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Lessons learned from a VGI initiative for Land Use monitoring

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Abstract:

Land Use (LU) mapping and monitoring at fine spatial and temporal resolutions requires many efforts. Remote-sensing based change detection approaches exist (Lu et al., 2014), though use is not trivial and not necessarily related to cover. Considerable interest has then emerged in using Volunteered Geographic Information (VGI) (Goodchild, 2007) as an alternative source of data (Fonte et al., 2013; Fritz et al., 2015). The goal of this paper is to discuss the lessons learned from a VGI data collection initiative which have aimed to collect change and local LU observations (*i.e.* quarry activity, usage and number of floors of a building, construction in progress) for updating and enriching authoritative LU data.

This work was part of the Toulouse (south of France) pilot run by IGN France, one of the pilots of LandSense H2020 project. The study area is an urban and peri-urban environment located around the city of Toulouse and covering an area of 1,181 km^2. The authoritative 2016 LU data OCS-LU 2016 was set as the initial date and the target was the production of a 2019 LU data set (VGI-LU 2019) with a finer classification. Our approach was to generate located alerts automatically (*i.e.* by using a change detection service) or manually (i.e. function to the needs) to be validated or classified by contributors. A collaborative platform involves tools implementing tasks, a community of contributors and data collection and sharing. Thus, the first step was to identify the needs and to design appropriate tasks as well as a strategy of data collection. We defined two main tasks: (1) a change validation task for which contributors are asked to validate automatically detected changes and if so, to assign the updated LU class among a list of pre-defined classes; (2) a LU classification task for which contributors are asked to classify the manually generated alerts either in industrial (LU2), commercial (LU3), residential (LU5) and agriculture (LU1.1). The second step was to develop the platform, called *PAYSAGES*. The platform includes three tools: *PAYSAGES* desktop, *PAYSAGES* mobile and *PAYSAGES* wiki (see Olteanu-Raimond et al., 2017 for a complete description of the tools). The third step was to build a community, and to launch and engage with contributors to collect observations. Concerning the community, we identified different target groups: experts in LU data from the local authorities, research experts in LU data, surveyors from the production department of IGN (the French national mapping agency), citizens, and students (*e.g.* engineering, master degree) in which includes classes about GIS and remote sensing (Olteanu-Raimond et al., 2020). For the data collection, we proposed the concept of campaigns: (1) Online or *in-situ*, and (2) opportunistic, guided, or mapathons (Olteanu-Raimond et al., 2017). The first category describes how the campaign is planned to be carried out (*e.g.* in front of the computer or on the field) whereas the second describes the types of interaction that the organisers have with the community (*i.e.* no interaction in opportunistic campaigns, small interaction with the community in guided campaigns and strong interaction in mapathons) as well the duration of the campaigns (*i.e.* long period for opportunistic, short period for guided and limited to few hours for mapathons). We organized one opportunistic online campaign in 2018, one *in-situ* guided campaign in 2018 and nine online and *in-situ* mapathons in 2019. In total, 130 contributors participated to the campaigns and more than 7000 observations were collected. The fourth and last step is to integrate the collected data/observations about alerts in order to update and enrich the authoritative LU data. The workflow for the integration of collected alerts is based on data fusion techniques and is described in Liu et al. (2021).

In the following, we discuss the lessons learned (LL) from this pilot.

LL1. *Time length of the campaigns*. The campaigns organised with the desktop tool was faster than the mobile application. When using the mobile app, contributors need to physically visit each location in order to validate/classify the alert, and this traveling took much time. One way to go forward could be to mix web and *in-situ* campaigns, *e.g.* to first use desktop application to carry out a task and highlight areas that need to be visited with the mobile application.

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LL2. *Stakeholders' involvement*. The tools were updated after different campaign, by adapting the functionalities thanks to the stakeholders' feedbacks. Some of them were involved in the entire process: definition of needs, development of tools, data collection. They are feeling to be part of the project and not only contributing to the project.

LL3. *Gamification*. The gamification functionalities were appreciated by the contributors; some of them mentioned that they have continued to contribute to get a better ranking among the contributors.

LL4. *Difficulties to engage with citizens*. Few citizens tested the proposed applications. One reason was the lack of awareness related to the existence of the PAYSAGES platform, despite posts published on social media. This low engagement with citizens was more or less expected since collaborative initiatives are quite new for the mapping agencies and effort is still needed to build a community around a spatial data platform. Producing together a "common good" is one of the key of success for VGI-NMA interactions. The second reason was the motivation for participate to LU monitoring (i.e. updating LU authoritative data was not sufficient). Finally, LU data are complex; citizens participating to the campaigns found difficult the classification task.

LL5. *Variability of the contributors profiles*. The validation task was considered as easy by all the contributors. Nevertheless, citizen and students found that the nomenclature for change validation was appropriate, whereas the experts found that it was not enough detailed. The classification task using LU nomenclature was difficult for non-LU experts. Thus, one recommendation is to adapt the task to the expertise of the contributors to maintain the quality of the observation and the motivation during the on-going campaign and for campaigns to come.

LL6. *Win-to-win relationships*. The stakeholders are part of the mapping process and use produced data immediately, without waiting their integration into the authoritative data. The students applied theoretical concepts into practice by being involved in concrete implementations. The NMAs can collect change observations (typically a costly task) or missed detailed information (*e.g.* identify if a building in a rural area is a dwelling occupied by humans or animals).

LL7. *Very positive feedback on mapathons*. What came out was the shared experience on the sides of contributors and organisers, the user-friendly interface and conviviality of the event). Organizing web mapathons for data collection is a source of motivation for contributors. The *in-situ* mapathons were appreciated but the social aspect was missing since the travelling from place to place was done individually or in groups by two. It also seems that the *in-situ* campaigns are less adapted to mapathons and more adapted to opportunistic or guided campaigns.

LL8. *Underestimation of changes due to the low number of alerts* The LU dataset obtained by integrating the observations was compared with the authoritative 2019 LU data release. Among all, the initial generated alerts corresponding to changes, 87% has produced an update. This shows that the alerts are real changes. Nevertheless, our method detected only 15% of the total changes on the study region. This is due to the difficulties we manage in mobilizing contributors to visit all the alerts on the field and to the quite low rate of changes automatically detected.

LL9. *Inaccuracy of the geometry of automatically detected changes*. In general, the surface areas of changes are underestimated. Detecting changes by a fully automatic process remains a challenge and further research is needed. More efforts should be made to improve the rate of change detection and location and shape accuracy. It is more costly to detect changes than to assign a land use class to the change.

To conclude, the results from the Toulouse pilot showed that building a data collection platform is challenging, and much energy is needed to build a community and continuously propose new activities for motivation and sustainability. A successful strategy was to engage with few, but motivated contributors. The results also showed that VGI can enrich LU classification despite the complexity of LU data: Agricultural, Residential, Industrial and Commercial classes representing 5.774 km 2 are better classified with respect to the authoritative LU data.

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