Experimental Analysis of Geo-spatial Data to Evaluate Urban Greenspace: A Case Study in Dortmund, Germany

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Abstract
Urban greenspace is of high importance for the general public from different points of view. Among others, it is beneficial for recreational activities as well as for cooling effects during summer in urban climate. Many studies investigate urban greenspace from perspectives related to environmental justice or health geography that are usually based on environmental and sociodemographic data of diverse scales or spatial levels of detail and often suffer from high degrees of generalization. To demonstrate the benefit of a higher degree of spatial detail, a representative part of the city of Dortmund (Germany) is selected as study area. A time series of freely available Sentinel-2 images and a freely available digital object height model (DOHM) are used to analyze and describe the spatio-temporal distribution of urban vegetation and its potential effects on the population. Doing so, the Sentinel-2 images are used for the calculation of vegetation indices to identify the active green period of different vegetation land covers. In addition to that, the three-dimensional appearance of vegetation is correlated with the green period to assume the relevance of green land covers for the general public. The results show that an appropriate selection of cloud-free satellite images is of importance for a greenspace analysis. The combination of high resolution 2D and 3D data sets, namely NDVI and plant height information, reveals the spatial distribution of well-equipped greenspace areas with high recreational and health potential as well as poorly-equipped areas in urban neighborhoods, that could be improved.

Keywords NDVI · Sentinel-2 · Urban greenspace · Urban climate · Health geography · Geo-spatial data · Dortmund

Experimentelle Analyse von Geodaten zur Bewertung städtischer Grünflächen: Eine Fallstudie in Dortmund, Deutschland

Zusammenfassung
Städtische Grünflächen sind für die Bevölkerung unter verschiedenen Gesichtspunkten von großer Bedeutung. Unter anderem sind sie für die Freizeitgestaltung und für die sommerliche Abkühlung im städtischen Klima vorteilhaft. Viele Studien untersuchen städtische Grünflächen unter umwelt- oder gesundheitsgeographischen Gesichtspunkten, die in der Regel auf Umwelt- und soziodemographischen Daten unterschiedlicher Größenordnungen oder räumlicher Detailebenen beruhen und oft einen hohen Grad an Generalisierung aufweisen. Um den Nutzen eines höheren räumlichen Detaillierungsgrades zu demonstrieren, wurde ein repräsentativer Teil der Stadt Dortmund als Untersuchungsgebiet ausgewählt. Eine Zeitreihe von frei verfügbaren Sentinel-2-Bildern und ein frei verfügbares digitales Objekthöhenmodell (DOHM) werden verwendet, um die räumlich-zeitliche Verteilung der städtischen Vegetation und ihre möglichen Auswirkungen auf die Bevölkerung zu analysieren und zu beschreiben. Dabei werden die Sentinel-2-Bilder für die Berechnung von Vegetationsindizes verwendet.
Urban greenspace is of high importance for the general public from different points of view. Among others, it is beneficial for recreational activities as well as for cooling effects during summer in urban climate. Earlier studies investigate urban greenspace from perspectives related to environmental justice or health geography that are usually based on environmental and sociodemographic data of diverse scales or spatial levels of detail and often suffer from high degrees of generalization. Here, the benefit of a higher degree of spatial detail is demonstrated with high resolution satellite images and a freely available digital object height model (DOHM) to analyze and describe the spatio-temporal distribution of urban vegetation and its potential effects on the population.

Earth observation is a discipline that monitors the earth and the condition of its surface for more than 50 years now. Special earth observation satellites are able to acquire timely data in frequent intervals (Albertz 2016; Lillesand et al. 2015; Jürgens 2020). One of the most prominent land surfaces is vegetation, of which urban greenspace has to be considered as an environmental resource having positive effects on health and well-being of the urban population. Due to the complex material composition of urban areas, it is helpful to use high resolution satellite images with small pixels. According to Juergens et al. (2019), such images provide timely information of high geometric and semantic quality, especially in urban areas. Such data can ideally support urban planning as well as other public duties. Due to high temporal revisit rates, the benefit of earth observation data is its ability to keep pace with the development and to keep track of changes and additions within urban greenspace.

To describe vegetation coverage from the vertical perspective of earth observation platforms, the leaf area index (LAI) was introduced by Sellers (1985), which describes the amount of green leaves. All values above 1.0 describe plants (like trees) with more than 100% ground covered by vegetation due to the fact that the plant has more than one level of leaves. Values below 1.0 describe sparse vegetation covers consisting of soil and vegetation in one pixel.

For vegetation monitoring and judging the condition of photosynthetic active plants, the Normalized Difference Vegetation Index (NDVI), as proposed by Rouse Jr. et al. (1974), is commonly used. Due to specific needs, many other vegetation indices have been developed. For environments with sparse vegetation covers, Huete (1988) introduced the Soil-Adjusted Vegetation Index (SAVI) which was later improved by the Optimized Soil-Adjusted Vegetation Index (OSAVI) developed by Baret et al. (1993). Many vegetation indices are addressing specific needs, like the modified Normalized Difference Vegetation Index (mNDVI) (Jurgens 1997), which is used to estimate frost damages in agriculture based on Landsat data.

Despite all these possibly more sophisticated vegetation indices and the more specific problem-oriented vegetation indices, the NDVI is still the most used vegetation index today, due to its simple formula and ease of use. It allows quantitative evaluations and comparisons of different vegetation covers as well as analysis of vigor and growth dynamics (Xue and Su 2017). Consequentially, vegetation indices in general, and the NDVI in particular, are a widely accepted and applied to assess and monitor spatio-temporal vegetation changes also in urban and sub-urban environments.

Vegetation in cities mainly consists of trees, bushes, agricultural fields and meadows/pastures that comprise recreational (e.g. parks, forest), natural (e.g. forests) and agricultural (e.g. fields and pastures) land covers. In general, vegetation is thought to improve our well-being, our health and our quality of life. According to that, one could believe that high degrees of vegetation correlate positively with higher quality of life and better individual health. This rather broad perspective does not account for different quality of vegetation, related to its height and individual perception or the time period in which the vegetation appears green (e.g. fields are a rather temporary land use and meadows/pastures could be cut and change their appearance). In addition to that, one neglects other influencing environmental factors that could stress individuals and their perception and health situation, such as environmental pollution, noise etc.

Vegetation cover in non-tropical regions correlates with seasonality aspects which stem from the different seasons during a year. For regional or continental studies, one can identify the start of the growing season for large regions by calculating the NDVI (Beck et al. 2005). In addition to that,
one can observe the regional differences in the NDVI values during a period of one year, which correspond to vegetation dynamics.

For investigations at larger scales, such as cities or urban neighborhoods, high spatial resolution images are beneficial to identify as much vegetation details as possible. This is necessary as cities include a high number of different surface materials. The smaller the image pixels the higher is the chance to get pure vegetation pixels. However, if the geometric resolution of the sensor is rather coarse, so-called mixed pixels, consisting of different materials in one pixel, occur. In such cases, isolating vegetation information is almost impossible. For instance, Feng et al. (2017) use high resolution satellite images for an urban vegetation phenology analysis in the city of Nanjing, China. Urban vegetation is characterized by a seasonal cycle of plant processes and is connected to urban temperature and precipitation characteristics. Obviously, high or very high resolution satellite images are advantageous for most studies in urban areas.

Besides phenology driven studies, other authors use urban green indicators for environmental justice or inequality research. For instance, Flacke et al. (2016) use the Spatial Urban Health Equity Indicator Framework (SUHEI) (see also Bolte et al. 2018) to relate urban green to other urban factors with social context, such as air pollution or noise, to estimate health inequalities for different neighborhoods in the city of Dortmund, Germany. The study is based on the percentage of green area (each area > 1 ha) in an administrative subdivision based on a previously existing land cover map. Here, satellite derived NDVI’s could deliver up-to-date information on the current quality of green spaces and help to adapt the SUHEI-results to the true situation and location, e.g. in dry weeks or months of a year, where the green lawn is no longer green.

According to Wagner (2015), social sciences increasingly recognize the meaning of georeferenced and geo-spatial data including remote sensing imagery. He also asserts that more and more social scientists are able to link their data with remote sensing data. For instance, Zepp et al. (2018) use NDVI data calculated from a Landsat satellite image of 2003 along with Urban Atlas data from 2012. However, the study suffers from the time gap of nine years between the data sets used.

Another example of NDVI integration is from Möller and Bartlomiejczak (2020), investigating the potential of satellite image-based information for planning authorities to improve inhabitants’ quality of life. Besides concentrating on the NDVI values, other studies (Colunga et al. 2015; Hart and Sailor 2008; Duarte et al. 2015; Alves and Lopez 2017) consider additional variables that could affect the local climate.

This paper addresses the limits and potential of the NDVI satellite images, it is intended to precisely characterize the vegetation types in the study area. The authors observed that parameters like the acquisition date (in relation to other data sets and the vegetation period) or the temporal and geometric resolution of satellite imagery could influence greenspace analysis. The calculated NDVI values will be analyzed together with object height information to characterize greenspace with respect to different land-cover types.

2 Materials and Methods

This section presents the geospatial data used and the respective geospatial analysis approach. All geospatial calculations were performed with ArcGIS Pro. The study area (Fig. 1) is located in the city of Dortmund, North Rhine-Westphalia, Germany. It includes all relevant land cover/land use types and is representative for the region.

2.1 Land Use/Land Cover Dataset FNK

The first data set in this study is the land cover/land use mapping FNK created in 2017 by the Regionalverband Ruhr (RVR 2017). It is a very detailed map product that needs to be simplified for the purpose of this study and to comply with the vegetation cover. Originally, this product consists of 151 individual categories, from which 57 are meaningful for this study. Those are reclassified to seven main classes for this investigation (Table 1), as lots of them are only different in usage rather than surface appearance. For different administrative reasons, the FNK does not cover the whole study area. Therefore, maps that are based on this data set have a different extent than those of other geospatial data not affected by administrative border lines.

2.2 Sentinel-2 Imagery

Further, freely available cloud-free high resolution Sentinel-2 satellite images (ESA 2020) (see Table 2) are used to investigate the study area during the vegetation period of 2019. From all 12 available spectral bands, only the four bands with 10 m geometric resolution are used. In the authors opinion, bands with coarser resolutions are not suitable for urban environments.

From the satellite images, the NDVI is calculated to monitor the urban vegetation cover as follows:

\[
\text{NDVI} = \frac{(\text{nIR} - \text{RED})}{(\text{nIR} + \text{RED})}.
\]

The resulting NDVI values appear in the range of −1 to +1. Values below or close to 0 are not related to healthy green vegetation, rather to water, bare soil or abiotic urban surfaces like roofs and road materials. The higher the NDVI
value, the more it is related to vegetation cover and high vitality. During the vegetation period, the reflectance characteristics of vegetation varies among trees (forests, parks), bushes, meadows or agricultural fields with different crops, due to varying cultivation techniques (as well as cutting cycles) or phenology reasons. Other surfaces like roads or buildings are rather invariant over time. This is illustrated for a few typical locations in Fig. 2.

The five satellite images are displayed in Fig. 3 in false colors. They clearly reveal seasonal differences between the different land cover/land use categories: the false colors pronounce vegetation in red. Seasonal effects are also evident in the NDVI-images of the respective dates (Fig. 4). Areas with low NDVI could suffer from little or no vegetation and could be areas of environmental burdens like heat vulnerability during summer months. On the contrary, a high degree of tall vegetation (e.g. trees) generates cooling effects of the neighborhood in summer and therefore leads to healthier conditions of life in this particular area.

2.3 Digital Terrain Model

To determine object heights, laser scan data of 2018 (Land NRW 2020) with 1 m raster cells are used. The last pulse based digital terrain model (DTM) is subtracted from the first pulse based digital surface model (DSM) to receive the

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Table 1 Land cover/land use class reduction for this study (base data from RVR 2017)

| Original FNK land cover/land use category | Main land cover/land use category |
|------------------------------------------|----------------------------------|
| 370                                      | Field                            |
| 400, 410, 420, 431, 432, 441             | Forest                           |
| 361, 362                                 | Grassland                        |
| 10, 20, 30, 40, 51, 52, 54, 72, 75, 83, 84, 85, 87, 91, 93, 140, 151, 152, 171, 174, 211, 221, 281, 381 | Impervious                        |
| 291, 292, 293, 382                       | Open space                       |
| 53, 223, 301, 302, 303, 306, 308, 309, 331, 383, 452 | Other                             |
| 233, 271, 273, 282, 305, 321, 451, 471, 472 | Other vegetation                 |

Table 2 Sentinel-2 satellite images (ESA 2020) used for the vegetation period April 1st to August 31st 2019

| Acquisition date | Used bands | Pixel size |
|------------------|------------|------------|
| 2019-04-20       | 2, 3, 4, 8/B, G, R, nIR | 10 m × 10 m |
| 2019-05-15       |            |            |
| 2019-06-29       |            |            |
| 2019-07-24       |            |            |
| 2019-08-26       |            |            |
object height of trees, buildings and other rather vertical objects in a digital object height model (DOHM) that is presented in Fig. 6. For consistency reasons, the 1 m raster cells are resampled to 10 m raster cells using nearest neighbor to match the 10 m NDVI raster cells (Fig. 5).

2.4 Calculation of Different Mean NDVIs

Monotemporal NDVI values like in Fig. 4 offer further aggregation possibilities. Besides the calculation of pixel-based NDVI values per image acquisition date or the calculation of NDVI differences between adjacent image dates, further unconventional NDVI calculations help to gain more insight into vegetation dynamics etc.

Among such calculations is the aggregation to spatial, temporal or spatio-temporal mean or maximum NDVI values to characterize and spatially differentiate greenspaces representing different land cover types as outlined in Table 3.

In this study, the first NDVI analysis (type A) is based on mean NDVI values over time for all pixel locations. These temporal mean NDVIs per pixel allow insights into seasonality aspects, as these calculated mean values give an overview of the NDVI level within a season. Rather low temporal mean NDVI’s indicate pixels with sparse or no vegetation during most of the season. Rather high values indicate a high amount of photosynthetic active vegetation during most of the season. Medium values could represent fields with cultivated intensively green periods and harvested situations characterized by rather low NDVI values.

Another reasonable approach is to average mean NDVI values spatially for each land cover/land use polygon. The authors call this a spatio-temporal mean NDVI per FNK polygon (type B), which allows insights into an annual or seasonal average NDVI per polygon. This appears to be more meaningful for individual land cover/land use categories than single pixel based calculations. Moos (2020) does so for the vegetation period for the city of Dortmund in Germany. Due to his intention to study the mean NDVI for a complete city, he used a coarse grid (cell size 100 m × 100 m) and combined the temporal mean NDVI calculation with the spatial mean NDVI calculation. Disadvantageous for the coarse grid cells is, that land surfaces with no or little vegetation are included in the calculation and consequently lower the resulting mean NDVI value. To overcome this disadvantage, the authors calculate the spatial–temporal mean on a field or parcel basis (FNK polygon) with homogeneous land cover/land use within each polygon. This gives a much more realistic

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Fig. 2 Selected seasonal NDVI values of different land cover/land use types from Sentinel-2 images (ESA 2020)
and sophisticated representation of greenness in the urban neighborhood.

In addition to temporal mean NDVI calculations, the temporal maximum NDVI per pixel (type C) for the period of observation (April–August 2019) is extracted. Aside from identifying the maximum value per pixel, the authors also extract the month associated with that maximum value. This is the month in which greenness is most intense.

In a further step, the most frequent (statistical modus) of these date/month-related temporal maximum NDVI (type C) is calculated on a field or parcel basis to identify the month of the spatio-temporal maximum NDVI per polygon (type D) of each land cover/land use class (field boundary). This helps to understand the temporal variability of slightly generalized maximum NDVI values. Having those calculations with maximum NDVI and the modus of the spatio-temporal maximum NDVI per field boundary, one can identify the maximum intensity value of the NDVI (or greenness) per vegetation period and isolate the month with the maximum greenness for the respective FNK polygon.

Fig. 3 Study area as seen from Sentinel-2 satellite (ESA 2020) in false colors (R,G,B = 8,4,3) with land cover/land use polygons (yellow) on 2019-04-20 (a), 2019-05-15 (b), 2019-06-29 (c), 2019-07-24 (d), 2019-08-26 (e) and as the FNK mapping. Data source: RVR 2017) (f)
For health-related studies, the physical appearance of urban green could be of great importance. For that kind of investigation, one should differentiate different heights of vegetation as human beings perceive vegetation depending on their size. Green meadows probably have another individual perception than tall green forests. Since NDVI does not necessarily account for vegetation height, it makes sense to compare NDVI to plant height and create a limited number of meaningful height classes for studies on urban greenspace.

Based on the DOHM, the individual vegetation height is reduced into three meaningful categories relevant to the human perception of vegetation: smaller than 2 m, 2–5 m and above 5 m height, that easily correspond with the land cover classes. This height categorization is intended to distinguish vegetation categories with typical physical height appearance.

In this experimental study, the combination of vegetation height data and NDVI data in a bivariate choropleth map (Götze and van den Berg 2017; Moos 2020) is applied to gain additional information from the used data sets. Moos (2020)
applies three NDVI classes for the characterization of green urban infrastructure: < 0.3; 0.3–0.6 and > 0.6. The higher the value, the better the amount of green infrastructure and its condition. This classification scheme with three categories is adopted here according to its practicability and the easy readability of the resulting map.

In addition to the bivariate choropleth map, a correlation between the land cover/land use categories and the nine object height/NDVI-classes could be meaningful. For this analysis, the bivariate choropleth map is calculated on a raster cell basis instead of parcel polygons. Afterwards, a simple frequency analysis of each of the nine classes reveals the class composition.

### Table 3  Overview of different NDVI calculations

| Type | Name of NDVI product | Characteristic of NDVI product |
|------|-----------------------|-------------------------------|
| A    | Temporal mean NDVI per pixel | Arithmetic mean NDVI over time per pixel |
| B    | Spatio-temporal mean NDVI per FNK polygon | Spatially averaged temporal mean NDVI values (type A) per FNK polygon |
| C    | Temporal maximum NDVI per pixel (value and date/month) | Selection of highest NDVI value per pixel within the time series |
| D    | Month of spatio-temporal maximum NDVI per FNK polygon | Most frequent month of temporal maximum NDVI value (type C) per FNK polygon |

### 3 Results

This study focusses on greenspace analysis based upon the NDVI as a widely used indicator of urban green vegetation and vegetation height. Figures 2, 3, and 4 reveal seasonality in the set of images as well as in the NDVI images across the vegetation period. Some land cover/land use classes are very stable while others are highly variable. Forests are very stable, while fields and meadows are affected by harvest operations. As long as the crop/grass is not harvested, it appears in most cases as a green surface. Depending on the individual crop calendar,
during a season different stages of green vegetation can be observed.

The temporal mean NDVI (type A) illustrates such seasonality aspects of vegetated areas (Fig. 6). In case of forests, relatively high NDVI values can be observed, which are caused by the stable green appearance of forests. With fields or pastures, harvesting leads to points in time with no or less green. The related low individual NDVI for those moments has a lowering effect on the temporal mean NDVI. In short, the temporal mean helps to judge intensity and duration of green appearance throughout a year or vegetation period.

The spatio-temporal mean NDVI per FNK polygon (type B, Fig. 7) allows insights into an annual or seasonal average NDVI per polygon, that appears to be more meaningful for individual land cover/land use categories than single pixel-based calculations of type A. Typically, the general interpretation is similar to the interpretation of pixel-based values (type A). High values indicate green vegetation for a long period. Lower values are results of less intense green intervals during the vegetation period (e.g. harvested fields).

Figure 8 shows the values of the temporal maximum NDVI per pixel (type C) for the period of observation (April–August 2019). Based on the calculated temporal maximum NDVI values, it is also possible to determine in which month the greenness is most intense (Fig. 9).

Figure 10 shows the month with the spatio-temporal maximum NDVI per FNK polygon (type D) or field boundary of each land cover/land use class. The extracted month is based on the calculation of the most frequent/statistical modus of these date/month-related temporal maximum NDVI (type C) on a field or parcel basis. The resulting month associated with the maximum spatio-temporal NDVI indicates the highest level of greenness per land us/land cover polygon. This could be helpful in judging the effects of green vegetation for health and well-being of the urban population.

The extraction of the NDVI values of type C and type D provides a time stamp that identifies the moment with the highest green appearance. This helps to temporally arrange green vegetation areas for a well-balanced mixture of land covers/land uses for recreational and well-being aspects.

Due to seasonality aspects, which offer additional analytical options, the authors conclude, that the examination of urban vegetation or urban greenspace via NDVI based on only one observation is not sufficient for urban greenspace analysis related to quality of life, health or well-being.

The results show the importance of additional NDVI calculations based on high resolution satellite images. Such images are of high timeliness and provide up-to-date information on vegetation surfaces.

Another aspect relates to vegetation height, since the perception of high-rise green vegetation types like forest are more beneficial to the individual and result in positive health aspects. Therefore, for planning purposes, a high degree of vertical green infrastructure is necessary to support goals like good quality of life, well-being and health. Depending on the land cover/land use class, varying typical heights can
Fig. 7 Spatio-temporal mean NDVI (type B) (data source: ESA 2020) per FNK polygon (data source polygon overlay: RVR 2017)

Fig. 8 Temporal maximum NDVI per pixel (type C) (data source: ESA 2020) for the vegetation period 2019 (data source polygon overlay: RVR 2017)
Fig. 9  Date of temporal maximum NDVI per pixel (type C) (data source: ESA 2020) (data source polygon overlay: RVR 2017)

Fig. 10  Date of spatio-temporal maximum NDVI per FNK polygon (type D) (data source: ESA 2020) (data source polygon overlay: RVR 2017)
be identified. This height categorization helps to distinguish vegetation categories as is demonstrated in Fig. 11.

The major observations regarding the height of the different land cover/land use categories can be summarized as follows. All agricultural fields are in the lowest height category, while forested areas are completely in the highest category. About 76% of the impervious surfaces are in the range of 2–5 m. Impervious surfaces below 2 m are very likely to be streets; higher impervious surfaces than 5 m are very likely higher buildings. 89% of the grassland is lower than 2 m. The remaining grassland probably is partly covered by trees and bushes. For the remaining classes (Open Space, Other & Other Vegetation) the authors find out that their maximum ground coverage ranges between 2 and 5 m (ca. 62%, ca. 59%, ca. 50%). The remaining areas are probably partly covered by trees and bushes as well.

The combination of vegetation height and (spatio-)temporal mean NDVI reveals the spatial distribution of potential areas of high recreational and health value, as well as poor areas: taller green areas are believed to have more positive effects on human health than lower green areas. For instance, areas with high temporal mean NDVI and tall objects represent most likely forests. These represent relatively cool areas during summer months, which results in healthier and more comfortable life conditions. Analyzing the bivariate choropleth map assists in optimizing the urban land cover/land use mixture with respect to environmental health aspects. The frequency analysis of the land cover/land use classes related to the nine height/NDVI-complexes reveals which land cover/land use units can be improved for a beneficial and healthy neighborhood.

Figure 12 shows the combination of mean object height and mean spatio-temporal NDVI (each per FNK polygon) to evaluate if the vegetation height is of importance for well-being and health aspects of the nearby population. Forested areas are represented by the darkest map color as they combine a tall appearance with high spatio-temporal mean NDVI values. In contrast, flat areas with low spatio-temporal mean

![Fig. 11 Distribution of land cover/land use categories for three height categories](image1)

![Fig. 12 Bivariate choropleth map showing the spatio-temporal mean NDVI (data source: ESA 2020) per land cover/land use polygon against the mean object height per land cover/land use polygon (data source polygon overlay: RVR 2017)](image2)
NDVI values represent impervious surfaces and fields. Many residential areas have intermediate spatio-temporal mean NDVI values and object heights between 2 and 5 m (central raster cell of the legend). This means that residents have houses with similar height as the surrounding green area. Thus, the authors assume that the residents’ view out their windows mostly consists of green vegetation. This situation probably is advantageous for the residents’ perception of green vegetation and related health aspects. In the upper left corner of Fig. 12, a few high-rise buildings (> 5 m) exist and a NDVI class surrounding those buildings with vegetation heights less than 5 m. This means that residents in upper stories most likely have different experiences as they see vegetation rather from above or only when standing in front of their windows. As the perception of green vegetation has positive effects on human health, analysis of building heights and vegetation heights is helpful to identify areas with positive effects and those with deficits. However, for real-world applications, the obscuring effect of vegetation needs to be considered as well, as this works contrary.

The analysis on how land cover/land use categories correspond to the nine object height/NDVI classes (Fig. 13) is based on a bivariate choropleth map on a raster cell basis instead of parcel polygons to enable a frequency analysis of each of the nine classes, revealing the class composition. To refer to the individual combinations of object height and NDVI, the nine fields are labelled according to Fig. 14.

The frequency analysis of individual raster cells shows the following distribution (compare Fig. 15):

- Field 1A (low temporal mean NDVI and low mean object height) is composed mainly by impervious flat surfaces (71.07%) like parking areas or streets and agricultural fields, that were harvested during observation (21.88%).
- Field 1B (low temporal mean NDVI and intermediate mean object height) is composed predominantly by impervious surfaces like small buildings (97.26%).

![Fig. 13 Bivariate choropleth map showing the temporal mean NDVI (data source: ESA 2020) per raster cell (A) against the mean object height per raster cell (data source polygon overlay: RVR 2017)](image-url)

![Fig. 14 Labels of the legend of the bivariate choropleth map presented in Figs. 12 and 13](image-url)
• Field 1C (low temporal mean NDVI and high mean object height) is composed predominantly by impervious surfaces like taller buildings (98.73%).
• Field 2A (intermediate temporal mean NDVI and low mean object height) is composed similar to 1A with impervious flat surfaces like parking areas or streets (40.92%), agricultural fields (13.03%) and additional areas of grassland (23.22%), other vegetation (6.15%) and open space (15.18%).
• Field 2B (intermediate temporal mean NDVI and intermediate mean object height) is composed mainly by impervious surfaces (73.42%) like small houses or open space (17.96%).
• Field 2C (intermediate temporal mean NDVI and high mean object height) is composed mainly by impervious surfaces like taller houses (68.47%), other vegetation (6.11%) and open space (13.33%).
• Field 3A (high temporal mean NDVI and low mean object height) is dominated by grassland (26.09%), open space (32.87%) and other vegetation (16.56%), in total which all belong to rather flat vegetation surfaces. 12.38% impervious surfaces are present as well. This is probably due to obscuring effects of vegetation such as bushes (as seen from the satellite) over impervious materials listed in the land cover/land use map.
• Field 3B (high temporal mean NDVI and intermediate mean object height) is composed by open space (33.22%), forest (21.22%), other vegetation (16.88%), grassland (26.09%) and impervious surfaces (16.26%). The latter are represented in this category probably due to the same obscuring effects of vegetation over impervious materials listed in the land cover/land use map.
• Field 3C (high temporal mean NDVI and high mean object height) is composed predominantly by forest (72.23%).

Grassland is a typical flat land cover/land use type, nevertheless it is present in categories above 2 m height. For this study, the authors join the originally separately mapped grassland classes meadows and pastures and meadows and pastures with scattered fruit trees to keep things simple. Figure 16 shows such individual trees at 1 m resolution, which are integrated in the grassland class and are therefore the reason why grassland is present in height classes above 2 m.

The same applies for other grassland-like land cover/land use classes. Even fields have high NDVI values with
corresponding tall height information as trees often grow along their borders and therefore influence the analysis.

Most residential areas are characterized by category 2B as these consist of a mixture of small houses and garden vegetation mostly without very high trees. However, sometimes trees obscure buildings and/or impervious surfaces like roads (see Fig. 17). Some larger properties are characterized by solitary trees and meadows with bushes and fall into 3B.

The examples show that the explanation of height inconsistencies can be performed by visual inspection of the relevant parcels. Scattered tall vegetation is present in almost all land cover/land use categories. The calculated relationships between NDVI and object height are valid and the authors conclude that high temporal mean NDVI values in the two-dimensional choropleth map correspond mostly to trees scattered in other categories. For an analysis interested in the value of green vegetation, it is beneficial to know that even on rather flat green surfaces one can find tall vertical green structures that increase the value for recreation and health aspects.

4 Discussion

The discussion of the results and other observations is structured to address limitations as well as potentials of NDVI application in urban greenspace studies.
4.1 Limitations

The application of NDVI values in urban environments is limited due to various reasons. First of all, the growing seasons of plants are different from plant species to plant species including times when some areas are not covered with photosynthetic active vegetation. This is obvious for agricultural fields, e.g. there is no biomass after harvest. Also, deciduous trees lose their leaves and look different in winter and fall compared to spring and summer.

Pixel size affects NDVI calculation as well. The smaller the pixel size, the higher is the chance that 100% of the pixel area is covered by vegetation. So, larger pixels tend to result in mixed pixels compared to smaller pixels. Such mixed pixels reduce the pure information content since they are composed from more than one land cover type (Juergens 2020). This means that they do not represent one specific land cover type or class, but a mixture of at least two with an unknown spatial composition and unreliable information. Mixed pixels are present in any image. Therefore, reducing the covered area by reducing the pixel size is the best way to gain more information. A rule of thumb is: the smaller the pixel size, the smaller the area covered by mixed pixels.

Optical satellite images suffer from clouds. Cloudy situations obscure the view to earth’s surface. Consequently, proper NDVI values require cloud-free satellite images. For time series investigations, this could be problematic since data gaps destroy optimal time series analysis using equal interval image dates. Depending on the type of investigation, calculation of maximal NDVI values per season can

Fig. 17 Tall vegetation obscuring impervious surfaces. Height data source: Land NRW (2020)
overcome this problem. However, seasonality information is lost in this case. Tracking the exact date of the maximum NDVI value per pixel can serve as a compromise.

Spatio-temporal mean NDVI values should not be calculated for administrative areas as this includes not only vegetation but also water, buildings and streets into the calculation. This automatically reduces results due to the fact that water and artificial surfaces have NDVI values close to 0 or below 0. Another problem could be the comparability of mean NDVI values of differently sized administrative areas.

4.2 Potential

Calculation of different NDVI products in urban areas offers high potential to identify relatively well-equipped greenspace areas with high potential for well-being and a healthy neighborhood and on the opposite relatively poor-equipped green areas with rather low potential for well-being and a healthy neighborhood. For instance, the high repetition rates of open access optical satellites like Sentinel-2 (5 days) allow to detect changes in the NDVI response of the vegetation cover on a weekly basis. From this, monitoring approaches could be carried out. Certain monitoring periods could allow to give advice to planners for improving the green situation, for instance, towards longer periods of visible green areas due to height considerations. In this context, the length of green periods of individual land cover types could be investigated to perhaps find a good mixture of land cover types for long green periods in specific neighborhoods.

Exact assessment of urban vegetation is beneficial for assessing local climate situations. Typically, intense vegetation covers (and therefore high NDVI values) correspond to cooler air temperatures in summer (Krelaus et al. 2021) and result in healthier life conditions. The degree of green vegetation is an environmental indicator/parameter that is related to health risks. High vegetation intensity corresponds to low health risks, while on the contrary, the degree of sealing is its antagonist.

5 Conclusions

This study is motivated to investigate the applicability of NDVI and vegetation height data for urban greenspace analysis. From an urban test site in Dortmund, Germany, the authors draw conclusions which are summarized hereafter.

NDVI calculations from remotely sensed earth observation images are an easy task but require some degree of data literacy. One should be aware of the later use of generated data and be able to judge which image acquisition date is appropriate. In case of time series data for monitoring purposes, one should be aware of clouds, that obscure the ground and affect the NDVI calculation.

The temporal mean NDVI per pixel as well as the spatio-temporal mean NDVI per FNK polygon allow identifying land use/land cover types with different intensity or green duration within a period of time.

The calculation of the temporal maximum NDVI per pixel makes sense only for a time series like a vegetation period, to identify the date of maximum chlorophyll activity. Having the date of maximum greenness per pixel enables to extract the respective date for each land use/land cover polygon.

The calculation of NDVI values help to determine plant activity during a year and allows to identify environmental burdens (e.g. heat) at specific points in time. In months with much vegetation and high NDVI values respectively environmental burdens are rather low.

Bivariate maps are suitable for investigations of two phenomena such as NDVI and vegetation height as they display both at once while keeping maximum visibility for each of them. Using intuitive color mixing, possible correlations become already visible by color. They are increasingly accessible in GIS for eased generation, making manual generation obsolete. Bivariate maps are helpful to visualize and locate environmental concerns or consternation of population, e.g. heat vulnerability due to low quality green vegetation infrastructure and therefore assist in statements related to environmental burdens, well-being or health issues. The combination of vegetation height and NDVI revealed the spatial distribution of potential areas of high recreational and health value as well as poor areas. Here, appropriate greenspace planning could be put in place to improve the urban living conditions.

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Availability of Data and Materials The land use map data that support the findings of this study are available from Regionalverband Ruhr but
restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Regionalverband Ruhr. All other datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code Availability Not applicable.

Declarations

Conflict of Interest The authors declare that they have no competing interests.

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