Recent trends in Land use land cover Analysis using remote sensing

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Abstract: The present paper deals with the recent trends in land use land cover (LULC) analysis using remote sensing technology and machine learning modelling. Several recent studies from the last five years focused on satellite datasets used for LULC classification for urban regions. Most of the studies focused on hyperspectral remote sensing instead of multispectral. However, temporal information is essential in monitoring and planning urban changes. In addition, cloud resources like Google Earth Engine (GEE) provide the major source for satellite datasets with a programming platform for analysing satellite data.

Keywords: Land use land cover; Google Earth Engine; Urban classification; Remote Sensing; Sentinel-2.

Introduction

Understand the LULC trends is one of the main challenges facing the sustainable management of natural resources and resolving modern environmental issues such as urbanization, deforestation and global warming [1]. UCS mapping previously relied on traditional techniques such as aerial photography and field surveys [2]. However, satellite remote sensing was a turning point in this field, offering multi-temporal data at broad extents with unmatched spatial and temporal resolutions [3]. Currently, with remote sensing and the with the increasing availability of high-resolution sensors and integration of advanced data processing techniques, such as machine learning and cloud computing, researchers have powerful tools to analyze and interpret changes in UCS with higher accuracy [4].

Advances in Remote Sensing Technologies for LULC Analysis

The possibility of gaining access to high-resolution satellite images spells the most significant advance in remote sensing [5]. Currently, operating satellites are Sentinel-2, Landsat 9, WorldView and PlanetScope, and these are providing imagery at 10-meter to sub-meter scale. Such high resolution enables the mapping of all types of land covers, from urban and constructed lands to forests and water bodies [6]. Also, the increased frequency of image acquisition from such satellites permits continuous monitoring of land cover, making them indispensable tools for resource planning and environmental management [7].

An advanced technology is hyperspectral imaging. In contrast to previous multispectral sensors that can be used to capture only a limited number of spectral bands, hyperspectral sensors capture hundreds of continuous bands [8]. The resulting spectral richness makes it possible to discriminate among land cover materials accurately by their unique spectral signatures. For example, in precision agriculture, technology allows the early identification of nutrient deficiency or disease in crops [9]. In forestry, it is applied to species identification and detection of plant pathologies. Space missions like NASA's Hyperion and the upcoming EnMAP mission highlight how technology can be deployed for UCS assessments of unmatched accuracy [10].

The integration of hyperspectral imaging with machine learning techniques, in particular convolutional neural networks (CNN), has automated and improved the accuracy of UCS classifications. These models can deal with an extensive amount of data and minimizes the heavy reliance on human interpretation, thereby opening up new avenues for monitoring landscape cover changes on a large scale [11]. The rise of cloud computing is changing the modalities in which remote sensing data can be stored, processed, and analyzed. Platforms like Google Earth Engine, Amazon Web Services, and Microsoft Planetary Computer represent scalable solutions for large-scale geospatial analysis. These platforms offer access to massive satellite libraries and powerful computing resources to provide lower technical and financial barriers to researchers [12].

Google Earth Engine has become an increasingly popular piece of software within the scientific community. The great amount of satellite imagery it holds, mainly Landsat, Sentinel, and MODIS data, enables GEE efficient and rapid assessment of UCS changes. The platform also integrates machine learning algorithms, like Random Forest and Support Vector Machines, for automated classification and change detection [13]. Henceforth, and being a viable one, more researchers could pursue remote sensing works within the field, which propagate increased international cooperation.

AWS, along with Azure, provides vital cloud computing infrastructure to host large-scale applications. Space agencies such as NASA and ESA are making use of AWS for real-time environmental monitoring and disaster management [14]. A recent trend in this area is the use of AI for geospatial data analysis, either semi-automatically or fully automatically. Fully using deep learning models to analyze large data sets, Microsoft's AI for Earth speeds up and improves UCS analyses [15]. The combined potential of AI and cloud computing has the opportunity to further increase the efficiency and access of remote sensing applications.

Applications of LULC Analysis Using Remote Sensing

Urban Planning and Land Management

Remote sensing is a crucial instrument for urban planners and political policymakers [16]. It can help to monitor urban sprawl, assess land cover change, and optimize land use measures. For example, high-resolution satellite images from Sentinel-2 and Landsat 9 provide a way to identify informal settlements, the destruction of green areas, and the expansion of transportation infrastructure [17]. One interesting application of remote sensing in urban contexts is research into urban heat islands (UHI). By utilizing thermal infrared mapping from satellites such as MODIS and Landsat, researchers can plot the temperature differences and suggest some mitigative measures against the effects. Among some of the measures proposed is increasing vegetation or using reflective material. Furthermore, the integration of remote sensing data with GIS is crucial in developing smart cities [18]. The technologies can facilitate efficient waste disposal, transportation systems and energy consumption, as well as urban sprawl pattern forecasting for more efficient decision-making planning.

Feature-level integration combines remote sensing characteristics and geospatial big data to build a generalized urban land use map (Figure 1). The analysis is mainly geared towards parcel or object level since these are representative of both modalities [19]. The key features extracted include spectral and textural characteristics for RS, and spatial, semantic, and sequential, including POI data, as well as real-time user activity features for GBD. Feature integration is mainly performed through the RF, SVM, DT, and the new additions of CNN and AE, contributing to notorious precision in classifying urban area realities [20].

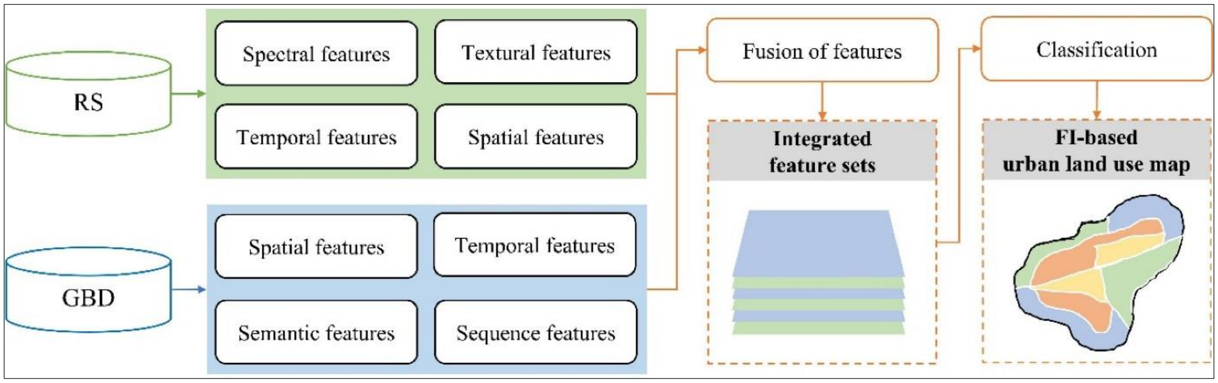

Figure 1. IF-based strategies for categorization [19].

Agricultural and Forestry Applications

Remote sensing has transformed traditional agricultural practices by enabling real-time monitoring of crops (Figure 2). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) provide valuable information regarding plant health and water stress conditions [21]. Hyperspectral imagery, however, enables early identification of nutrient deficiencies and diseases, thus improving agricultural productivity [22]. In forest management, remote sensing has been used to monitor deforestation, estimate biomass and assess forest health. For example, the Global Forest Watch initiative uses Sentinel-1 SAR imagery to detect deforestation in near real time. LiDAR, however, is also widely used to measure tree height and canopy density in order to render forest management more sustainable [23].

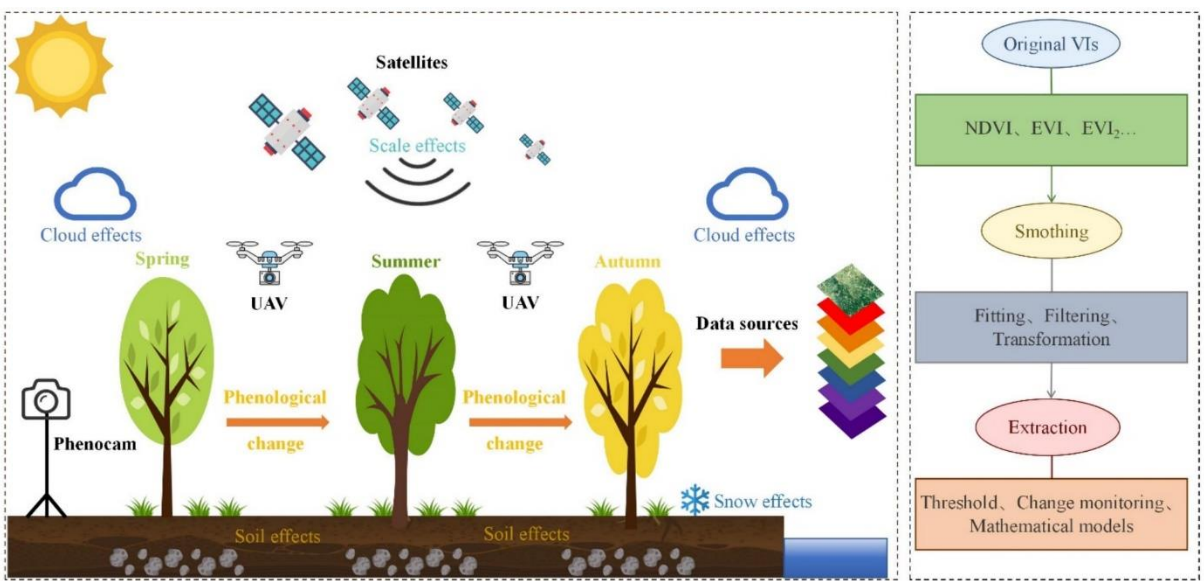

Figure 2. Illustration of remote sensing vegetation monitoring [24].

Climate Change and Environmental Monitoring

The UCS modifications have profound implications on the environment and climate. Remote sensing provides valuable data for desertification and deforestation tracking, land degradation, and policy making for combatting climate change [25]. For example, satellite missions such as GRACE monitor the loss of groundwater, while Sentinel-5P observes air pollutant concentrations [26]. One of the key applications of remote sensing in the industry is carbon accounting, quantifying greenhouse gas emissions related to land-use change. REDD+ (Reducing Emissions from Deforestation and Forest Degradation) projects are premised on such data for tracking carbon stock changes [27].

Disaster Management and Risk Assessment

Remote sensing plays a critical role in disaster management as it facilitates immediate monitoring and rapid damage assessment [28]. For example, Sentinel-1 SAR data is used to detect flooding despite cloud cover, while MODIS and VIIRS thermal sensors are used to monitor forest fires. Indeed, progress in remote sensing technology, supplemented by the pairing of AI with cloud computing, has revolutionized our capacity for analyzing and knowing the UCS dynamics. With these technologies come promising opportunities to better manage natural resources sustainably and respond effectively to environmental stressors [29].

Conclusions

Remote sensing technology is essential in detecting the LULC features with minute details. It has several applications in urban planning and land management, agricultural sectors, forestry, climate change, environmental monitoring, disaster and risk management, etc. However, artificial intelligence methods must be used to analyze the remote sensing data to detect minute details and monitor them accordingly. Spatial and spectral features are essential for urban land classification. Nevertheless, high-resolution remote sensing data is required to deal with the spatial features. Thus, in the future, spatial feature extraction methods could be developed to detect major and minor urban features.

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