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Editorial

Opportunities and Challenges in the Smart and Comprehensive Monitoring of Complex Surface Systems

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The trade-offs between wetland and cropland generate new challenges in understanding the balance between humanity and nature regarding the global carbon cycle, biological diversity, and food supplies [1]. Effective monitoring techniques can be used to acquire valuable information to improve the accuracy, efficiency, and decision making of system construction via bio–physical–chemical interconversion [2]. Moreover, large, curved, and diverse data sets involved in the monitoring process require high-level intelligence and visualization to process [3]. In addition, the fast development of high-quality sensors leads to the dramatic enrichment of a field monitoring data source. Therefore, effective, accurate, and comprehensive information from varied sensors becomes crucial in figuring out the constitutive mechanism of wetland and cropland systems.

Field observation sensors are commonly deployed in the field to automatically acquire data from various physical, chemical, or biological parameters of the environment [4]. Such devices can be either active or passive, depending on whether they provide their own source of energy or detect energy from the environment, such as wave samplers, current meters, water quality sensors, fiber optic sensors, etc. [5]. Field observation sensors can be used to monitor the environmental dynamics and changes over time and space, supporting the research and management of natural resources and ecosystems and, more importantly, providing validation data for remote sensing and modeling [6].

Using sufficient data from various sensors, monitoring platforms and techniques are widely investigated to accomplish the complex monitoring process. Satellite remote sensing is a commonly used method that exploits sensors on satellites, aircrafts, or drones to collect real-time or near-real-time data on the Earth's surface without direct contact [7]. Remote sensing provides information from large-scale Earth observations, producing regional-, continental-, and even global-scale visions on environmental change and responses to human activities [8], and further supports various applications, such as environmental monitoring, agricultural development, geological exploration, etc. [9]. However, the limitations of spatial, spectral, and temporal resolutions hinder the practice of mature satellite remote sensing techniques for small-scale targets, e.g., a specific parcel [10]. Benefiting from the efficient acquisition of high-resolution images of small targets or areas at low altitude, UAVs (unmanned aerial vehicles) have various applications such as 3D modeling, terrain surveying, ecological monitoring, geological hazard monitoring, search and rescue, etc. [11,12]. Hence, UAVs are an effective additional platform for small-scale monitoring missions, effectively enhancing the monitoring accuracy of remote sensing despite the lack of continuous observation [13]. Moreover, a ground-based monitoring platform employ sensors and cameras attached to the ground or a fixed structure to comprehensively measure the deformation or movement of the targeted field [14]. Ground-based monitoring techniques, such as hyperspectral detecting, IoT-supported continuous photography, and soil parameter monitoring, can be used for monitoring landslides, volcanoes, bridges,

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dams, and other significant civil infrastructures in current crop and wetland monitoring missions [15,16].

Technical accuracy and efficacy require sufficient data to support potential practical and theoretical studies. Sensors with different targets and at various distances supply multi-sourced large-scale data sets, which are critical for achieving the effective and depictive models as theoretical guidance. Hence, proper techniques facilitate comprehensive data utilization in formulating the predicted models. Verdugo-Vásquez et al. [17] developed a climate-based model to estimate grapevine phenology, taking into account meteorological data and microclimate data at the plant level. Cooper et al. [18] proposed a predictive modeling framework that integrates genetic, environmental, management, and phenotype data to predict crop performance across diverse scenarios. Furbank and Tester [19] reviewed the advanced mathematical and statistical methods for predicting plant development performance using multiple traits, as well as the integration of experimental metadata within data schemas. Such traditional statistical models effectively estimate plant phenotype factors and water quality.

Nevertheless, theoretical derivations among multi-source data still require in-depth studies. Theoretical inversion models can be significantly developed using multi-source data, in terms of the analyzed information, to reduce the uncertainty and error of the inversion results. Wang et al. [20] used multi-source data fusion of near-surface spectral reflectance, vegetation index, and soil moisture to estimate the growth parameters of summer maize, such as leaf area index and chlorophyll content. Zhang et al. [21] proposed a data integration method that combines the time series monitoring of satellite-based synthetic aperture radar interferometry and leveling data to extract fine subsidence information. Sun et al. [22] developed a multi-source, multi-scale, source-independent full waveform inversion method that uses both surface and borehole seismic data to invert the velocity distribution of the subsurface.

Deep learning techniques are capable of integrating large multi-source data in crop growth and hydrodynamic models to develop in situ monitoring equipment to detect fast-changing phenomena, as they can extract complex features and patterns from remote sensing data, such as spectral, spatial, temporal, and contextual information. Li et al. [23] used a deep neural network (DNN), recursive neural network (RNN), and convolutional neural network (CNN) to classify crops based on remote sensing data, and achieved a higher accuracy than traditional methods. Liu et al. [24] reviewed data fusion techniques that employ multi-source satellite data sets to monitor the hydrological, vegetation, and topographic characteristics of wetlands, which are important indicators of wetland health and function. Alsharif et al. [25] presented object-based and pixel-based deep learning techniques to classify agricultural crops via unmanned aerial vehicle (UAV) imagery, showing that these can improve agricultural field management and productivity.

In summary, the comprehensive monitoring of croplands and wetlands is has potential but is also a huge challenge. This Special Issue is a collection of reviews and original research articles related to space-, aerial-, and ground-based monitoring techniques, which are used to orient crops, wetlands, freshwater areas and their complex interactions, including both algorithms, theoretical models, applications, and hardware development.

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