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Gradual or abrupt? An algorithm to monitor urban vegetation dynamics in support of greening policies

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ABSTRACT

While greening becomes a more and more popular strategy to address multiple urban challenges and to enhance wellbeing and human-nature connectedness, there is an increasing need for usable methods and indicators to monitor its implementation. Earth observations produce a wealth of data on vegetation dynamics, but their use for monitoring urban greening policies is still limited. In this article, we develop and test an algorithm for the analysis of urban vegetation dynamics based on NDVI time series. Specifically, we focus on yearly greenest pixel composites that illustrate the maximum value of NDVI during the year ("greenness"): a key structural attribute to monitor urban ecosystems in the European Union. The algorithm is inspired by earlier examples of segmentation algorithms but fits the specific requirements of the targeted use in urban areas. It takes the series of NDVI values associated to each pixel, detects existing (multiple) break points, and quantifies related abrupt changes, as well as significant gradual changes that occurred during a selected period. We tested the algorithm on a 30-year Landsat series in Berlin and partially validated the output through a comparison with infrared ortophotos. The results reveal a net increase in NDVI between 1988 and 2017 in 84% of the pixels, with an average change over the whole city of + 0.096. Around 20% of the pixels show at least one abrupt change. Most abrupt changes (71.5%) were positive, but the negative ones had on average a greater absolute value (−0.170 vs +0.085). However, considering the cumulative impacts during the whole period, 97% of the total change is attributable to gradual changes. The validation proves that abrupt changes successfully capture variations in the extent of vegetation due to land cover changes (e.g., vegetation removal or new greening interventions), while gradual changes can be associated to vegetation growth or decline. We discuss the strengths and limitations of the proposed algorithm, and how the spatially- and temporally-explicit results can be a step forward in the interpretation of urban vegetation dynamics towards an effective monitoring of the impacts of local greening policies.

1. Introduction

Greening is gaining popularity as a strategy to increase the sustainability and resilience of urban systems (Adem Esmail et al., 2022; Dorst et al., 2019). In addition to its biodiversity value (Dearborn and Kark, 2010), urban vegetation is the closest form of nature experienced by most people globally, and it contributes substantially to their health and wellbeing (Gómez-Baggethun and Barton, 2013; van den Bosch and Ode Sang, 2017). With the aim of strengthening the provision of ecosystem services by urban vegetation (Babí Almenar et al., 2021), greening is more and more frequently advocated and adopted as a multifunctional strategy that, among others, can help to mitigate and adapt to climate change (Cortinovis et al., 2022; Kabisch et al., 2017), as well as to counterbalance the negative impacts of densification (Madureira and Monteiro, 2021), often in an economically advantageous way (Elmqvist et al., 2015). Several cities have already set ambitious greening targets in their plans (Dong et al., 2020; Lin and Wang, 2021; Mees and Driessen, 2011), and more are expected to follow pushed by initiatives such as the European Union Biodiversity Strategy for 2030. The Strategy calls for all cities with more than 20,000 inhabitants to draft ambitious *Urban Greening Plans,* which should become the main tools to coordinate greening actions at the urban scale and to ensure their systematic integration into urban planning and design (European Commission, 2020). In addition, the proposal of a new EU Nature Restoration Law currently

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under scrutiny (European Commission, 2022) promotes urban greening by setting three targets to reach by 2050, compared to the situation in 2021: i) a 5% increase of urban green spaces; ii) a minimum of 10% tree canopy cover in every city, town, and suburb; and iii) a net gain of green space integrated to buildings and infrastructures.

These targets demonstrate that, compared to a previous emphasis on public green spaces, recent greening policies include a wider range of actions that permeate the whole urban environment (Jones et al., 2022). Such actions are promoted by multiple actors and implemented at different scales, from reconverting large brownfield sites (Mathey et al., 2015) to planting trees (Lin and Wang, 2021), installing green roofs (Dong et al., 2020), or de-sealing both public and private spaces (Stobbelaar et al., 2021). It should also be noted that urban green spaces show a high temporal variability, due to the frequent changes in land use and land cover that happen in urban areas, to the point that greening actions are sometimes conceived as temporary uses (Németh and Langhorst, 2014). Overall, these factors result in complex and variable vegetation dynamics, which require indicators able to capture changes in both public and private areas at high spatial and temporal resolution. These specific needs come in addition to more general requirements for monitoring methods aimed at supporting policymaking, which must be relevant to the issue at hand and responsive to the associated changes; scientifically sound, verifiable, and reproducible; simple, usable, and cost-effective, and perceived as legitimate by all stakeholders involved in the process (Carter et al., 2021; van Oudenhoven et al., 2018).

Remote-sensing based indicators meet most of these requirements and can effectively support vegetation monitoring in urban areas (Wellmann et al., 2020a). One of the most popular remote-sensing indicators is the Normalized Difference Vegetation Index (NDVI), an index calculated using the spectral reflectance measurements stored in the red and near infrared bands of satellite images. NDVI is linked to the photosynthetic capacity, i.e., the energy absorbed by plant canopies, hence to the amount and conditions of vegetation. Small values close to 0 indicate standing waters, snow, sealed surfaces, and bare soil, while higher values indicate progressively denser and healthier vegetation. NDVI has been first applied to studies on agricultural areas and forests, but it has more recently become popular also for urban applications due to its simple formulation and the availability of data at high resolution. Many studies have used NDVI as an indicator of the "overall amount" of urban vegetation, especially to investigate the relationships with other factors. Correlations have been observed not only with environmental features such as presence of impervious surfaces (Kaspersen et al., 2015), but also with several aspects of human health and wellbeing (Gascon et al., 2016).

NDVI has also been adopted as a standalone indicator to investigate vegetation dynamics. In this context, the term "greening" commonly refers to an increase in NDVI as an indicator of vegetation expansion or enhancement, while "browning" indicates a loss of vegetation or its degradation. In the literature, it is possible to distinguish three main approaches to detect and quantify vegetation changes based on NDVI. The first approach is to convert the continuous variable into a categorial classification by setting thresholds to discriminate between different land covers (Zhu, 2017). This method has been mainly applied to binary classifications of vegetated vs non-vegetated areas (Dobbs et al., 2018; Mackey et al., 2012; Stathopoulou et al., 2007), but some authors extended it to more detailed classifications of land covers characterized by different vegetation densities (Abutaleb et al., 2021; Jin et al., 2020; Muratet et al., 2013). The approach is very simple and allows comparing the extent of different types of vegetation in selected years based on the average or maximum yearly NDVI values. On the other hand, thresholds vary depending on the location (Jin et al., 2020), and changes within the ranges defined by the thresholds are overlooked. This limitation is especially critical for urban applications, where low NDVI values and associated small changes are frequent, since pixels often include a mix of land covers of which vegetated areas are only a fraction (Wellmann et al., 2020b).

The second approach approximates NDVI series, usually seasonal or yearly composites (i.e., average or maximum values calculated over the year or the in-leaf season), through linear models, where a non-null slope indicates the presence of a trend. Since NDVI series do not meet the assumptions of independent observations and normal distribution required for linear regression, non-parametric methods such as the Sen's slope to approximate the trend and the Mann-Kendall test to assess its significance are commonly used. A limitation of the approach is that a significant slope may well approximate gradual changes due to vegetation growth or succession, but it may also hide abrupt changes due to urbanization or regreening. Some authors suggest that greater values of the slope can be interpreted as an indicator of abrupt change (i.e., a major break point in the original series), but thresholds are set arbitrarily (Zulian et al., 2022). To overcome this limitation, a Pettitt test is sometimes used in combination with the Sen's slope to detect the presence of one main break point in each series (Zhou et al., 2020). However, this method is unsuitable to capture the multiple transformations that may occur in urban locations during a period of two or three decades (Forkel et al., 2013).

The third and most complex approach approximates NDVI series with segmented linear models. This allows the identification of multiple break points, which correspond to abrupt changes in the series, and of trends -or gradual changes- between each pair of consecutive break points. Examples of segmentation algorithms are DBEST - Detecting Breakpoints and Estimating Segments in Trend (Jamali et al., 2015), LandTrendr - Landsat-based detection of Trends in Disturbance and Recovery (Kennedy et al., 2010), and BFAST - Breaks for Additive Season and Trend (Verbesselt et al., 2010). BFAST is arguably the most popular break point detection algorithm applied to NDVI series (Zhu, 2017). It decomposes them into three components: a long-term component approximated by a piecewise linear trend, a seasonal component defined by a sequence of harmonic terms, and a noise component (Verbesselt et al., 2010). Break points can be identified in both the long-term and the seasonal component. BFAST was originally developed to detect vegetation changes in 16-day MODIS composite time series, but it is applicable to a variety of input datasets.

The availability of long-term temporal series of high-resolution satellite images and the increasing ease of manipulation through platforms such as Google Earth Engine (Gorelick et al., 2017) is rising the interest on NDVI as a potential indicator to monitor the implementation of urban greening policies. The European Commission has recently published the *EU-wide methodology to map and assess ecosystem condition,* which sets the guideline to monitor the progress towards the targets of the EU Biodiversity Strategy to 2030 and the Nature Restoration Law (Vallecillo et al., 2022). The methodology identifies greenness, defined as the maximum value of NDVI during the year (also called "greenest pixel composite"), as a *key structural ecosystem attribute* that should be monitored in urban ecosystems, and highlights the importance of discriminating between abrupt and gradual changes. However, the method proposed for the analysis, based on Zulian et al. (2022), adopts the second of the above-described approaches, i.e., the slope approximation. No segmentation algorithm suitable for monitoring and with proven applicability to urban contexts is currently available to analyze yearly NDVI composites such as the greenness indicator. In fact, segmentation approaches have been rarely applied to urban areas and mostly to analyze large-scale urbanization dynamics from a scientific perspective, with no ambition to support policy monitoring (see e.g., the recent application of BFAST in the region of Delhi, India, by Chaudhuri et al. (2022)).

Our aim in this article is to develop and test a segmentation algorithm for the analysis of NDVI yearly greenest pixel composites time series. The algorithm must be able to identify and date multiple break points in the series and to quantify gradual and abrupt changes during a selected period. To this aim, we take inspiration from earlier examples of segmentation approaches applied to NDVI series, but we develop an algorithm that fits the different types of input data and the specific requirements posed by the desired use in urban areas. We present the workflow of the algorithm, its application to a 30-year Landsat series in Berlin, and the validation conducted in the case study. We then discuss the potential use of the algorithm to support the monitoring of urban greening policies, highlighting its strengths, as well as the limitations that should be considered when interpreting the results.

2. Materials and method

2.1. NDVI annual greenest pixel composites

Our approach focuses on the analysis of NDVI greenest pixel composites. Such composites are created from all the scenes available for the same calendar year, using the pixel with the highest value of the NDVI (i.e., the greenest pixel) as the composite value. This process produces a series of images already cleaned from the effects of seasonal variability and characterized by a complete (or very high) coverage, since the presence of clouds and other disturbances is automatically removed. NDVI greenest pixel composites offer a picture of the best conditions achieved by vegetation during the year, accounting for the fact that, in different areas, this may happen in different periods depending on a combination of species characteristics and local factors (e.g., due to the increasing frequency of draughts in many cities, summer scenes might capture the best conditions in some areas but show early signs of degradation in others) (Miller et al., 2022).

While composites can be created from several collections of multiband satellite images, including MODIS and Sentinel, the most used for local-scale applications are composites created from Landsat images (Corbane et al., 2020; Zulian et al., 2022). With a spatial resolution of 30 m and a frequency of acquisition of 16 days, Landsat imagery captures human-scale processes related to urbanization and land cover change. Moreover, Landsat missions 4, 5, 7 and 8 provide comparable data (see the transformations implemented in Corbane et al. (2020)), thus covering a longer period than Sentinel-2. Landsat greenest pixel composites, which have the same spatial resolution as the original images, are considered an effective way to synthesize information about greenness in urban areas and a suitable basis to analyze the related trends (Corbane et al., 2020; Zulian et al., 2022). NDVI annual greenest pixel composites based on Landsat are available as ready-made products on Google Earth Engine (Gorelick et al., 2017), where they can be conveniently and efficiently manipulated.

2.2. Algorithm for time series analysis

We developed an algorithm that runs on the individual time series corresponding to each pixel. The analysis process consists of five main steps (Fig. 1).

Step 1: identifying potential break points. This step is implemented by testing the series for the presence of structural change using an Empirical Fluctuation Process (EFP) based on Ordinary Least Square Cumulative Sum of Residuals OLS-CUSUM (Zeileis et al., 2002). We run the test considering both a null and a linear model. If the test indicates a significant change in the series ($p \leq 0.05$), potential break points are identified as those that correspond to the optimal (minimum BIC) partition of the series considering a defined maximum number of breaks (Zeileis et al., 2003). After running some tests, and considering the length of the analyzed period in the application described in this article (Section 2.3), we set the latter to 4. The first step produces a preliminary list of potential break points.

Step 2: testing each candidate break point using Bayesian change point analysis (Barry and Hartigan, 1993; Erdman and Emerson, 2007). We run the test in the two cases of univariate analysis (i.e., constant mean in the segment) and linear regression (i.e., linear models appropriate within each segment). The test is based on the distribution of the posterior probability of change. We check the values in an interval of ± 1 year around each candidate break point in the list produced in the previous step. If any point within the interval has a probability $\geq 95\%$, the year corresponding to the maximum probability is retained as a break point, with associated information about which type of analysis gave the results. The outputs of the second step are three lists of potential break points: those classified as significant only in the case of univariate analysis (null model), those classified as significant only in the case of linear regression (linear model), and those classified as significant in both cases.

Step 3: testing the trends associated to each break point using a non-parametric test. This is necessary as the assumptions of the models used to approximate the trends in the previous steps of break point detection may not hold for the analyzed series. While being free from autocorrelation due to seasonality, the greenest pixel composites are characterized by scattered values and outliers (e.g., due to clouds in the original data). We therefore run a non-parametric Mann-Kendall test on each segment in which the series is subdivided by the selected break points. The test determines whether the trend can be considered monotonic ($p \leq 0.05$) or not (Kendall, 1975). The results of the Mann-Kendall test are used to further refine the selection of break points. Break points identified through the Bayesian change point analysis in both the univariate and the linear regression cases are retained without further investigation, while those found in only one case are retained only if the trend in the two segments before and after the break complies with the model that had identified the break (i.e., monotonic trend for linear regression, non-monotonic trend for univariate analysis).

Step 4: defining suitable models to approximate the trend in each segment. Once the final list of break point and related segments have been identified, we define suitable models to approximate the trend in each segment and to calculate the changes corresponding to each break point. We repeat the Mann-Kendall test on each of the final segments to calculate their parameters (slope and intercept). Segments with a monotonic trend are approximated by a linear model (Eq.1)

$$y = s^{*}x + i \tag{1}$$

where s is the Sen's slope (Sen, 1968), and the intercept i is calculated as the median of the residuals between the original values and the values approximated by the Sen's slope. Segments with no monotonic trend are approximated by a null model taking the average value as intercept. Abrupt changes (i.e., jumps) corresponding to each break point are calculated as the difference between the values of the two models used to approximate the trends before and after the break point.

Step 5: Refining the results. This might be needed, for example, to filter the final list of break points based on the value of the abrupt changes associated with them, in order to eliminate those that are considered not relevant in the specific application. In the case study described in this article, considering the results of the validation, we decided to filter out the break points associated with abrupt changes smaller than 0.1 in areas with high values of NDVI (i.e., managed forests and natural woodlands). Once these break points are removed, the fourth step must be repeated on the final list to re-define the models to approximate the trends in the new segments and to calculate the related changes corresponding to each break point.

The algorithm is coded in R (R Core Team, 2022) using the packages 'strucchange' for the EFP (Zeileis et al., 2002; 2003), 'bcp' for the Bayesian change point analysis (Erdman and Emerson, 2007), and 'rkt' for the Mann-Kendall test (Marchetto, 2021). A version running in parallel has been prepared for the application using the package 'parallel'.

2.3. Case study application

We applied the algorithm to analyze vegetation dynamics during a 30-year period in the city of Berlin, Germany. With a population of around 3.7 million inhabitants (Destatis - German Federal Statistical Office, 2022), Berlin is among the largest cities in Europe, marked by a

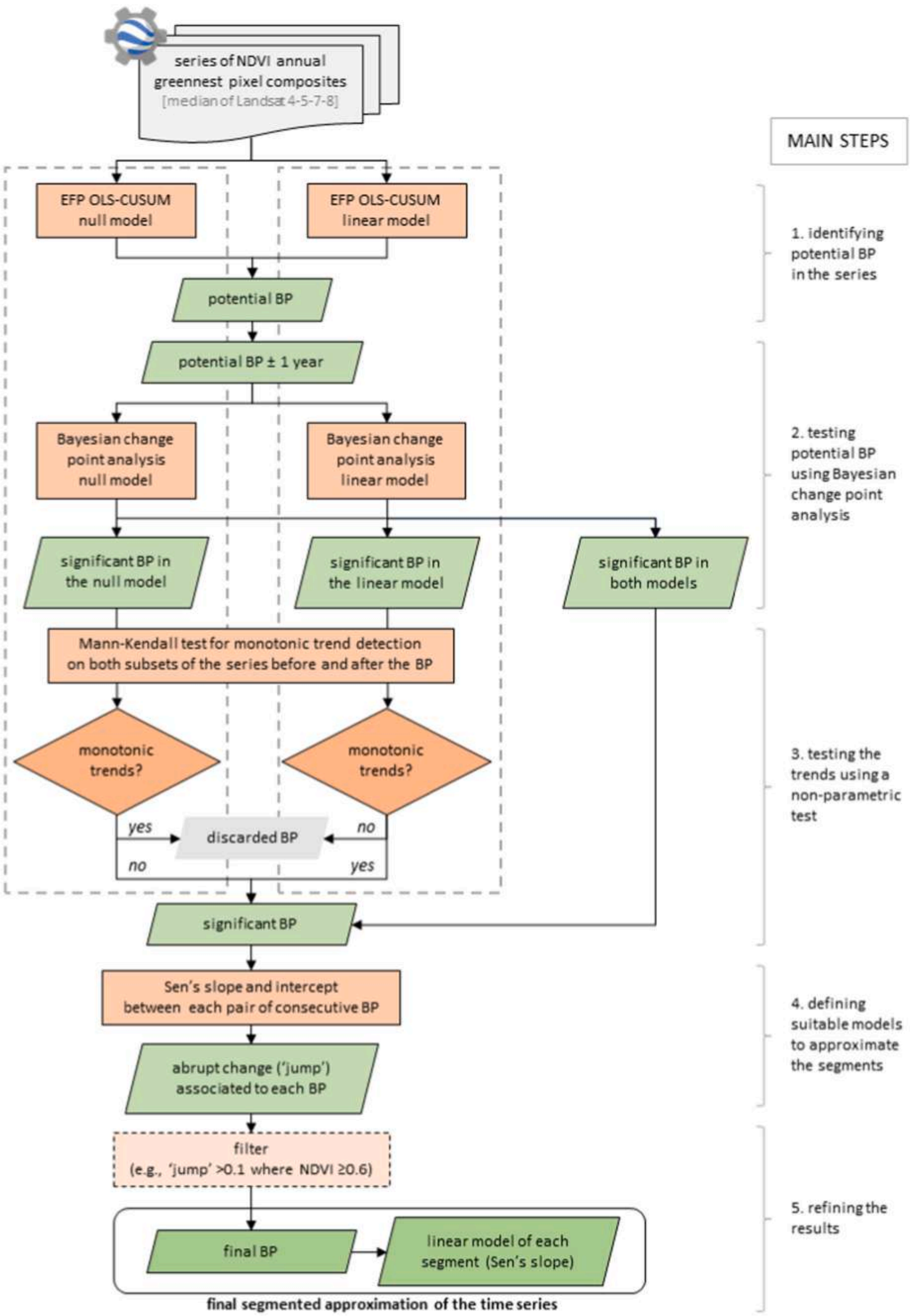

Fig. 1. Workflow of the segmentation algorithm. BP = break points, EFP OLS-CUSUM = Empirical Fluctuation Process with Ordinary Least Square – Cumulative Sum of Residuals. Orange boxes indicate processes and decisions; green boxes indicate products.

peculiar urban development in the last four decades. After World War II, the large territory of the city, covering more than 900 km^2, was divided into East Berlin, capital of the German Democratic Republic (GDR), and West-Berlin, an enclave politically aligned with the Federal Republic of Germany, part of the Western Block. During the Cold War, the two parts of the city followed separate urban development pathways. In East Berlin, GDR policies promoted the construction of large scale pre-fabricated housing units and industrial plants, leading to the vacancy of many Wilhelminian perimeter blocks that, on the contrary, were refurbished and remained in constant use in West Berlin (Arandelovic and Bogunovich, 2014; Wellmann et al., 2020b).

Following the reunification in 1990 and the proclamation of Berlin as the capital city of Germany in 1991, intense transformations took place in many parts of the city (Schwedler, 2001): in the center, to accommodate new governmental buildings and transport hubs; along the former path of the Wall, where derelict land conveniently located in attractive central areas suddenly turned into a valuable real-estate asset; in the eastern peripheries, with several interventions to enhance the quality of prefabricated buildings and their surroundings; and in the many brownfields left all over the city by former industrial plants and unused transport infrastructure. These dynamics, unique in the European panorama in terms of nature and intensity, included also many greening interventions, not limited to the realization of new parks in many re-development areas (e.g., Mauerpark along the former path of the Wall, Natur-Park Südgelände and Park am Gleisdreieck on former railway areas) but including also diffused actions of de-sealing and integration of small green areas inside existing residential districts (Wellmann et al., 2020b).

As input data for our application, we used time series of NDVI greenest pixel composites derived from Landsat Top-Of-Atmosphere reflectance available in GEE. We combine the composites from Landsat missions 4, 5, 7 and 8 following the procedure in Zulian et al. (2022), which implements the transformations suggested by Corbane et al. (2020) to allow comparison between the different missions and then calculates the median of the values available for each year. The collection produced is downloaded for the area of interest (the bounding box around a 1 km buffer of the administrative boundary of Berlin) as a raster image with a 30 m resolution in ETRS89, where each band corresponds to one year. Since a minimum of four points must be available to apply the Mann-Kendall test included in the algorithm, break points in the first and last four years of the time series are not detected. We therefore downloaded a dataset covering the period 1984–2021, which allows analyzing the trends in the 30 years from 1988 to 2017.

The results presented in Section 3 refer to the pixels inside the administrative boundary of Berlin, excluding water areas. To mask the latter, we used the Copernicus "Water & wetness 2018" product available at 10 m resolution for the whole European Union, selecting only the areas classified as "permanent waters". The final raster maps are composed of 942,971 unmasked pixels.

2.4. Validation and accuracy assessment

A complete and proper validation was not possible due to the lack of a reliable reference that could represent the "ground truth" at the same (or ideally higher) spatial and temporal resolution of the results produced by the analysis (Congalton and Green, 2009). This is a common challenge for break point detection algorithms (Kennedy et al., 2010), which are frequently tested on synthetic time series (Awty-Carroll et al., 2019; Ben Abbes et al., 2018). While land cover classifications derived from remote-sensing data and their changes over time can be easily compared with other images, e.g., obtained through aerial photography and freely accessible on platforms such as GoogleEarth™, the same comparison was not feasible in our case due to two main limitations. First, as for most locations, also for Berlin yearly series of georeferenced high-resolution color images are available only for the last few years, while in the past they were taken with lower frequency, and they hardly existed before the turn of the millennium. Second, as it is common practice in urban applications, most images have been collected in the leaf-off period, so that buildings and soil cover types are more visible. This strongly limits the assessment of vegetation type and extent. However, we designed a protocol for validation making use of available data that could serve at least as a partial reference for the results produced by our analysis. The aim is not to carry out a complete assessment of the accuracy of the results, but rather to confirm their interpretation and to identify potential error sources.

Whenever applicable to our case, we referred to the good practices described by Olofsson et al. (2014) for assessing the accuracy of land cover and related change maps. We mainly focus on the timing and trajectory of the abrupt changes. Like Chaudhuri et al. (2022), we compared the break points detected by the algorithm with a visual interpretation of aerial images. To aid in the interpretation of vegetation, we selected the infrared ortophotos available on the geoportal of Berlin for the years 2005, 2010, 2015 and 2020, purposely collected during summer to capture the maximum vegetation extent. We conducted the validation at the pixel level, selecting pixels through a stratified random sampling strategy. The partition was based on the presence in our results of at least one abrupt change during the 5-year period between two consecutive reference images (or three years in the case of the last period, since the analysis covers the years 1988–2017). For each period, we randomly selected 100 pixels in each stratum (with and without abrupt change), for a total of 600 validation points. Compared to the proportion of pixels classified in each stratum, this selection is unbalanced in favor of pixels affected by an abrupt change. The rationale is that, beyond their detection, we wanted to gain an understanding of the different possible errors in the estimation of abrupt changes. This unbalanced selection affects the quantification of the standard error associated to the accuracy estimations but is not expected to produce any bias in the estimated accuracies themselves (Olofsson et al., 2014).

The visual interpretation was conducted by comparing two consecutive images, focusing on the 30 by 30 m grid cells corresponding to the selected pixels. For each cell, an interpreter filled in a form recording the presence of vegetation in general and of trees both at the beginning and at the end of the period, the presence of visible changes in the area covered by vegetation between the two images, and the presence of visible signs of vegetation growth (e.g., tree crown expansion). The interpreter could fill in the latter entry with a good level of certainty only in few cases, which prevented a proper validation of the results about gradual changes. We then compared the results of the visual interpretation with the results from the algorithm. Besides calculating overall, user's, and producer's accuracy, we further investigated every case of disagreement to understand the underlying reason. More information on the validation protocol and detailed findings not reported in the main text can be found in the Supplementary Material.

3. Results

3.1. Thirty years of vegetation dynamics in Berlin

Most of Berlin shows a net increase in NDVI during the 30 years' period between 1988 and 2017 (Fig. 2). A net positive change characterizes 84% of the pixels inside the city boundary, while a net negative change can be observed only in 4% of the pixels. The main negative changes are visible in the city center and along some infrastructural axes departing from the center towards the west and the south, as well as in correspondence with new urban expansions close to the north-eastern border. Large areas characterized by a net positive NDVI change are in the eastern part (former GDR area, where the land use maps show an increase in urban green areas), and along the former path of the Berlin wall. The latter is clearly marked in the map by areas with a net increase in NDVI both along some portions of the current southern and western city boundary, and in areas immediately northern and southern to the

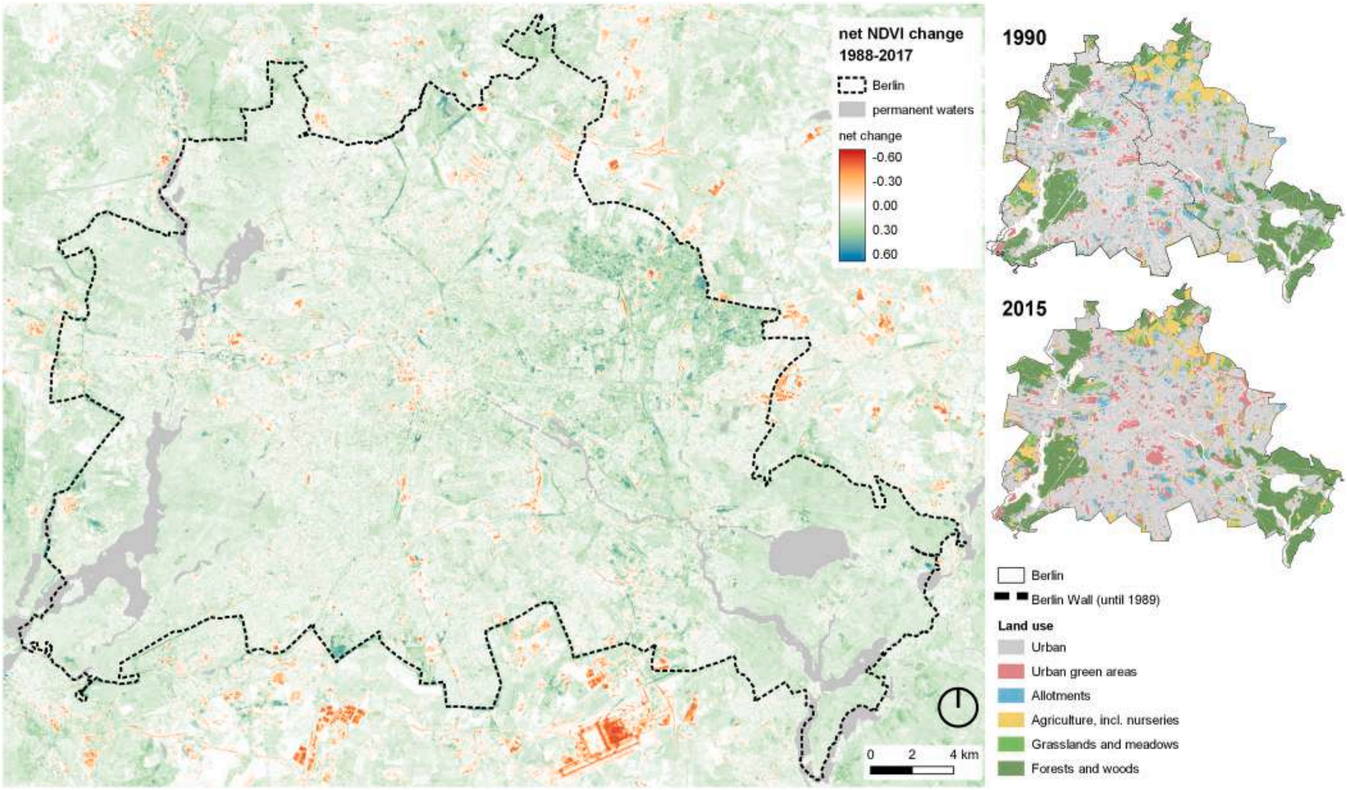

Fig. 2. Net NDVI change between 1988 and 2017 in Berlin (left) and main land uses close to the beginning and the end of the analyzed period (right). Source of the land use maps: Berlin Environmental Atlas (https://www.berlin.de/umweltatlas/en/land-use/actual-land-use/).

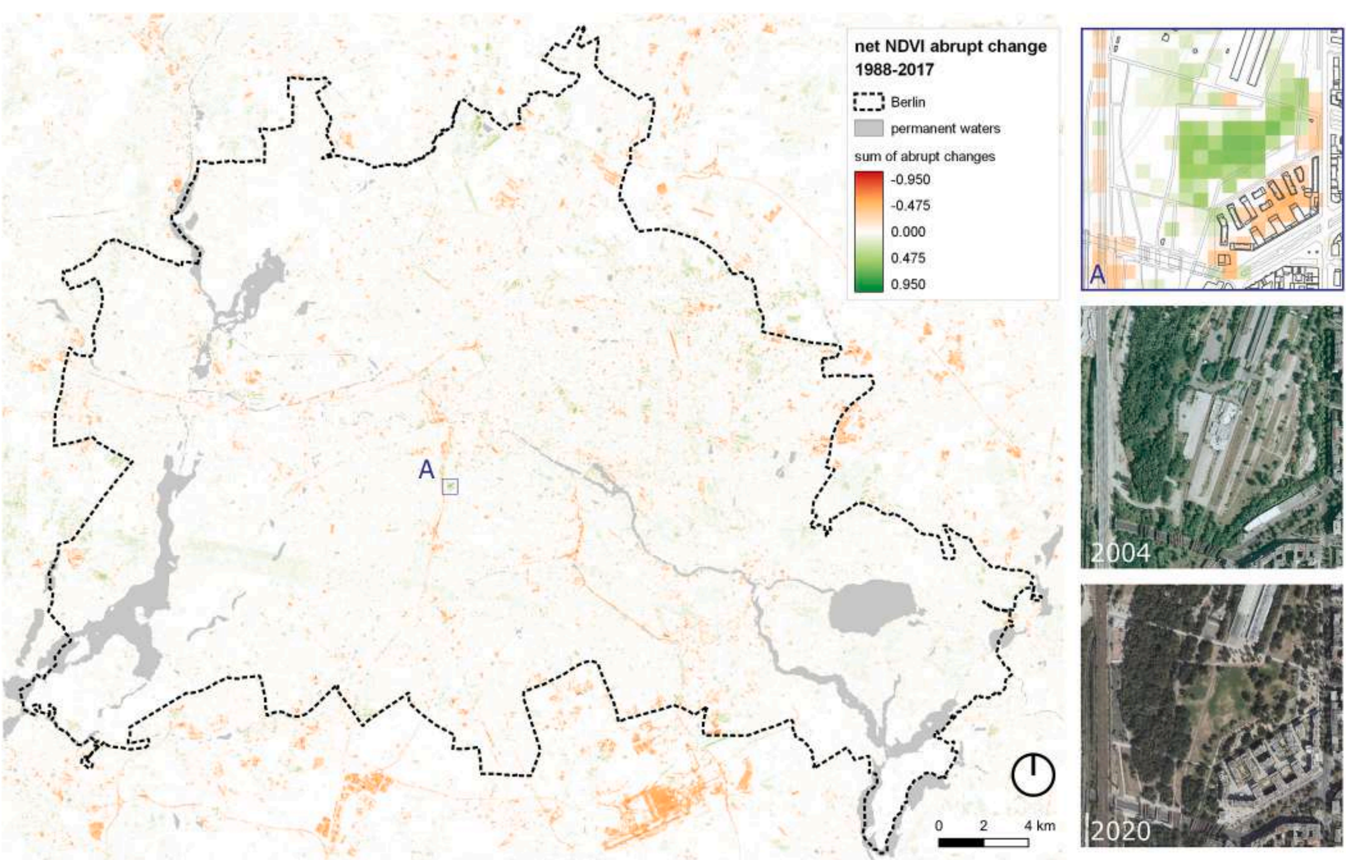

Fig. 3. Net NDVI change due to abrupt changes (i.e., changes corresponding to break points in the temporal series) between 1988 and 2017 in Berlin. On the right: a zoom on an illustrative area compared with aerial images before and after the changes.

city center. The average change over the whole city during the analyzed 30 years' period is + 0.096. The average change in greening and browning areas is + 0.12 and − 0.10 respectively.

The algorithm distinguishes between abrupt and gradual changes during the analyzed period. Around 20% of the pixels show at least one abrupt change (Fig. 3), while more than one break point -with a maximum of 5- was found in the 2.85% of the cases (see Fig. S2 in the Supplementary Material). Most net abrupt changes (71.5%) are positive, while only 5.6% of the pixels show an overall negative abrupt change. However, negative abrupt changes tend to be bigger, with an average value of − 0.17, twice as much as that of positive changes (+0.085). The map clearly highlights areas of negative abrupt changes in correspondence with new transport infrastructures and with new urban developments close to the city boundaries built during the analyzed period. The biggest hotspots in the south, outside the city border, correspond to a big logistics platform and to the Berlin Brandenburg airport opened in October 2020. Positive abrupt changes are more scattered, but larger hotspots can be identified in two former mining areas close to the western and northern border targeted by environmental restoration programs.

Fig. 3 also shows an example of how the mapped abrupt changes look like in reality. A former brownfield close to the city center recently refurbished into a large park (Park am Gleisdreieck) with some housing estates on its margins is taken as an example. The algorithm identifies both positive and negative abrupt changes corresponding respectively to regreening activities to create the new park and soil sealing associated with new construction. The overall accuracy associated to the estimation of abrupt changes, considering the period between 2005 and 2017 (as detailed in Section 2.4) is of 0.83. User's accuracy is 0.91 for pixels with no change and 0.75 for pixels with an abrupt change in the period considered for validation. Producer's accuracy is 0.79 and 0.89 for the two classes of no change and change, respectively. More details on the validation results and on the limitations that apply to these estimations can be found in the Supplementary Material.

A gradual NDVI change (Fig. 4) lasting at least some of the years between 1988 and 2017 affected 82% of the analyzed pixels. Indeed, for 67.7% of them the gradual change was continuous during the whole 30 years' period (see Fig. S3 in the Supplementary Material). The large majority of the pixels (98.6%) experienced a positive change, with an average value of + 0.12. Negative gradual changes instead are detected only in 1% of the city area, with an average value of − 0.07. The greatest positive gradual changes are concentrated in the eastern part and in some areas along the city boundary. Fig. 4 shows an example from one of these areas in a former GDR neighborhood where intense gradual changes in the last years, adding up to + 0.35, correspond to a progressive increase of canopy cover inside a courtyard after the planting of small trees.

3.2. The temporal dimension of NDVI changes

The algorithm detects abrupt and gradual NDVI changes in a temporally-explicit way, i.e. every change is associated to a specific year. Thanks to this feature, it is possible to track variations in vegetation dynamics during the analyzed period (Fig. 5). For example, Fig. 5a and Fig. 5b show the number of pixels involved respectively in abrupt and gradual changes during each year. Positive abrupt changes peaked in 1992, but the number of pixels involved in positive changes consistently exceeded that of pixels involved in negative changes between 1988 and 1993, and then again between 1996 and 1999. On the contrary, despite the smaller total area involved, the frequency of negative changes consistently surpassed that of positive changes in most recent years, from 2013 till the end of the analyzed period. The number of

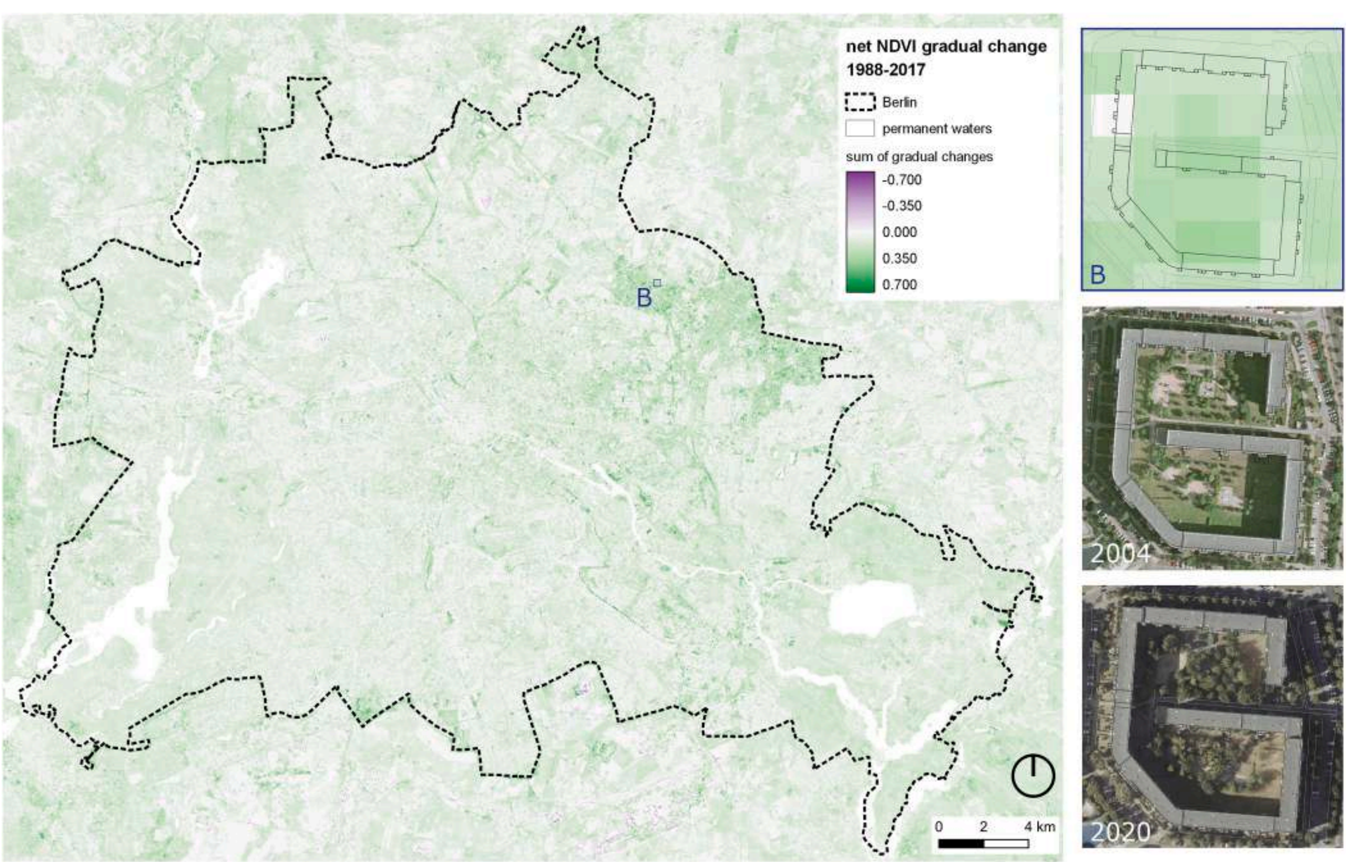

Fig. 4. Net NDVI change due to gradual changes (i.e., changes corresponding to the slopes of the segments between consecutive break points in the temporal series) between 1988 and 2017 in Berlin. On the right: a zoom on an illustrative area compared with aerial images before and after the change.

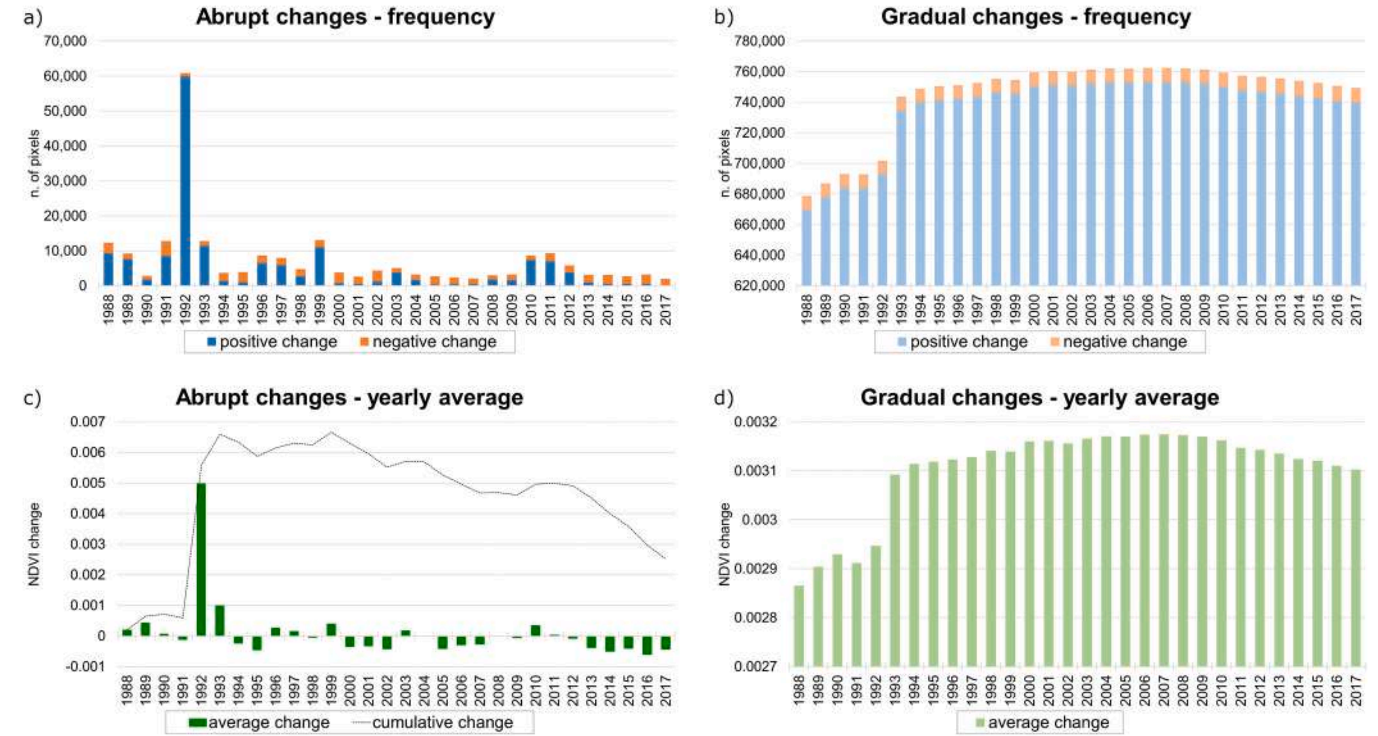

Fig. 5. Temporal evolution of NDVI changes in Berlin between 1988 and 2017: frequency of abrupt (a) and gradual changes (b), and average yearly change over the whole city due to abrupt (c) and gradual changes (d). Note that the scale of the y axis differs between panels a) and b), and that panels b) and d) are enlargement of the entire graphs, hence the y-axis does not start from 0. To aid in the interpretation of panel a), a zoomed-in version of the graph with y values from 0 to 15,000 is available in the Supplementary Material (Fig. S4).

pixels involved in gradual changes shows a sudden increase in 1993: a clear consequence of the high number of abrupt changes recorded in 1992, as the vegetation installed in the new green areas started to grow. The frequency of gradual changes grew constantly during the first decade of analysis (until 1998) but decreased progressively during the last decade (from 2007), while the number of pixels characterized by a negative gradual change continued to increase (from 2010).

If we consider the intensity of the observed changes, we can calculate the yearly average of abrupt and gradual changes and monitor the evolution of their cumulative impacts (Fig. 5). During the analyzed 30 years' period, negative abrupt changes prevailed in 18 years, with the longest row of consecutive negative values from 2012 to 2018 (Fig. 5c). The cumulative curve calculated over the entire city considering only abrupt changes reached its maximum in 1999 with a value of 0.0067, not far from the local maximum already reached in 1993. The cumulative value at the end of the period is 0.0025, less than half of the maximum of 1999. Among gradual changes (Fig. 5d), the positive ones linked to vegetation growth largely prevail over the whole period, but the constantly decreasing values of the last years brought the average close to the minimum observed in 1993, after the jump that followed the high number of (abrupt) greening interventions in 1992. That year also marked the only exception when the average effect of abrupt changes over the city was greater than that of gradual changes (0.005 vs. 0.003). In all other years, gradual changes produced a larger average effect compared to abrupt changes. This prevalence of gradual changes becomes even more evident when looking at the cumulative impacts (Fig. 6). In a 30 years' period, vegetation dynamics have produced an average cumulative NDVI change of 0.096 over the whole city of Berlin,

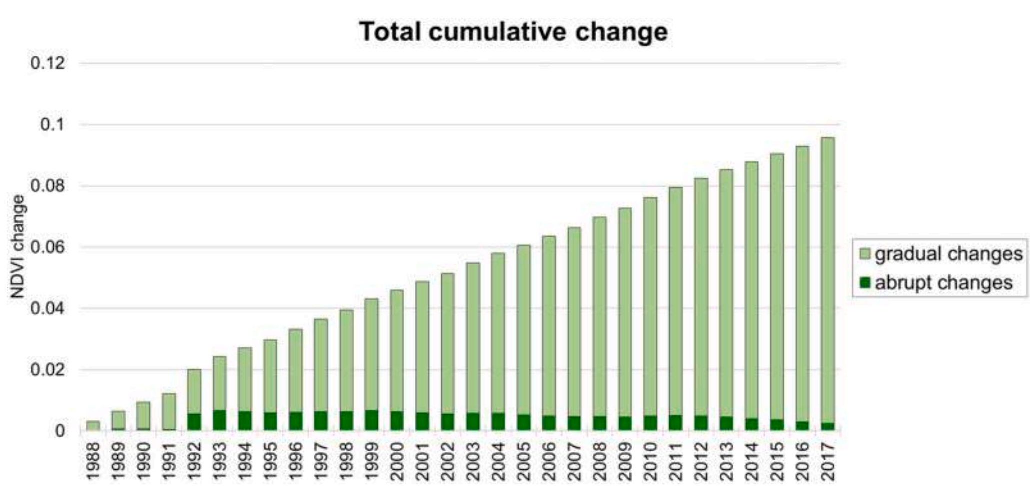

Fig. 6. Temporal evolution of cumulative impacts of abrupt and gradual changes on the average NDVI value over the city of Berlin between 1988 and 2017.

97% of which is attributable to gradual changes.

4. Discussion

4.1. Berlin, a gradually greening city

The results show a net positive change in NDVI (greening) in the large majority of the 30 by 30 m pixels within the city of Berlin during the last 30 years. The fact that Berlin is becoming greener is not surprising and is consistent with findings from previous studies. Kabisch and Haase (2013) found a measurable increase in urban green spaces between 1990 and 2006 even in the low-resolution CORINE land cover data. More recently, Wellmann et al. (2020b) calculated vegetation cover and related trends in Berlin based on Landsat data and found that many districts showed a prevailing greening trend in the last 30 years.

A progressive increase in NDVI has been recorded in other cities. In their study on more than 10,000 cities across the globe, Corbane et al. (2020) compared NDVI greenest pixel composites for the years 1990, 2000, and 2014 to measure changes in greenness associated to urbanization. They found a prevailing positive trend (greening) in most cities, including the majority of the 32 analyzed megacities. Fast-growing Chinese cities stand out as an exception, in line with the results of previous studies (Sun et al., 2011). However, while confirming the overall decline of vegetation during the last four decades in most metropolitan areas in eastern and central China, Du et al. (2019) also observed a characteristic U-shape in the relationship between urbanization and vegetation, with initial negative impacts of urbanization that tend to turn into positive ones in the later stages of development.

The average value of NDVI increase that we found in Berlin, slightly less than 0.1 in 30 years, is comparable with the 0.002 yr^{-1} observed in Seoul (Hwang et al., 2022) and with the values recorded in Las Vegas and Seattle by a study focusing on Pacific cities (Jin et al., 2020). Similar values were also found in Stockholm, where the average increase in NDVI in neighborhoods characterized by different population density along an urban-to-rural gradient ranged from 0.0018 yr^{-1} to 0.0029 yr^{-1} in the period between 1990 and 2015 (Persson et al., 2018). Samuelsson et al. (2021) report an average NDVI increase of 0.028 over 20 years in Denmark. The lower value can be attributed to the fact that they just considered the immediate surroundings of residential addresses, hence changes in green areas are only partially considered.

While all these studies only looked at overall NDVI trends, our analysis distinguished between gradual and abrupt changes. The results reveal that, despite the great impacts that abrupt changes may have at the small spatial and temporal scale, gradual changes, far more common across the city, produce larger effects in the long run. Similar findings were obtained by Zhu et al. (2016), who looked at gradual and abrupt changes in EVI (Enhanced Vegetation Index) in Guangzhou between 2000 and 2014. Contrary to their results, however, abrupt changes in Berlin had an overall positive impact on vegetation dynamics in the last 30 years. This speaks to the different urban development trajectories of the two cities. Fast urban expansion and associated impacts prevailed in Guangzhou during the analyzed period (Zhu et al., 2016). In Berlin, on the contrary, the post-reunification period was mainly characterized by first a partial abandonment of rail areas and then by a subsequent re-development combining densification and greening (Wellmann et al., 2020b). However, positive abrupt changes prevailed only in the first decade, while the overall impact of abrupt changes in more recent years was negative, reducing the positive effect of gradual changes.

4.2. A different perspective on urban vegetation dynamics

The results presented for the city of Berlin are illustrative of the new perspective on urban vegetation dynamics offered by our analysis. We highlight here three main aspects in which our approach differs from other approaches commonly adopted to analyze urban greening trends, and discuss their relevance for monitoring vegetation dynamics in urban areas.

A first aspect is that the analysis based on remote-sensing data covers the whole city, contrary to other studies on urban greening that often focus on specific types of areas or selected land use classes (e.g., Kabisch et al., 2016). Considering only gains and losses in the extent of parks or green areas available for public use (net of all the specific barriers that may prevent access, see Wolff et al., 2022) fails to capture many other components of the urban green infrastructure that are smaller or integrated in prevalently non-green areas. Among others, these include domestic gardens, street trees, and green roofs, which contribute substantially to the provision of ecosystem services within the city and are increasingly targeted by specific urban greening policies (Dong et al., 2020; Goddard et al., 2010; Lin and Wang, 2021). Indeed, NDVI started to be used as an indicator in urban areas to respond to the need of investigating not only the quantity and extent of publicly available green areas, but the overall "greenness" to which the population is exposed (Gascon et al., 2016).

A second feature of our approach is that it analyzes the continuous temporal evolution of vegetation dynamics, as opposed to comparing only the values in selected years. The study of the temporal evolution of NDVI has recently gained popularity in the scientific research thanks to the availability of longer series of remote-sensing imagery and of platforms to handle them (see e.g., Corbane et al., 2020; Du et al., 2019; Sun et al., 2011). Besides reducing the effect of potential errors that might affect individual values, considering the whole trend is of great help in the interpretation of the observed changes, since it can reveal if they are linked to slowly evolving processes or to specific events. Despite the interesting insights that it produces, this type of analysis has been rarely applied in urban areas. The few urban applications of BFAST, possibly the most popular algorithm for NDVI time series segmentation and break point detection, all focused only on identifying abrupt changes linked to land cover transitions, disregarding any information about gradual changes (Chaudhuri et al., 2022; Pandey et al., 2018; Tsutsumida et al., 2013). On the contrary, methods based on linear approximations tend to emphasize gradual changes and do not capture the presence and impact of individual events.

Linked to the previous aspect, a third key feature of the proposed approach is that it can detect multiple break points during the analyzed period, corresponding to different abrupt changes. This aligns with the concept of non-linearity of land transitions (Pandey et al., 2018) and with the observation that interrupted and reverted trends are not uncommon, especially in urban areas undergoing fast alterations in population dynamics and respective land demand/(over)supply dynamics (Chaudhuri et al., 2022; Zhu et al., 2016). While this non-linearity is generally assumed for land use changes, we extended the approach to local vegetation dynamics, which are not necessarily linked to land use transitions. In Berlin, around 20% of the pixels show at least one abrupt change during the period between 1988 and 2017, and 2.85% more than one.

These results question the use of linear approximations, such as linear regressions or the Sen's slope, but also of other approaches like the Hurst exponent (Geng et al., 2022; Jiang et al., 2015), which predicts future trends based on the long-term memory of time series. Those analyses are suited to capture the overall trends of NDVI dynamics at the city scale (Corbane et al., 2020), where our results show that gradual changes prevail in terms of area involved and impact produced. Linear approximations can also be instrumental to reveal hotspots of (positive or negative) change in specific urban areas (Zulian et al., 2022). However, they fail to capture non linearities and trend reversions (i.e., abrupt changes), which produce the greatest impacts at the local level. The proposed algorithm therefore fills a gap in the methods available to quantitatively estimate changes at the small (down to the pixel) scale, where the assumptions underlying the results of linear approximations do not always hold.

4.3. Peculiarities and limitations of the proposed algorithm

To distinguish between gradual and abrupt changes in NDVI time series, the proposed algorithm builds on previous approaches for break point detection and segmentation (Jamali et al., 2015; Kennedy et al., 2010), with BFAST (Verbesselt et al., 2010) being the main conceptual reference for the development of our approach. We note here some key similarities and differences, and discuss some limitations of the proposed algorithm of which potential users should be aware.

Considering the type of input data, the proposed algorithm has been purposely designed to work on NDVI annual greenest pixel composites, contrary to other algorithms such as BFAST developed to analyze dense time series (Verbesselt et al., 2010). This implies a loss of information related to phenological cycles, but eliminates the associated seasonal correlation structure, hence the need for a computationally-intensive decomposition of the time series into seasonal and trend components. As a result, the algorithm is simpler and faster, and the amount of input data that the user must provide is reduced by at least a factor of 10. The number of outputs is also reduced, and their interpretation is more straightforward, which is an important aspect in view of their potential use for policy support. In fact, previous applications in urban areas seem to suggest that, if the user is not interested in characterizing the phenological cycle, the results of a decomposition such as the one performed by BFAST might be difficult to interpret. For example, authors were uncertain whether the most suitable piece of information to detect land cover changes was the seasonal (Tsutsumida et al.,2013; Pandey et al., 2018) or the trend component (Chaudhuri et al., 2022).

Compared to dense NDVI time series, time series of the annual greenest pixel composites are more scattered and may be affected by the presence of artifacts due, for example, to masked or missing values corresponding to the best conditions during the year. This might introduce some errors in the analysis. However, the comparative test performed by Forkel et al. (2013) suggest that it is reasonable to expect only a marginal loss of overall performance when annual aggregate values are used instead of full seasonal series. Moreover, the potential effect of artifacts and outliers in the series is mitigated in two ways: i) upstream in the selection of input data, by using the median of the greenest pixel values from the different Landsat missions running in the same year (Zulian et al., 2022; Corbane et al., 2020), and ii) by the segmentation approach that does not allow for isolated points.

Another feature of the proposed algorithm is that it does not require any specific parameter to be defined by the user. The only parameter that can be adjusted relates to the maximum number of “potential” break points that can be detected in the first step of the process, but the limit is not strict and the process of testing and validation, which considers both a null and a linear model, may produce a larger number of final break points. Other algorithms offer more possibilities of customization. For example, DBEST workflow includes both a trend generalization and a detection algorithm, and the user can control them through several parameters, including the generalization percentage, the number of required changes and the change threshold (Jamali et al., 2015). Considering the potential use of the algorithm for policy monitoring, we believe that a process that does not require tailoring and customization is more usable and credible, since it is easy to run in different contexts and ensures reproducibility of the results.

The users should also be aware that, as all other algorithms for break point detection and segmentation of time series, also our algorithm runs at the pixel level. This prevents errors to spread and guarantees that the overall results are produced and valid even if the processing of specific pixels encounters some issues or cannot be performed. The drawback is that spatial proximity, which can be used as an additional information to check the results of close-by pixels likely characterized by contemporaneous changes, is not considered.

Finally, it should be noted that, in the described application, we have refrained from setting any general threshold for abrupt changes. Any statistically significant break point has been retained in the results, irrespective on the change in the associated NDVI values. The reason for this decision is that, due to the 30 m resolution of the input data, pixels in urban areas usually include a mixture of land covers, of which vegetated areas are often only a portion (Welmmann et al., 2020b). Hence, NDVI values are often small, and the intensity of change is also small. The only limitation that we included was a minimum change of 0.1 for pixels with an NDVI value above 0.6, mainly corresponding to forests. This correction was added after a first validation of the results in Berlin and helped to remove many break points that seemed unrelated to any real change in vegetation. The validation of the results presented here still revealed uncertainties related to break points in forested areas, which could not be linked to any visible change in land cover. This aspect requires further investigation. The possibility and implications of setting an absolute or relative threshold below which changes associated to break points are considered as not significant should also be explored in further applications.

4.4. Potential use for policy monitoring

In order to use indicators derived from NDVI trends for policy monitoring, we need to connect the observed trends to their specific drivers. Our validation confirmed the hypothesis that abrupt changes are linked to changes in the extension of vegetation coverage, i.e. to land cover changes. This was a common assumption already tested in previous studies (Chaudhuri et al., 2022; Pandey et al., 2018; Zhu et al., 2016). Positive abrupt changes correspond to the implementation of new green infrastructure, such as parks or green roofs. Negative abrupt changes are associated to the removal of existing vegetation, mostly due to soil sealing and construction. Only for some validation points located in forest areas it was impossible to link the abrupt changes detected by the algorithm to any visible change in the extension of vegetation coverage.

We also hypothesized that gradual changes are linked to vegetation growth or degradation, the latter recently observed in the form of tree crown dedensification after summer droughts (Haase and Hellwig, 2022). While we could not test this assumption systematically, evidence obtained by comparing historical pictures and by checking familiar places around the city confirms that positive gradual changes correspond to vegetation growth or succession in existing green or partly-green areas, such as abandoned ruderal brownfields and succession sites (Wolff et al., 2023). This interpretation is also supported by the observation that positive gradual changes often follow the establishment of new green areas, suggesting that vegetation -and especially tree-growth plays a key role in driving gradual changes.

Previous studies that observed a greening trend in cities have pointed at the role of anthropogenic factors and specific urban environmental conditions in enhancing vegetation activity, resulting in faster growth in urban areas than in their rural counterparts (Pretzsch et al., 2017). These factors include warmer temperatures (especially at night) due to the urban heat island, which can extend the length of the growing season (Dallimer et al., 2016; Zipper et al., 2016), lower ozone concentration that limits vegetation growth at rural sites (Gregg et al., 2003), as well as greater concentration of tropospheric CO_2 and higher deposition of atmospheric nitrogen that promote faster metabolism (Searle et al., 2012; Zhao et al., 2016).

The fact that similar NDVI changes and trends have been observed in distant cities and urban areas across the world have often led authors to emphasize large-scale drivers, such as the effect of CO_2 fertilization. However, it is important to note that associating gradual changes to vegetation growth does not mean that they are not correlated to anthropogenic processes. This is clearly demonstrated by our results on the temporal evolution of the changes. The peak in the frequency and total amount of positive abrupt changes observed in 1992 is also reflected in the evolution of gradual changes, which shows a sudden increase in 1993, when the small trees planted in the new green areas started to grow. On the other hand, while land cover changes in cities are mostly due to human interventions, we must be aware that natural events such as fires, floods, or landslides, can also modify the extent of vegetation coverage, although the impacts of such phenomena on urban vegetation is still to be quantified.

The information produced by our approach can support the monitoring of urban greening policies, revealing both the short-term and long-term impacts of their implementation. Combining the results with data on land uses and human activities, as done by Hwang et al. (2022), can be a way to strengthen the identification of the underlying drivers. The possibility of dating the abrupt changes and associating the gradual changes to a specific period is certainly helpful in this endeavor. The results produced by the algorithm can therefore complement quantitative information on the extent of (public) green areas, and enrich with spatial and temporal details the outputs of other methods that provide only an overview of the main trends.

5. Conclusions

Urban greening policies are rising their targets, with actions that permeate the whole urban environment. Earth observations provide a wealth of data that can be used to investigate vegetation dynamics, but supporting policymaking requires innovative methods able to synthesize the information into useful indicators (Wellmann et al., 2020a). The proposed algorithm has been purposely designed to analyze time series of NDVI greenest pixel composites, which represent the "greenness" recently identified by the *EU-wide methodology to map and assess ecosystem condition* as a key structural ecosystem attribute to monitor in urban ecosystems (Vallecillo et al., 2022). We believe that the spatially- and temporally-explicit perspective offered by the results, as illustrated by the application to Berlin, can be a step forward in the monitoring and interpretation of urban vegetation dynamics and of the urban development trajectories that they reflect. More applications are needed to further validate the approach and the interpretation of the outputs in different contexts, and to compare the algorithm with alternative methods applicable to the same dataset.

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CRediT authorship contribution statement

Chiara Cortinovis: Conceptualization, Methodology, Software, Validation, Formal analysis, Visualization, Data curation, Writing - original draft, Writing - review & editing. **Dagmar Haase:** Conceptualization, Validation, Formal analysis, Methodology, Writing - review & editing. **Davide Geneletti:** Conceptualization, Formal analysis, Methodology, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Research data statement

The input data and the code to reproduce the results are available open-access at the following links: doi:10.6084/m9.figshare.23668842 (input data), doi:10.6084/m9.figshare.23668941 (code). The maps are available for download in raster format at the following link: doi:10.6084/m9.figshare.23669142.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.128030.

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