Reproducibility review of "Knowledge-Based Identification of Urban Green Spaces: Allotments"

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Reviewed paper

Ismayilova, I., and Timpf, S.: "Knowledge-Based Identification of Urban Green Spaces: Allotments”, AGILE GIScience Ser., 5, 8, https://doi.org/10.5194/agile-giss-5-8-2024, 2024

Summary

The paper addresses the issue that allotment gardens are not recognized as separate land use / land cover category, although they are unique among urban green spaces and provide highly significant benefits. The research uses semantic characteristics of allotment gardens, such as density of garden huts and proximity to water bodies, to “create distinctive spatial representations” in a three-step procedure: First, a random forest classifier identifies green spaces from digital orthophotos; second, garden huts are extracted; and third, a density-based clustering identifies areas of allotment gardens. The workflow was employed on two different case study areas.

The input data (orthophoto at the resolution of 40 cm) for the first step (identifying green spaces from ortho imagery) is freely available and provided by the authors (see references).

For the second step (of extracting garden hut features), several input data sources are required (compare Figure 2 in the paper): The output of the first analysis step, and additional geospatial information (infrastructure, water bodies, land use, building footprints), and a normalized Digital Surface Model. The latter is created by subtracting the Digital Elevation Model from the DSM. The DEM is available for free at 1m resolution (and then resampled to 40 cm), while the DSM is available at 40 cm but only for purchase. All the other geospatial information is available for free, but not included with or linked from the paper.

The third analysis step (clustering) only uses derived data sets from the second analysis step.

The computational environment relies on a mix of free and open source software (R software for the random forest classification) and proprietary GIS software (ESRI ArcGIS for the height thresholds, refinement of the classification, and density-based clustering).

Upon request, the authors provided the digital orthophoto, training data and code for step one, as well as a sample data set (smaller area) and executable workflow for the ArcGIS Modelbuilder as an ArcGIS project package. The reproducibility review can therefore only confirm that that the analysis runs as intended, but not check the validity of the outputs shown in the paper.

All the provided code was run and executes without errors, generating valid output. The clustering algorithm does not find any clusters, but that may be due to the small size of the sample area.

This reproducibility review was thus able to validate the entire analysis workflow. With the provided documentation, code, and sample data (see references), other researchers should be able to succeed in replicating the results. The functionality used in the proprietary software is available in free and open software packages and can thus be implemented without access to ArcGIS. However, to ensure using the exact same parameters, an export to Python or another free and open software would be preferable.

Reproducibility reviewer notes

The reproducibility review highlighted once more that documentation and meta data on exact software and library versions as well as computational environment is necessary. After adjusting file paths, the R script executed fine on a Windows 11 laptop with 16 GB RAM but slightly different R and package versions, but it crashed repeatedly during the prediction step on a Ubuntu 22.04 VM with 16 GB RAM but exactly matching R and package versions. It turned out that the prediction step requires in total about 24 GB of memory, and the swapfile of the Ubuntu VM was configured too small. After increasing its size, the prediction step worked fine. In both cases, it took about 2 hours to complete because it uses only one core (of an AMD Ryzen 7 PRO 6850U in this case). Since the original figures could not be reproduced because of the different input data, this review does not contain any figures.

References

The materials used for this reproducibility review are available at
https://doi.org/10.6084/m9.figshare.25683828.v1