when delineating housing sub-markets. This approach also demonstrated the viability of using satellite imagery for this task when individual housing level data are scarce.

### *2.2. Changes in Land Cover and Land Use over Space and Time*

The second theme of this collection was spatiotemporal changes in land cover and land use. The first two papers that relate to this theme discuss urban applications, the third paper considers land cover and land use changes more generally, and the fourth paper is focused on changes in cropland.

In the first paper, authored by Shih et al. (List of Contributors, 3), the authors investigated the relationship and relative timing between changes in population and land use that occurred from 1990 to 2015 in an area of northern Taiwan. The authors integrated data from population registers with maps of urban expansion and land use derived from Landsat time series. Three land use types were mapped: transportation corridors, areas of employment, and residential areas. Lagged correlation analysis was then used to determine the relative timing between land use expansions and population growth, testing two hypotheses for change: the land available for employment increases, followed by an increase in residential land and then in population, or the population increases after the land available for employment increases, followed by residential land. The results showed that all types of urban land use increased over the time period even though some areas also experienced population decreases. The time lag analysis showed that all three types of land use are drivers of population increase, occurring at different times before rises in population were detected. The two hypotheses were found to be true in many areas, but when different patterns were detected, possible explanations were provided as to why. Overall, such an approach demonstrates how the remote sensing of time series and statistical information can be used to understand drivers of change.

In the next paper, authored by Li et al. (List of Contributors, 4), the authors used remote sensing in combination with statistical and geospatial data sets to determine the rate, spatial distribution, and drivers of urban expansion in the Dianchi Lake Basin in China. Numerous combinations of input features derived from Landsat images and various classification algorithms were tested, and the best-performing model was chosen for the subsequent analysis. The rate of urban expansion was then calculated for different time periods between 2000 and 2022 and mapped using hotspot analysis to identify where expansion had happened and what changes occurred over time. Using a PLS-SEM model and variables derived from statistical information, the main drivers of urban expansion were determined, including population density, GDP, and the growth of tourism. Finally, the authors examined changes in the quality of the ecological environment over time and showed that urban expansion had negative effects in this regard.

In the paper authored by Thomas and Guiliani (List of Contributors, 5) the authors explored the patterns of land cover change in Switzerland between 1985 and 2018. They used official land cover data provided by the Swiss Federal Office of Statistics. This data set comprised point locations that were visually interpreted from aerial imagery and classified into 27 detailed land cover types (as well as 46 categories of land use). The authors used data from four survey periods, each covering a 6-year time frame. The point locations were rasterized to a 100m resolution and the changes over time were then quantified as absolute and relative values in addition to the intensities of change. The authors also examined the spatial patterns of change over time. Although various patterns of change were discussed, the most important finding was that the temporal resolution of the data was too coarse, meaning that only slow changes and not rapid ones were captured. Yet, it is the rapid changes that occur at a fine scale that are of the most interest from a planning and sustainability perspective.

Finally, in the paper authored by Copenhaver (List of Contributors, 6), the author integrated many different data sources to determine cropland-to-grassland changes in the USA between 2008 and 2020, exploiting the strengths of each data set in the analysis. The author first identified counties with increasing cropland based on the United States Department of Agriculture's Farm Services Agency data. Data from the agricultural census were then used to identify the amount of available land for conversion and the county-level changes over time. Those counties with increasing cropland and declining rangeland were then identified based on data from the National Resources Inventory. The USDA's Cropland Data Layer, produced using remote sensing, was then used to find areas where relevant changes had occurred. Then, at the parcel level, aerial imagery was used to identify the types of change using visual interpretation. Finally, for those counties where rangeland changed to cropland, LandTrendr was used to verify the types of change. The results showed that counties with increasing cropland had similar amounts converted from fallow compared to the amounts converted from grassland, and that counties with declining cropland had many more acres converted to grassland. This study highlights the importance of using multiple sources of data to produce change information compared to using remote sensing alone, which tends to overestimate the level of grassland-to-cropland conversion.

### 2.3. Applications in Other Domains

The final theme of papers in this collection is applications in other domains of land cover and land use, including cropland (also dealt with in the previous theme), forestry, and ecological restoration. In the first paper, authored by Ghassemi et al. (List of Contributions, 7), the authors integrated satellite imagery from Sentinels 1 and 2 in combination with ground-based data from the LUCAS survey for 2018 to produce a 10 m resolution map of 19 different crop types and two classes covering woodland/shrubland and grassland. In 2018, the LUCAS survey included a subset of locations with area information (compared to point information for the full survey) to facilitate remote sensing classification. A random forest classifier was used to train the features derived from both types of sensors using the LUCAS polygon data and then validated with other LUCAS data points located in homogeneous areas. The results showed that integrating data from both types of sensors improved the overall accuracy compared to using data from only one type of sensor. Overall accuracies varied from 78.3% for all 21 classes to 82.7% when grouping crops into broader classes such as cereals, root crops, etc. Hence, the benefits of integrating multi-sensor remote sensing data and in situ data from LUCAS have been clearly demonstrated.

In the next paper, Borgogno-Mondino et al. (List of Contributions, 8) demonstrated that by combining digital aerial photography with a ground-based forest inventory, the number of ground-based plots to be surveyed, as well as the overall cost associated with carrying out a forest inventory, could be reduced. The other advantages of this method include spatially comprehensive mapping of the main parameters of forestry, including tree height, density, and count, and the ability to collect data more frequently. Other parameters still require ground-based surveys, such as diameter at breast height and wood volume, but models can be developed that use remotely sensed information for input in their calculation. This paper is also intended to act as a best-practice guideline for those interested in integrating remote sensing into forest inventories, providing many technical details on useful products, programming the flights, and processing and validating the data.

Finally, in the area of ecological restoration, the technical note by Morales et al. (List of Contributions, 9) outlined a prototype of the 'RePlant alpha' system for prioritizing areas for restoration activities. This interactive geospatial decision-making tool is based on integrating R with Google Earth Engine and visualization through ArcGIS Online (although open visualization options were also discussed). Indicators from remote sensing, statistical information, and other geospatial data sets were integrated (including ecological, social, and economic variables) to demonstrate how the system would operate for a case study area in Chile. The advantages of their approach over other proprietary solutions are that the solution is based on free and open access tools, and that the indicators are pre-calculated so that users simply need to view the restoration areas with the highest priority. In future versions, more indicators will be added and estimated costs per hectare for some restoration activities will be provided. As such, the system will be easy for decision makers and stakeholders who need to implement ecosystem restoration to use, and clearly demonstrates the integration of remote sensing and geospatial data sets.

## 3. Conclusions

This Special Issue has brought together a set of papers under the general theme of integrating remote sensing with geospatial data for land cover and land use mapping and monitoring. Although urban areas were covered in four out of nine papers, interest was also shown in mapping spatiotemporal change and understanding the drivers of this change, as well as other types of land cover and land use. As this is an area of research that will clearly continue to generate much interest in the future, a second edition of this Special Issue is now accepting papers.

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