URBAN SITES CHANGE DETECTION BY MEANS OF SENTINEL-1 AND SENTINEL-2 TIME SERIES

Mattia Stasolla[1], Sophie Petit[2], Coraline Wyard[2], Gérard Swinnen[2], Xavier Neyt[1] and Eric Hallot[2]

[1]Signal and Image Centre, Royal Military Academy, Brussels, Belgium
[2]Remote sensing and geodata unit, Institut Scientifique de Service Public (ISSeP), Liège, Belgium

ABSTRACT

The Walloon Region is currently managing a database of more than 2000 'redevelopment sites', i.e. urban sites that were previously used for industrial activities and/or housing and that are now abandoned. The administration needs to keep this inventory up-to-date so that the necessary urban planning could be done; however, at the moment, this information is obtained via time-consuming on field campaigns. Thanks to the launch of the Copernicus programme, free satellite data are now provided at high temporal resolution, and new monitoring approaches can be implemented. Leveraging a well-established changepoint detection method, this paper shows some preliminary results on how time series of Sentinel-1 and Sentinel-2 data could be jointly used to automatically detect changes in urban areas, thus providing the Walloon Region with a tool that can be exploited for a more efficient management of the 'redevelopment sites'.

Index Terms— change detection, time series, urban area, Sentinel-1, Sentinel-2.

1. INTRODUCTION

In the 19th century Wallonia was a highly developed industrial region, whose activities were mainly related to coal, metal and textile production. From the 1950s, the deindustrialization of the region led to a progressive abandonment of factories and other production sites. In this paper, we will refer to these areas as redevelopment sites (RDSs). If on the one hand, the presence of RDSs negatively impacts on the urban fabric, on the other hand it represents an opportunity for sustainable urban planning. To this end, the Walloon Region is currently managing a publicly available inventory of the RDSs [1] in order to provide up-to-date information about the sites that have been regenerated and those that are still in disuse. At the moment, the inventory contains more than 2200 sites, and updating it is costly and time-consuming, as it is mainly done through on field campaigns and/or manually analysis of aerial orthophotos. Moreover, since most of the sites tend to remain unchanged (it is estimated that less than 10% would change from one year to the next), it is important to ensure that the visits are prioritized according to the actual needs in order to optimize the available resources.

Thanks to the Copernicus programme, which is freely distributing Sentinel-1 and Sentinel-2 data, new opportunities have been opened up, and a more efficient management of the RDS inventory is now possible. Several studies have investigated and highlighted the potential that a combination of these two complementary sensors has for urban area mapping and vegetation monitoring [2],[3]. Moreover, the short revisit time that the Sentinel satellites can guarantee enables a consistent and detailed analysis of changes over time.

The goal of the paper is therefore to discuss how Sentinel-1 and Sentinel-2 time series could be exploited to develop a tool for the automatic monitoring of RDSs.

2. METHODOLOGY

2.1 Study Area

The analysis here presented focuses on a subset of the whole RDS database and it comprises 22 sites chosen within the areas of Liège and Charleroi. This allowed us to specifically cover all the types of changes in which we were interested. According to the needs of the Walloon Region, these include changes (increase/decrease) in buildings, vegetation and soil. The map of the RDSs under study is shown in Fig. 1, which also provides three examples of possible changes.

2.2 Sentinel data

For this study, all the Sentinel-1 and Sentinel-2 data from June 2016 to June 2020 have been analyzed. The processing has been carried out in cloud computing via Terrascope [4], the Sentinel Collaborative Ground Segment for Belgium.

As far as the Sentinel-1 products are concerned, the Terrascope catalogue, along with the original Interferometric Wide (IW) Single Look Complex (SLC) and Ground Range Detected (GRD) images, also contains the corresponding calibrated and orthorectified sigma0 products, whose VH bands have been used for the analysis.

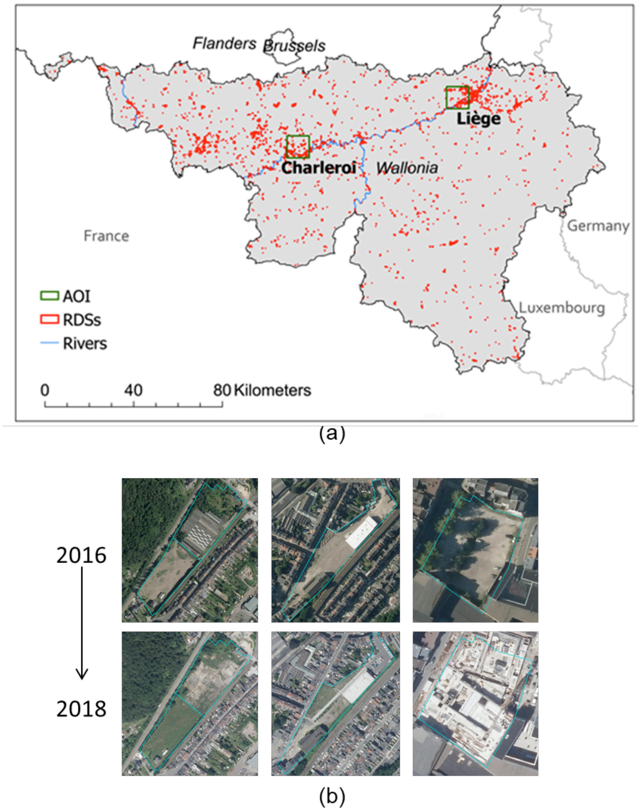

Fig. 1. (a) Spatial distribution of the RDSs in Wallonia (red marks). In green, the areas studied in this work; (b) Close-ups of three RDSs located in Liège, showing some possible types of change: building demolition (left), vegetation increase (center), and building construction (right).

For each image, the average sigma0$_{VH}$ of each RDS has been computed. Since an RDS is typically present in images taken from 3 to 4 different passes of the satellite (both ascending and descending), the final time series has been obtained by averaging the backscattering profiles of the multiple observations.
As regards the Sentinel-2 data, the platform contains atmospherically corrected images, obtained from L1C products that have been processed using iCOR [5]. For each image, a Sen2Cor scene classification is also provided. After discarding the images with more than 25% cloud cover and removing the pixels classified as clouds or shadows in the remaining ones, the average Normalized Difference Vegetation Index (NDVI) for each site is calculated and used to populate the time series.
Both Sentinel-1 and Sentinel-2 time series are first linearly interpolated (1 sample per day) to fill the data gaps and then smoothed using a Gaussian kernel with a standard deviation of 61. The smoothing of the temporal profile is expected to reduce the effect of speckle noise in SAR data and compensate for the values in the Sentinel-2 time series that are missing due to cloud cover.

2.3 Ground Truth

Every summer the Walloon Region organizes an aerial survey to acquire orthophotos (25 cm resolution) of the entire territory. Based on the orthophotos available for the years 2016, 2017, 2018, 2019, and together with two Pleiades images (4-band pan-sharpened products at 0.5 m resolution) taken in June 2020, a ground truth has been created by visual analysis. For each of the 22 RDSs, year-on-year changes in vegetation, buildings and soil were recorded. A breakdown into types of change is reported in Table 1. The last column of the table ('Aggregate') shows the total number of changes when multiple changes per site are counted as a unique change (e.g. if from one year to the next, an RDS is assigned both a building and a vegetation change, this would count as a single change). In the 4-year span we counted 31 changes out of 88 possible cases. The 'no change' occurrences are therefore 57. This information will be used in Section 3 for the performance assessment.

Table 1. Ground truth: number of changes and breakdown into change types.

Year	Building	Vegetation	Soil	Aggregate
2016/2017	5	6	7	**7**
2017/2018	3	8	11	**11**
2018/2019	2	4	5	**6**
2019/2020	2	5	6	**7**
2016-2020	*12*	*23*	*29*	***31***

2.4 Time series change detection

The approach used in this paper to address the change detection problem is based on changepoint analysis, which is largely employed for the study of time series in many application domains, from speech processing to climatology [6]. As far as satellite remote sensing is concerned, this remains a rather unexplored topic [7], although in recent years the availability of archives of imagery has increasingly drawn the attention to this family of techniques [8],[9]. Leveraging the large amount of data that is now supplied by the Copernicus programme, the idea is to apply changepoint detection to time series of features extracted from Sentinel-1 and Sentinel-2 images.
There are three main reasons behind the choice of this type of approach. First, changepoint detection has proved valuable in many applications, yet it is still underexploited in remote sensing. Second, the methodology is unsupervised and requires no a priori knowledge. Considering the low change rate of the RDSs, if we were to opt for supervised learning, we might not be able to collect a sufficient number of training samples. Third, depending on the chosen changepoint detection algorithm, the methodology can be computationally efficient.
Amongst the others, the Pruned Exact Linear Time (PELT) method is a well-established algorithm for changepoint detection proposed in 2012 by Killik et al. [10]. It provides

an exact segmentation of the time series with a linear time complexity. Given a time series $s = (s_1,\ldots,s_k)$, the number n and time position $t_{1:n} = (t_1,\ldots,t_n)$ of the changepoints is obtained by solving the penalized minimization problem:

$$Q_n(s_{1:k}, p) = \min_{n, t_{1:n}} \left\{ \sum_{i=1}^{n+1} [C(s_{(t_{i-1}+1):t_i})] + p \right\}$$

where C is a segment-specific cost function, and p a penalty term to control overfitting. In our analysis, the least squares cost function and a penalty term $p=\log(k)$ have been used.

3. RESULTS

The performance of the presented method is assessed in terms of true positive rate (TPR) and false positive rate (FPR). The overall problem can be in fact seen as a binary classification where either a ‘change’ (1) or a ‘no change’ (0) has to be detected. As we discussed in the previous Section, in order to compare the results with the ground truth, the latter has been coded so that any yearly change in any of the 3 classes (building, vegetation, soil) is assigned the value 1; in the case of no change for all the 3 classes, the ground truth is given the value 0. A confusion matrix is then generated so that the number of true positives (TPs), true negatives (TNs), false positives (FPs) and false negatives (FNs) could be used to compute the TPR and FPR. To provide a unique measure that takes into account both detection and miss rates, the F_1-score has also been calculated.

3.1 Sentinel-1 change detection

The results obtained using the Sentinel-1 sigma0$_{VH}$ feature are reported in Table 2. Each row indicates the changes that have been detected in each 1-year interval from 2016 to 2020. The aggregate values for the 4-year period are reported in the last row. Overall, the performance is not satisfactory. Although the number of FPs remains quite low (it corresponds to an FPR of only 5%), the high number of FNs biases the results and limits the TPR to 16%. This is reflected in a low F_1-score (0.26). Some explanations for such behavior are the resolution of the images (about 20 m), which can significantly limit the sensitivity with respect to small changes, and the nature itself of the sensor, which is less effective when it comes to detecting changes such as the transition from bare soil to grass. If we look at the values obtained in each 1-year interval, we can notice that the performance can significantly vary depending on the type and combination of changes that have occurred in a certain year. In particular, between 2016 and 2017, 5 out of 7 changes were related to buildings, to which SAR is more sensitive, yielding a TPR of 43% and an F_1-score of 0.55. The 2017-2020 changes, instead, were mainly due to differences in vegetation and soil, causing a higher number of FNs and therefore a significant drop-off in the F_1-score.

Table 2. Sentinel-1 (sigma0$_{VH}$ feature) changepoint analysis: confusion matrix and performance metrics.

Year	TP	FP	FN	TN	TPR	FPR	F_1-score
2016/2017	3	1	4	14	43%	7%	0.55
2017/2018	1	1	10	10	9%	9%	0.15
2018/2019	0	0	6	16	0%	0%	0
2019/2020	1	1	6	14	14%	7%	0.22
2016-2020	**5**	**3**	**26**	**54**	**16%**	**5%**	**0.26**

3.2 Sentinel-2 change detection

On the contrary, Sentinel-2, particularly using the NDVI feature, is expected to perform better on changes in vegetation/soil. Also, the available spatial resolution is higher: 10 m. The expectations are confirmed looking at the results presented in Table 3. As can be seen, the errors are almost evenly spread out over the 4 years, with slight fluctuations mainly due to the fact that the number of changes per year is not constant. The overall performance is satisfactory, with an average TPR of 52% and an FPR of 7%. The F_1-score is on average 0.63.

Table 3. Sentinel-2 (NDVI feature) changepoint analysis: confusion matrix and performance metrics.

Year	TP	FP	FN	TN	TPR	FPR	F_1-score
2016/2017	3	0	4	15	43%	0%	0.60
2017/2018	8	2	3	9	73%	18%	0.76
2018/2019	2	2	4	14	33%	13%	0.40
2019/2020	3	0	4	15	43%	0%	0.60
2016-2020	**16**	**4**	**15**	**53**	**52%**	**7%**	**0.63**

3.3 Sentinel-1 and Sentinel-2 change detection

To benefit from both SAR and multi-spectral sensors’ characteristics, we finally tested the joint use of sigma0$_{VH}$ and NDVI. The merging is possible directly at the input level by feeding PELT with a bi-dimensional time series.

A detailed example of how the change detection accuracy can be improved by using both features is shown in Fig. 2, which presents the full processing for one of the RDSs. According to the ground truth orthophotos in Fig. 2(a), a building has been removed between summer 2017 and summer 2018, and vegetation has progressively grown between summer 2018 and summer 2019. If we only use the sigma0$_{VH}$ time series (Fig. 2(b)), we are able to correctly detect the building demolition, but we have no means of spotting the change in vegetation. Conversely, as shown in Fig. 2(c), by exploiting the NDVI we can identify the change date in 2019, but we miss the one in 2017. Finally, if we provide as input both the features, the changepoint detection successfully returns the two dates (Fig. 2(d)).

The results for the whole dataset are provided in Table 4. As can be seen, the combination of the two features has mainly an impact on the detection of the changes with which one single feature was not able to cope.

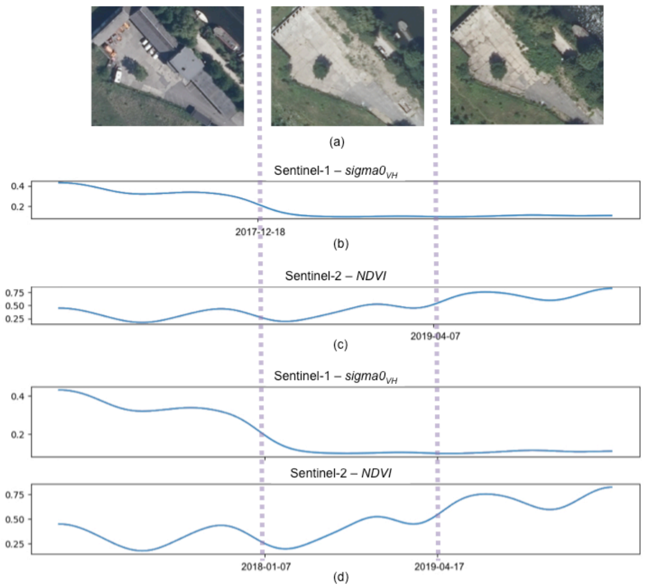

Fig. 2. Changepoint analysis for the RDS "Service voirie d'Angleur" in Liège. (a) Ground truth (left: summer 2017, center: summer 2018, right: summer 2019); (b) Sentinel-1 time series (sigma0_{VH} feature); (c) Sentinel-2 time series (NDVI feature); (d) Bi-dimensional time series (sigma0_{VH} and NDVI).

Table 4. Sentinel-1 and Sentinel-2 (sigma0_{VH} and NDVI features) changepoint analysis: confusion matrix and performance metrics.

Year	TP	FP	FN	TN	TPR	FPR	F_1-score
2016/2017	6	1	1	14	86%	7%	0.86
2017/2018	8	3	3	8	73%	27%	0.73
2018/2019	3	1	3	15	50%	6%	0.60
2019/2020	3	0	4	15	43%	0%	0.60
2016-2020	**20**	**5**	**11**	**52**	**65%**	**9%**	**0.71**

In general, the number of FNs decreases as more changes in building or vegetation/soil are detected thanks to Sentinel-1 and Sentinel-2, respectively. To quantify the improvements achieved with the data fusion, we can use as a baseline the results obtained with the NDVI feature, which provided the highest F_1-scores. As can be seen, other than for the year 2017/2018, where the presence of an additional FP is slightly lowering the F_1-score, for all the other 1-year intervals the F_1-scores are greater or equal than the corresponding NDVI-only ones. If we look at the entire period of time, the TPR increases by more than 10 percentage points (pp), while the FPR only increases by 2 pp, yielding an F_1-score of 0.71.

4. CONCLUSIONS

In this paper, the PELT method was applied to Sentinel-1 and Sentinel-2 time series in order to automatically detect changes in urban areas. The starting point was to provide the Walloon Region with a change detection tool that could help them managing in a more efficient way their database of redevelopment sites, for example by prioritizing the on-site visits according to a ranking list automatically generated.

The presented results, based on a subset of 22 RDSs, suggest that by combining radar and multi-spectral information it is possible to identify changes with a relatively good precision, given that there are inherent limitations due to the spatial resolution and characteristics of the sensors. Further tests for the whole set of 2000+ RDSs are now needed to confirm these preliminary results. Also, the use of additional features such as the VV band and other spectral indexes will be studied in order to improve the overall accuracy. Finally, different types of spatial segmentation will be investigated, as the size of the RDSs may vary considerably and only localized changes might occur.

5. ACKNOWLEDGMENT

The research presented in this paper is funded by BELSPO (Belgian Science Policy Office) in the frame of the STEREO III programme – project SARSAR (SR/00/372).

6. REFERENCES

[1] http://lampspw.wallonie.be/dgo4/site_sar/index.php, retrieved May 28, 2021.

[2] Jan Haas, Yifang Ban, "Sentinel-1A SAR and Sentinel-2A MSI data fusion for urban ecosystem service mapping", *Remote Sensing Applications: Society and Environment*, Vol. 8, pp. 41-53, 2017.

[3] G. Satalino et al., "Sentinel-1 & Sentinel-2 Data for Soil Tillage Change Detection", *Proceedings of IGARSS'18*, pp. 6627-6630, 2018.

[4] https://terrascope.be/en, retrieved May 28, 2021.

[5] L. De Keukelaere, S. Sterckx, S. Adriaensen, E. Knaeps, I. Reusen, C. Giardino, M. Bresciani, P. Hunter, C. Neil, D. Van der Zande, D. Vaiciute, "Atmospheric correction of Landsat-8/OLI and Sentinel-2/MSI data using iCOR algorithm: validation for coastal and inland waters", *European Journal of Remote Sensing*, 51:1, pp. 525-542, 2018.

[6] C. Truong, L. Oudre, N. Vayatis, "Selective review of offline change point detection methods", *Signal Processing*, 167:107299, 2020.

[7] Militino A.F., Ugarte M.D. and Pérez-Goya U., "Detecting change-points in the time series of surfaces occupied by pre-defined NDVI categories in continental Spain from 1981 to 2015", *The Mathematics of the Uncertain*, pp. 295-307, Springer, 2018.

[8] Hethcoat M.G., Carreiras J.M., Edwards D.P., Bryant R.G. and Quegan S., "Detecting tropical selective logging with SAR data requires a time series approach", *bioRxiv*, 2020.

[9] Stasolla M., Neyt X., "Applying Sentinel-1 Time Series Analysis to Sugarcane Harvest Detection", *Proceedings of IGARSS'19*, pp. 1594-1597, 2019.

[10] R. Killick, P. Fearnhead, and I. Eckley, "Optimal detection of changepoints with a linear computational cost", *Journal of the American Statistical Association*, 107(500), pp. 1590–1598, 2012.