GISTAM 2019

5th International Conference on
Geographical Information Systems Theory, Applications and Management

PROCEEDINGS

Heraklion, Crete, Greece

3-5 May, 2019

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GISTAM 2019

Proceedings of the
5th International Conference on
Geographical Information Systems Theory,
Applications and Management

Heraklion, Crete - Greece

May 3 - 5, 2019

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Edited by Cédric Grueau, Robert Laurini and Lemonia Ragia

Printed in Portugal

ISSN: 2184-500X

ISBN: 978-989-758-371-1

Depósito Legal: 454350/19

http://www.gistam.org

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Critical Analysis of Urban Vegetation Mapping by Satellite Multispectral and Airborne Hyperspectral Imagery

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Keywords: Multi-temporal, Satellite Imagery, Airborne Hyperspectral Imagery, Vegetation Species, NDVI.

Abstract: The monitoring and management of urban vegetation is an important issue nowadays due to the multiple benefits of vegetation for people well-being and for maintaining the balance of ecosystem. In that context, the following study explore to what extent remote sensing imagery could be used to detect and to characterize urban vegetation. Two types of imagery were tested which are low-resolution satellite (i.e. Sentinel 2 and Landsat 8 OLI) and high resolution airborne (i.e. Rikola hyperspectral sensor), the study assessed the detectability of vegetation species over Kaunas city (Lithuania) for different seasonal acquisitions. Satellite imagery showed accurate detection of 3 coarse classes of vegetation with overall accuracies (O.A.) superior to 90%, and airborne hyperspectral imagery showed decent detection of 13 fine classes of vegetation with O.A. of up to 73%.

1 INTRODUCTION

Urban vegetation mapping using remote sensing imagery is an emerging branch, indeed, the interest of studying, mapping, and managing green spaces is of capital importance for several actors including agronomists, urban architects, and environmental scientists. The availability of satellites imagery including Sentinel and Landsat programs permits several possibilities in terms of green areas detection, including temporal monitoring, extraction of specific species depending on the season of acquisition, and extraction of useful green areas maps for urban architects and cities actors. Nevertheless, due to the limited spatial and spectral resolutions of these data, recognition of trees species will be not feasible.

The recognition if tree species is a complex procedure, which requires high spectral and spatial resolution imagery. Indeed, 1) if pixels size are not small enough, misclassifications could occur due to mixed-pixels phenomenon and 2) intra-class and inter-class spectral variabilities of vegetation species could affect badly the classification performance (i.e. appearance of salt and pepper effect within classes).

In this context, several studies have explored vegetation species mapping, and the obtained performance is mixed. In (Brabant et al., 2018), 19 vegetation species were mapped using 4m and 8m airborne hyperspectral imagery (i.e. up to 192 bands). The authors showed that a band reduction using Minimum Noise Fraction (MNF) (Green et al, 1988), or using a number of uncorrelated spectral indices permits an increase in term of identification accuracy (i.e. best Overall accuracy (O.A.) equal to 55%). In (Ouerghemmi et al., 2018a), 8 vegetation species were mapped using airborne hyperspectral data (i.e. up to 64 bands at 0.5m). The authors compared a distance based and a machine learning classifier using fixed training samples number, best results were obtained with machine learning classifier with MNF transform, with best O.A. equal to 46%. In (Mozgeris et al., 2018), the authors used an objects-based method for 6 trees species identification over 0.5m hyperspectral and 0.2m color infrared images. Several classifiers were trained using the segmented objects, best accuracies were obtained using hyperspectral images and Multilayer Perceptron with O.A. of 62%. Several studies claimed superiority of objet-based approach over pixel-based approach for vegetation species identification (e.g. Kamal and Phinn, 2011; Ballanti et al., 2016). Nevertheless, such approaches are more time consuming and final result

Gadal, S., Ouerghemmi, W., Barlatier, R. and Mozgeris, G.
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In *Proceedings of the 5th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2019)*, pages 97-104
ISBN: 978-989-758-371-1

will depends on the accuracy of the used segmentation methods.

In this study, a critical analysis on the use of different types of remote sensing imagery to identify vegetation species was carried. The goal was to first define the classes of interest in accordance to the image spatial resolution, and then to evaluate the accuracy performance for each type of imagery and for different seasonal acquisition when available.

2 MATERIALS AND METHOD

2.1 Data and Study Zone

For this study, 4 satellite images of different dates were used; a Landsat 8 OLI image (i.e. summer: 15-08-2015), and 4 Sentinel 2A images acquired at different seasons (i.e. respectively spring: 12-05-2017, summer: 28-08-2016, autumn: 17-10-2016 and winter: 25-01-2017) were used. Landsat 8 image was pan-sharpened to 15m with 9 bands in VIS-NIR-SWIR domain, Sentinel-2A images were pan-sharpened at 10m with 13 bands in VIS-NIR-SWIR domain, pan-sharpening step was carried using nearest-neighbour (NN) interpolation method. For Sentinel-2A, the acquisition of four seasonal mono-annual images was not possible due to cloud presence, images of 2016 and 2017 were used instead. In parallel, two summer images from airborne hyperspectral imaging system Rikola were used, with respectively 16 bands and 64 bands in VIS-NIR domain at 0.7m and 0.5m of spatial resolution (i.e. acquired respectively at July 2015 and September 2016).

The study zone concerns Kaunas city (Lithuania) (Figure 1) which is characterized by an important green areas inside and around the city consisting in a heterogeneous scheme combining public parks, individual gardens, urban forests, and free green spaces. With such an important green area, the use of aerial and satellite imagery could facilitate the management and monitoring of these areas.

Ground truth validation and training points were extracted from a tree inventory over Kaunas (Straigytė and Vaidelys, 2012), and from google street images. Indeed, the inventory was first released in 2012, and slightly updated since, thereby, some trees were missing or badly georeferenced when comparing to our test images, 2012 inventory and dated google street images were used in conjunction to produce accurate ground truth samples that will be used for classification training and for results validation. Ground truth points were then, manually converted to each dataset resolution, in order to fulfill the fineness of identification scale of each dataset. Coarser images will require less effort in ground truth point's definition. The gap between the inventory data acquisition and images acquisition, will not affect too much the ground truth accuracy since few changes were made to the existing trees. Furthermore, an additional verification was carried using other available datasets (i.e. Google Street pictures, ground pictures, and field verification).

Figure 1: True colour composition of the study zone, Kaunas city (Lithuania), Sentinel 2A (October 2016).

2.2 Method

The proposed method is composed of three main steps which are 1) optimal Normalized Difference Vegetation Index (NDVI) thresholding calculated over reflectance images, 2) vegetation species mapping using Support Vector Machine (SVM) classifier (Vapnik, 1995), and 3) seasonal vegetation monitoring (Figure 2).

$$\mathrm{NDVI} = ((\mathrm{Nir\_IR} - \mathrm{Red}))/((\mathrm{Nir\_IR} + \mathrm{Red}) \qquad (1)$$

First, the images were pre-processed if necessary, satellite imagery were pan-sharpened to the highest spatial resolution, no atmospheric correction was needed since the available images were already corrected. Airborne imagery doesn't requires pan-sharpening since all bands were acquired at the same resolution, they were nevertheless converted to reflectance using MODTRAN radiative transfer model (Matthew et al., 2000). First step of the method aims at defining an optimal threshold of NDVI for vegetation pixels extraction, for that purpose, a precise study of NDVI useful bands (i.e. red and infrared) was carried for all the available datasets. The goal was to test NDVI index behaviour over vegetated pixels, for this purpose, ten pixels were randomly chosen from a collection of ground truth vegetation pixels, the bands corresponding to minimum and maximum peaks in red and infrared intervals were extracted for each pixel, optimal NDVI bands will corresponds to the most recurrent bands from the 10 test samples. Sometimes, more than one combination of optimal NDVI bands are revealed, the determined combination or set of combinations are then used to calculate a threshold of NDVI, best threshold will correspond to the narrower one.

Second step concerns vegetation species identification at different scales depending on the input datasets. From satellite imagery, coarse identification of 3 vegetation classes was carried, and from airborne hyperspectral imagery, finer identification of 13 vegetation species was carried. For each dataset, SVM classifier was trained using two strategies; 1) fixed and limited amount of training samples (i.e. 100 samples from ground truth data, per class), 2) variable amount of training samples (i.e. 50% of ground truth data, per class). The vegetation mapping was validated using the whole ground truth data available.

Last step concerns seasonal vegetation monitoring, using times series imagery. Four Sentinel-2A were used to extract a climatic optimum for vegetation extraction, and to monitor vegetation behaviour along different seasons, the results were compared to a Landsat 8 OLI at coarser resolution for summer season. Second aspect of this part concerns the feasibility assessment of specific vegetation species identification following specific seasonal acquisitions.

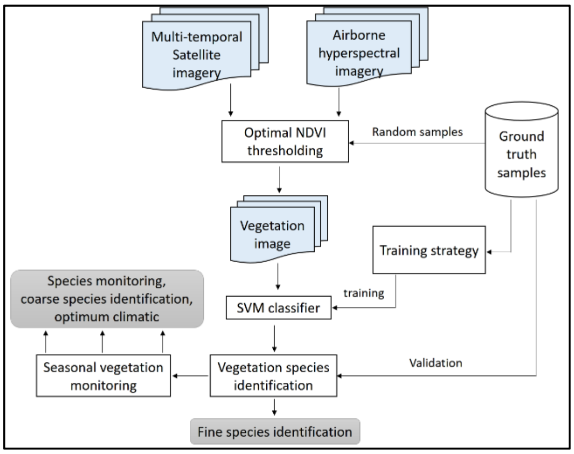

Figure 2: Vegetation species mapping by multi-temporal satellite imagery and airborne hyperspectral imagery (Method).

3 RESULTS

3.1 NDVI Thresholding

For Landsat 8 OLI, bands 4 and 5 (i.e. respectively at 654nm and 864nm) have been revealed for all tested pixels as optimal NDVI bands, once the NDVI bands revealed, an NDVI mask of [0.08-max] was determined for the OLI 8 summer image (e.g. Ganie and Nusrath, 2016).

For Sentinel 2A, band 4 (i.e. at 665nm) was revealed as red optimal band for all tested pixels, and three bands were revealed as potentially optimal infrared bands which are band 7, band 8 and band 8A (i.e. respectively 783nm, 842nm and 865nm). For the spring image, the combination of bands 4 and 8 seemed to be the most adequate with an NDVI mask of [0.46-max]. For the summer image any of the used bands combination resulted in the same NDVI thresholding with a mask of [0.46-max]. For the autumn image, the combination of bands 4 and 8 seemed to be the most adequate with an NDVI mask of [0.46-max], the chosen mask almost fulfil the recommendation of Sentinel Hub platform for green vegetation extraction (i.e. from 0.4 to max-value, e.g. Gao, 1996; Piragnolo, 2018). Finally, for the winter image, previous mask was not enough efficient for vegetation detection (e.g. Sicre et al., 2016), the combination of bands 4 and 8 seemed to be the most adequate with an NDVI mask of [0.2-max], this latter mask was a good compromise for winter season and permit an accurate extraction of coniferous trees.

Concerning hyperspectral images of 16 bands, the study revealed more combination of NDVI bands for the 10 test pixels, the best combination concerned bands 7 and 13 (i.e. respectively at 653nm and 803nm) with an NDVI mask of [0.7-max]. The 64 bands image was more stable in terms of NDVI bands selection, indeed, any of the used bands combination resulted in the same NDVI thresholding with a mask of [0.55-max]. This last result could be explained by the increasing of bands number that compensate the spectral variability of the test pixels. The chosen vegetation thresholds for hyperspectral images are slightly different from conventional thresholds of [0.4 – max] and [0.5 – max], which are commonly used for green vegetation extraction (e.g. Ouerghemmi et al., 2018a; Piragnolo, 2018), nevertheless, we have checked their accuracy in preventing non-vegetation pixels inclusion after NDVI masking.

3.2 Vegetation Species Discrimination by Satellite Imagery

In the following study, several satellite images acquired at different seasonal intervals were used for vegetation species discrimination over Kaunas city. The idea was to evaluate the identification accuracy of three main group of vegetation species that are deciduous trees, coniferous trees and grass areas. The classes of interest were defined in accordance to the available spatial resolution offered by Sentinel-2A and Landsat 8 OLI that range from 10m to 15m in pan-sharpened mode. Given these resolution it was not reasonable to consider identifying trees individual species, nevertheless such resolution could be a useful tool for large-scale species identification.

For Sentinel-2A, the identification concerned four acquisition dates corresponding to four different seasons. The best accuracies were obtained for spring and summer seasons (Figure 3.a-b), with O.A. superior to 90%, and individual accuracies superior to 66% (Table 1). Spring season seems to be slightly accurate than summer one in terms of statistical accuracy, and could be considered therefore as optimum season for vegetation extraction; deciduous trees and grass accuracies were higher in spring season, while coniferous trees accuracy increased in summer season. Grass accuracy decreased in summer season due to its sensibility to drought conditions. For the autumn season (Figure 3.c), the identification accuracy of coniferous trees and grass was not much affected, the identification accuracy of deciduous trees was nevertheless decreased to 66% (Table 1) due to an important decrease in chlorophyll concentration. O.A. decreased also slightly under 90%. Winter image gives best identification accuracy of coniferous trees, while no detection of deciduous nor grass was possible, due to snow coverage and leaves loss (Figure 3.d). When comparing Landsat 8 OLI result with Sentinel-2A result of summer acquisition; O.A. are comparable with values superior than 95% (Table 1), nevertheless, Sentinel-2A showed to be more efficient in individual classes' identification thanks to more efficient spatial resolution and spectral resolution. Landsat 8 OLI showed an important decrease of deciduous trees accuracy compared to Sentinel-2A due to its coarser resolution, coniferous trees accuracy slightly decreased, and grass was over-classified.

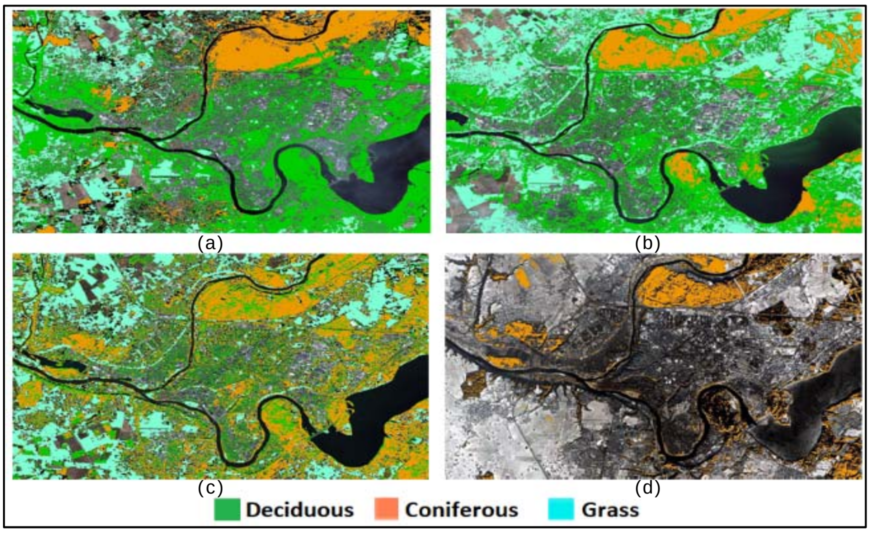

Figure 3: Vegetation species mapping by Sentinel-2A images of a) spring (12-05-2017), b) summer (28-08-2016), c) autumn (17-10-2016), and winter (25-01-2017) at 10m resolution.

Table 1: Vegetation species identification accuracy by satellite imagery.

Vegetation species	S2A Spring	S2A Summer	S2A Autumn	S2A Winter	Landsat 8 OLI Summer
Deciduous trees (%)	100	98.3	66.4	0	69.4
Coniferous trees (%)	96.6	99.3	97.5	100	98.4
Grass (%)	94.7	90.5	94.7	0	100
O.A. (%)/Kappa	**98.0/0.97**	**97.5/0.96**	**89.1/0.80**	**96.3/0.00**	**96.3/0.84**

3.3 Individual Vegetation Species Discrimination by Airborne Hyperspectral Imagery

In the previous study, three vegetation classes were identified using satellite images at 10m and 15m of spatial resolution, given such resolution, it was not possible to identify vegetation individual trees species. In the following study, two images acquired using hyperspectral camera Rikola were used, with respectively 0.7m and 0.5m of spatial resolution, and a number of bands equal to 16 and 64 bands. Airborne hyperspectral imagery offers technically more efficient images than satellite imagery in terms of both spectral and spatial resolution, in the other hands such solution is less cost effective but still relatively more profitable than other airborne acquisition solutions (Mozgeris et al., 2018).

Two training strategies were used to train the SVM classifier; 1) using 100 fixed spectral samples from the available samples, and 2) using 50% of the available total samples per class. First strategy would be useful in case of limited availability of training samples, second strategy will ensure better classes modeling (Zhang and Xie, 2013, Fassnacht et al., 2014). The comparison include a 16 and 64 bands images with respectively 0.7m and 0.5m of spatial resolution, first part of results concerned identification of 13 vegetation species including deciduous trees, coniferous trees and a grass variety (Figure 4.a-b), second part include coarser classification of the vegetation species into 3 classes.

The identification accuracy showed an important dispersion per species, some species are well identified, some other are less accurately identified or not identified at all (Table 2, 1st part). The first training strategy seems less efficient in terms of classification accuracy, with O.A. less than 30%, the second training strategy showed much better identification performance with O.A. of up to 73% and an increase of accuracy performance of up to 59%. Second strategy permits the identification of certain species that were not detected by first training strategy, in the other hand, some previously detected species were not detected using second training strategy; when increasing the training samples, some outliers could be added and then cause this behavior.

The second part of this study consists in identifying 3 coarser classes which are deciduous trees, coniferous trees and grass (Table 2, 2nd part). For the first training strategy, the identification accuracy slightly increased compared to individual species identification, nevertheless, the overall performance still poor (i.e. barely superior to 30% at best). The second strategy gives on the other hand, more accurate identification accuracy (i.e. slightly inferior to 80% at best), when comparing to satellite imagery case, the identification accuracy is less efficient, with a percentage of decrease that vary from 32% to 23% approximatively. The decrease could be explained by the fact that the grouping of classes was carried using individual species maps, and the validation was carried using a grouping of ground truth pixels of individual species. Knowing that some individual species were not detected using hyperspectral imagery (Table 2, 1st part), the global accuracy after grouping classes was therefore affected by the undetected fine species.

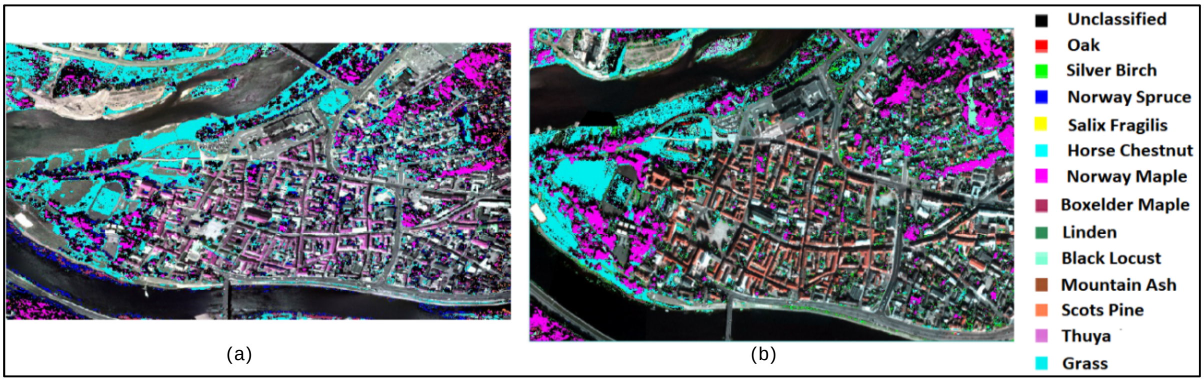

Figure 4: Vegetation species mapping by airborne hyperspectral images of a) 16 bands at 0.7m resolution (08-2015) and b) 64 bands at 0.5m resolution (09-2016).

Table 2: Vegetation species identification accuracy by airborne hyperspectral imagery of 16 bands and 64 bands.

Vegetation species	16 bands hyperspectral Rikola		64 bands hyperspectral Rikola	
	100 samples	50% of total samples	100 samples	50% of total samples
Oak (%)	0	0,21	0	1,56
Silver Birch (%)	0	0	13,51	44,66
Norway Spruce (%)	71,32	43,38	64,41	0
Salix Fragilis (%)	0	0	0	0
Horse Chestnut (%)	0	2,29	12,8	12,98
Norway Maple (%)	55,18	77,9	12,06	80,39
Boxelder Maple (%)	28,85	45,45	0,57	16,38
Linden (%)	0	23,89	0	75,65
Black Locust (%)	42,13	38,07	45,66	40,98
Mountain ash (%)	4,29	6,75	16,39	15,57
Scots Pine (%)	19,18	0	46,6	0
Thuja (%)	0	14,38	9,09	29,09
Grass (%)	31,98	87,14	22,78	97,9
O.A. (%)/kappa	**27,39/0.27**	**63,22/0.47**	**14,72/0.10**	**73,29/0.65**
Deciduous (%)	28,42	39,16	15,62	69,48
Coniferous (%)	31,27	22,54	36,01	12,44
Grass (%)	31,98	87,14	22,78	97,9
O.A. (%)/Kappa	**30,51/0.12**	**65,75/0.47**	**18,89/0.08**	**79,28/0.65**

4 CONCLUSION

Satellite imagery presents a cost effective solution for main urban vegetation classes, with accurate identification accuracy (i.e. superior to 90%), such solution is nevertheless not suited for trees species identification due to not sufficient spatial resolution. High repetitiveness satellite imagery (e.g. Sentinel and Landsat programs) offers an interesting solution for inter/intra-seasons vegetation monitoring, we showed in this study, an inter-season monitoring using Seninel-2A imagery that permits first to determine an optimum climatic for three main vegetation classes identification, and second to determine an optimum climatic for coniferous vegetation identification.

The second part of the study focused on the individual trees species identification using high spatial resolution airborne imagery with higher spectral resolution of up to 64 bands. The goal was to identify 13 vegetation species within Kaunas city, the strategy of fixed training samples gives poor identification accuracy (i.e. O.A.<30%), second training strategy was more convincing, with 50% of the total samples per each class. For the second training strategy, SVM classifier showed accurate identification accuracy for both images (i.e. O.A. of up to 73%). In parallel, the 64 bands image gives better accuracy performance than the 16 bands one. The increase of bands number permits better modelling of the classes of interest and therefore, better identification of the corresponding vegetation species (e.g. Mozgeris et al, 2018; Ouerghemmi et al; 2018b), at the price of an increase in terms of processing time due to higher resolution and bands number.

High temporal satellite imagery (e.g. Sentinel-2A), showed to be an accurate solution for coarse scale vegetation identification and monitoring, thanks to a large spectral interval, and to a good acquisition repetitiveness, it could be therefore useful to several fields of interest such urban architecture, urban planning, agronomy, forest management, etc. At the same time, hyperspectral imagery offer more potentialities in terms of fine vegetation species identification and also determination of other plants characteristics such as health condition (e.g. Mozgeris et al., 2016), thanks to its better technical characteristics. Such imagery could be useful for achieving finer studies at individual vegetation species scale and could therefore be complementary to satellite imagery.

The fusion of multi-sensor satellite imagery could be an interesting perspective for identification accuracy enhancement (e.g. Zhang and Xie, 2014; Alonso et al., 2014; Gintautas et al., 2018). The use of an airborne hyperspectral of 16 and 64 bands and 0.7m and 0.5m of spatial resolution permits to identify most of the species of interest, nevertheless, some additional investigations must be carried to improve the identification accuracy. Ground truth samples must be enriched and rectified for some specific species, the integration of vegetation indices in the classification process could be tested (e.g. Erudel et al., 2017; Launeau et al., 2017; Brabant et al., 2018), the use of some pre-processing steps could be taken into consideration for optimal data processing (e.g. MNF).

ACKNOWLEDGEMENTS

This research was funded by CNES THEIA program (CES artificialisation urbanisation). This work was supported by public funds received in the framework of GEOSUD, a project (ANR-10-EQPX-20) of the program "Investissements d'Avenir" managed by the French National Research Agency.

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