Ecotopes v2.9 technical report

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Delineation

Ecotopes are delineated automatically using the multiresolution segmentation algorithm from Baatz and Schape (2000). The input data for the segmentation include hillshades derived from a LIDAR-based DEM and spectral values of 2-m resolution visible and near infrared orthophotos of 2015. Different parameters have been tested (Delangre et al, 2017) to derive an optimal size. The selected size and shape combination proved to be most of the time better than alternative solution, even if it did not systematically outperform other parameters combination.

Classification

The characterization of the land cover is performed by computing the proportion of 2-meter resolution pixels inside each polygon. The pixels are labelled using an ensemble of classifiers including random forest and maximum likelihood with multiple sources of data (LIDAR-derived height resampled at 2 meter from 0.8 pt/m² point cloud, Visible and Near-Infrared orthophotos resampled at 2 m from 25cm original data, time series averages of ascending Sentinel-1 data resampled at 10 m and temporal composite of Sentinel-2 data at 10 m using spring and summer images.) Training samples are automatically selected by stratum after conservative spatial erosion as described in Radoux et al (2014) Open areas of interest have been consolidated by photointerpretation using local expert knowledge.

Quality assessment of the pixel-based classification

A rigorous validation was performed in 2016 for the map of 2015. Good practices in point-based map validation have been followed according to the state of the art (Olofsson et al, 2014). The detailed methodology is described below.

Response design

The validation was based on photo-interpretation of the 2015 orthophotos (25 cm resolution) complemented with field verification when there was a doubt about the photo-interpreted class. In total, 1200 points were visually classified. The uncertain points (121) were verified on the field, out of which 64 points were correct (giving a 95% accuracy of the operator). Fifteen of the unsure points could not be verified on the field due to accessibility constraints. Those were double-checked by a second operator and existing ancillary data to gather confidence on the first photointerpretation. Because of the risk to have underestimate the classification accuracy due to positional errors, the closest class in a 5 meter radius was also provided by the operator.

Sampling design

The samples were selected in a double stratified sampling design scheme in order to get clusters of points and hence potentially reduce the displacements for the field-based verification stage. The first stratification level is based on 5 biogeographical regions of Wallonia. The second stratification level are 5 km by 5 km squares. When a cell square was located across several biogeographical regions, its labels was defined based on the location of its centroid. Ten cells have been randomly selected for each region, and a total of 25 points was randomly selected inside each square. Points lying out of Walloon region have been discarded, so that a total of 1201 remained for the validation.



Analysis

Due to the stratification based on biogeographical area, the sampling effort was not the same everywhere. The proportion of correctly classified pixels was therefore computed for each region. Those values were then aggregated for Wallonia with weight that is inversely proportional to the sampling probability (in other words, directly proportional to the area of the biogeographical region). Errors from the cell based coverage of Wallonia are neglected because the matching between the regular grid and the true extent is more than 99%: this sample is therefore considered as fully representative of the sampled area.

Results

The raw results are presented in table 1. Photointerpretation results were adjusted take into account errors due to slight misregistration (2 meter pixel) and residual parallax errors. Furthermore, the definition of the diversified class changed between the first validation exercise (designed for the v2.7 of the ecotopes) and the v2.9 map. Finally, small gaps or roads under the trees are not visible on the orthophotos and therefore do not appear in the validation dataset. The LIDAR data was therefore trusted for the detection of small forest gaps (in addition to the orthophotos) and ancillary data were used for the road network.

	water	Bare	Artif	Arable	Int	Div	Dist borb or	Needle	Broad	UA (%)
		5011			TIELD	TIELD	shrub	leaveu	leaveu	
Water	13									100
Bare soil		1	1		2					25
Artif		1	63	1						97
Arable				227	12					95
lnt herb		1	4	4	273	5	2		2	94
Div herb						8				100
Dist herb			4		3		44	1	5	77
Needle leaved			2				3	126	7	91
Broad leaved			4		1		2	11	370	95
PA (%)	100	33	81	98	94	62	86	91	97	

Table 1 : Raw confusion matrix directly derived from the point samples. The columns contain the reference class and the lines are for the map's labels.

The corrected overall accuracy, accounting for the sampling probability, is equal to **94.5** percent (+/-1.2%). The worst classification accuracy (~90%) is observed in Gaume and the best classification accuracy (~95%) is observed in the "Région Limoneuse". User's and producer's accuracy were most of the time larger than 85%, but poor results were achieved with bare soils. It is already worth noting that the LIDAR dataset on the Western part of the Walloon region is less reliable than on the Eastern part, yielding lower detection accuracy of small forest gaps as well as false detections.

Bibliography

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