JURSE 2022
Online Lounge

Work title: EO-based garbage detection in complex urban environments - a case study in Medellin, Colombia

Authors: Yrneh Ulloa-Torrealba[1,2,3], Hannes Taubenböck[2,3], Andreas Schmitt[1,4]

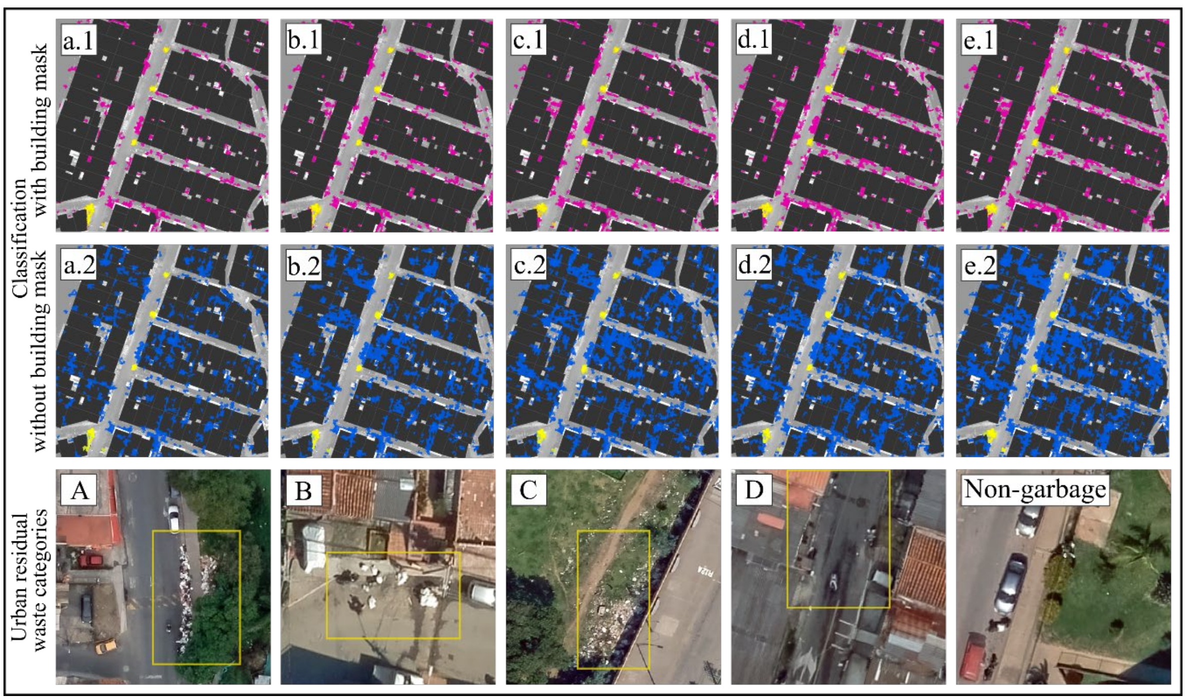
[1]Munich University of Applied Sciences. Munich, Germany.

[2]German Aerospace Center. Oberpfaffenhofen, Germany.

[3]University of Wuerzburg. Wuerzburg, Germany.

[4]Institute for Applications of Machine Learning and Intelligent Systems (IAMLIS), Munich, Germany.

Project Image:



Short project summary (max. 250 characters):

This work evaluates the possibility of detecting residual waste in an urban landscape in Medellín, Colombia, by a combination of a super-pixel segmentation and a supervised machine learning providing information for infrastructural services and serving as proxy for deprived areas.

Title: EO-based garbage detection in complex urban environments - a case study in Medellin, Colombia

Keywords:
Urban deprivation, residual waste, super-pixel segmentation, machine learning, Medellín.

1. Introduction:

Sanitation, defined as a human right, refers to the access and usage of facilities to dispose appropriately solid waste, among others. The lack of proper sanitation, affects human life quality, which in turn, enhances poverty [1]. Poverty eradication is of supreme importance for all countries, and a priority of the United Nations Agenda of Sustainable Development (SDG N°5) [2]. Solid waste refers to objects or materials, which are of no use anymore to humans, and therefore are discarded [3].

At a local scale, usually the municipalities are the ones in charge of the collection, transport, and final disposal of the solid waste [3]. An improper management of solid urban waste contaminates ground water [4], attracts pests and animals (e.g. rats) that transmit diseases, contaminates the air, among others [5]. In general, a lack or poor management of the urban solid waste deprives the population from basic hygiene and health, therefore leading to a lower quality of life [4] [5].

Using remote sensing methods, urban solid waste has been researched so far for diverse purposes: management of solid waste, selection and monitoring of landfills for solid waste [6] [7], waste bin detection [8], and the health effects on the population, among others [6]. Satellite and UAV [9] imagery was analyzed via regressions, machine learning approaches, and combinations with GIS and socioecological data [6] [8]. However, no approaches are known that identify and categorize the residual waste dumped on the streets. The objective of this research is to test a combination of machine learning approaches to conceptualize and detect the residual waste that is lying on the streets, like bags, construction debris, among others. This way, we could provide a reliable method to decision makers on where insufficient waste management affects the citizens of a given city.

2. Methods:

Our study sites are 25 Areas of Interest (AOI) (each subset of $0.25 km^2$) distributed across the city of Medellín, Colombia. The data utilized in this study includes raster and vector datasets, namely: (1) orthorectified VHR aerial images from the year 2019 [10], (2) a building mask from the year 2017 [11], and (3) training/test data.

The training and test data are composed of two main elements: polygons that include garbage or urban residual waste objects (G), and polygons sampled on objects that are not garbage (nG).The creation of the G-dataset was done manually via visual recognition of the garbage accumulations on the orthorectified images and their posterior digitization on ArcMap. The nG-dataset was created using a SLIC segmentation [12]. A sensitivity analysis based on Quality Rate [13] allowed selecting the most appropriate values for the segmentation parameters “ns” and “c”, in other words, the number of segments, and compactness, respectively [12]

For the urban residual waste elements (G), we conceptualized four categories labeled into probability classes, based on visual inspection and on-site experience of the researcher on a similar city: A: Sure, B: Half-sure, C: Not-sure, and D: Dispersed. The class "Sure" refers to garbage objects mostly packed in white and black bags. Objects with a 50% or 0% probability of being garbage, belong to the classes "Half-sure" and "Not-sure", respectively. "Dispersed" objects are small, no compact elements of garbage, distributed over a large area. "Non-garbage" objects (nG) do not belong to the aforementioned categories. Additionally, we grouped these five categories into five different treatments. We trained a Random Forest model [14] on each treatment. The combination of all factors: AOIs, treatments, SLIC segmentations, and building mask, produced 750 different classification scenarios.

3. Results:

In general, we found that the small and heterogeneous urban residual waste can be identified in VHR aerial images using a Random Forest classifier with high accuracy. The choice of the values of the SLIC segmentation parameters “ns” and “c”, influenced the classifications. The classifier performed best with the segmentation 8000ns-0.3c, with an overall accuracy (OA) of 80.18%, followed by 10000ns - 0.1c with an OA of 77.95%, and 12000ns - 0.1c with an OA of 75%.

The addition of a building mask increased the OA on average by 6.05%. The OA is higher in the results where the classification is limited to areas outside building rooftops (from 71.53% to 95.76%). In approaches without these additional geodata, the OA was measured lower (from 59.51% to 90.18%). The algorithm located residual waste objects mostly on the sidewalks, which is where usually the garbage is illegally dumped. However, the classifier seldom identified residual waste objects on open areas like streets, river, and vegetation.

The detection of urban waste was successfully achieved with the probability classes "Sure" and the treatment with classes "Half-sure + Sure". The first had an OA that ranged from 79.62% to 95.76%, whereas the latter had an OA that ranged from 80.57% to 90.18%. On the other hand, the "non-Garbage" category scored the highest user and producer accuracy in all treatments (>70%).

4. Conclusions:

The model is capable to identify categories of garbage “Sure” and “Half-sure”, as well as “Non-garbage” with high accuracies. However, the model struggles to differentiate among the lower probability classes for garbage such as "Dispersed" and "Not sure". In general, the method proves to be able to detect the random waste that is disposed on the streets serving as a valuable information for decision-makers in terms of the waste management.

References:

[1] Centre on Housing Rights and Evictions, Ed., Sanitation: a human rights imperative ; a document defining sanitation in human rights terms, describing the value of treating sanitation as a human rights issue and outlining priority actions for governments, imternational organisations and civil society. Geneva: COHRE, 2008.

[2] UN Committee. General Assembly. 2nd, ‘Sustainable development : implementation of Agenda 21, the Programme for the Further Implementation of Agenda 21 and the outcomes of the World Summit on Sustainable Development and of the United Nations Conference on Sustainable Development : report of the 2nd Committee : General Assembly, 74th session’, New York, UN, Dec. 2019.

[3] M. Medina, ‘Solid Wastes, Poverty and the Environment in Developing Country Cities. Challenges and Opportunities. Working Paper No. 2010/23’, UNU-WIDER, Mar. 2010.

[4] P. Vasanthi, S. Kaliappan, and R. Srinivasaraghavan, ‘Impact of poor solid waste management on ground water’, Environ. Monit. Assess., vol. 143, no. 1–3, pp. 227–238, Aug. 2008, doi: 10.1007/s10661-007-9971-0.

[5] H. Yang, M. Ma, J. R. Thompson, and R. J. Flower, ‘Waste management, informal recycling, environmental pollution and public health’, J. Epidemiol. Community Health, vol. 72, no. 3, pp. 237–243, Mar. 2018, doi: 10.1136/jech-2016-208597.

[6] A. Singh, ‘Remote sensing and GIS applications for municipal waste management’, J. Environ. Manage., vol. 243, pp. 22–29, Aug. 2019, doi: 10.1016/j.jenvman.2019.05.017.

[7] J. Gill, K. Faisal, A. Shaker, and W. Y. Yan, ‘Detection of waste dumping locations in landfill using multi-temporal Landsat thermal images’, Waste Manag. Res. J. Sustain. Circ. Econ., vol. 37, no. 4, pp. 386–393, Apr. 2019, doi: 10.1177/0734242X18821808.

[8] W. Xia, Y. Jiang, X. Chen, and R. Zhao, ‘Application of machine learning algorithms in municipal solid waste management: A mini review’, Waste Manag. Res. J. Sustain. Circ. Econ., p. 0734242X2110337, Jul. 2021, doi: 10.1177/0734242X211033716.

[9] G. Jakovljevic, M. Govedarica, and F. Alvarez-Taboada, ‘A Deep Learning Model for Automatic Plastic Mapping Using Unmanned Aerial Vehicle (UAV) Data’, Remote Sens., vol. 12, no. 9, p. 1515, May 2020, doi: 10.3390/rs12091515.

[10] Servicios de Imágenes de Medellín, ‘Alcaldía de Medellín’, 2021. https://www.medellin.gov.co/mapas/rest/services/ServiciosImagen (accessed Aug. 10, 2021).

[11] Portal Geográfico del Municipio de Medellín. Alcaldía de Medellín, ‘GeoMedellin’, 2020. https://www.medellin.gov.co/geomedellin/ (accessed Aug. 13, 2021).

[12] R. Achanta, S. Appu, K. Smith, A. Lucchi, P. Fua, and S. Suesstrunk, ‘SLIC Superpixels’, Jun. 2010.

[13] N. Clinton, A. Holt, J. Scarborough, L. Yan, and P. Gong, ‘Accuracy Assessment Measures for Object-based Image Segmentation Goodness’,

Photogramm. Eng. Remote Sens., vol. 76, no. 3, pp. 289–299, Mar. 2010, doi: 10.14358/PERS.76.3.289.
[14] M. Belgiu and L. Drăguţ, ‘Random forest in remote sensing: A review of applications and future directions’, ISPRS J. Photogramm. Remote Sens., vol. 114, pp. 24–31, Apr. 2016, doi: 10.1016/j.isprsjprs.2016.01.011.