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Editorial

Advanced GIS and RS Applications for Soil and Land Degradation Assessment and Mapping

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Land refers to the planet's surface not covered by seas, lakes or rivers, but by different types of vegetation (e.g. natural or managed grassland, cropland, and wetlands) and artificial surfaces (e.g. roads and buildings). Soil is one of the essential components of land. The upper, weathered, solid mantle of the Earth, called the pedosphere, results from the complex influence of soil forming factors (parent material, topography, climate, living organisms, human activities, and time) and soil forming processes at the zone of interactions of the lithosphere, atmosphere, hydrosphere, and biosphere, as well as reflecting variations and changes of these natural components. Soils are active and passive factors in most natural cycles and processes, consequently soil is a multifunctional natural resource. Soil functions and services may be endangered by the effects of natural factors, processes accelerated by human activities (i.e. erosion, deflation) and by human-induced damages (pollution, acidification, etc.).

Soil degradation associated with wind and water erosion, physical and chemical deterioration, is increasing at an alarming rate all over the world, but it remains difficult to model and quantify the regional extent and severity of these processes. Soil degradation is not an unavoidable consequence of intensive agriculture and social development. Most of the degradation processes and their unfavorable consequences can be prevented, eliminated, reduced, or at least moderated. Soil degradation is usually a complex process in which several component features of soil deterioration can be recognized to be contributing to the loss of land or its "productive capacity", to the limitation of normal soil functions, and/or the decrease of soil fertility due to unfavorable changes in soil processes and, consequently, in soil properties [1,2]. However, soil is a (conditionally) renewable natural resource, it is cheaper to preserve land and soil resources than to restore or remediate them [3], consequently soil and land require rational use, conservation, and awareness from human society.

UN Sustainable Development Goals aim to achieve Land Degradation Neutrality, a state whereby the amount and quality of land resources, necessary to support ecosystem functions and services and enhance food security, remains stable or increases within specified temporal and spatial scales and ecosystems. Knowledge, mostly in the form of spatial information is needed for actions to take steps towards sustainable land and soil management to maintain their functions and services. To support these goals, the spatial assessment of land and soil degradation is necessary, which requires adequate information provided by Earth Observation together with reliable ground truth data and advanced GIS tools (including geostatistics and machine learning) to elaborate relevant and reliable spatial information to support decision making. Digital soil and environmental mapping provide powerful tools for the spatial inference of various land related surface features, however spatially explicit assessment of soil functions, processes and services is still a challenge. Remote sensing is one of the key tools in monitoring regional environmental processes, Earth Observation can play an important role in detection of different soil and land

degradation processes. There have been numerous initiatives on the application of satellite imagery for detecting, mapping and/or monitoring various types of land degradation processes, but spreading of advanced geostatistical, data mining, machine and deep learning methods in spatial and process modelling provides new possibilities for efficient soil and land degradation assessment and mapping.

A special issue was dedicated to research papers presenting innovative approaches for the spatial assessment and mapping of soil and land degradation at various scales and applying advanced GIS and RS methods. The twelve collected research papers published in this special issue present innovative approaches, which were elaborated and used at various (from plot to national) scales, applying advanced GIS and RS methods representing a snapshot of the recent advances.

Mass movements in various forms of erosion and landslides were spatially assessed and mapped by several authors. Borrelli et al. [4] presented the preliminary results of an integrated geomorphological study carried out in a 1.6 ha catchment area to produce a detailed map of landslides and water erosion phenomena based on unmanned aerial vehicle (UAV) images. Fernández et al. [5] used Digital Elevation Models obtained with aerial photogrammetric and LiDAR data for multitemporal analysis of gully erosion in olive groves. They produced digital surface models (DSMs) and orthophotographs using historical flights aligned in a common coordinate reference system with a recently assessed LiDAR point cloud for the analysis of the DSM of differences, which made the identification of gullies possible, together with the calculation of the affected areas as well as the estimation of height differences and volumes between models. Liu et al. [6] proposed an innovative approach to calculate the instability index by preparing an annual landslide inventory, determining the optimum sub-watershed, compensating for shadow effects on the time series of the landslide area ratio, and classifying the standard deviations to different levels of instability on the watershed level in Taiwan. The results have been made available on the Big Geospatial Information System. The identification of gullies, which reduce both the quality and quantity of productive land, posing a serious threat to sustainable agriculture, hence, food security, can assist in strategic decision-making relevant to soil conservation. Phinzi et al. [7] successfully identified gullies using pan-sharpened SPOT-7 product and selected Machine Learning (ML) algorithms. Waltner et al. [8] investigated the effects of land cover change on soil erosion at the national level in Hungary between 1990 and 2018. The spatiotemporal modeling scheme included the application and cross-valuation of two internationally applied methods, the Universal Soil Loss Equation (USLE) and the Pan-European Soil Erosion Risk Assessment (PESERA) models.

Soil organic carbon (SOC) can be considered as one of the most important properties of soil, which shows not just spatial but also temporal variability. In addition, SOC storage capacity is one of the key functions of soil that influences various soil related functions and services, such as agricultural productivity, water-holding capacity, stabilization of soil structure, and retention and release of plant nutrients. Soil is a key medium in climate change mitigation since soil can be either a net sink or a net source of greenhouse gases. As a consequence, there is an increasing global demand on the reliable knowledge on spatiotemporal variability of SOC. Indirectly various mapping approaches of land mass movements can be considered as spatial assessment of SOC changes, nevertheless there are more direct approaches. Chen et al. [9] compared six typical methods in three types of DSM techniques (Geostatistical, Machine Learning, and Hybrid Approaches) for mapping topsoil organic carbon content in an area surrounding Changchun in Northeast China.

Soil nutrient content plays a key role in plant growth through mineral nutrition and toxicity. Monitoring soil nutrient contents using remote sensing technology is of great significance for farmland soil productivity, food security, and sustainable agricultural development. Peng et al. [10] mapped soil nutrient contents in large areas using hyperspectral techniques introducing a GA-BPNN method, which combined a back propagation neural network (BPNN) with genetic algorithm optimization (GA).

Boluwade [11] regionalized and partitioned three soil health indicators (namely organic carbon, bulk density, and total nitrogen) using spatially contiguous clustering to support management decisions such as tillage, nutrient application, and soil and water conservation.

Yu et al. [12] targeted grassland degradation assessment in semiarid regions of China. The spatial distribution of grassland was measured with information mined from multi-temporal remote sensing images using an object-based image analysis combined with classification and decision tree methods. Based on 166 field samples, the random forest algorithm was used for predicting soil electrical conductivity and aboveground net primary production as indicators of grassland degradation.

Two water related studies are also included in the present special issue. Inland excess water represents a specific interrelated natural and human induced land degradation phenomenon. It is temporary water inundation that occurs in flat-lands due to both precipitation and groundwater emerging on the surface as substantial sources. Two hybrid spatial prediction approaches were used by Laborczi et al. [13] for spatial modelling to identify areas with high risk, that is to map this degradation process. Halmai et al. [14] targeted underwater land by the development of a novel, complex, and integrated surveying technique which is affordable, robust, and applicable even at low water levels to create a hydomorphologically correct, underwater elevation model of shallow lakes/rivers, which is able to survey relatively large areas, like the longer sections of a river.

The introduced spatial assessment methods used are as follows:

- multivariate statistical tools, like linear discriminant analysis [7],
- various machine learning techniques (most frequently Random Forest, but also Support Vector Machine) [7–9,12,13,15] as well as
- geostatistics and hybrid predictions [9,13],
- or supported by modelling [8].

Multitemporal analysis of digital elevation models [5] and land cover changes [8] as well as the instability index derived from a landslide inventory [6] supported specific mapping approaches. SoLIM-FilterNA method was used for void-filling of covariates in general Digital Soil Mapping [15]. Spatially Contiguous Clustering was used to divide administrative units into a possible number of regions while optimizing a sum of squares deviation [11].

Various platforms provided spatial information. Digital Elevation Models were obtained with airborne LiDAR Data for gully erosion monitoring [5]. Gully feature extraction was carried out based on a SPOT-7 pan-sharpened multispectral image [7]. A recreational-grade interferometric sonar system was developed for bathymetric survey and monitoring [14]. An integrated geomorphological study used LiDAR and the UAV system data to analyze recent morphological changes in a small drainage basin [4]. Landsat OLI imagery was used to assess grassland degradation [12]. Africa Soil Information Service database provided reference data on three soil health indicators to derive the optimal number of spatially contiguous regions of Nigeria's 774 Local Government Areas [11]. Prediction of soil nutrient contents was carried out using visible and near-infrared reflectance spectral data provided by HuanJing-1A Hyperspectral Imager [10].

The presented studies were carried out in three continents, in the countries of China, Hungary, Italy, Nigeria, South Africa, Spain, and Taiwan. Two of them covered the whole country, in Hungary and Nigeria, however, the extent of three of the Chinese, province-wide study areas was also similar. The smallest pilot area measured only 1.6 ha in Northern Calabria, South Italy, the next ones 1.26 km^2 and 7.5 km^2 in South Africa and in Jaén (Andalusia, Spain) respectively. One study area was characterized in linear measure, namely 128.6 km long, along the Drava River, Hungary. Study areas were designated as specific (semi)-natural, administrative, landuse defined, or even hybrid spatial entities

like the lowland excess water protection section, watershed, olive groves, and small drainage basins.

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