reviewed paper

Categorizing Urban Structural Types using an Object-Based Local Climate Zone Classification Scheme in Medellín, Colombia

Marlene Kühnl, Marta Sapena, Hannes Taubenböck

(MSc Marlene Kühnl, Company for Remote Sensing and Environmental Research (SLU), Kohlsteiner Straße 5, 81243 München, Germany, marlene.kuehnl@slu-web.de)

(Dr. Marta Sapena, German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Münchner Straße 20, 82234, Wessling, Germany, marta.sapena-moll@dlr.de)

(PD Dr. Hannes Taubenböck, German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Münchner Straße 20, 82234, Wessling, Germany; Institute for Geography and Geology, Julius-Maximilians-Universität Würzburg, 97074, Würzburg, Germany, hannes.taubenboeck@dlr.de)

1 ABSTRACT

Climate change is reshaping societies. As we see more and more people moving to urban areas an ever-increasing number settles in low-cost and more hazardous areas. However, due to the rapid growth and sheer scale of informal settlements, knowledge gaps often exist on location or quantity. In this sense, Earth Observation combined with machine learning techniques allows to generate reliable geo-information. In this study, we classify the morphologically heterogeneous entire urban area of Medellín, Colombia into urban structural types. We do this by the Local Climate Zone (LCZ) scheme. Our specific focus is on one structural type, i.e. informal settlements. We test whether it is feasible by the LCZ concept to localize and quantify these vulnerable areas. The LCZ scheme is generic, replicable, neutral, and has become widespread in urban studies. We use urban blocks to perform a scene-based image classification into nine LCZs. We refer to multi-modal remotely-sensed data: high-resolution multispectral image data and elevation data. We apply an optimized random forest algorithm using shape metrics, as well as spectral and texture features. In general, we find the LCZ classification, measured with an overall accuracy of 82%, shows a reliable representation of urban typologies and functions across the city. Specifically, we compare the urban blocks classified as the LCZ lightweigth low-rise to the informal settlements provided by the city of Medellín. Here we reach an agreement of 86%. Besides, our approach complements the official dataset by including recently developed areas which are not yet considered by the city.

Keywords: Earth Observation, Machine Learning, Informal Settlements, Random Forest, Local Climate Zone

2 INTRODUCTION

Climate change and upgrading living conditions are two well known push and pull factors of the rural-urban movement and migration between countries. Urban areas are now home to the majority of the world's population and are expected to record a continuous flow of migrants (UN, 2019). Cities have a higher economic growth, more opportunities, better access to education, health, employment, and in general, many services that makes moving to a city seem attractive (Glaeser, 2011). But it can also be disadvantageous, since cities are more unequal than rural areas, i.e. wealth coexists with severe deprivation (UN, 2020). Besides, climate change displaces people due to a higher frequency of natural hazards like wildfires, storms, or droughts, and making some places less livable and productive, which results in an ever-increasing number of people migrating to cities (Adger et al., 2020).

The Sustainable Development Goals (SDGs), set by the United Nations in 2015, pursue a sustainable future for people and the planet by ending poverty and addressing social needs, while protecting the environment and fighting climate change (UN, 2015a). Cities as a habitat for more than half of the world's population are crucial for the successful implementation. Thus, the functioning and evolution of urban systems have been in the spotlight for planners, policymakers and researchers (e.g. Lobo et al., 2020; Oliveira, 2016), and several studies have been conducted in this regard. For instance, the impact of the morphology and functions of a city on many different factors, such as heat distribution and ventilation performance (e.g. Zhao et al., 2020; Jin et al., 2018a), air and noise pollution (e.g. Han et al., 2018; Edussuriya et al., 2014), or resilience in case of natural hazards (e.g. León & March, 2014). Moreover, a recent study evidenced that spatial structure in cities is indeed related to the quality of life and sustainability, the configuration of urban structural types within cities is linked to socio-economic functions (Sapena et al., 2021).

Within the urban conglomerate informal settlements are underdeprived neighborhoods, which lack basic services (UN, 2015b) and are often located in low-cost and more hazardous areas of the city as a result of low urban planning capacities and failing formal land markets. Especially in the Global South they are part of the persistent contemporary urbanization process (Stark et al., 2020; Kuffer et al., 2016; Lall & Deichmann, 2012) and even though they often represent a large proportion of the population, there is a general lack of understanding about their role within the city (Patel & Baptist, 2012). Besides, due to their high dynamic and rapid growth rates (Kraff et al., 2020), frequent monitoring in near real-time and high resolution data is necessary (Mahabir et al., 2018) in order to produce valuable information for governance, risk assessment studies, etc. (e.g. Wurm et al., 2019; Kuffer et al., 2018).

Earth observation (EO) enables the creation of up-to-date, consistent and extensive information on urban environments with a high degree of objectivity, transferability and automation (Voltersen et al., 2014). The characterization of large-scale urban morphology relies on remote sensing data and methods. Depending on available satellite images and objectives, different classification methods, e.g. parametric/nonparametric supervised/unsupervised, pixel-/object-/scene-based (Tsoeleng et al., 2020; Liu et al., 2017; Phiri & Morgenroth, 2017; Zhang & Du, 2015), can be used to classify the urban land cover. However, regarding informal settlements, their intra- and interurban variability makes their identification sometimes difficult (Stark et al., 2020; Taubenböck et al., 2018; Kuffer et al., 2016).

Image classification into land use types is an important source of information for urban studies, however, it often lacks three-dimensional information (Wentz et al., 2018). Therefore, the characterization of cities into urban structural types and land cover with the Local Climate Zone (LCZ) classification scheme (Stewart & Oke, 2012) produces high-level semantic data by adding information on urban form and function to traditional land use legends and it has great potential that is worth exploring. LCZs represent the strcutural appearance of cities in a conceptually consistent manner, is intuitive and replicable. The classification scheme comprises ten built-up structural types and seven natural land cover types with uniform surface cover, structure, material, as well as human acitivity, having inherent information on the physical composition of cities, by their density, building types, heights, greenness, and land cover (Taubenböck et al., 2020; Bechtel et al., 2015; Stewart & Oke, 2012). Even though LCZ were originally created for urban temperature studies, now the concept is becoming popular in many other research areas. Some examples are: urban planning, risk assessement, building energy consumption or human health, to name a few (Xue et al., 2020).

With this background, in this study we aim to physically characterize the complex urban agglomeration of the city of Medellín, Colombia. We specifically focus on the identification of informal settlements using high-resolution EO data and additional geospatial datasets based on machine learning techniques. In doing so, we test the suitability of the LCZ concept to locate and quantify informal settlements.

3 MATERIAL AND METHODS

In this section we introduce the study area, describe the datasets used as well as their pre-processing steps and explain the methodology and validation proposed for the classification of urban structural types using EO data.

3.1 Study area

Medellín is the second largest city in Colombia, the capital of the Department of Antioquia and of the Metropolitan region of the Aburrá Valley. The latter forms a political and administrative unit of ten municipalities (Garcia Ferrari et al., 2018). The municipality of Medellín had around 2.4 million inhabitants in 2018 (DANE, 2018). Our area of interest (AOI) is represented by urban and expansion areas, as well as the urbanizing regions outside of the official urban border (Fig.1). Urban expansion areas are in the process of being added into the administrative urban border within the current planning period (2014 – 2027), but are not yet fully included (Alcaldía des Medellín, 2014 a, b), while urbanized areas are defined in this study as the regions at the border of the city, which are urban but not yet included in the official urban and expansion areas, characterized mostly by informal settlements in the official rural part of the city (Fig.1, in blue).

3.2 Data

This section introduces the data used for the classification into urban structural types (detailed methodological explanation in 3.3.1) and for the validation of identified informal settlements (detailed methodological explanation in 3.3.2).

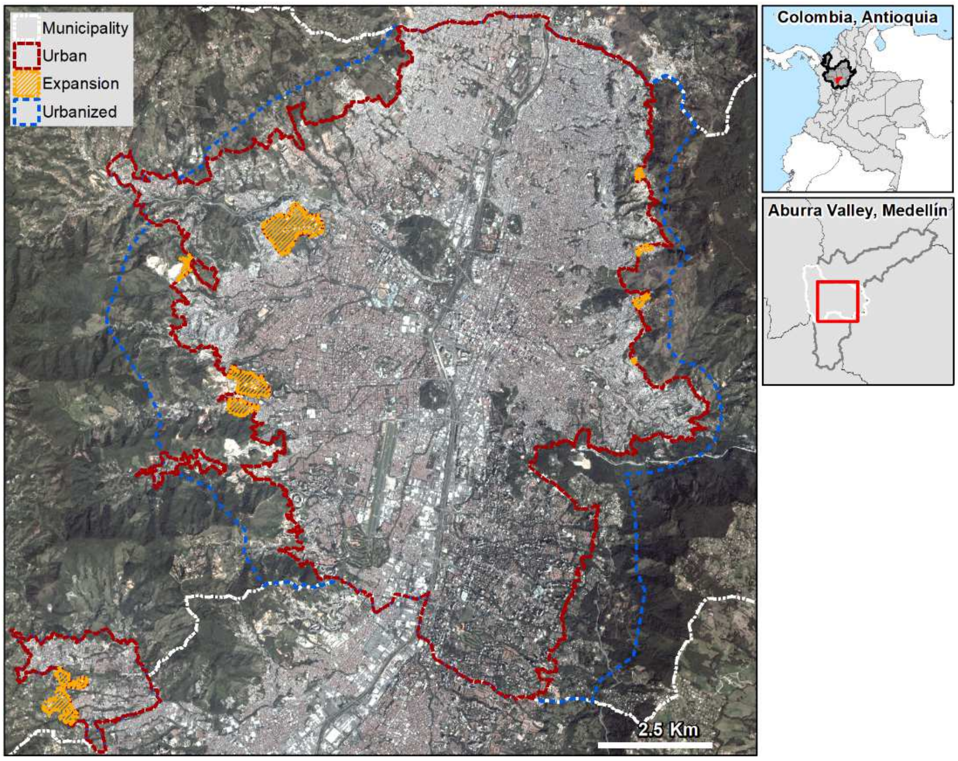


Fig. 1: Location of the study area: Urban, expansion and urbanized areas in the Municipality of Medellín within the Aburrá valley in Colombia. A PlanetScope image is used as background (Planet Team, 2019).

3.2.1 Input data and pre-processing steps

The first objective of this study is to classify Medellín into urban structural types with the LCZ concept. Therefore, we combine satellite data, elevation data, and open administrative geo-information. First, we use high-resolution image data (3m/pixel) from the PlanetScope constellation (approximately 130 satellites) launched in November 2018 and scanning the earth's surface every day, providing scenes with four spectral bands: red, green, blue and near infrared (RGB NIR; Planet Labs Inc. 2021). We acquire 13 scenes with 0% cloud coverage from the 1st of January 2019 to build one image mosaic covering the Aburrá valley (Table 1). By combining the different bands, we initially calculate the Normalized Difference Vegetation Index (NDVI), a spectral index showing the normalized difference between the red and infrared bands and providing spectral information on vegetation greenness (Rouse et al., 1973). This index has been widely used in land-use/land-cover (LULC) classifications to improve the performance of the classifier (Weigand et al., 2020; Jin et al., 2018b). Thereafter, we calculate the Grey Level Co-occurrence Matrix (GLCM) for each visible band (RGB), a method proposed by Haralick et al. (1973), and we extract eight textural features: mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation. The use of texture improves classification results since it mitigates confusion between spectrally similar classes (Li et al., 2014a; Vadakkenveettil et al., 2012). Secondly, we use an open digital elevation model (DEM) from the year 2019 covering the Aburrá valley with a spatial resolution of 10m that provides the height for each pixel (Table 1). The DEM is utilized to calculate the slope for each pixel, used as additional feature in the classification. Thirdly, we use the boundaries of the urban blocks from the administrative planning department of Medellín (Table 1) as polygons to perform a scene-based image classification into the urban structural types (see section 3.3). Compared to the spatial units of pixels and objects, scenes as a collection of different objects have the ability to provide high-level semantic information on urban functions, land use patterns and environmental issues, additional to LULC information (Liu et al., 2017; Zhang & Du, 2015). For each polygon from the urban blocks (i.e. scenes), we compute two well-known shape metrics: the compactness and shape index. The former indicates the compactness of a polygon, and the latter gives information on the overall shape complexity, both are calculated following the formulas by Jiao et al. (2012). Finally, we combine the four spectral bands, the NDVI, the twenty-four texture features (eight per band) and the slope with the urban blocks for the scene-based image analysis. We use the polygons as spatial reference to extract ten statistics for each scene: the mean, median, standard deviation, minimum, maximum, range,

ISBN 978-3-9504945-0-1. Editors: M. SCHRENK, V. V: POPOVICH, P. ZEILE, P. ELISEI, C.BEYER, J. RYSER, G. STÖGLEHNER

variance, minority, majority and variety. To summarize, each scene stores 302 features composed by 50 spectral, 240 textural, 10 topographical and two shape metrics.

3.2.2 Informal settlements reference data

The second objective of this study is testing the ability of remote sensing to identify the specific structural type of informal settlements using the LCZ scheme. As reference data for the validation we use the Land Use Treatments (Table 1) from the official Land Use and Zoning Plan 2014 (Plan de Ordenamiento Territorial, POT) published by the city of Medellín. The POT 2014 defines the economic, environmental, urban, and social future of the city from 2014 till 2027. The treatments are homogeneous morphological areas that have different management strategies. For the validation we use two specific treatments: Comprehensive improvement (Mejoramiento Integral, MI) and Consolidation level 3 (Consolidación Nivel 3, CN3). The former are areas of incomplete and inadequate development, located on the edges of the city with low living conditions due to marginality and socio-spatial segregation, poverty, limited development opportunities and access to essential public services. CN3 areas already show a more stable development trend, but still have a deficit of several indicators like public space and services, or road infrastructure (DAP, 2014). We use the treatments MI and CN3 as a reference data since the city administration considers them as precarious settlements (Alcadía de Medellín ISVIMED, 2019, p.116). In this study this is taken as a proxy for informal settlements since "precariousness" or "precarious settlement" are often used as a characteristic or synonym of informal settlements (e.g. Furtado & Renski, 2021).

Dataset	Description	Resolution	Year	Source
Classification input data				
PlanetScope mosaic	It is a satellite image mosaic with four bands (red, green, blue and near infrared).	3 meters/pixel	2019	(Planet Labs Inc., 2021; Planet Team, 2019)
Elevation	It is a digital elevation model covering the Aburrá valley.	10 meters/pixel	2019	(AMVA, 2019)
Urban blocks	It consists of the lower administrative level and usually covers buildings, green space and pavement.	-	2019	(DAP,2019)
Informal settlements reference data				
Land Use Treatments	They define the objectives of development in the municipality, guide the actions required to achieve the policies and objectives established for the land and occupation model of the territory in the framework of the Land Use and Zoning Plan (POT 2014).	-	2014	(POT, 2014); (DAP, 2014)

Table 1: Description of datasets used for the classification and validation.

3.3 Methodology

In this study we perfom a scene-based LCZ classification by means of the machine learning algorithm Random forest (Breiman, 2001). For the classification we use the LCZ concept adapted to Medellín. Initially, we identify eight built-up LCZ classes in the AOI, as shown in Fig. 2 (1- 8). Moreover, to meet the local conditions, we adapt the standard LCZ scheme: we create a new LCZ consisting of coexisting high-rise, midrise and low-rise compact structures within one urban block (Fig. 2, 9). In a second step, after the classification, we extract and compare the lightweight low-rise LCZ (Fig. 2, 7) against the reference data (section 3.2.2). The lightweight low-rise class represents informal settlements from a morphological perspective. It is defined mainly by lightweight construction materials (bricks, wood and metal) with one to three stories in compact arrangements. The land cover often consists of paved or hard-packed soil and few trees.

3.3.1 Random Forest classification and validation

Random forest (RF) is a supervised and nonparametric ensemble classifier that has been shown to produce high accuracies for LULC classifications (e.g. Weigand et al., 2020). The classifier uses decision trees to apply the class membership by the majority rule. The number of trees must be sufficient to get high accuracies; therefore, we use the default value of 500 (Maxwell et al., 2018). In this study we use the 'randomForest' package in R (https://www.r-project.org/). The RF algorithm relies on ground truth sample data to train the model and validate its performance. The quantity, quality, and representativeness of the sample data is decisive for the accuracy of the classification (Li et al., 2014b). In this study, we manually create 1,120 blocks with ground truth information by means of Google Street View image interpretation. The number of samples per LCZ is determined depending on their representation in the city. The number of samples is shown in Fig. 3 (top right). To measure the accuracy of the RF model we split the sample data into training data (50%) to fit the model and test data (50%) for the validation. However, the splitting into training and test data is done randomly, as well as the generation of the decision trees; therefore, the impact of randomness has to be considered. For this reason, we follow the steps proposed in Weigand et al. (2020) and create 100 different RF models (with different sample splittings and trees), and select the one with the highest Overall Accuracy (OA; Congalton, 1991) measured with the test samples. Then, we calculate the Producer's (PA) and User's accuracies (UA), these statistical measures provide information on the performance of each individual LCZ. We also remove features from our set that lower the accuracy. After quantifying and reporting the accuracies, the best performing model is applied to all urban blocks (in total 10,515) to create the final LCZ classification map.

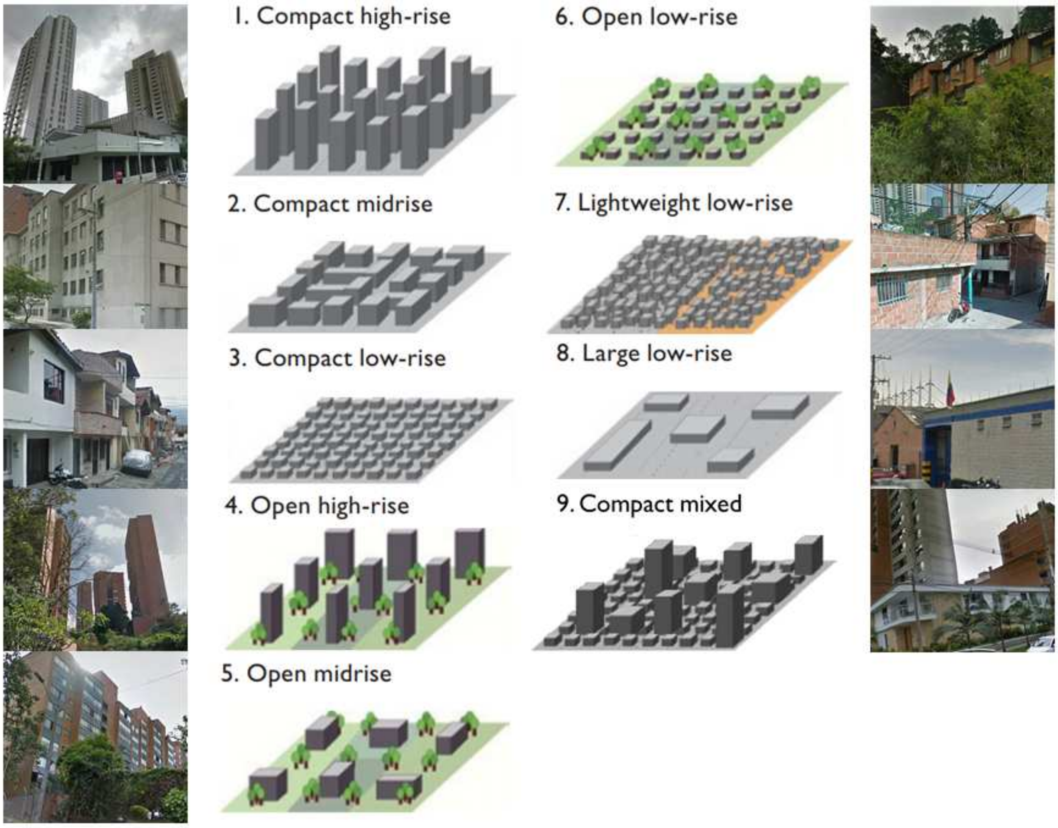


Fig. 2: The nine Local Climate Zones (LCZ) present in our AOI. The photos (from © Google Street View 2021) are examples for the physical expressions of the LCZ classes in our AOI, while the 3D representations are the definitions based on Stewart & Oke (2012).

3.3.2 Evaluation of informal settlement identification

On one hand, we assess the ability of the model to detect informal settlements by means of the UA and PA of the lightweight low-rise (LLR) class. On the other hand, we compare the area and spatial distribution of the LLR urban blocks to the informal settlement reference data. This evaluation is conducted by overlaying the area of the LLR urban blocks with the area of the reference data and deriving the confusion matrix and accuracy statistics.

4 RESULTS

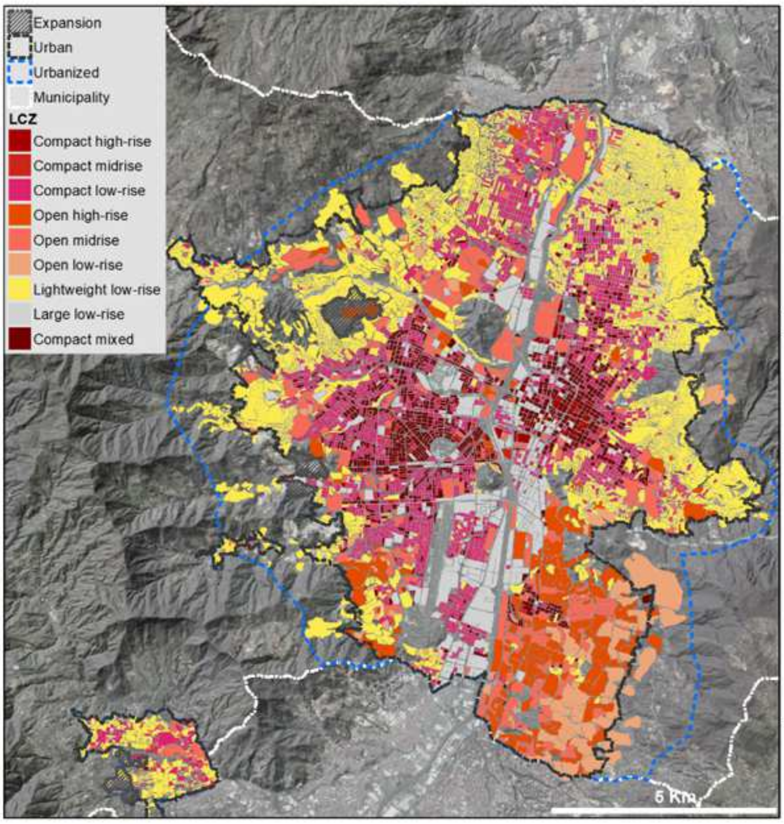
This section explains the results of the accuracy assessment of the LCZ classification and the operability of the LCZ concept to remotely detect informal settlements.

4.1 Classification of LCZs

The classification of the urban blocks into LCZs using the best performing RF model has an OA of 81.9%. The resulting map, shown in Fig. 3 (left), separates the morphology of the city into different urban structural types. The distribution shows a cluster of commercial and production site urban blocks along the Medellín river comprised of large low-rise areas as well as a cluster of compact high-rise, mid-rise and mixed structures in the heart of the city. Open high-/mid- and low-rise structures are predominant in the southeast of the city, where the social status is comparably higher, and LLR areas are located mostly in the (north-)eastern and (north-)western edges of the city in increasingly hilly and steep terrains (Garcia Ferrari et al.,

ISBN 978-3-9504945-0-1. Editors: M. SCHRENK, V. V: POPOVICH, P. ZEILE, P. ELISEI, C.BEYER, J. RYSER, G. STÖGLEHNER

2018). The accuracy assessment for each individual class (Fig. 3, bottom right) shows that more than half of the LCZs have a UA of above 70%, up to 90%, which indicates that only in around 10% to 30% of the cases the classification result deviates from the sample data, i.e. the actual LCZ is different to the predicted class. The PA shows fairly high values for the same LCZs. The highest PA is measured for LLR with over 96%, meaning only 4% of the sample data was underestimated and not classified as LLR. The high UAs for compact high-rise and compact midrise LCZs originate from zero missclassifications, as can be seen in Table 2. But the results have to be interepreted together with their PAs, which are very low. This indicates that a large amount of sample data representing these two LCZs were not correctly classified by the model, which can be interpreted as underclassification. These contradictory accuracies result from the class underrepresentation in the city, and therefore having particularly small sample sizes, making it difficult to distinguish them from other classes. Especially the LCZ compact mixed is classified instead of compact high-rise and midrise (see Table 2). A similar problem occurs for the LCZs open midrise and low-rise. For the UA and PA, having both rather moderate outcomes, Table 2 reveals confusions with other LCZs.



Local Climate Zone	Samples (train/test)
1. Compact high-rise	22 (11/11)
2. Compact midrise	37 (19/18)
3. Compact low-rise	254 (127/127)
4. Open high-rise	56 (28/28)
5. Open midrise	65 (33/32)
6. Open low-rise	57 (29/28)
7. Lightweight low-rise	448 (224/224)
8. Large low-rise	76 (38/38)
9. Compact mixed	105 (53/52)
Total	*1120 (562/558)*

Local Climate Zone	UA	PA
1. Compact high-rise	100%	9.1%
2. Compact midrise	100%	11.1%
3. Compact low-rise	84.2%	88.2%
4. Open high-rise	90.9%	71.4%
5. Open midrise	59.3%	50.0%
6. Open low-rise	75.0%	32.1%
7. Lightweight low-rise	84.8%	96.9%
8. Large low-rise	87.2%	89.5%
9. Compact mixed	69.7%	88.5%
	OA	**81.9%**

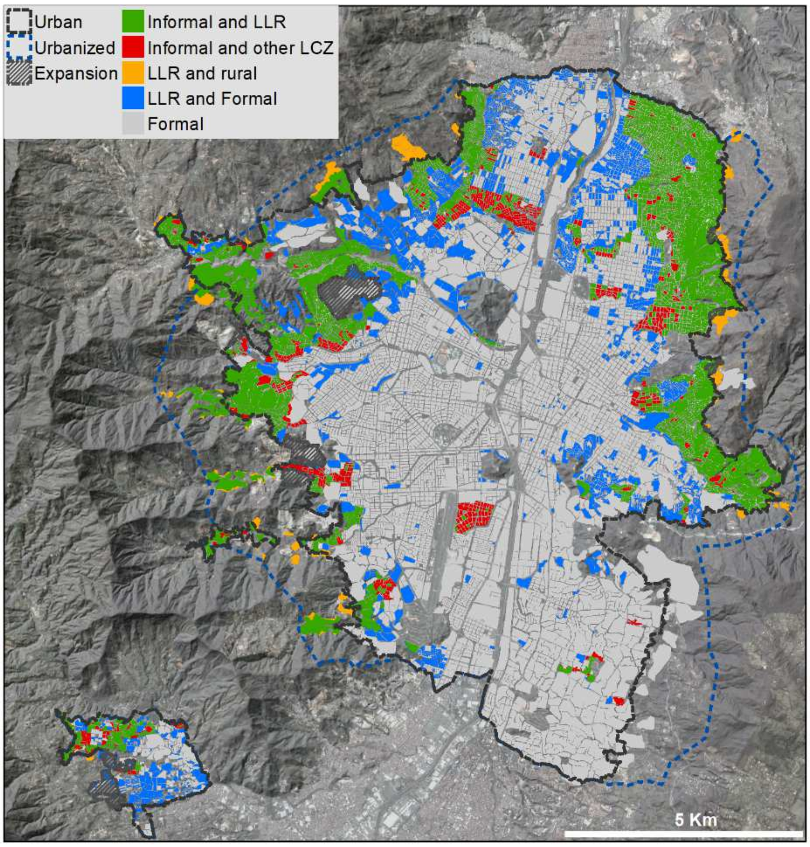
Fig. 3: Left: Local Climate Zone (LCZ) classification of Medellín, Colombia. Top right: Count of samples per LCZ class, determined based on their representation in the city. Bottom right: Accuracy assessment of the LCZ classification, represented by the User's (UA), Producer's accuracy (PA) as well as the Overall accuracy (OA).

		Sample data (ground truth)									
	LCZ	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**total**
Classification	**1**	**1**	0	0	0	0	0	0	0	0	1
	2	0	**2**	0	0	0	0	0	0	0	2
	3	1	5	**112**	0	2	4	4	2	3	133
	4	0	0	0	**20**	2	0	0	0	0	22
	5	2	1	0	1	**16**	7	0	0	0	27
	6	0	1	1	0	0	**9**	1	0	0	12
	7	1	2	9	5	12	7	**217**	2	1	256
	8	0	0	1	1	0	0	1	**34**	2	39
	9	6	7	4	1	0	1	1	0	**46**	66
	total	11	18	127	28	32	28	224	38	52	**558**

Table 2: Confusion matrix of the best performing model. The test data is used to create the table.

4.2 Comparison between LLR and informal settlements

Results regarding the suitability of the LCZ classification scheme to identify informal settlements show that our method is able to correctly identify 86% of the official delimitation of informal settlements (Fig. 4 in green, PA), and has an underestimation rate of 14% (Fig. 4 in red). From the point of view of the LLR informal settlements, 57% of the identified area corresponds to the official informal settlements (Fig. 4 in green, UA), while 43% are not correctly classified in regards to the reference data, composed of 38% formal and 5% rural areas (Fig. 4 in blue and orange respectively). This shows that even if our method is capable to recognise most of the informal areas in the city, it also overestimates informality that is not officially considered as such even if the morphology and building structures are very similar to other precarious neighborhoods.



Classification LCZ (ha)	Reference data (ha)			
	Informal	Formal	Rural	*Total*
LLR	**1638.9**	1101.0	153.7	*2893.5*
Other	272.7	**4559.3**	0.0	*4832.0*
Total	*1911.6*	*5660.3*	*153.7*	*7725.6*

	UA	PA
Informal	57%	86%
Formal	94%	81%

Fig. 4: Left: Overlay of the urban structural type of informal settlements (lightweight low-rise, LLR) extracted from the Local Climate Zone (LCZ) classification with the informal settlements reference data. Right: Confusion matrix in hectares and User's (UA) and Producer's accuracies (PA). The color used in the table shows the same area in hectares that is shown on the map.

5 DISCUSSION AND CONCLUSION

In general, we can state that with our approach - multisensory remote sensing data, machine learning techniques, and the LCZ concept - we are able to derive the complex settlement area in its morphological variability with high accuracy. This means the maps do have a high usability in the panning context. The LCZ classification scheme is standardized and thus shows to be very applicable to Medellin. Nevertheless, due to the special structural situation, we had to add an additional mixed class to the standard wheel in order to be able to adequately describe the urban body. The reached probabilities of a scene to actually represent the LCZ given is considerably high for most of the classes, based on the UA. The PAs are good for most classes as well. The approach proves to be feasible for urban structural types and land cover classification and is therefore an adaptable and good basis for urban analyses. Since the accuracies are affected by the sample count, especially evident for compact high-rise and midrise structures, future applications should consider more ground truth data for these two LCZs if possible, to improve the discrimination between morphologically similar classes. Alternatively, a combination of classes with similar characteristics (compact high-rise, midrise, mixed) might improve the performance of the model, since the confusion between classes will be reduced.

Moreover, this study had a particular interest in assessing the ability of the LCZ classification to identify the specific thematic class of informal settlements based on a morphological foundation. In a broader context, this information is especially relevant for risk assessment, as informal settlements have a higher vulnerability compared to the rest of the city and are often located in low-cost areas and steep slopes with a higher probability of natural hazards (Müller et al., 2020). The LLR class had good accuraccies in the RF model, showing low missclassification rates. Regarding its comparison with reference data, we were able to correctly identify 86% of the reference informal settlements, while the rest is attributed to other LCZs. And even though many urban blocks classified as LLR are officially formal or located in the rural area, our approach using EO data allows to extend the official urban border and include up-to-date information, which let us to identify 154ha of informal settlements that are related to fast and unplanned urbanization in the city edges and thus, are areas not yet officially considered by the city administration. In this case, remote sensing allows to look at the bigger picture and provides a more recent view of informality in the risk-prone hilly areas of the city. Besides, the classification of formal areas as LLR might partly arise from the different underlying conditions between morphological and official informal settlements. For a large part of the scenes classified as LLR, that are officially formal, the morphological definition of informality is still evident in Google Street View images. A possible explanation is an improvement of the social status with remaining morphological conditions and therefore, the classifier is not able to identify the correct class. Another factor, which has to be considered, is the misdetection of informal areas that have a morphologic formal appearance (i.e. structured housing rows or ordered street network). The official informal areas that were not detected by our RF model (Fig. 4 in red) are often loacted in the core of the city and are, according to Google Earth and Google Street View images, morphologically rather structured. To summarize, the identification of informal areas with EO data has its limitations and local knowledge is needed to better understand the reasons for misclassifications. Nevertheless, our model is able to detect a large amount of officially informal areas and furthermore, gives a more realistic and recent picture of the vulnerable areas at the city's edges. It can be concluded that the LCZ concept is a valuable instrument to identify not only urban structural types in general, but also informal settlements in particular.

6 ACKNOWLEDGEMENTS

This research was funded by the German Federal Ministry of Education and Research as part of the FONA Client II initiative, grant number 03G0883A-F, Inform@Risk – Strengthening the Resilience of Informal Settlements against Slope Movements. German partners: Leibniz Universität Hannover (Coordinator), Technische Hochschule Deggendorf, Technische Universität München, Deutsches Zentrum für Luft- und Raumfahrt e.V., AlpGeorisk, Sachverständigenbüro für Luftbildauswertung und Umweltfragen; Colombian partners: EAFIT University - URBAM, Alcaldía de Medellín, Área Metropolitana del Valle de Aburrá, Sistema de Alerta Temprana del Valle de Aburrá, Sociedad Colombiana de Geología, Colectivo Tejearañas, Corporación Convivamos, Fundación Palomá, Red Barrial Bello Oriente.

7 REFERENCES

ADGER, W.N., Crépin, A.S., Folke, C. et al: Urbanization, Migration, and Adaptation to Climate Change. In: One Earth, Vol. 3, Issue 4, pp. 396-399. 2020.

ALCALDÍA DE MEDELLÍN: Acuerdo 48 de 2014. Medellín, 2014a. Url: https://www.medellin.gov.co/irj/portal/medellin?NavigationTarget=navurl://0d6e1cabff217197f515823e5bb58bb6 (Accessed 11.03.2021).

ALCALDÍA DE MEDELLÍN: El nuevo POT. Una ciudad para la gente, una ciudad para la vida. Medellín, 2014b. Url: https://acimedellin.org/wp-content/uploads/2017/06/RevistaPOT2014.pdf (Accessed 25.03.2021).

ALCALDÍA DE MEDELLÍN ISVIMED (Instituto Social de Vivienda y Hábitat de Medellín): Plan Estratégico Habitacional de Medellín. PEHMED 2030. Diagnóstico del Sistema Municipal Habitacional Volumen 1. Medellín, 2019. Url: https://drive.google.com/file/d/1AN_RGJWuUrla0Tk0nXNC1fsVmeQ3hYS3/view (Accessed 19.03.2021).

AMVA (Aburrá Valley Metropolitan Area): Digital elevation model for the Aburrá Valley. 2019. Url: https://datosabiertos.metropol.gov.co/dataset/modelo-de-elevaci%C3%B3n-digital-para-el-valle-de-aburr%C3%A1 (Accessed 31.03.2021).

BECHTEL, B., Alexander, P.J., Böhner, J., Ching, J., Conrad, O., Feddema, J., Mills, G., See, L. & Stewart, I.: Mapping Local Climate Zones for a Worldwide Database of the Form and Function of Cities. In: ISPRS Int. J. Geo-Inf. Volume 4, pp. 199-219. 2015.

BREIMAN, L.: Random Forests. In: Machine Learning, Vol. 45, pp. 5-32. 2001.

CONGALTON, R.G.: A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. In: Remote Sens. Environ., Vol. 37, pp. 35-46. 1991.

DANE: Censo Nacional de Población y Vivienda – CNPV 2018. Antioquia, 2018. Url: https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/censo-nacional-de-poblacion-y-vivenda-2018 (Accessed 26.03.2021).

DAP (Administrative Department of Planning, Sub-directorate of Information and Strategic Evaluation, Medellin): Manzana 2019. Medellín, 2019. Url: https://www.medellin.gov.co/geonetwork/srv/metadata/1f4d1006-acf1-4c20-9f7c-48f47cbd0e6b (Accessed 23.10.2019).

DAP (Administrative Department of Planning): Revisión y Ajuste al Plan de Ordenamiento Territorial – Medellín. Documento técnico de soporte tabla de contenidos – tomo 4b. Medellín, 2014.

EDUSSURIYA, P., Chan, A. & Malvin, A.: Urban morphology and air quality in dense residential environments: correlations between morphological parameters and air pollution at street-level. In: Journal of Engineering Science and Technology, Vol. 9, Issue 1, pp.64-80. 2014.

FURTADO, L. & Renski, H.: Place attachement in self-built informal housing: improving spaces of crime. In: Journal of Housing and the Built Environment, Vol. 36, pp. 283-301. 2021.

GARCIA FERRARI, S., Smith, H., Coupe, F. & Rivera, H.: City profile: Medellin. In: Cities, Vol. 74, pp. 354-364. 2018.

GLAESER, E.: Triumph of the city. How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier. New York. 2011.

HARALICK, R.M., Shanmugam, K. & Dinstein, I.: Textural Features for Image Classification. In: IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-3, Issue 6, pp. 610-621. 1973.

HAN, X., Huang, X., Liang, H., Ma, S. & Gong, J.: Analysis of the relationships between environmental noise and urban morphology. In: Environmental Pollution, Vol. 233, pp. 755-763. 2018.

JIAO, L., Liu, Y. & Li, H.: Characterizing land-use classes in remote sensing imagery by shape metrics. In: ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 72, pp. 46-55. 2012.

JIN, H., Cui, P., Hien Wong, N. & Ignatius, M.: Assessing the Effects of Urban Morphology Parameters on Microclimate in Singapore to Control the Urban Heat Island Effect. In: Sustainability, Vol. 10, Issue 206, pp. 1-18. 2018a.

JIN, Y., Liu, X., Chen, Y. & Liang, X.: Land-cover mapping using Random Forest classification and incorporating NDVI time-series and texture: a case study of central Shandong. In: International Journal of Remote Sensing, Vol. 39, Issue 23, pp. 1-21. 2018b.

KRAFF, N.J., Wurm, M. & Taubenböck, H.: The dynamics of por urban áreas – analyzing morphologic transformations across the globe using Earth Observation data. In: Cities, Vol. 107, Issue 102905, pp. 1-15. 2020.

KUFFER, M., Wang, J., Nagenborg, M., Pfeffer, K., Kohli, D., Sliuzas, R. & Persello, C.: The scope of earth-observation to improve the consistency of the SDG slum indicator. ISPRS International Journal of Geo-Information, Vol. 7 (11), Issue 428, pp.1-28. 2018.

KUFFER, M., Pfeffer, K. & Sliuzas R.: Slums from Space-15 Years of Slum Mapping Using Remote Sensing. In: Remote Sens., Vol. 8, Issue 455, pp. 1-19. 2016.

LALL, S.V. & Deichmann, U.: Density and Disasters: Economics of Urban Hazard Risk. In: World Bank Research Observer. Vol. 27, Issue 1, pp. 74–105. 2012.

LEÓN, J. & March, A.: Urban morphology as a tool for supporting tsunami rapid resilience: A case study of Talcahuano, Chile. In: Habitat International, Vol. 43, pp. 250-262. 2014.

LI, M., Zang, S., Zhang, B., Li, S. & Wu, C.: A Review of Remote Sensing Image Classification Techniques: the Role of Spatio-contextual Information. In: European Journal of Remote Sensing, Vol. 47, Issue 1, pp. 389-411. 2014a.

LI, C., Wang, J., Wang, L., Hu, L. & Gong, P.: Comparison of Classification Algorithms and Training Sample Sizes in Urban Land Classification with Landsat Thematic Mapper Imagery. In: Remote Sens., Vol. 6, Issue 2, pp. 964-983. 2014b.

LIU, X., He, J., Zhang, J., Liang, H., Wang, H. & Hong, Y.: Classifying urban land use by integrating remote sensing and social media data. In: International Journal of Geographical Information Science, Vol. 31, Issue 8, pp.1-22. 2017.

LOBO, J., Alberti, M., Allen-Dumas, M., et al.: Urban science: Integrated theory from the first cities to sustainable metropolises. In: Report submitted to the NSF on the Present State and Future of Urban Science. 2020.

MAXWELL, A.E., Warner, T.A. & Fang, F.: Implementation of machine-learning classification in remote sensing: an applied review. In: International Journal of Remote Sensing, Vol. 39, Issue 9, pp. 2784-2817. 2018.

MÜLLER, I., Taubenböck, H., Kuffer, M. & Wurm, M.: Misperceptions of Predominant Slum Locations? Spatial Analysis of Slum Locations in Terms of Topgraphy Based on Earth Observation Data. In: Remote Sens., Vol. 12, Issue 2474, pp. 1-19. 2020.

OLIVEIRA, V: Urban Morphology. An introduction to the Study of the Physical, Form of cities. Switzerland, 2016.

PATEL, S. & Baptist, C.: Editorial: Documenting by the undocumented. In: Environment & Urbanization, Vol. 24, Issue 1, pp. 3-12. 2012.

PHIRI, D. & Morgenroth, J.: Developments in Landsat Land Cover Classification Methods: A Review. In: Remote Sens., Vol. 9, Issue 967, pp. 1-25. 2017.

PLANET LABS INC.: Planet Imagery Product Specifications. 2021. Url: https://assets.planet.com/docs/Planet_Combined_Imagery_Product_Specs_letter_screen.pdf (Accessed 09.03.2021).

PLANET TEAM: Planet Application Program Interface. In: Space for Life on Earth. San Francisco, CA, 2019. https://api.planet.com

POT, Plan de Ordenamiento Territorial: GDP POT Acuerdo48 de 2014. Medellín, 2014. URL: https://geomedellin-m-medellin.opendata.arcgis.com/datasets/gdb-pot-acuerdo48-de-2014 (Accessed 11.03.2021).

ROUSE, J.W., Haas, R.H., Schell, J.A. & Deering, D.W.: Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation. In: NASA/Goddard Space Flight Center Type II Report for Period September 1972-March 1973. Greenbelt, Maryland, 1973.

SAPENA, M., Wurm, M., Taubenböck, H., Tuia, D. & Ruiz, L.A.: Estimating quality of life dimensions from urban spatial pattern metrics. In: Computers, Environment and Urban Systems. Vol. 85, pp. 101549. 2021.

STARK, T., Wurm, M., Zhu, X.Z. & Taubenböck, H.: Satellite-Based Mapping of Urban Poverty With Transfer-Learned Slum Morphologies. In: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 13, pp. 5251 – 5263. 2020.

STEWART, I.D. & Oke, T.R.: Local Climate Zones for Urban Temperature Studies. In: Bulletin of the American Meteorological Society, Vol. 93, Issue 12, pp. 1879-1900. 2012.

TAUBENBÖCK, H., Debray, H., Qiu, C., Et Al.: Seven city types representing morphologic configurations of cities across the globe. In: Cities, Vol. 105, pp. 102814. 2020.

TAUBENBÖCK, H., Kraff, N.J. & Wurm, M.: The morphology of the Arrival City – A global categorization base don literatura surveys and remotely sensed data. In: Applied Geography, Vol. 92, pp. 150-167. 2018.

TSOELENG, L.T., Odindi, J. & Mhangara, P.: A Comparison of Two Morphological Techniques in the Classification of Urban Land Cover. In: Remote Sens., Vol. 12, Issue 1089, pp. 1-14. 2020.

UN, United Nations: General Assembly, Transforming our world: the 2030 Agenda for Sustainable Development, A/RES/70/1. 2015a. URL: https://www.refworld.org/docid/57b6e3e44.html (Accessed 20.05.2021).
UN, United Nations: Habitat III Issue Papers. 22 – Informal Settlements. In: Conference on Housing and Sustainable Urban Development. New York, 2015b.
UN, United Nations: Department of Economic and Social Affairs, Population Division. World Urbanization Prospects: The 2018 Revision. ST/ESA/SER.A/420. New York, 2019.
UN, United Nations: World Social Report 2020: Inequality in a Rapidly Changing World. New York, 2020.
VADAKKENVEETTIL, B.S., Unnikrishnan, A. & Balakrishnan, K.: Grey Level Co-Occurrence Matrices: Generalisation and some New Features. In: International Journal of Computer Science, Engineering and Information Technology, Vol. 2, Issue 2, pp. 151-157. 2012.
VOLTERSEN, M., Berger, C., Hese, S. & Schmullius C.: Object-based land cover mapping and comprehensive feature calculation for an automated derivation of urban structure types at block level. In: Remote Sensing of Environment, Vol. 154, pp. 192-291. 2014.
WEIGAND, M., Staab, J., Wurm, M. & Taubenböck, H.: Spatial and semantic effects of LUCAS simples on fully automated land use/land cover classification in high-resolution Sentinel-2 data. In: Int. J. Appl. Earth Obs. Geoinformation, Vol. 88, Issue 102065, pp. 1-9. 2020.
WENTZ, E.A., York, A.M., Alberti, M., Conrow, L., Fischer, H., Inostroza, L, Jantz, C., Pickett, S.T.A, Seto, K.C. & Taubenböck, H.: Six fundamental aspects for conceptualizing multidimensional urban form: A spatial mapping perspective. In: Landscape and Urban Planning, Vol. 179, pp. 55-62. 2018.
WICKI, A. & Parlow, E.: Attribution of local climate zones using a multitemporal land use/land cover classification scheme. In: Journal of Applied Remote Sensing, Vol. 11, Issue 2, pp. 026001: 1-16, 2017.
WURM, M., Stark, T., Zhu, X. X., Weigand, M. & Taubenböck, H.: Semantic segmentation of slums in satellite images using transfer learning on fully convolutional neural networks. ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 150, pp. 59-69. 2019.
XUE, J., You, R., Liu, W., Chen, C. & Lai, D.: Applications of Local Climate Zone Classification Scheme to Improve Urban Sustainability: A Bibliometric Review. In: Sustainability, Vol. 12, Issue 8083, pp. 1-14. 2020.
ZHANG, X. & Du, S.: A Linear Dirichlet Mixture Model for decomposing scenes: Application to analyzing urban functional zonings. In: Remote Sensing of Environment, Vol. 169, pp. 37-49. 2015.
ZHAO, Z., Shen, L., Li, L., Wang, H. & He, B.-J.: Local Climate Zone Classification Scheme Can Also Indicate Local-Scale Urban Ventilation Performance: An Evidence-Based Study. In: Atmosphere, Vol. 11, Issue 776, pp. 1-20. 2020.