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Mapping the development of green in gardens over time: is your neighbour's garden really greener?

Lynn Bouwknegt [1,2], Eric Koomen [1], and Jan Rouwendal [1,3]

[1]Vrije Universiteit Amsterdam (VU) - Boelelaan 1105, 1081 HV Amsterdam
[2]Environmental Assessment Agency (PBL) - Bezuidenhoutseweg 30, 2594 AV Den Haag
[3]Tinbergen Institute Amsterdam (TI) - Gustav Mahlerplein 117, 1082 MS Amsterdam

Correspondence: Lynn Bouwknegt (l.j.bouwknegt@vu.nl)

Abstract. Private gardens are an important aspect of small urban green space and help provide a wide range of ecosystem services. This contribution is increasingly recognised and several local governments now stimulate residents to replace garden pavements with vegetation. Tracing such greening efforts is difficult, however, because of their small scale and absence in official mapping efforts. Therefore, we propose an approach to map the greening of gardens by analysing a time series of highly detailed aerial photographs. Our approach overcomes several challenges: the temporal variation in the green signal because of seasonal differences in green cover or shade, the small size of gardens and the obstruction of vision by overhanging trees. We present the results of this analysis and assess their accuracy by using a confusion matrix.

Keywords. Small urban green space, gardens, remote sensing

1 Introduction

Green space greatly contributes to sustainable development of urban areas (e.g., Salm et al. (2023) and Mullaney et al. (2015)). Parks, trees, and gardens all help improve air quality, retain water, and help decrease temperatures in summer. This has resulted in increased policy makers attention and plans to improve the greenness of cities (e.g., Lin et al. (2022) and Been and Voicu (2007)). Comparatively, the activities in private space to aid the environment are less regulated than other small public green space. As residents in cities are responsible for their own gardens, they might not prioritize the public benefits of having more green in the city (Beumer (2017)).

When it comes to mapping small urban green space, few studies are done on private green (Baker and Smith (2019)). Because gardens take up a significant amount of space in the built environment, it is important to study them considering the potential for increasing green space. A trend in taking out tiles from gardens and replacing these tiles with green space in the Netherlands has motivated us to study the change in gardens over time. This contributes to the literature because other studies look at one time period (e.g. Baker and Smith (2019)).

Detailed and reliable information on gardens is difficult to obtain over time for a number of reasons. Firstly, gardens are relatively small spaces and thus require high resolution data, which is not available everywhere. Hence, most studies have small sample sizes (e.g. Domene and Saurí (2006)). Remote sensing offers a solution to this, but can have comparability issues over time as images usually differ in resolution, angle, cloud cover and more (e.g. Balikçi et al. (2021)). However, the high resolution images can offer more reliable results than estimating garden surface area based on grids, such as in Cristina et al. (2012). Because we have this data available, we can offer a large sample of household gardens with a high resolution over time. Furthermore, vision of gardens from above is complicated by obstruction of sight from (public) trees. When it comes to studying gardens over time, it is important to deal with this obstruction as they could lead to misinterpretation of green(er) gardens. In this paper, we try and overcome these challenges to construct a data set for gardens over time for the municipality of Alkmaar, the Netherlands.

1.1 Method

Gardens in the Netherlands make up about 1.6% of all land cover. On average, the gardens are about $125m^2$ (Bade et al. (2009)). Dutch residents in particular seem to let practical functionality of gardens overrule the aesthetic quality and ecological functionality (Beumer (2017)). The result is that many Dutch gardens are paved to minimise maintenance. By contrast, Beumer (2017) found that most respondents do value community, public values, and ecological ideals. In effect, even though Dutch gardens are paved to some extent, their visual preference would be to have lush gardens full of wildflowers.

The municipality of Alkmaar has an extensive green policy, and made an especially large contribution towards this goal with so-called 'pocket parks' since 2020. This led to the municipality winning the greenest city in Europe award in 2022 [1]. However, whether the municipalities' subsidies for increasing private green space have paid off is yet to be studied. Because the municipality is this invested in green policy in recent years, it makes an interesting case to study over time.

1.2 Data and Software Availability

We use four main data sources to map the gardens. Similar to Runfola et al. (2013), we combine different data set to get a high resolution data set. Through the Dutch Environmental Assessment Agency (PBL), we can utilize (1) aerial photographs with 25 cm resolution. The images are available on a yearly basis from 2016 to 2020, and the stepping stone to our data set. Remote sensing is a common and intuitive method to map changes in urban green space (e.g., Balikçi et al. (2021) & Zhou and Wang (2011)). Aerial photographs are useful, as they store reflection values from the earth in different bands with values from the electro-magnetic radiation spectrum. To measure the actual 'greenness' of green space, researchers often use the Normalized Vegetation Index (hereafter: NDVI) (e.g., Akbar et al. (2019) & Davies et al. (2008)).

In addition, we use the Basisregistratie Grootschalig Topografie (BGT/2) and the Basisregistratie Adressen en Gebouwen (BAG/3) datasets. These data sets are used to delineate gardens, similar to Baker and Smith (2019). The BGT can be used to distinguish the 'erf' or gardens around the houses. However, sometimes when apartments or houses are in block shape, i.e., the buildings surround the gardens fully, the garden layer in the BGT will show a single large even though there are multiple gardens within. The BAG does show these finer distinctions, in their governmental barriers' dataset, but for much larger areas than just gardens. The datasets from BGT and BAG are thus linked to each other in QGIS by overlaying the BAG on the BGT, cutting out the area for the gardens. In the interest of studying the change in green for these gardens, houses with the gardens cannot be newly builds as these gardens are impossible to study in the past. Thus, we only include gardens that are present in our whole-time frame.

Lastly, we use Tree register (Boomregister) data on trees (4) to remove the trees from the gardens. While the trees themselves are valuable green elements, they obscure the view on the ground and make it impossible to detect whether the garden is paved or not. For these reasons we employ a data set with tree crown cover to exclude the obscured. This is done to help make interpretation of whether gardens become greener over time easier. The tree register data consists of all the trees in the Netherlands, including geolocations, height, crown cover, and more. The results are analyzed using R studio.

1.3 Data processing

1.3.1 Geometric correction

In this section we will discuss how we processed two papers by Zhou and Wang (2011) and Balikçi et al. (2021) to highlight how we processed our aerial photographs for comparability and to study small green space. Balikçi et al. (2021) study the change in green space over time for Amsterdam and Brussels. Zhou and Wang (2011) study the spatio-temporal changes in urban green space in China. Zhou and Wang (2011) use geometric correction to correct the image coordinate system to the geographic coordinate system. The gardens may not be exactly aligned in all years because images are not taken from the exact same spot, because the earth is slightly curved, the earth's rotation, and relief displacement which is certain distortion from highest point of the photo. To correct for this, georeferencing can be used to correct the geometry. This is important, because if the already small gardens do not line up right, it is easy to make mistakes in mapping their greenness over time. Georeferencing was done to all images by selecting the same recognizable features in OpenStreetMap and correcting the same features on the images towards those points. Zhou and Wang (2011) clip the data to deal with border issues - which we will do for the gardens as well as it makes more sense here than to clean the boundaries of the cities as per Balikçi et al. (2021). Both Balikçi et al. (2021) and Zhou and Wang (2011) review the original images to ground-truth assess the result as well, which is something that we will do also by using a confusion matrix in section 2.

1.3.2 NDVI and harmonization

Calculating the NDVI will help us determine whether gardens are green and whether they become greener over time. The NDVI is a value between -1 and 1 based on, when utilizing aerial photography, the difference between the red and color-infrared bands. I.e., green space reflects to the plane and is therefore relatively easy to map. Zhou and Wang (2011) argue that to accurately capture small urban green space, or in this case, gardens, we will need high spatial resolution imagery because of gardens' scatteredness and relatively small size. Furthermore, the authors find that high spatial resolution and continued cov-

[1] https://nl.thegreencities.eu/alkmaar-winnaar-green-cities-europe-award-nederland/

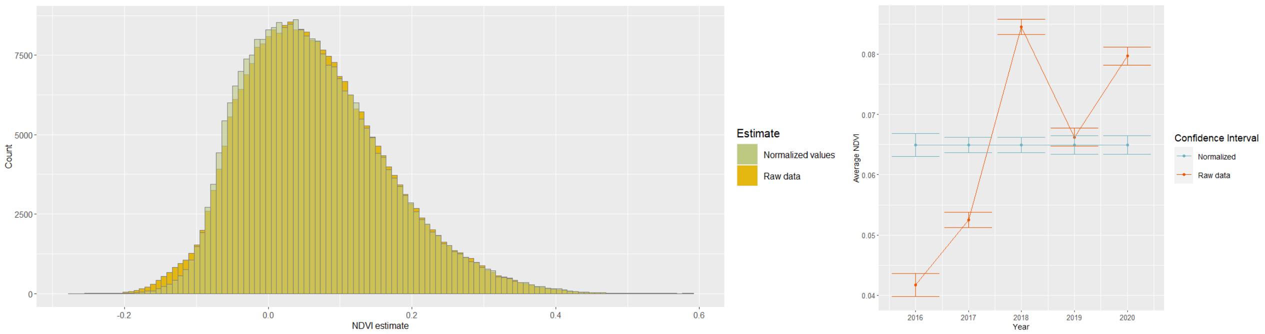

Figure 1. Results harmonization (Own edit of data, 2024)

erage provides a more accurate and extensive understanding of green space patterns over time. The exact NDVI threshold that portrays green space is somewhat different for each country and aerial photograph. This is where we propose a trade-off; high resolution images lead to detailed garden data but can also be noisy when it comes to mapping green. However, we do need high resolution images to separate the green and the grey within the small garden. This implies that we straightforwardly choose to leave the noise and cannot distinguish so well what 'type' of green there is in the garden. For the purpose of this paper, this will not be necessary, only that there is a change in total green.

2 Results

The NDVI was calculated for all 5 years to see how much the summary statistics differ. The zonal statistics for the gardens always report mean, min, max and standard deviation. This can also be used to harmonize the results, as every year shows not just differences in individual gardens, but also in summary statistics. The NDVI values of all gardens that resulted from the zonal statistics were harmonized towards the average of all gardens over all years. The results are shown in table 1.

Year	Raw mean	Std deviation	Min	Max	Harm. mean
2016	0.042	0.094	-0.273	0.567	0.065
2017	0.053	0.063	-0.147	0.439	0.065
2018	0.085	0.060	-0.102	0.436	0.065
2019	0.066	0.075	-0.176	0.568	0.065
2020	0.080	0.074	-0.151	0.560	0.065

Table 1. Summary statistics

The results from the harmonization of aerial photographs are also shown in figure 1 by plotting a distribution of raw and harmonized NDVI values. As can be seen in the figure, the tails change a bit but of course the average stays the same. This makes sense as the values for individual years are harmonized to the mean for all years. Secondly, in a confidence interval, a plot of all harmonized values compared to their raw estimate. As can be seen in the figure 1. The harmonized values are much more in line, even though their corresponding confidence intervals do slightly vary.

The second issue with the aerial photographs that we looked at was the obstruction of vision that trees cause. As mentioned before, trees obstruct vision of the gardens from above. Thus, we took out the trees from the data set and were left with a garden data set where we can observe what is happening within the gardens. In other words, gardens that are fully obstructed by trees are left out of our analysis. See figure 2 for a visualization of this process.

Figure 2. Main data sets applied in the definition of garden area. The grey area depicts the parts of the gardens that are considered in the analysis (Own edit of data, 2024).

To show an example of our data, in figure 3 we depict the NDVI results for a few gardens in Alkmaar from the year 2020. The results depict the mean NDVI, and show for one of the houses that the garden is much greener than the others. When we look at the adjacent aerial photographs, we compare the 'real' gardens to the NDVI results. We can see that in the greenest garden there is a lot of grass, unlike the neighboring gardens which are mostly tiled.

Looking at our results, we see that the mean change of the NDVI is 0. This suggests that most gardens stay the same. We therefore introduce three categories; greener, no change and less green. We cut off values for more (less) green by adding (subtracting) the standard deviation from

Figure 3. NDVI values and the underlying aerial photograph in 2020 (Own edit of data, 2024).

the mean. We found that over time, around 12% of gardens became greener, and 11% became less green. Accuracy was determined by using a confusion matrix similar to Baker and Smith (2019). The assessment is based on greener versus less green. Literature suggests to ground truth at least 30 observations per category, so we looked at 31 gardens that were predicted to be greener, and 30 to be less green. Because comparatively more gardens are predicted to neither become greener or less green, we looked at 71 gardens that were predicted to have no change. The predictions were compared to both the aerial photographs and where possible google maps images over time. Especially the category 'greener' seems to be predicted well. The total accuracy is 79%. The Kappa statistic is 77%, which indicates substantial agreement.

	Pred.	Greener	No change	Less green	Total
Actual	Greener	24	2	4	80%
	No change	4	63	5	88%
	Less green	3	6	21	70%
Total		77%	89%	70%	79%

Table 2. Confusion matrix

3 Conclusion & Discussion

In this paper, we propose an approach to trace changes in green space within private gardens. Such changes relate to, for example, the removal of tiles and are difficult to map as they often concern small areas. Detection is, furthermore, hampered by seasonal variations in vegetation cover and overhanging trees that obscure the ground underneath. We make use of a time series of high-resolution aerial photographs, cadastral data to delineate gardens and a data set of tree crown cover to overcome these challenges. Our approach relies on geometric correction, harmonization of the obtained NDVI values to adjust for variation between years, and removal of tree-covered area. Removing the trees from the gardens helped identify whether the remaining garden area got greener. We thus ignore the tree-covered area where such greening is impossible to detect. The resulting data set characterizes changes in greenness within gardens over time and can be used to evaluate green policies targeted at increasing green space in private gardens.

The full coverage of the municipality offered by the available aerial photographs allowed us to assess changes for a large sample of gardens, i.e. almost 55,000, between 2016 and 2020. For comparison, Domene and Sauri (2006) studied 532 gardens. Because we used highly detailed aerial photography, harmonized values, and took out trees, our total accuracy of ∼79% is slightly lower than the ∼86% accuracy Baker and Smith (2019) found for their garden data set. The method was better able to recognize greening of gardens (accuracy 77%) than the loss of green (accuracy 70%). No change has an accuracy of 89%. For future research, the method to detect gardens that became less green could be improved. We do believe that we found a good way to only detect greening of gardens with more drastic changes such as taking out all tiles, rather than label those gardens that get slightly more green because time passed due to our harmonization.

Our analysis benefits from the availability of several detailed data sets that cover multiple years. These data are available for most municipalities in the Netherlands, so the analysis can easily be up-scaled to other parts of the country. Application in other countries may be more limited as data on, for example, tree crown cover or garden boundaries may be less readily available. Data on tree crowns can, however, also be extracted from the same high resolution imagery data by for example object recognition. Using larges areas increases data volume and thus computing time, but with data tiling or cloud computing facilities such issues can be overcome. For the sake of precision, we believe that high resolution imagery is essential to successfully recognize the green of gardens. Additionally, the method we suggest in this paper could be used for other purposes. For example, using the Normalized Difference Water Index, research could be done on swimming pools or ponds. In that case, we also recommend using high-resolution imagery.

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