remote sensing

Editorial

Editorial for Special Issue: "In Situ Data in the Interplay of Remote Sensing"

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1. Introduction

The importance of remote sensing in solving challenges in rural and undeveloped areas where there is a lack of in situ data or financial resources is undeniable. In addition, remote sensing has been recently implemented in densely populated areas to monitor a variety of potential future issues. Due to advancements in sensor technology, many datasets with a high resolution and frequent visit cycles have been generated. There are now several sites online where you may obtain remote sensing datasets for free. Furthermore, a plethora of user-friendly methods, algorithms, and software are available to assist in the extraction of information and measurements from datasets. Interpretation, calibration, and assessment are all necessary parts of the technical process before remote sensing data may serve as a viable substitute for in situ observations. In order to optimally use the value of remote sensing data, in addition to ensuring data continuity and integrity, issues such as performance, standardization, and information retrieval, as well as a low-threshold provision of value-added products for an interested user group or geoinformation market, must be considered. This aspect also applies, above all, to the expensive and labor-intensive provision of in situ data. Standards must be found that allow for the provision of in situ data of sufficient quality and quantity. Additional methods and procedures should also be developed that are based on a limited number of in situ data, but still provide helpful information for the intended objective. Furthermore, it makes sense to combine remote sensing data with real measured in situ data in such a way that the respective advantages of the data sources (in situ data: precisely measured local data; remote sensing data: data measured simultaneously over a wide area) are utilized.

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2. Overview of Contributions

The contributions to this Special Issues targeted two main topics. One deals with applications for vegetation monitoring, and the other with the quantification of precipitation.

2.1. Vegetation

Deforestation and forest degradation are two main sources of problems in the context of vegetation; therefore, Cappello et al. [1] proposed a significant procedure for monitoring national forests to eliminate these problems. The process considers both the National Forest Conservation Program (PNCB) from a satellite-based alert perspective and community participation in forest monitoring through the use of 1853 community-based monitoring

(CBM) alerts in addition to 455 satellite-based alerts. To power their alert-driven monitoring, the PNCB uses satellite-based forest disturbance alerts. When a forest is affected, the PNCB sends out notices to the surrounding communities with printed maps showing the precise location of the incident. If an alert is received, a vigilance committee will go to the site to verify the information. The PNCB is able to receive alerts from space thanks to Landsat 8 (30 m). The level of involvement from the neighborhood was measured. The results show that the community played an important part in gathering information about forest shifts. The paper also discusses the problems with the current system and reports that mobile devices that respond to alerts provide better and faster data on land use, a higher response rate, and the ability to monitor specific areas of interest. In order to better monitor forests, they argued that more communities should be provided with mobile devices. To estimate above-ground live forest fuel loads, Li and He [2] proposed a semi-empirical retrieval model based on optical data (Landsat 7 ETM+) and spaceborne synthetic aperture radar (SAR) data (ALOS PALSAR) (FLAGL). Vegetation coverage information was accounted for in the water cloud model by including optical data (WCM). Additionally, they compared the accuracy of fuel load estimates using a standard WCM to those obtained using data from a single spaceborne L-band SAR (i.e., ALOS PALSAR). The aforementioned two comparison experiments were validated using field measurements (i.e., Bi-oSAR-2008) and the leave-one-out cross-validation (LOOCV) technique. A reasonable performance (R^2 = 0.64 or higher and RMSEr = 35.3% or less) was achieved by the WCM using a single SAR dataset; however, underestimation occurred, especially in dense forests. With an increase in R2 of 0.04 to 0.13 and a reduction in RMSEr of 5.8 to 12.9%, the proposed method outperformed the control group. They also found that the underestimation problem (i.e., the saturation problem) was alleviated even when vegetation coverage reached 65% or the total FLAGL reached about 183 Tons/ha. They used a publicly available Swedish dataset to verify the accuracy of the FLAGL estimation technique.

Following changes in vegetation cover allowed Morsy et al. [3] to estimate changes in groundwater use; they found that irrigation accounted for 70% of total water consumption. To implement the proposed method, they fused together two distinct datasets. First, there are satellite-based datasets (Landsat 7 and 8). (Sentinels 2A), whereas crop varieties, irrigation methods, soil composition, and climate data all fall under the second category of data. Sentinel-2A (30 m) datasets were compared with Landsat datasets from 2015 to 2021, and Landsat 7 and 8 (30m) datasets were used to reveal the change in vegetated areas from 2001 to 2021. Since their results were very similar, Sentinel-2A (10 m) was chosen to round out the rest of the proposal. The authors used five indices to determine land parcel area; develop an improved index (AVI); categorize parcels as light, moderate, or heavy; and estimate a spectrum of irrigation rates.

2.2. Precipitation

Reliable precipitation data are essential for primitive areas. Morsy et al. [4] provided an intriguing example using five gauges. The authors looked into precipitation because it is the most important factor in aquifer recharge at the experimental site (Sinai Peninsula, Egypt). They determined the degree of similarity and dissimilarity between the data from the five gauges: the TMPA data (with a resolution of 0.25° to 0.1°) and the IMERG data (with a resolution of 0.1°). The information above covered four precipitation events (from 2015 to 2018) of varying intensities. Both the TMPA and the IMERG showed a satisfactory performance during the low-intensity events, as shown by the results. However, the certainty was low for the extreme events. As a whole, the IMERG datasets performed better than the TMPA at every criterion. The results of this study lend credence to the idea that IMERG performs better than TMPA in arid and semi-arid regions, but this conclusion cannot be drawn more broadly. Based on the results of the analyses of RS precipitation products, Morsy et al. [4] recommend extending rain gauge networks. Therefore, Morsy et al. [5] also analyzed and improved the performance of a network of rain gauges across the Sinai Peninsula. As a result of a deficiency in precipitation data, this method was implemented. Following the calculation of the elbow graph, the IMERG data were stacked with the digital elevation model (SRTM90 × 90 m), and the clustering procedure was applied with the three different cluster sizes (3, 6, and 9). The centers of each cluster size were determined. The optimal cluster size was then determined by calculating the empirical cumulative distribution function (ECDF). Unfortunately, not a single tested centroids' coverage included the full range of test site altitudes and precipitation. Because of this, the authors opted to use the five pre-existing gauges and the nine cluster centers as a complementary set of data. To further reduce the error, additional points were added to the original 14 using the Kriging of standard error. Thirty-one additional gauges were recommended, and the ECDF verified that these gauges would be suitable for the experiment.

Wang et al. [6] addressed a similar concept as Morsy et al. [5]. They used daily records from 40 rain gauge stations and three types of remote sensing data (GPM IMERGE Early V06, GSMap NRT V6, and PERSIANNCCS) (Wang et al. [6]) to optimize the design of the rain gauge network in the Oujiang River Basin in China. The daily precipitation records at 35 fictitious stations were obtained using the Kriging interpolation method, which was applied to the data from the 40 existing gauges. In total, 3 satellite-based precipitation datasets had their records adjusted by subtracting the daily readings from all 75 gauges, both real and imagined. Seventy-five locations' daily rainfall deviations were collected in three different sets of data. The authors employed a hierarchical algorithm to perform a layer-by-layer decomposition of the daily rainfall deviation data at the stations, ultimately arriving at the joint information entropy. This allowed the gauge with the highest compatible entropy to remain at the top of the network optimization list. The study found evidence that demonstrated that the optimization and ranking of the rain gauge station network was stable and consistent. In addition, the combined entropy of the outlier was larger than that of the precipitation data measured at ground level. This allows for more accurate and easily understood network optimization by using deviation data instead of traditional ground-based precipitation data.

3. Conclusions

This Special Issue's articles are aimed at informing scientists about the importance of in situ measurements and how they will affect the credibility and quality of data gathered through remote sensing imaging. The in situ information used for this must be reliable, accurate, impartial, timely, and relevant. Impressive examples of this are given by Li and He [2], Wang et al. [5], and Morsy et al. [4,5]. The proposed ideas by Morsy et al. [5] and Wang et al. [6] describe approaches to how in situ networks could be developed to establish a better reliability of RS products.

As was previously mentioned, in situ measurement collection is prohibitively expensive, time-consuming, and spatially constrained (Section 1). Nevertheless, Cappello et al. [1] were able to provide some really great solutions to get past the majority of these obstacles. The proposed solution calls for widespread community involvement during the in-person data collection phase, allowing it to encompass more and larger areas of impact. Benefits will be amplified and obstacles eliminated if governments and ministries can be convinced to participate in and enable data collection.

The topic of properly highlighting the importance of in situ measurement collection and its impact on remote sensing datasets is extremely interesting, and the author's outstanding contribution may give the scientific community new techniques to acquire proper in situ measurements and integrate them with remote sensing data. For this reason, the Editorial Board and Guest Editors have decided to publish a second volume of the same Special Issue. Please see the following link for further information:

Remote Sensing | Special Issue: "In Situ Data in the Interplay of Remote Sensing II" (mdpi.com).

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