Mapping Pb/Zn-stressed plant communities: challenges of centimetre- to millimetre-scale UAV sensing for training deep-learning schemes

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Plant interactions play a pivotal role in ecosystem functioning. In stressed ecosystems, dominant plants often mitigate environmental stress in their immediate vicinity enabling maintenance of low stress-tolerant species. In that case beneficiary plants are clustered around their benefactors. This process increases plant diversity and develops corresponding plant communities. Metals/metalloids rich environments challenge vegetation development making their remediation intricate. The ANR-funded SixP project investigates the role of facilitation in Zn/Pb contaminated sites as a potential tool for their remediation. Plant mapping is a key project component to discover clumped spatial distributions. For this, a set 24 459 plants spread over 352 m² , split in 24 distinct sampling patches were identified, located with differential GNSS and measured. That is 30 full man-days of effort. UAV acquisition could presumably ease the mapping endeavor in three ways: (i) surveying much larger surfaces, hence broadening statistical and environmental representativeness; (ii) archiving land cover state when the manual survey is performed; (iii) providing continuous explanatory variable layers such as topographic context and multispectral surface response to feed seemingly effortless deep-learning classification algorithms. This contribution means to highlight the challenges of providing accurate and trustworthy labels for training AI schemes.

A lead/zinc mining district, in Sentein, central Pyrenees mountains (southern France) was active up until the 1960's. Remaining toxic wastes act as stress control variable, while the vertical distribution of mining activities, over 1000 m of elevation, bring climate control on plant ecosystems. L'Avion Jaune company performed Uncrewed Aerial Vehicle (UAV) flights, before the growing season (march/june 2020) and at full growth (june/july 2020). Lidar was used for overview ground topography (with canopy top density ca. 50 pts/m²) and SfM-photogrammetry at two resolutions for land cover: 20 mm/pixel (RGB) before growth and 2-3 mm/pixel (RGB+near-infrared) at full growth season. Millimetric resolution is justified by metallic toxicity constraining dwarf plant development. Full growth mm-resolution covered 7 zones for a total of 1.34 ha (40 times the ground-truth surface), while overview cm-resolution data covered 36.6 ha, 1000 times the reference.

The first lesson: differential-GNSS survey in mountain terrains is not trivial. No phone coverage meant no real-time corrections, nor accurate national geodesic network tie. A GNSS base station was freely deployed alongside a rover unit to broadcast real-time corrections. Base-to-reference-network post-processing tied surveys to IGN's RGP network, but only with a limited accuracy (ca. 20 cm). Stationing a known benchmark with the base station would have improved accuracy. Fortunately, plant and UAV surveys were performed in a common spring-summer 2020 reference frame, with temporary UAV targets positioned by the plant-mapping teams. GNSS plant positions are coherent with UAV data to within 10-30 mm.

The second lesson: producing UAV photogrammetric coverages at 2-3 millimeter pixels of plants is incredibly challenging. The UAV flew 10-m above ground to reach image resolution. But flying low strains photographic and photogrammetric processing to the limit. The UAV blew wind on the tiny gracile leaves and stems. Fast shutter speed of 1/1000 s counter-acted both motion blur and pixel ovalization due to UAV vibrations but imposed a wide aperture (f/3.5). This mitigated vignetting, refaction and diffraction issues of small apertures. Yet narrower apertures would have increased the depth-of-field, but at the cost of increasing image electronic noise to preserve shutter speed. Sensor sentivity was set at 200 ISO. While with these settings, plants were reasonably sharp, the wind shifted the position of mobile plant organs between photos. This challenged photogrammetric surface reconstruction and orthophotos mosaicking. Finally, RGB and Near-Infrared imagers were flown simultaneously, back-to-back to generate 4-band ortho-imagery. But with two points of view, even if only 8 cm apart, the base-line was sufficiently large to generate differential parallax between images, challenging orthorectification along elevated object edges. This means that RGB pixel signatures do not always match the underlying NIR signal depending on the local topography.

The third lesson: training AI models for class (here species) segmentation requires a trustworthy training set. GNSS-tagged labels link a 1D position with a plant label and radius. In raster form, it is a label disk map. But the plant may not be exactly, at pixel scale, below the GNSS point, due to geometric imprecision. We innovated with a fuzzy edge labelling map to accounts for location uncertainty (Guiotte et al., in prep.)

Finally, can trained models be transposed to different sites? ImageNet feature mapping clustered with t-SNE (Castillo-Navarro *et al.*, 2022) maps image features to predict the chances of successful classification.

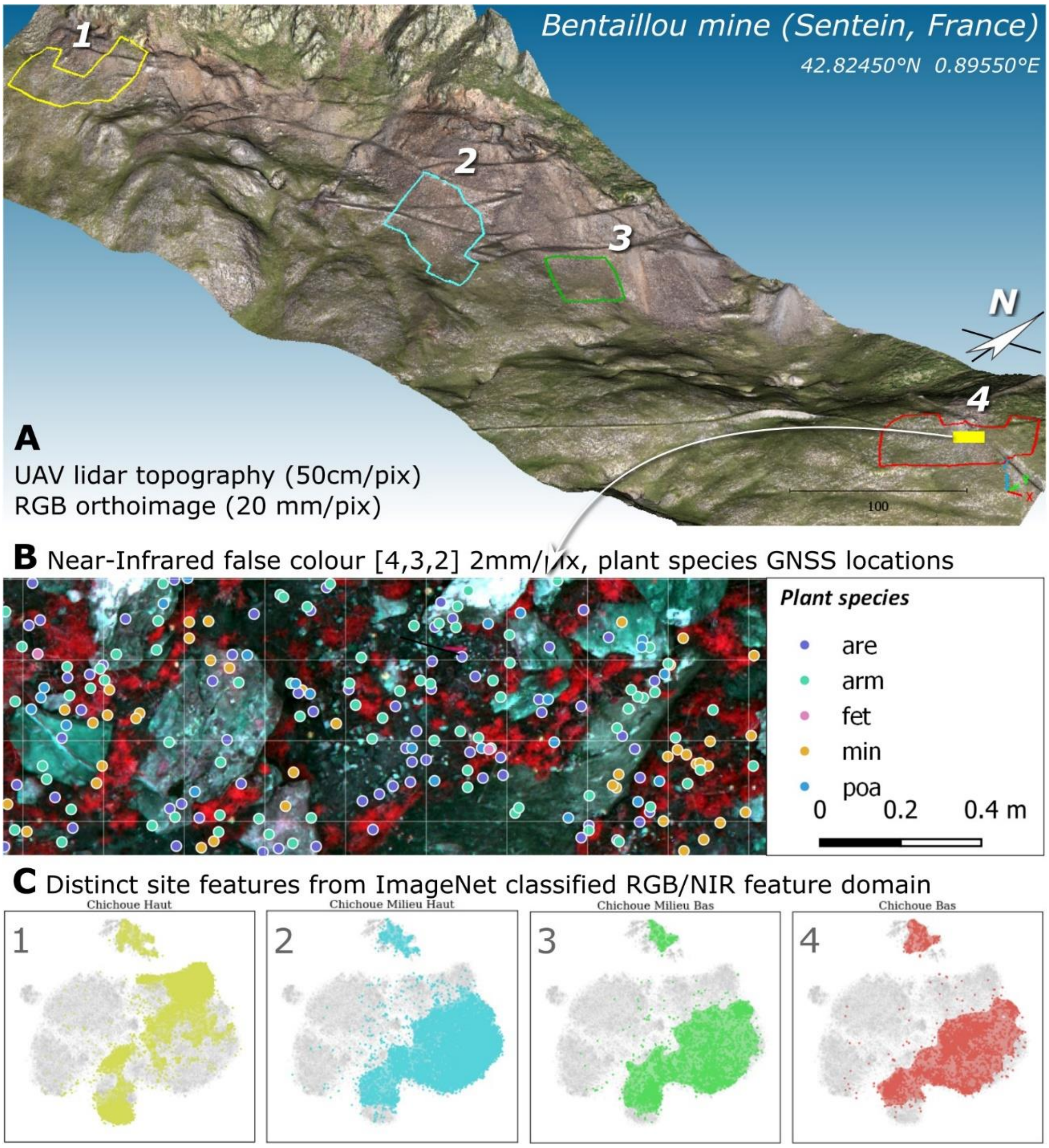

Figure 1 : From field data sensing (A) and GNSS plant mapping (B) to classification features (C). In C, distinct sites only contain a restricted set of ImageNet features. Site 1 does not contain a large part of features present in other sites (sectors to the right of feature space), which raises caution.

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