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Semantic Identification of Urban Green Spaces: Forest

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Abstract. Urban Green Spaces (UGSs) are recognized as crucial parts of the human-nature ecosystem in densely populated urban centers. Even though they have been intensively studied, an ultimate list of all types of UGSs in Europe still does not exist. This challenges decision making on whether an area should be considered an UGS or belong to another land-use class. Furthermore, the means of precise identification of UGSs are dependent, among others, on their type and semantics. Therefore, in this paper, we investigate forests as UGSs and automatically identify them using their distinct characteristics from Sentinel-2 images as well as descriptive properties derived from them, i.e., vegetation indices and texture metrics. We enrich these properties with forest relevant features such as minimum vegetation height and homogeneity. To assess the reliability of the proposed workflow, we test our approach in two German cities and compare the results with existing governmental land use data sets. With the implemented approach we precisely identify over 90% of the existing forests in the study areas. The main restriction of the approach is the transferability of the thresholds of predictor variables such as homogeneity and dissimilarity.

Keywords. urban green spaces, forests, Sentinel-2, rule-based classification

1 Motivation

The importance of Urban Green Spaces (UGSs) for human well-being is highly recognised. Research into their benefits is hampered by diverging definitions of the underlying types of UGSs. Definitions and types of UGSs seem to be quite variable and highly case dependant. Existing Land Use and Land Cover (LULC) maps are not helpful since they either eliminate certain UGS types due to the minimum mapping unit or consider them as parts of different LU classes. Therefore, in a previous study, we proposed an ontology of UGSs where we defined eight UGS types based on their dominant LC and LU characteristics (Ismayilova and Timpf). These types include forests; parks; green corridors; urban gardens; provision for children and young people; cemeteries and other burial grounds; amenity green space, and urban agriculture. Since none of the existing LULC maps include those defined classes as separate UGS categories, there is a need to accurately map all the existing "green" in cities into these new classes. Therefore, in this paper, we focus on the first class of the ontology: forest, and attempt to develop a methodological framework that would allow its accurate identification using its semantic characteristics.

Defining Forest

"Forests, the goods and services they provide are essential for human well-being" (Louman et al., 2009). But what is a forest? Due to the complexity of the concept, there is no universally agreed definition of forest. According to the Food and Agriculture Organization (FAO), forest is "Land with tree crown cover of more than 10 percent and area of more than 0.5 hectares where trees should be able to reach a minimum height of 5 meters at maturity in situ" (FAO, 2000). In Germany, an area is considered a forest if it is covered with forest plants, is at least 0.1 hectares large and 10 meters wide. Moreover, areas within a forest that are temporarily not covered with trees (gaps, bare land) are also considered part of a forest (BMEL, 2012).

In the existing LULC maps, forest definitions are also not consistent. According to the Corine LC map, forests are defined as areas "with a vegetation pattern composed of native or exotic coniferous and/or broad-leaved trees, which can be used for the production of timber or other forest products". The forest trees under normal climatic conditions should be higher than 5 m with at least 30% of canopy closure (Bossard et al., 2000). OpenStreet Map (OSM) defines forests as "natural or semi-natural area covered by trees, which may or may not be used to produce forestry products such as wood and timber".

Changing definitions of forest makes the identification process of forests extremely challenging. Therefore, there is a need for harmonized definition of forests.

2 Forest Mapping

A forest inventory is critical due to various reasons including but not limited to planning, fire management and conservation. Inventorying forest through mapping is not an easy task as forests can exhibit tremendous variability in composition, volume, quality and topography (Kelly et al., 2015). Initially, forest mapping hugely relied on manual digitization of forest boundaries using aerial imagery. Manual forest inventories are time consuming and expensive, which makes their repetition at regular intervals very difficult (Diedershagen et al., 2004). With an increase of earth monitoring satellite missions, forest mapping practices became highly automated and cost efficient. Light Detection and Ranging (Lidar) data is the most commonly utilized forest mapping data source. For instance, using aircraft borne lidar and SAR data in Howland, Maine, USA, Sun et al. (2011) identifies forest biomass with over 70% accuracy. Other novel methods of forest mapping include the use of optical remote sensing (RS) imagery with various machine learning (ML) or deep learning (DL) algorithms. As such, Dorren et al. (2003) combines Landsat TM imagery with a digital elevation model (DEM) to map forest tree stand types in steep mountainous terrain and obtains high classification accuracy. However, similar approaches heavily rely on the availability of training and ground validation data to achieve good classification results. Providing high quality training data is laborious as either manual and/or field work might be required. Furthermore, these applications are computationally expensive and not intuitively understandable. An alternative to these resource intensive methods is a traditional Rule-Based Classification (RB). The RB classification is an approach to classify data sets with the help of a series of "if-then" rules. This approach can combine different types of data sets in the process similar to ML methods such as Random Forest. However, a rule-based approach contains semantic information in rule-sets and is simpler to understand (Bolstad and Lillesand, 1992). Although RB classification is a well-known and frequently used approach for LULC classification in general, it has not been intensively used for the identification of a single class, such as forest. Therefore, in this paper we use RB classification approach in a combination with forest-relevant semantic parameters.

3 Case Study

In this study we define forests using a combination of several existing definitions that are suitable for spatial analysis as well as for the selected study areas. Therefore, forests (here) are areas that are comprised of woody vegetation growing in a very close proximity to each other. Further, forest area should be at least 0.1 hectares large and be covered with trees at least 2.8 meters high. Therefore, we will identify forests in the selected study areas using the following forest-specific characteristics:

- Forests appear as relatively large areas (more than 0.1ha)
- In heterogeneous urban areas, forests emerge as very homogeneous and continuous areas
- Texture dissimilarity of forests is lower than of that in e.g. built-up areas
- Forests can be differentiated from other green homogeneous urban areas (e.g. crop fields, vineyards) based on a certain minimum vegetation height

Some of the selected parameters can be narrowed down to precise numbers. As such, tall green crop plants such as maize can reach up to 2.5-3 meters (Pereira and Lee, 1995), while vineyards can reach up to 1.8-2.7 meters. Therefore, the minimum vegetation height of 2.8 meters might be a good forest identifier. Other parameters, such as homogeneity or dissimilarity are very scene dependent. Therefore, we derive their thresholds using a rule-based classification approach.

3.1 Study Areas

In order to build a reliable methodology and then test it we consider two Southern German cities: Augsburg and Wuerzburg. Vegetation can be spatially and spectrally dynamic and possess difficulties to separate the same vegetation types in two different areas. Therefore, we select these two cities due to their relative similarity in terms of vegetation coverage. Forests in the selected study areas are populated mostly with spruce, pine, beech, and oak trees (Welle et al., 2022).

With a total area of 146 km^2, Augsburg accommodates two major forests in the south-east and south-west of the city which are called city forest (Stadtwald) and western forest (Westliche Wälder) accordingly. Further woody vegetation is located alongside the rivers Wertach and Lech. According to actual land use data ("Tatsächliche Nutzung", TN), the forest covers 36km^2 of the area of Augsburg. The city of Wuerzburg encompasses around 88 km^2, 14km^2 of which, as per TN, constitute forest. Spatially, forests are distributed in the south-western, northern, and north-eastern parts of the city. Unlike Augsburg, Wuerzburg accommodates approximately 2.5km^2 of vineyards. These areas as well as crop fields appear similar to forests and therefore must be handled carefully.

3.2 Data and Modelling

In this section we describe in detail the data pre-processing steps as well as the implemented methodology. The overall procedure utilized in this paper is depicted in Fig. 1.

To identify forests, we use single date Sentinel-2 imagery as an input to derive relevant forest features. Sentinel-2 data is freely available to download at the Copernicus Sentinels Scientific Data Hub. With very high revisit frequency and 13 spectral bands, Sentinel-2 is useful for a

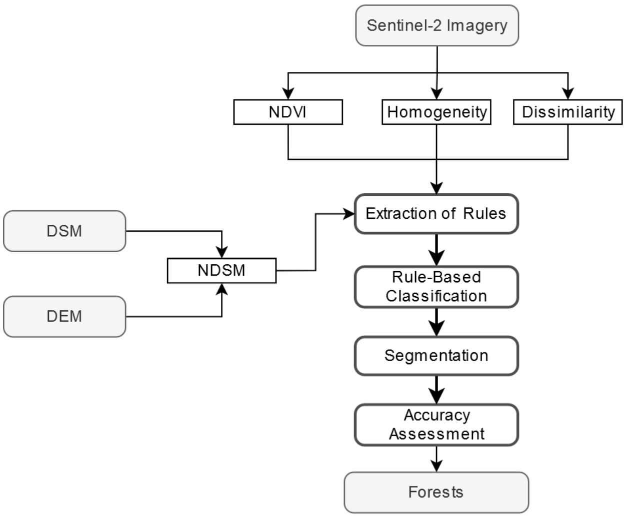

Figure 1. Workflow for identification and mapping of forests in urban areas.

vast variety of application. For further analysis, we select the 1C product as it provides radiometrically corrected and orthorectified images.
The Sentinel-2 imagery of Augsburg is a Level-1C product acquired by Sentinel-2B on the 30th of July, 2021. The utilized imagery of Wuerzburg is also a 1C product but collected by Seninel-2A on the 18th of July, 2021. We preprocess these images, where we adjust their extents and reproject the images to ETRS89 / UTM zone 32N. We utilize the red, green, blue, and near-infrared bands of both images, which have a spatial resolution of 10 meters. Selected bands are used to derive indices and metrics that are given in Table 1.
In order to delineate "green" areas from other surface objects we obtain the Normalized Difference Vegetation Index (NDVI). NDVI values range from -1 to +1, where positive values represent healthy vegetation and negative values indicate an absence of or sparse vegetation (Myneni et al., 1995). Forests can also be discriminated based on their texture metrics. This is particularly relevant for species with similar spectral characteristics but with different spatial patterns (Mohammadpour et al., 2022). Texture information can be calculated using the gray-level co-occurrence matrix (GLCM) (Haralick et al., 1973). We utilize homogeneity and dissimilarity metrics, since they are shown to be particularly helpful for identification of tree types in forests (Huechacona-Ruiz et al., 2020). According to Humeau-Heurtier (2019), the GLCM $P(i,j|d,\theta)$ represents the relative frequency of the occurrence of the same intensity value i (reference pixel) adjacent to a different intensity value j (neighbor pixel) in a specific spatial relation at the distance d and direction of θ. Consequently, homogeneity expresses the level of homogeneity and is high when the same adjacent pairs of pixels are found. Whereas heterogeneity expresses the level of heterogeneity and shows high values when the pixel pairs do not mach. In this paper, we calculate texture metrics with a windows size of 11x11, using the Probabilistic Quantizer with 32 levels in SNAP version 8.0.

Table 1. Vegetation Indices & Texture Metrics derived from Sentinel-2 imagery.

Vegetation Indices & Texture Metrics	Formula
NDVI	$\frac{NIR-Red}{NIR+Red}$
Homogeneity	$\sum_{i,j=0}^{N-1} \frac{iP_{i,j}}{1+(i-j)^2}$
Dissimilarity	$\sum_{i,j=0}^{N-1} iP_{i,j}\lvert i-j\rvert$
NDSM	$DSM - DEM$

We further calculate normalised digital surface model (NDSM) to extract vegetation height information. We use ALOS Global Digital Surface Model (DSM) (Tadono et al., 2014) as well as a Digital Elevation Model (DEM). ALOS DSM is a freely available data set with approximately 30 meters resolution (depending on latitude) produced by the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) on board of the Advanced Land Observing Satellite "ALOS". The DGM with 25 meters spatial resolution is provided by the Agency for Digitisation, High-Speed Internet and Surveying of each Land in Germany. We first resample the DSM and DGM data sets to 10 meters and then calculate NDSM. NDSM is a derivative elevation product, calculated by subtracting DEM values from DSM, thus indicating the height of objects on the earth surface.

3.2.1 Rule-Based classification & Accuracy assessment

To identify forested and woody areas, we establish threshold values for the selected variables. The best threshold is often chosen based on known ground data. Thus, we utilise forest polygons from TN data to extract values for the selected variables. In total we use 206 pure training points to train a classifier. The Partial Decision Tree based Classifier (PART) developed by Frank and Witten (1998) is one of the most straightforward rule-based classifiers. In order to create a single rule, a pruned decision tree is built for the current set of instances, the leaf with the largest coverage is made into a rule and the tree is discarded.This model is more time saving compared to e.g. the C4.5 model (Frank and Witten, 1998). Rules extracted from PART are non-compound and are straightforward to interpret.
We build three separate PART models for each study area using the caret library in RStudio version 4.2.2. Each model contains one predictor variable and one predicted variable to avoid composite rules. The three predictor variables are NDVI(M1), homogeneity(M2) and dissimilarity(M3). We do not include NDSM into the models as we fix its threshold at 2.8 meters under forest definition.

The predicted variable in all three models is the same: forest/non-forest information that we extract from TN. To train and test the models we use a 10-fold cross validation, where every sample in the data set is used for training and testing purpose. After we obtain rules for each variable, we perform classification of the entire study areas. Resulting raster data sets is a binary data set.

We calculate the final forest locations using a logical AND operation. We further use the clustering based Mean Shift Segmentation (Comaniciu and Meer, 1999) to group the single pixels into forest objects. Mean Shift is a non-parametric iterative algorithm used for image segmentation where for each data point mean shift defines a window around it and computes the mean of the data points. Then it shifts the center of window to the mean and repeats the algorithm till it converges. In case of raster data, segments are formed by grouping adjacent pixels together that have similar spectral and spatial characteristics. We utilize ArcGIS Pro Version 2.3. to perform the Mean Shift segmentation. We find suitable values for the segmentation parameters by trial and test and establish that spectral detail of 15.50, spatial detail of 20 and minimum segment size of 200 yield the most realistic results. Once we are satisfied with the results of the segmentation we use TN data to compare and validate our classification results.

3.2.2 Data and Software Availability

The rule-based classification can be replicated using the R-code file here: https://doi.org/10.6084/m9.figshare.22656451.v1. Some parameters, such as homogeneity and dissimilarity can be separately calculated using SNAP software.

The utilized Sentinel-2 images are free to downloaded at the Copernicus Sentinels Scientific Data Hub (https://scihub.copernicus.eu/dhus/#/home). Exact image tiles and dates are described in the Section 3.2. The DSM data can also be downloaded freely from the ALOS web page (https://www.eorc.jaxa.jp/ALOS/en/dataset/aw3d30/aw3d30_e.htm). We use the data provided under version 3.2, where we extract DSM data for Augsburg from the grid with N045E010_N050E015 coordinates and for Wuerzburg from the grid with N045E005_N050E010 coordinates. The Utilised DGM25 data, that is provided by the Agency for Digitisation, High-Speed Internet and Surveying, is currently not free of charge (https://www.ldbv.bayern.de/produkte/3dprodukte/gelaende.html).

4 Results

The accuracy distribution of the utilised models is given in Table 2. In the tested setup, most models reach prediction accuracy above 97%. The models that contain homogeneity and dissimilarity as predictor variables in Augsburg show slightly lower accuracy and reach 84% and 92% respectively.

Table 2. Accuracy distribution of utilised PART models in each study area.

Models	Accuracy	
	Augsburg	Wuerzburg
M1	0.98	0.99
M2	0.84	0.97
M3	0.92	0.97

Table 3. Rule-sets extracted for forest classification for both Augsburg and Wuerzburg using PART classification approach.

Variables	Rule-sets	
	Augsburg	Wuerzburg
NDVI	> 0.55	> 0.57
Homogeneity	> 1.5	> 0.66
Dissimilarity	$<= 3$	$<= 4.27$
NDSM	> 2.8	> 2.8

After we reach a satisfying prediction accuracy we extract one single rule for each model/variable in both study areas. The extracted threshold rules are given in Table 3. We observe similar rule thresholds, for some of the variables in both Augsburg and Wuerzburg. As such, the thresholds of NDVI 0.55 and 0.57 in Augsburg and Wuerzburg respectively, whereas homogeneity exhibits comparably higher divergence values in the two study areas: 1.5 and 0.66. The threshold rule of NDSM remains constant at 2.8 meters.

We estimate the final identification accuracy using the forest distribution from TN data as ground truth data. According to TN, forested areas cover 35.43 km^2 of Augsburg, while this number constitutes to 13.70 km^2 in Wuerzburg. Consequently, we identify 94% of the existing forests in Augsburg which constitute to 33.29 km^2. Whereas we identify 93% of forest in Wuerzburg which makes up 12.66 km^2. Figure 2 shows the identified forests based on the proposed methodology as well as the reference TN data. The map of the identified forests in Wuerzburg is shown in Fig. 3.

When looking in greater detail at the identified and non-identified areas we calculate 0.68 km^2 of forest area in Augsburg that is TN but has not been identified by the implemented methodology. Moreover, 0.47 km^2 of the area were identified as forest that are not mapped as forest in TN. Similarly, in Wuerzburg we compute 0.30 km^2 of forested areas that are in TN data but have not been identified with the selected methodology. Nearly the same area, 0.38 km^2, is identified as forest while not being mapped as forest in TN.

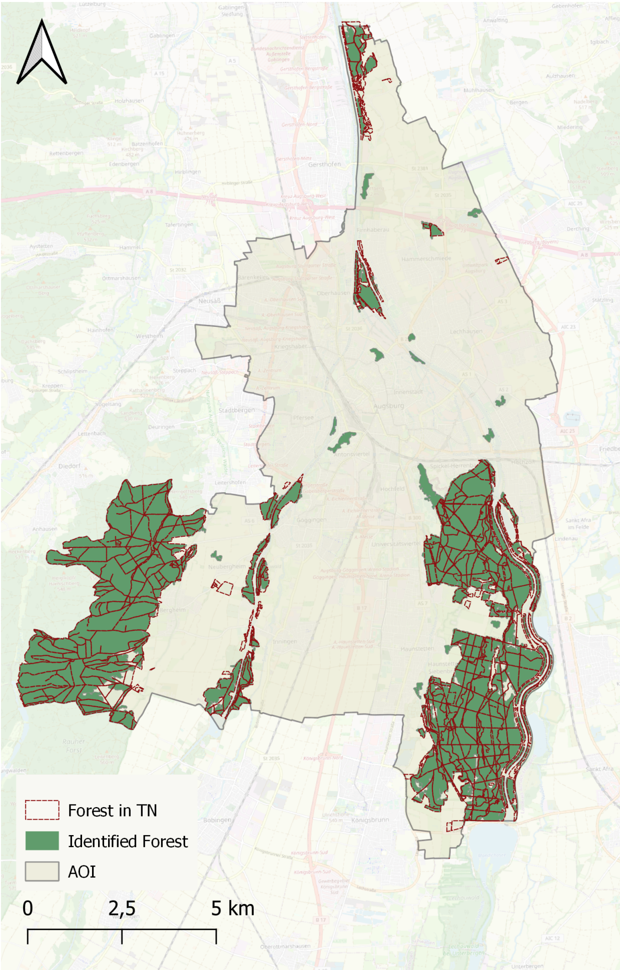

Figure 2. Map of identified forests as well as forests according to TN data in Augsburg.

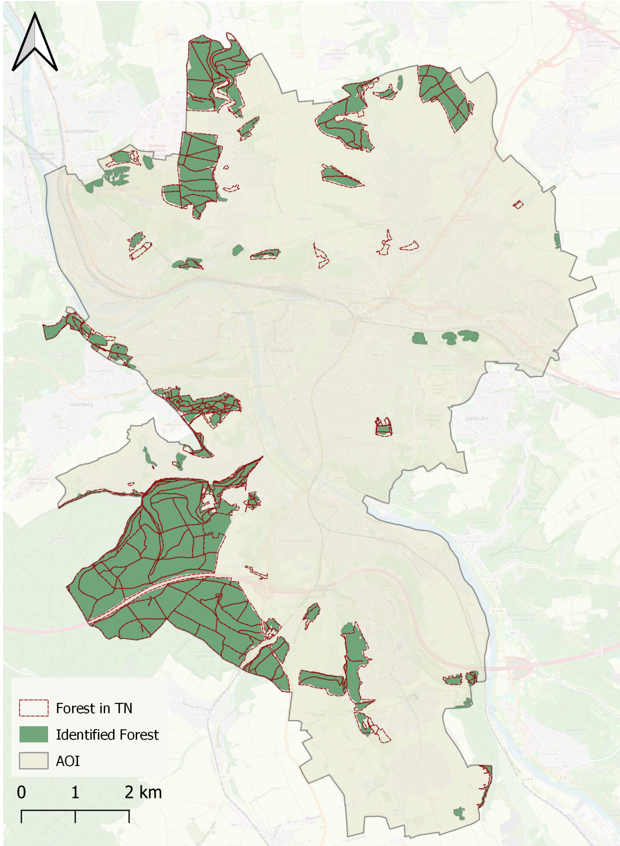

Figure 3. Map of identified forests as well as forests according to TN data in Wuerzburg.

5 Discussion and Conclusions

The main goal of this study is to map forests in urban areas in the context of UGSs. To achieve this, we use distinct characteristics of forests and extract minimum but adequate number of modelling parameters from these characteristics. As such, we choose to use NDVI to highlight vegetated areas, homogeneity and heterogeneity metrics to reduce all green areas to only "forest-like" areas and finally use NDSM to extract "forest-like" areas that are covered with exceptionally woody vegetation (and not e.g. grass or bush). Furthermore, we utilize PART classification model to derive rule-thresholds for all the selected parameters with an utmost goal of transferring the analysis to new study areas.
The first explored parameter is NDVI. The threshold values that we extract based on the rule-based classification vary only slightly in both study areas. The implemented classifier sets NDVI thresholds at around 0.55 which is in line with existing works, where vegetated areas fall below a value of 0.19 and values ranging 0.5-1 representing a tree class (Aryal et al., 2022).
We further study homogeneity and dissimilarity of vegetated areas to be able to tell whether an areas is a forest or not. We observe that the threshold values derived from the PART classifier vary greatly for both study areas. In Augsburg, homogeneity of higher than 1.5 and in Wuerzburg higher than 0.6 represent forested areas. While dissimilarity values below 4.2 in Wuerzburg describe forests, values below 3 are suitable for forest identification in Augsburg. This might be due to the high dependency of selected metrics from the image quality (Huechacona-Ruiz et al., 2020). Thus, homogeneity and dissimilarity are not directly transferable across various study areas due to the discussed dependencies. However, the incorporation of texture indices increases the classification accuracy of vegetation (Mohammadpour et al., 2022), which we can clearly observe when examining our results. Since we define forest as areas covered with woody vegetation, we use a NDSM threshold to distinguish "green" trees from the rest of the available "green".
Implementation of rule-based classification approach proves to be very useful in the case of forests identification. This is especially valid, just like here, if only few parameters are taken into account. Nevertheless, we can still spot areas that are not forests, yet are classified as such. We eliminate this confusion by including tree-height threshold similarly to Helber et al. (2019). However, this also results in some forest areas to be abolished, where trees have not yet reached the height of 2.8 meters. We accept this to be

in line with our forest definition, where tree height is set to minimum 2.8 meters.

Usage of only threshold-based classification might result in over-prediction. We eliminate it by introducing segmentation step into the analysis. Dorren et al. (2003) express that for tree identification in forests, minimum segment size is the most important parameter. The authors set this parameter at 21.6 pixels. While this value might be suitable for single tree identification, we find it to be too fine for forming large forest objects. Therefore, after testing different sizes, we establish 200 pixels as a suitable patch size in both study areas. This value can eliminate remaining small green patches that are not forests, yet adequately represent actual forests. Segmentation produces patches with an area above 0.1 ha and therefore, once again, meets the criteria set in our forest definition.

In conclusion, our results show that forests can be identified using minimum number of parameters that are closely related to their semantic characteristics; height of trees, close and homogeneous distribution of trees etc. However, in terms of transferability of our analysis to other areas, where forests might appear optically different as in Southern Germany, adjustments to the utilized variables or selection of different variables might be necessary. As such, within Southern Germany, NDVI threshold can be transferred to a new study area, homogeneity and heterogeneity are strictly scene dependant and cannot be directly utilized in new test sites. Therefore, in future works, we will test further semantic characteristics of forests to find out the most robust parameters, that can be used across study areas.

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