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A NOVEL APPROACH FOR ENVIRONMENTAL MONITORING BASED ON THE INTEGRATION OF MULTI-TEMPORAL MULTI-SOURCE EARTH OBSERVATION DATA AND FIELD SURVEYS IN A SPATIO-TEMPORAL FRAMEWORK

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ABSTRACT

To perform specific environmental analyses with high accuracy and spatial resolution, typically dedicated Earth Observation (EO) data are acquired via aircraft or drones. Although valuable, these data can be: (i) limited and sparse in time and space due to their acquisition cost, and (ii) asynchronous to field data collection. To consistently ingest asynchronous EO data and field surveys, this paper generates a spatio-temporal framework by exploiting the ability of Sentinel-1 satellites to provide frequent EO data with global coverage. Experiments, conducted in Indonesia to estimate changes in forest Above-Ground Biomass (AGB) between 2017 and 2019, demonstrate the ability of the spatio-temporal framework to integrate Light Detection and Ranging (LIDAR) data acquired in 2020. The method achieved a R^2 of 0.76 and a RMSE of 21.24 compared to 0.50 and 0.57 and 28.65 and 23.93 for the standard bi-temporal approach (using field data and Sentinel-1 data) and the bi-temporal approach including the LIDAR data without any adaptation, respectively.

Index Terms— Spatio-Temporal Integration, Sentinel data, Multi-source data, Multi-temporal data, Asynchronous data, Google Earth Engine (GEE).

1. INTRODUCTION

Continuous monitoring of the Earth' surface is necessary to understand ongoing environmental processes such as desertification, deforestation or arctic greening. In this context, the intrinsic multi-temporal nature of satellite Earth Observation (EO) data can be used to systematically control dynamic environmental phenomena [1]. Satellite data represent a valuable source for continuous monitoring [2], however, some analysis may require dedicated acquisition campaigns to collect specific EO data. For instance, to measure the 3D structure of the forest at very high resolution, aerial Light Detection and Ranging (LIDAR) data are typically acquired [3]. Although drone or aircraft acquisition campaigns allow for the collection of EO data tailored to specific environmental analysis, two main problems typically arise: (i) the collection of these data can be sparse in space and time, (ii) due to the acquisition cost they are restricted to a relatively small area and to a specific acquisition date. Moreover, even though the flight should be ideally contemporary to the field data collection, a non-simultaneous data acquisition is more realistic. Note that this is mostly the case in reality, in particular in vast areas, which are difficult to access (e.g., tropical forests).

To solve these problems, this paper aims to take advantage from the global and frequent acquisition of the Sentinel satellites to create a continuous observation component of the whole study area, i.e., a spatio-temporal framework. Such a framework is used to: (i) exploit the continuous satellite observations to track the main changes from the spatial and temporal view point, and (ii) integrate field surveys or EO data acquired trough dedicated drone or aircraft campaigns in a consistent way. To assess the effectiveness of the method, we estimate Above-Ground Biomass (AGB) changes in a forest located in Indonesia, where repetitive field surveys were conducted in 2017 and 2019 and LIDAR data were acquired in 2020. The Sentinel-1 data acquired from 2017 to 2020 were processed in the Google Earth Engine (GEE) platform to efficiently perform the analysis for the entire study area.

2. BACKGROUND AND PROBLEM FORMULATION

The estimation of AGB changes is typically conducted using active Remote Sensing (RS) techniques such as LIDAR or Interferometric Synthetic Aperture Radars (InSAR) due to their ability to penetrate tree canopies, thereby measuring the major components of biomass (i.e., trunks and branches) [3, 4]. Although the results demonstrate the effectiveness of LIDAR

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and InSAR data to estimate the AGB changes, these data are not publicly available and are not continuously acquired, thus hindering their use for long-term analysis. Due to their prohibitive acquisition costs, bi-temporal change detection analysis are typically carried out. Moreover, most of the methods assumes to have repeated and coincident field data are available [1], which may be a critical constrain from the operational view point. In this context, satellite missions such as Sentinel-1 and Sentinel-2, which frequently acquire EO data at global level, allow for continuous environmental monitoring. Such repeated acquisitions can be easily matched with field data collections from the temporal view point resulting in no particular need to plan coincident data acquisition campaigns. Although some studies demonstrate that AGB changes can be estimated using Sentinel data [1, 2], little has been done since they are sub-optimal in representing the 3D forest structure with respect to InSAR data from TanDEM-X or LIDAR data [2]. In this context, the possibility of consistently ingesting into the model an asynchronous EO data tailored to the specific environmental analysis can sharply enhance the results obtained.

Differently from the literature, this paper does not aim to define a regression model which links the features extracted from the Sentinel data to the field survey for estimating AGB changes. The main goal of this paper is to exploit the Sentinel satellites to define a spatio-temporal framework that allows us to: (1) perform a temporal analysis that can track major land cover changes for the entire study area, (2) integrate asynchronous field surveys and airborne EO data in a consistent way, and (3) enhance and better interpret the obtained AGB changes results. Let us assume that the observation period of the considered environmental analysis ranges from t_1 to t_2, where repeated field data are available, i.e., F_1 and F_2. Let Z_n be an EO data acquired at time t_n, with $n \neq [1, 2]$. Although Z_n can be extremely useful to improve the considered environmental analysis, due to land cover changes, its direct use has the risk to include inconsistent information. For this reason, we aim to exploit the Sentinel-1 data acquired in t_1, t_2 as well as in t_n to consistently integrate Z_n in the considered observation period. In the following, details are given.

3. PROPOSED INTEGRATION APPROACH

In the considered experimental analysis, we focus on estimating AGB changes in the forest area located in Indonesia, characterized by frequent forest cuts followed by regrowth due to the presence of timber and oil palm plantations. Due to the continuous land cover changes, this test case allows us to evaluate the effectiveness of the proposed approach. However, the proposed method can be adapted to any other environmental variable that requires continuous monitoring. Figure 1 shows the flow chart of the proposed approach, based on three main phases: (1) computation of the spatio-temporal satellite EO components, (ii) asynchronous data integration, and (iii) AGB changes model training.

3.1. Spatio-Temporal Satellite EO Components

To ensure a constant monitoring of the Earth' surface, satellite EO data should be considered due to their repeat coverage capability at global level. The considered satellite data are Sentinel-1 images, because of the heavy cloud coverage of the analyzed tropical forest. In particular, the Interferometric Wide Swath (IW) data with dual-polarization (i.e., VV & VH) of Sentinel-1 are processed to time series backscatter data. Data from one relative orbit was used in order to avoid potential look direction and incidence angle effects, which can appear particularly on forest edges. Consequently, speckle noise is reduced with a multi-channel filter based on the consistent Sentinel-1 time series data with 12 days repeat-pass time [5]

$$J_k(x,y) = \frac{\hat{\sigma}_k(x,y)}{M} \sum_{i=1}^{M} \frac{I_i(x,y)}{\hat{\sigma}_i(x,y)}, 1 \leq k \leq M \qquad (1)$$

where J_k means the filtered image for each input image I_i on its x and y position and M means the number of images. A 5 by 5 pixel kernel size was used in the adaptive Lee Sigma filter to calculate the local mean intensity $\hat{\sigma}_i(x,y)$. Furthermore, topographic effects on the Sentinel-1 SAR backscatter are normalized resulting in γ^0 assuming a volume scattering model [6]

$$\gamma^0 = \gamma^0_f \frac{\tan(90° - \theta_i + \alpha_{rg})}{\tan(90° - \theta_i)} \qquad (2)$$

where γ^0_f means the backscatter on flat terrain $\left(\gamma^0_f = \frac{\sigma^0}{\cos(\theta_i)}\right)$, α_{rg} means the slope steepness angle in range and θ_i means the incidence angle. Temporal information of Sentinel-1 backscatter is extracted from the filtered and topographically normalized individual images. The average and standard deviation of Sentinel-1 VH and VV backscatter are calculated for the time-frame that includes the considered asynchronous field data and airborne EO data, i.e., S_1, S_2 and S_n. Note that temporal information of C-band backscatter is considered high potential in forest mapping [7]. For this reason, the spatio-temporal components were computed at seasonal level per year (every 3 months). To reduce the burden of this computation (to be carried out at large-scale analysis for several years) we used the GEE platform which provides big data analytical capabilities and free access to Sentinel-1 data.

3.2. Asynchronous Data Integration

This step aims to consistently integrate the asynchronous acquisition EO data Z_n into the AGB change model trained using F_1 and F_2. To this end, we consider the spatio-temporal component S_1, S_2 and S_n calculated in the previous step that allows us to track major changes that have occurred on the ground (e.g. clear-cut). Indeed, the main risk of directly using Z_n to perform the AGB change estimation occurred between t_1 and t_2 is the introduction of information inconsistent

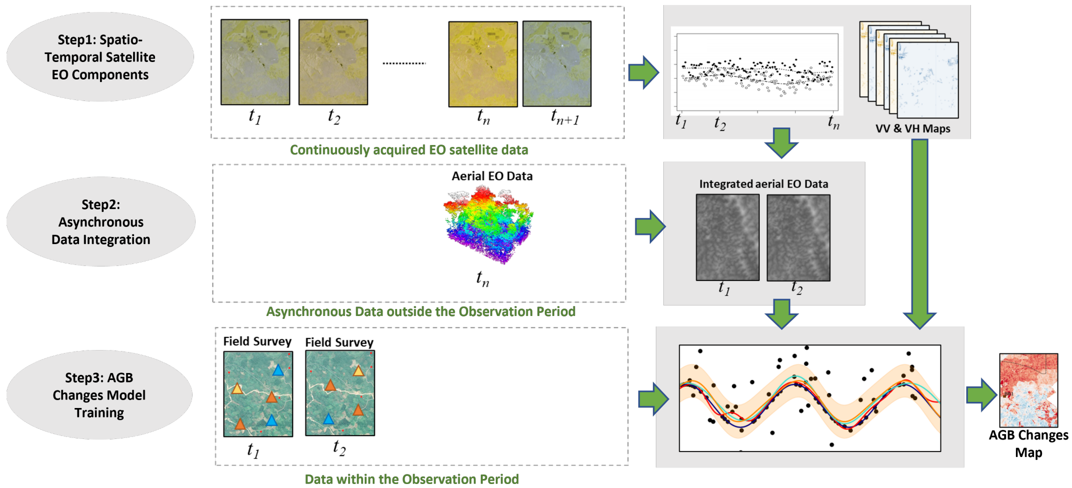

Fig. 1. Flow chart of the proposed approach which aims to exploit the spatio-temporal information provided by the continuous monitoring of the spaceborne EO data to enhance the AGB change estimate carried out using asynchronous airborne EO data and field surveys.

from the spatial and temporal view point. Here, for simplicity, we use a Random Forest machine learning regression model [8] to transfer the information provided by Z_n at time t_n to the considered observation time, i.e., t_1 and t_2. In particular, we train the regression model using the Sentinel-1 acquisition contemporary to the asynchronous acquisition EO data, S_n, to generate a simulated version of Z_n, i.e., $\hat{Z}_n$. This condition allows us to apply the same model to S_1 and S_2 to generate the adapted version of the considered EO data at time t_1 and t_2, i.e., $\hat{Z}_1$ and $\hat{Z}_2$. Because of the continuous information provided by Sentinel-1, it is reasonable to assume that these simulated data implicitly capture the land cover changes occurred on the ground. It is worth noting that more sophisticated deep learning techniques can be employed to "translate" one EO data into another, e.g., Generative Adversarial Network (GAN). However, the goal of this step is not simulating the aerial EO data trough the satellite one, but to consistently inject the asynchronous information collected at time t_n into the model trained using the field surveys collected in the considered observation period, F_1 and F_2.

3.3. AGB Changes Model Training

In the final step of the method, both the spatio-temporal components (S_1 and S_2) and the integrated asynchronous EO data, ($\hat{Z}_1$ and $\hat{Z}_2$), are used to train the AGB changes model using the repeated field surveys (F_1, F_2). To this end, we considered a Gaussian ernel Support Vector Regression (SVR) technique, widely used for the estimation of biophysical parameters from EO data because of its good generalization capability, limited complexity and high stability of the learning process [9]. The features ingested by the SVR model are the temporal average and standard deviation of Sentinel-1 VH and VV backscatter described in Sec. 3.1, i.e., S_1 and S_2, computed per sample plot. To inject the spatial information in the considered regression model, for each sample plot we calculate both the median and the standard deviation of each feature extracted from the time series of Sentinel-1 data from the spatial view point, i.e., for all the pixels of the sample plot.

4. DATASET DESCRIPTION AND RESULTS

The considered study area is a generally flat tropical landscape located in the Jambi province, Sumatra, Indonesia. The area is characterized by frequent conversions from rainforest to agroforests as well as large-scale mono-cultural plantations of rubber and oil palm. Consequently, it is a mosaic of smallholder plantations, plantations and natural forest patches.
In situ inventories were conducted in 2017 and 2019 in 37 stands plot randomly distributed in the Jambi province. The plots had a size of 0.25 ha (50 m $\times$ 50 m) and covered forested land use types in flat areas, i.e., natural rainforest and (jungle) rubber. The diameter at breast height (dbh), tree height and plant species identity of trees $\geq$10 cm were repeatedly recorded in 2017 and 2019. These measurements were used to estimate the AGB of the individual trees, which was further summed and area normalized resulting in a plot AGB in t ha^{-1}[10, 4]. An airborne LIDAR data acquisition was carried out in 2020 to objectively monitor the whole study area. A Riegl Q780 full waveform scanner was used for this study and the point cloud had a density of about 15 points/m^2, which increased in overlap areas to about 40 points/m^2. Figure 2 represents the asynchronous data available for the considered experimental analysis.

Table 1 shows the AGB changes obtained considering the proposed spatio-temporal framework and the standard bi-temporal approach typically used in the literature using

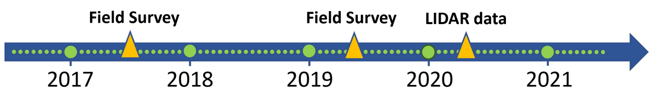

Fig. 2. Temporal representation of the considered dataset. The field surveys were collected in 2017 and 2019, while an airborne LIDAR data was acquired in 2020.

the Sentinel-1 features and the repeated field surveys, i.e., the baseline method. Moreover, to prove the importance of adapting the asynchronous LIDAR data from the temporal view point, we compared the results obtained by the proposed method with the baseline method using as feature also the highest height value of each plot measured in 2020, i.e., H^{max}. Different SVR models were trained for both the baselines and the proposed approach. The grid search strategy is adopted to cover a wide spectrum of possible parameter configurations selected according to the standard cross-validation strategy. The ranges for the grid search are [10^{-3}; 10^{3}], [10^{-4}; 10^{3}], and [10^{-4}; 10] for γ (the RBF kernel width), C, and ϵ, respectively. Due to the low number of available sample plots (37 samples), 33 samples were randomly selected to generate the training set, while a small test set of 4 samples was only used to perform independent evaluation of the obtained results. Five different datasets were generated to average the results over five statistically independent trials.

The results obtained demonstrate both the importance of the use of the asynchronous information provided by the LIDAR data and the need of integrating it in the considered observation period. As expected the Sentinel-1 information were not sufficient to achieve accurate estimation results in such a complex study area (i.e., a R^2 of 0.50 on the test set). By directly including the LIDAR data of 2020, the R^2 increased to 0.57 but it was still affected by land cover changes. However, the LIDAR data integrated with the proposed spatio-temporal framework increased the R^2 to 0.76.

5. CONCLUSION

This paper has presented a novel approach for environmental monitoring that aims to integrate multi-source multi-temporal airborne EO data and field survey in a spatio-temporal framework leveraging on spaceborne EO data. To assess the effectiveness of the method, we estimate AGB changes in a forest study area characterized by frequent land cover changes, where LIDAR data were acquired in 2020 and repetitive field survey were carried out in 2017 and 2019. From the experimental results obtained, we can conclude the spatio-temporal framework: (i) enhances the considered environmental analysis, and (ii) allows a better integration of the asynchronous multi-source multi-temporal considered data. As future development, we aim to test the proposed approach on different datasets for assessing its capability of ingesting different data source, which are sparse in time and space.

Table 1. MAE (t ha^{-1}), RMSE (t ha^{-1}) and R^2 of the AGB changes results computed with the Proposed Method (PM), the Baseline Method (BM) using only Sentinel-1 images acquired in 2017 and 2019 (S1), and BM using the Sentinel-1 images acquired in 2017 and 2019 and the LIDAR data acquired in 2020 (S1+H^{max}). The results, presented for both the test and training set, are averaged over five statistically independent trials.

Method	**Train Set**			**Test Set**		
	MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
BM (S1)	10.00	15.48	0.72	23.43	28.65	0.50
BM (S1+H^{max})	7.58	12.36	0.82	17.18	23.93	0.57
PM (S1+H^{max})	6.71	9.39	0.87	16.73	21.24	0.76

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