MAPPING URBAN GREEN SPACE DYNAMICS: A SEMANTIC EARTH OBSERVATION DATA CUBE APPROACH

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https://doi.org/10.31490/9788024846026-13

Abstract

Urban green space mapping based on satellite imagery is now possible more frequently and over shorter timespans thanks to dense time-series of open and free Earth observation (EO) images (e.g. the Copernicus Sentinel-2 mission). Despite this data availability, many approaches still focus on identifying the annual maximum extent of urban green spaces instead of utilising the entire dense image stack to characterise seasonal dynamics. We aim to temporally inform urban green space delineations, which could be relevant for applications like urban heat mitigation or citizens' urban green perception. We present a semantic EO data cube approach that allows ad-hoc, browser-based vegetation mapping for custom areas and timespans using transferable semantic models. We demonstrate the approach using a Sentinel-2 semantic EO data cube covering Austria, which makes use of every available Sentinel-2 observation since 2015 and where non-valid observations (e.g. cloud) can be masked out on an individual pixel basis to increase the number of valid observations for shorter timespans rather than relying on image-wide metadata. While we show results for the city of Vienna, the approach is transferrable to anywhere in Austria using the same infrastructure, or any other similar semantic EO data cube worldwide.

Keywords: urban green space, semantic EO data cube, semantic enrichment, semantic models, time series analysis

INTRODUCTION

Urban green space (UGS) is valuable for wellbeing and health and provides environmental benefits, such as mitigating urban heat or retaining storm water (Lee et al., 2015). There is a need for permanently monitoring urban green space and relevant changes in line with the United Nations Sustainable Development Goals (SDG), especially SDG 11, to improve availability of green spaces in cities and strengthen UGS's role in climate change mitigation. UGS mapping based on satellite imagery is now possible at a higher spatial resolution and over more frequent and shorter timespans than ever before due to the availability of open and free Earth observation (EO) images (e.g. Copernicus Sentinel-2 data, Landsat mission). Nevertheless, most approaches that map UGS mainly focus on the maximum spatial extent during a year. For example, Huang et al. (2021) analysed UGS for an enormous amount of 1039 cities worldwide, making use of the greenest pixel compositing method looking for the maximum extents of vegetation cover based on machine learning methods. Corbane et al. (2020) used annual greenest pixel composites for Landsat data on the Google Earth Engine platform in combination with the Global Human Settlement Layer to derive UGS and UGS-change by applying NDVI thresholds.

We focus on a different approach to mapping UGS, making use of the dense image stack to capture seasonal effects that could be relevant for applications like urban heat mitigation (Žuvela-Aloise et al., 2016) or investigating the perception of urban green (cf. Gonzales-Inca et al., 2022). We present a semantic EO data cube approach for UGS mapping that allows ad-hoc browser-based urban green space mapping for any user-defined timespan or area using transferable semantic models. The presented Sentinel-2 semantic EO data cube for Austria makes use of all Sentinel-2 observations available since 2015. Examples are presented for the city of Vienna, but the approach is transferrable to anywhere in Austria using the same infrastructure, or any other similar semantic EO data cube worldwide.

METHODOLOGY

An EO data cube allows organising EO data in respect to direct access based on spatial-temporal coordinates instead of file names, thus abstracting details of the storage system and aiming to make big EO data more accessible (Lewis et al., 2016). A semantic EO data cube or a semantics-enabled EO data cube is defined as 'a data cube, where for each observation at least one nominal (i.e., categorical) interpretation is available and can be queried in the same instance' (Augustin et al., 2019). We have implemented the first semantic EO data cube worldwide for all Sentinel-2 data available in Austria and provided it as Web application in a cloud-based environment (https://sen2cube.at, accessed on 28 January 2022). Automatic semantic enrichment of every Sentinel-2 data set provides semi-symbolic spectral categories for all observations as an initial interpretation of colour information on a big EO data scale. An interactive browser-based GUI allows users, to conduct analyses based on big EO imagery content using semantic querying without requiring programming or training samples (Sudmanns et al., 2021).

To illustrate the usefulness of time series analysis for UGS mapping, we developed some initial semantic models that are transferable to any city in Austria and applicable to any timespan (e.g. months or seasons) covered by Sentinel-2 observations since the start of the mission in 2015 (Sentinel-2A) and 2017 (Sentinel-2B) until the present. Since the semantic layers derived from the satellite data use categorical data (e.g. different vegetation intensity categories, cloud / snow observations, bare soil categories), we are able to include all available observations in our analysis so that filtering image data based on overall cloud estimations available in the metadata is not necessary. Non-valid observations are masked out on a per pixel basis as defined in the semantic model, which increases the amount of valid-observations in cloud/snow rich seasons to also derive statistically valid amounts of data for these timespans. In addition, the number of available valid observations per selected timespan can be considered for assessing the reliability of results. The main advantage of this approach is that UGS can be derived interactively for specific application cases rather than always relying on an annual maximum extent, e.g. to derive green cover in urban heat related summer months where some areas are not green anymore or for winter months in respect to leave-off conditions.

RESULTS

Figure 1 shows the results of our experiments using a semantic model that counts all pixels categorised as vegetation.

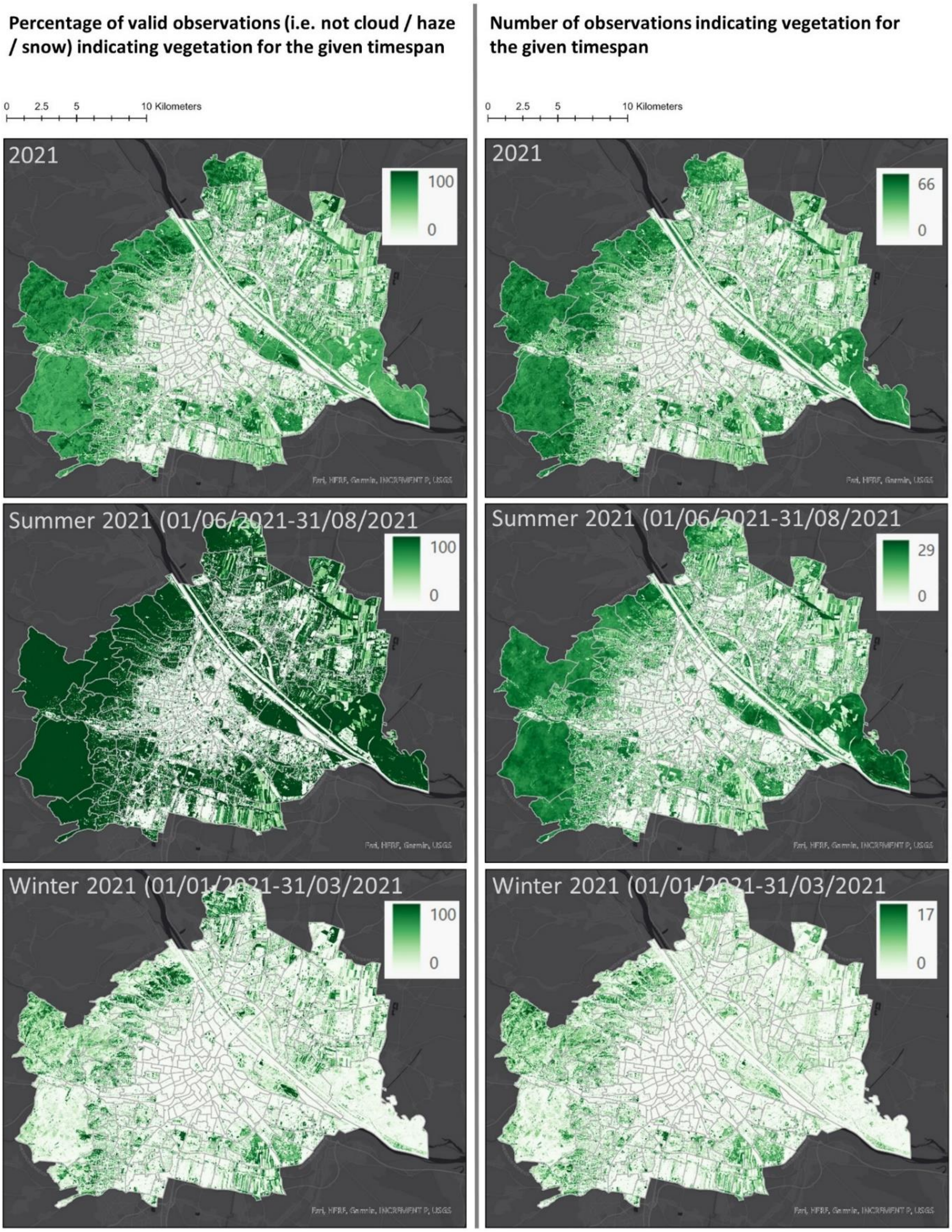

Fig. 1. Mapping UGS in Vienna for different timespans in 2021 based on all Sentinel-2 data. The top row shows results for the entire year and the rows below show seasonal differences between June to August (middle) and January through March (bottom). The left column shows the percentage of valid observations (i.e. not cloud, haze or snow) that were categorised as (green) vegetation. The right column shows the absolute number of observations categorised as vegetation.

Due to the generic semantic enrichment of all Sentinel-2 images in the semantic EO data cube, we can not only select vegetation observations, but also mask out spectral categories that indicate non-valid observations like clouds, haze and snow. We focused on Vienna during the year 2021 as well as subsets of 2021, but the same semantic model can be used for different user-defined timespans or areas of interest. Figure 1 illustrates that there are differences in actively vegetated areas between summer and winter months, especially for deciduous forest in the western part of the city. While most of the green spaces identified for the entire year of 2021 show permanent vegetation during the summer months based on valid observations, we also observe fluctuating values in agricultural areas, such as in the north-eastern part of the city. Relying only on maximum green extents for UGS mapping can therefore overstate UGS, which can in turn influence further analysis, such as assessing urban heat vulnerability and developing mitigation strategies. Figure 2 shows how vegetation peaks can be mapped to monthly timeframes to show the dynamics of the green vegetation in UGS based on the dense Sentinel-2 image stack.

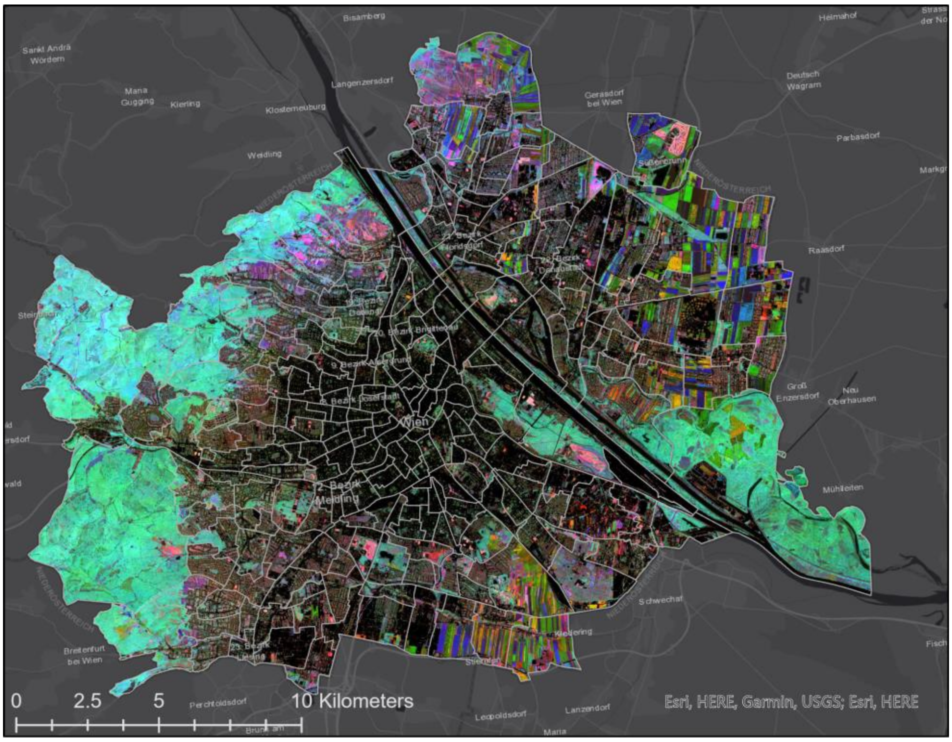

Fig. 2. Monthly percentages of all available Sentinel-2 observations showing (green) vegetation displayed in R-G-B for March (red), June (green) and September (blue) during 2021. Distinct colors indicate vegetation peaks in specific months. Red colors indicate areas mainly vegetated in early spring, blue colors indidcate areas vegetated in late summer/autumn and green for vegetation dominating in June. Mixed colors indicate green vegetation present in multiple months, generally indicating a longer time span of green vegetation or even the whole year.

CONCLUSIONS

We see great potential in the semantic EO data cube approach to improve UGS identification based on dense image time series, especially for intra-annual assessments in near-real time towards temporally informed UGS that may open up new possibilities for investigation. This approach uses all Sentinel-2 observations and goes beyond existing approaches that rely on maximum extents.

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