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Social factors of urban greening: Demographics, zoning, and social capital

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ABSTRACT

This study explored the association between greening and social capital in neighborhoods, considering demographics and zoning by urban planning. The target area encompassed the urban areas of Kyoto City, Japan, which has a long tradition of landscape policy and neighborhood associations. Greening was evaluated using two automated methods: 1) horizontal green coverage of the land was calculated via the Normalized Difference Vegetation Index in satellite images, and 2) green visibility in streetscape from a human perspective was estimated by combining Google Street View images and a machine learning model. Public government data were used for demographics and zoning, and social capital was evaluated using survey data from the local government. After performing the elastic net models, variables that had explanatory power for each greening index were selected. Similar reasonable associations were found for each of the indices with the zoning categories. However, for both zoning and demographics, different variables were selected. Importantly, the social capital variable was selected only for the green visibility in streetscape, showing a negative correlation between them, unlike in previous studies. These results suggest that the association between urban greening and social relationships can change depending on the context of the target regions and measurements of greening.

Introduction

Benefits of the interaction between urban greening and social capital

Greening is expected to have multiple benefits in urban planning and is aimed at contributing to people's well-being, beyond its simple aesthetic attribute. In terms of comfort of the physical environment, greening mitigates excessive increases in temperature owing to climate change [1,2]. There is also considerable interest in the beneficial effects of green spaces on individual health, with a multifaceted accumulation of reports noting that opportunities for contact with green spaces reduce the risk of physical and mental illnesses [3–5]. Regarding the health benefits of green spaces, it has been noted that they are mediated by social capital, which encompasses multiple aspects of social relationships [6]. According to the definition proposed by Putnam [7], which is widely referenced in discussions focusing on local communities, social capital is a concept that encompasses trust, norms of reciprocity and social networks. Its benefits have been discussed in terms of health (e.g., [8,9]), education (e.g., [10,11]), security (e.g., [12,13]), and democratic practices (e.g., [14,15]). Hence, the impact of urban greening on the social capital of the local population can potentially lead to an even wider range of benefits for people. However, the development of a systematic theory for building social capital for specific interventions is still ongoing. In particular, the interaction between social capital and the built environment, including greenery, has only recently begun to be discussed, although its importance has been previously highlighted [16]. Conversely, it was also suggested that social capital benefits people through the reverse pathway, such as maintenance of green spaces by policy-guided residents' collaboration that has resulted in a reduction in crime [17]. Therefore, from the perspective of comprehensive urban planning to realize people's well-being, the mutual interaction between urban greening, an element of the built environment, and social capital, an element of the social environment, is an important gap that needs to be addressed.

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Influence of urban greening on social capital

The discussion on the influence of plant greenery on social capital, such as social interaction, relationships, or neighborhood participation, has attracted scholarly interest for some time. An early quantitative study [18] suggested that green spaces in urban public housing contribute to the promotion of residents' interaction. Research targeting elderly people has suggested that having a park as a green space in the neighborhood is beneficial for building social capital [19], and that the greener the neighborhood in perception, the higher the level of social contacts [20]. Research targeting middle-aged and older adults has also shown that objectively measured green spaces in residential areas contribute to the mitigation of loneliness through social cohesion [21]. A common interpretation of the effects of green spaces is that they function as 'green magnets' [22], where local residents are more likely to gather, thus promoting interaction. Studies on the effects of green space on social capital have also suggested that respondent attributes modulate them [19,21]. Conversely, some studies have reported no association between green space and social capital [23–25]. Given the above, it seems that the effects of green spaces on social capital are unlikely to be simply generalizable. It should be noted, however, that this could be partly because there is no uniform methodology for assessing green space and social capital across studies. Additionally, previous studies have discussed the influence of green spaces on social capital, mostly examining their correlations. This does not negate neither the effect in the opposite direction nor the mutual interaction between them.

Horizontal and streetscape greenery and social capital

By employing a method and framework that could be applied in different regions, the present study is expected to offer valuable insights while preventing the discussion of the relationship between urban greening and social capital from becoming unnecessarily sprawled. First, there are two objective methods of assessing urban greening, widely used in recent research: horizontal measurement using satellite imagery and streetscape measurement. These methods could potentially be applied as similar measures in different regions, provided that imagery is available. Meanwhile, residents' perceptions of greenery have also been suggested to be important (e.g., [20]). Since this requires subjective reporting, comparisons between studies should consider the same option as the method of assessing social capital. However, streetscape measurement is closer to greenery as an object of people's perception, compared with horizontal measurement, while a potential substitutability for costly social surveys can be expected. Regarding methods of assessing social capital, although there is a widely referenced definition [7], it cannot be concluded that a certain unified scale is in widespread use. In research practice, it seems that measurement results from different scales are interpreted as the same concept within a shared theoretical framework, as is the case in the review by Mazumdar et al. [16]. While this makes simple comparisons between studies difficult, it is a constructive option that could broaden the possibilities for secondary analysis and cross-sectoral discussions.

This section focuses on studies that have examined the relationship between urban greening and social capital, using objective indicators of greenery that may be applied to different regions. The measurement of social capital covers one or more of the three elements discussed by Putnam [7]. An indicator of horizontal urban greening is the percentage of green coverage rate (GCR) using the Normalized Difference Vegetation Index (NDVI). Orban et al. [26] targeted a large metropolitan area in Germany and calculated the NDVI from the reflectance of near-red and red light in satellite images to assess the degree of greening around the dwellings of survey participants. The findings were compared with those of a social survey, indicating that the NDVI is positively related to social capital in a neighborhood. Samsudin et al. [27] conducted a survey of public residential areas in Singapore and compared associations of two greening measurements with social capital: 1) physical attributes objectively assessed as a proportion of green spaces, and 2) perceived attributes subjectively assessed as people's interpretation of quantity and quality of the green spaces around them. They showed that perceived attributes had more direct connection to social capital than physical attributes, and density of vegetation was also connected to social capital.

Meanwhile some studies used the GCR as an objective indicator of the horizontal amount of plant greenery, streetscape greenery is more similar than it to what people may perceive in their environment [27]. Although not limited to urban areas, Uchida et al. [28] explored the relationship between streetscape greenery and neighborhood social capital using big data from imagery and machine learning models. They introduced a method in Japan that applied machine learning models to large-scale image data from Google Street View (GSV; [29]), which has been widely used in various fields of research in recent years. The Green View Index (GVI), which is the percentage of green vegetation in a pedestrian's field of view, was estimated and compared with the results of social surveys. The results are contrary to those of the previously mentioned studies, indicating that the richer the plantings around buildings, the lower the social capital among residents. Wijnands et al. [30], who focused on metropolitan areas in Australia, attempted to use machine learning to detect landscape features in GSV images corresponding to high and low social capital in different regions. These results indicate that more grass and smaller trees tended to appear in streetscapes of areas related to higher social capital. These findings suggest that there may not always be a positive correlation between social capital and greenery, assessed as GCR.

From the studies cited above, it can be supposed that in the discussion of the relationship between urban greening and social capital, there is a need to analyze the aspects of greenery. This is not a question of whether horizontal or streetscape indicators are more relevant, but a discourse that has implications for the role of each as a target value when employed in urban planning. Additionally, in this discourse, the social context of the area, such as the attributes of the residents and area classification by urban planning (i.e., zoning), also needs to be considered in this discussion. First, the attributes of the residents can influence the association between urban greening and social capital [19,21]. Second, the aforementioned objective indicators of the amount of greenery do not provide information on whether the plants detected are publicly managed (e.g., trees in parks or roadside trees) or privately planted (e.g., plantings in private gardens). Thus, zoning categories (e.g., residential or commercial) comprise a useful factor to consider the types or meanings of greenery. However, studies that compare different aspects of urban greening in the discussion of its relationship to social capital are yet to be reported.

Present study

To broaden the scope of the discourse on the mutual interaction between urban greening and social capital, it is necessary to contemplate multiple aspects of greenery and the contextual elements of the area. Therefore, the present study compared the patterns of the explanatory power of demographics, zoning, and social capital for each of the different aspects of urban greening. We assessed greenery through two metrics used in previous studies: first, we quantified horizontal plant greenery as GCR using the NDVI of satellite images, and second, we estimated streetscape greenery as GVI using a method that combines GSV images and machine learning models.

With green spaces and plant greenery as target variables, multivariate models were created to establish a comparison through a data-driven approach using population composition from the census, urban planning classifications, and residents' feelings toward their neighborhoods, including social capital from social surveys. We then estimated the factors with explanatory power for greening and discussed the aspects of greening associated with these factors by comparing those two

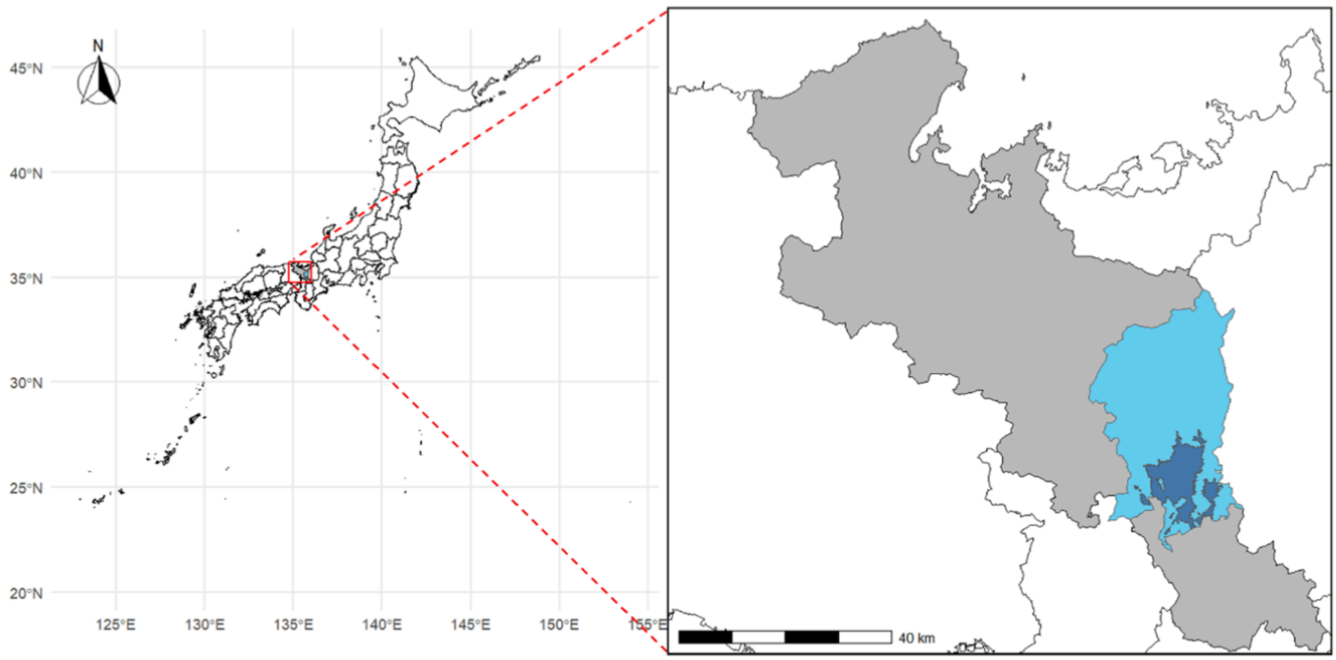

Fig. 1. The geographical location of the target area. *Note*: The grey, sky blue, and dark blue areas signify Kyoto Prefecture, Kyoto City, and its urban area, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

models.

Materials and method

Target area

To explore the relationship between greening and social capital in urban areas, the target area must be selected from urban areas where each of these elements exists. Regarding greening, urban planning by the local government and available geographical data were necessary for the analysis. In addition, autonomous associations between neighborhood residents imply that social relational capital has been constructed among them [7,14]. Therefore, the urban area of Kyoto City, which has a tradition of advanced landscape policies and neighborhood associations in Japan, was selected as the target area. Fig. 1 shows the location of the target area in Japan. The "Densely Inhabited District" (DID) defined by the Ministry of Land, Infrastructure, Transport, and Tourism was adopted as the definition of the urban area. According to the 2015 Census [31] which was referred to for the analysis, Kyoto City had a population of approximately 1.5 million, making it the ninth-most populous city in Japan at that time. Its GDP was approximately 6.3 trillion yen in 2015 [32]. Kyoto City is the capital city of Kyoto Prefecture and was the capital of Japan for a millennium, until 1869.

Regarding urban planning related to greening in Kyoto, the local government designated its districts for landscape protection in 1930 as the first large-scale city area in Japan [33], and successor measures are still in place. A series of policies can have an impact on greening, as they regulate not only changes to the appearance of structures, but also the cutting of trees and bamboo. The original unit of neighborhood associations was formed in the early 16th century (Muromachi period), and by 1869, the unit had become the elementary school district through legislation and residents' movements. This neighborhood association unit still exist, even though elementary schools have been consolidated due to the declining birth rate [34].

Kyoto City has set specific numerical values for green coverage and visibility as the target values for its greening policy for urban areas [35]. As previously mentioned, the difference between the two indicators lies in whether the amount of plant greenery within the target area is evaluated horizontally from a bird's eye view or from the perspective of pedestrians. Employing and comparing the indicators used in this study would allow for more direct policy recommendations in the target area.

Finally, this study focuses on subregions as the unit of analysis. A subregion is a geographical area defined by the government as the smallest unit in the census (described below). This area generally corresponds to the sub-groups of neighborhood associations derived from the elementary school districts mentioned above, and can be considered a 'neighborhood' in the common perception of the residents.

Estimating green coverage rate using the Normalized difference vegetation Index

To estimate the GCR in the target area as an indicator of the horizontal urban greening, NDVI plots were generated from satellite images of the area. The GCR of the area was then calculated for each subregion by defining "plant greenery" with a threshold value for NDVI. Because of its reliance on readily available multispectral bands, NDVI is one of the most common indicators used for vegetation assessment [36]. Hashim et al. [37] emphasized the importance of the NDVI as an indicator of urban vegetation cover. Although NDVI is a continuous variable, it was used to bisect the land in the target area into green and nongreen areas to calculate the ratio of the former (i.e., GCR) for comparison with GVI described in the next section.

The following analyses were performed to determine the NDVI thresholds: A Pleiades image (taken on June 9, 2021; 2-meter resolution) encompassing the entire area of interest was purchased and used. First, 2035 points were created in the Pleiades image at 370 m intervals. Stratified sampling was then performed in 11 administrative districts of Kyoto City and surrounding areas (12 areas in total), and 203 points were selected as validation points. Two assessors independently determined whether each point was plant greenery or not. Because the agreement rate between the two assessors exceeded 90 %, the result of one assessor was adopted as the true value. We then conducted an exploratory study to determine the lowest NDVI value that could be considered as plant greenery. First, the NDVI threshold was varied by 0.05 in the interval from 0.3 to 0.55, and the kappa coefficient compared to the true value was high enough at NDVI = 0.4 (=.92). Second, since

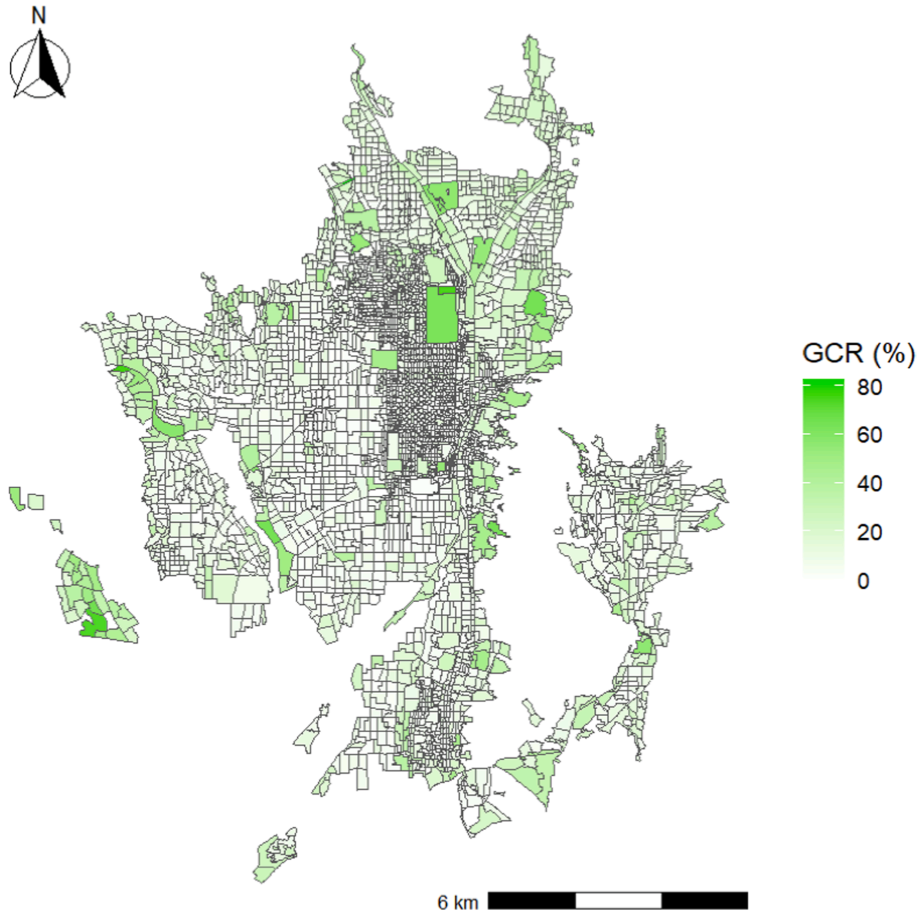

Fig. 2. Estimated green coverage rate by subregion in Kyoto City's Densely Inhabited District. *Note.* GCR: Green Coverage Rate. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the kappa coefficient and false negatives changed when the NDVI was between 0.35 and 0.4, we considered that there was a threshold where the kappa coefficient was maximized and both false positives and false negatives were fairly low when NDVI was between 0.40 and 0.45. Subsequently, we changed the NDVI threshold value in 0.01 increments between these values. When the NDVI was 0.42 and 0.43, the Kappa coefficient was maximized (=.95) and both false positives (=2.4 %) and false negatives (=2.5 %) were sufficiently low. To avoid overestimating the percentage of GCR, the NDVI = 0.43 was used as the threshold for plant greenery. Based on the above, geographic information system (GIS) data were generated to separate the green and nongreen areas in the Pleades image, with the portion of the target area in the image having an NDVI of 0.43 or higher being considered plant greenery. Thus, areas with an NDVI of lower than 0.43 were then considered to be non-plant green.

To calculate the percentage of the GCR for each subregion in the DID of Kyoto City, the following process was performed using QGIS: First, the area corresponding to the Pleiades image was extracted from the subregion polygons within the DID of Kyoto City obtained from e-stat. Topographic information obtained from the Geospatial Information Authority of Japan's [38] "Fundamental Geospatial Data Site" was overlaid, and the water system portion was deleted. Consequently, subregion polygons were created that encompassed the DID of Kyoto City and excluded water areas.

The percentage of the GCR in the polygons was calculated based on the percentage of the area corresponding to green vegetation and the remaining area in each subregion. Fig. 2 is a map which shows that the area around the Imperial Palace (the large rectangle in the upper center) has a high GCR, while the city center area in the south has a low GCR, which seems to be an estimation that corresponds to reality to some extent.

Green View Index estimated by Google Street View imagery and a machine learning model

To estimate the GVI in the target area as an indicator of the urban greenery in streetscape, a machine learning model was developed to analyze the GSV images. Because this study focused on greening as a part of the built environment, we targeted the landscape around buildings and estimated the GVI by referring to the procedure in Uchida et al.'s study [28]. First, the coordinates of the target in the GSV image acquisition were determined. The GIS data (as of January 2021) for buildings within the area encompassing Kyoto City were obtained from the Geospatial Information Authority of Japan [38]. QGIS 3.4.15 [39] was used to create a layer of center-of-gravity coordinates from the polygon data of the acquired buildings. This was combined with the layer of GIS data for the subregion used in the previous section. These center-of-gravity coordinates were referenced to obtain the GSV image metadata corresponding to each coordinate using the Street View Static API (API; application programming interface).[1] For each coordinate entered, this operation determined whether a GSV image was available in the

[1] The API did not allow users to acquire image data and its metadata together. In addition, there were monthly limits on the amount of image data that could be acquired. Therefore, when acquiring more than a hundred thousand GSV images, as in this case, the metadata was obtained first to limit the coordinates of the acquisition target, and then the image data was requested from the API.

Fig. 3. Example of Google Street View image taken from a single location in the target area.

vicinity, and if so, the metadata were output as the year and month in which the image was captured, the coordinates, and other information. Although this method does not always allow the collection of GSV images containing the front side of a building, it usually provides a landscape from a point on the street facing the building. Therefore, this is an efficient method to capture a typical view near a building from the available GSV images. The acquired metadata were linked to the original coordinates of the buildings, and points with no available GSV images or duplicate GSV images in each subregion were excluded. In addition, points where the coordinates of the GSV image were not included in the subregion to which the center-of-gravity of the reference building belonged were excluded. The remaining coordinate data, including 106,589 points, was then used as the reference source of coordinates (coordinate list) when acquiring GSV images through the API. The GSV images acquired ranged from January 2008 to December 2021, with October 2020 accounting for 23 % of the total. The programming language R 3.4.4 [40] and its package "sf" [41] were used for the metadata acquisition and subsequent processing.

Next, referring to the coordinate list, the GSV image data with each coordinate in the metadata were acquired using the Street View Static API. The parameters used to request data from the API were as follows: pixels were set to 640 × 640, which is the maximum value that can be obtained; the shooting location was outdoors; the vertical angle was horizontal; the horizontal angle was four orientations rotated by 90° from 0°, with the other parameters set to default. Four images were acquired at each location, forming a generally 360° panorama (Fig. 3 shows an example). Image data acquisition was conducted on three separate occasions from December 30, 2021 to February 4, 2022, and the acquired images were the latest available from the API at that time. Among the acquired images, those marked as acquisition failures or duplicates were excluded. Thus, 547,329 GSV images from 3,898 subregions were obtained and used in subsequent analyses. Descriptive statistics for the number of acquisitions per subregion were as follows: *Mean* = 140, *Median* = 80, *S.D.* = 156, *Maximum* = 2,160, *and Minimum* = 4.

A machine learning model was developed from a portion of the GSV images employed in the analysis, which was then used to analyze the remaining images for classification and to estimate the GVI in each subregion within the target area. To develop the machine learning model, the "chopped picture method" [42], which is a deep-learning-based method, was applied. Semantic segmentation is a well-known machine learning method for classifying amorphous objects such as plants, however, the chopped picture method allows us to reduce the effort required to annotate images [43]. We used this method to develop a new machine learning model specialized for estimating plant greenery in the GSV images acquired in this study. First, we stratified and extracted 1 % of the subregions per administrative district from the GSV images used in the analysis. Consequently, 39 subregions with 5,860 GSV images were separated as training data from the dataset for analysis. Subsequently, 173 images of plant greenery and 394 images of other elements were trimmed from the training data as supervised images that were positive and negative for plant greenery, respectively. Distant forests and mountains were not included in plant greenery. These images were then chopped into 32 × 32 pixel cells (50 % overlap with adjacent cells),[2] and 1,671 positive and 36,322 negative images were generated to train the model. Similar to the development of the machine learning model used by Uchida et al. [28], the schematic of the convolutional neural network architecture was built, as well as the model training setup and environment.[3] The validity of the model was evaluated based on human judgment. First, 0.5 % of the GSV images used for analysis was extracted from each subregion, and 2,336 images were selected for validation. In image classification using the chopped picture method, a 640 × 640 pixel GSV image was decomposed into 32 × 32 pixel cells, and each cell was assigned a binary value of positive or negative to determine whether the target object (plant greenery) was recognized. Therefore, the GSV images for the analysis were separated into square cells, forming a 20 × 20 grid. This grid was established for each GSV image for the validation test, and one of these cells was randomly selected as the verification target for each image. Two human judges independently made a binary judgment for each GSV image to determine whether the target cell contained plant greenery. The criterion for judgment was positive (Supplemental Fig. 1) if green vegetation occupied more than half of the cell, and negative (Supplemental Fig. 2) if it did not. However, distant forests and mountains were not included in the positive samples. Since the agreement between the judges was sufficiently high ($\kappa = 0.92$), the results of their judgments for each image were randomly adopted as the ground truth data. The evaluation indices were calculated by comparing the results of the model's judgments with correct human data and were found to be sufficiently valid: accuracy = 99 %, precision = 86 %, and recall = 99 %.

Finally, the model was used to calculate the percentage of plant greenery cells in each of the 541,469 GSV images in the 3,859 subregions targeted for analysis. For example, if 70 out of 400 cells in one image were classified as plant greenery, the positive rate for that image was approximately 18 % (see leftmost image in Fig. 4). The mean value was calculated for each subregion to estimate the GVI for that region. For example, as shown in Fig. 4, if a subregion had a total of four images to be identified, each with a positivity rate of 18 %, 40 %, 35 % and 32 %, the GVI of the area was estimated to be the average of these, approximately 31 % (as described below, subregions with fewer than 10

[2] The size of cells was set with reference to the settings in previous studies [42,43]. In the classification of plant greenery, larger cells resulted in rougher image segmentation, whereas smaller cells were less likely to capture plant texture features.

[3] For training the model, the Keras deep learning framework was applied using the Python 3.6.9 programming language [55] on Ubuntu 18.04. The batch size was set to 64; the Adam optimizer [56] was employed, and the learning rate was set to its initial value. The equipment used was a G-GEAR note N1573K-720/T with Intel Core i7-9750H processor, 16 GB RAM, and NVIDIA GeForce RTX2060. For the validation, 20% of the chopped images were used. They were trained in 30 epochs, and the training accuracy reached 99.9%.

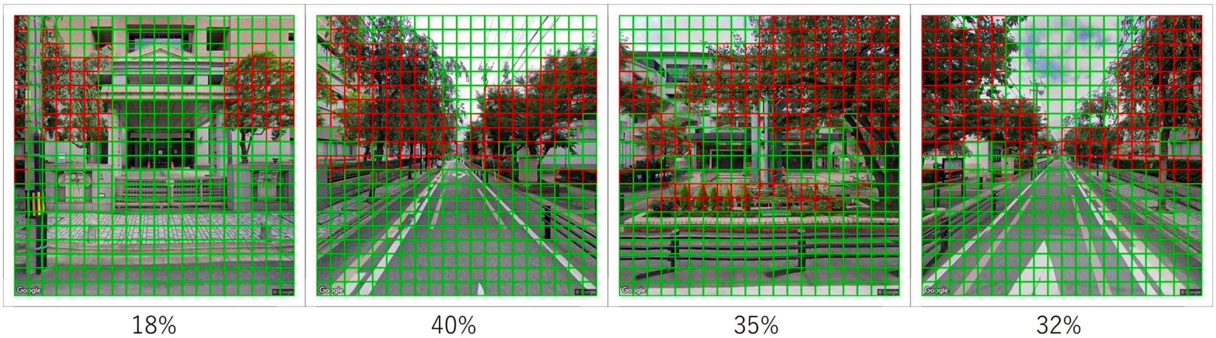

Fig. 4. Example of plant greenery detection by the machine learning model (percentages are positive rates).

GSV images to be classified were excluded from the analysis).

For the entire targeted subregion, the GVI estimates for the mean, median, standard deviation, and maximum were 4.9 %, 4.0 %, 4.0 %, 50.3 %, and 0.0 %, respectively. Fig. 5 shows the estimated GVI for the entire target area. This shows that the GVI was high near the Imperial Palace (a large rectangle near the upper center) and the northern mountains (the upper area), and low in the city center area (tiny cells near the center), indicating that the estimated results sufficiently reflected reality. The target subregions were encompassed by the DID, and in the training process and validation of the model, forests and mountains were not considered plant greenery when they were at a distance. Therefore, the estimated GVI was primarily dependent on vegetation in the built environment.

Demographic items from the census

When exploring the relationship between urban greening and social capital, it was necessary to consider the demographic situation as one of the related social factors (cf., [19,21]). For example, a typical trend can be predicted, namely, that subregions with a lower proportion of rental properties and single-person households are more likely to have house plantings facing the street. Such social factors were considered as candidate control variables in the multivariate models exploring the relationship between urban greening and social capital. As for demographic items, the Japanese Government's census was available, in which statistical information on the age, gender and household composition of the population, as well as housing patterns were compiled for each subregion in absolute values. All items of the acquired

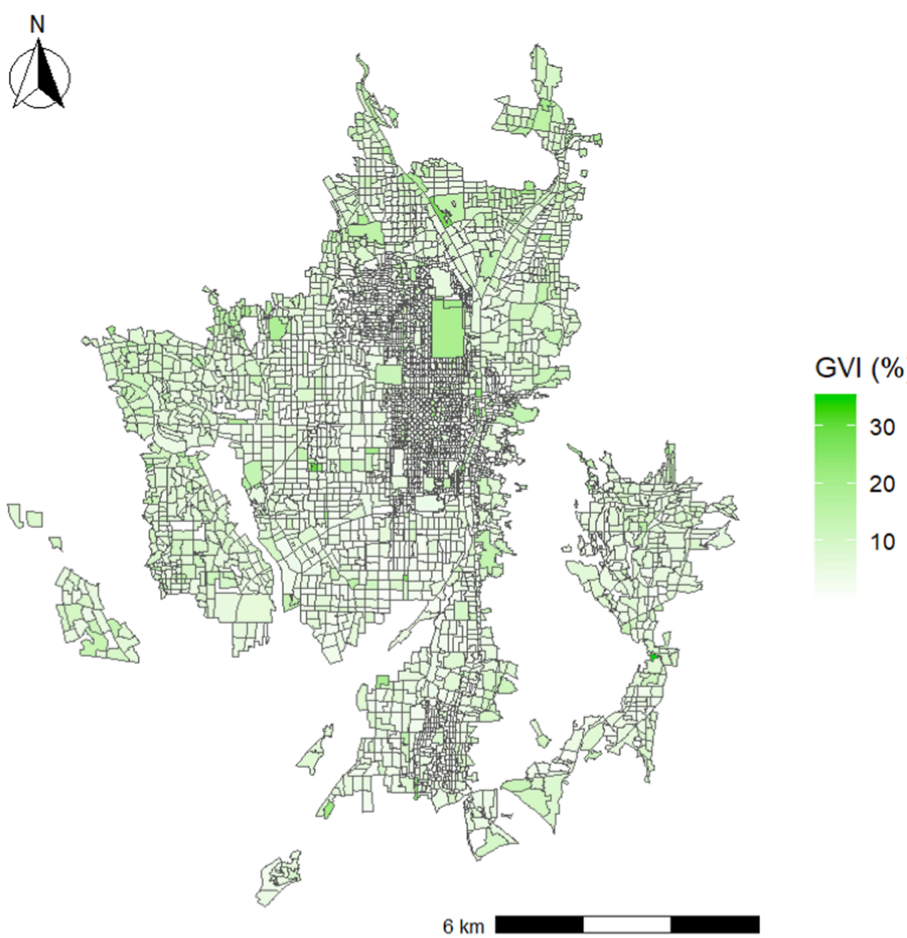

Fig. 5. Estimated Green View Index per subregion in the target area *Note*. GVI: Green View Index. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

data, excluding duplicates, unclassified categories and total age, were converted into proportions and used as candidate explanatory variables.

First, we obtained the original data from the 2015 Census, which is available online from Kyoto City [31] and classified as "subregional data (by census tract and town)" (covering 5,234 subregions in Kyoto City). Subsequently, items with duplicate data, "other" or "unknown" age groupings by five-year age groups, and total age were excluded from the variables used to avoid difficulties in statistical analysis and interpretation. For the absolute values of total population and total number of households, average age (overall and male/female), and average number of persons per household for the various categories (28 items in total), the original data were used in the analysis. The remaining variables were converted into ratios using the total population as the denominator for the various categories of population and the total number of households for the various categories of number of households (102 items in total). The variables with more than half the missing values (22 items) and one of the combinations of variables with correlation coefficients above 0.999 in absolute value (5 items) were excluded.[4] A total of 103 items used in the statistical analysis are shown in Supplemental Table 1 as descriptive statistics by subregion.[5]

Urban planning items from use district categories

As with the demographic situation, zoning in urban planning needs to be considered as one of the related social factors in the exploration of the relationship between urban greening and social capital. Because the amount of plant greenery was supposed to be typically influenced by zoning categories such as residential and commercial, the area ratio of those categories was considered a candidate for control variables. As items for considering urban planning in the target areas, the percentage of "use districts" in each subregion was calculated. Use districts are defined in Chapter II, Article 8 (Regional Districts) of the City Planning Act (Act No. 100 of 1968, promulgated on June 15, 1968), and regulations are set for buildings and facilities that can be constructed and operated in each of these zones. In governmental urban planning in Japan, this regulation is implemented to group land uses (e.g., residential, commercial and industrial), regionally under the same classification for efficient space utilization. Therefore, the ratio of each use district category can be seen as an urban planning feature of each subregion. However, three items in the category for which no applicable subregion existed were excluded. Descriptions of each category used for the analysis are provided in Supplemental Table 1.

The following procedures were used to calculate the area percentages of the zoning classifications for each subregion in the target areas. First, three types of GIS data publicly available on the Internet from government agencies were obtained from the National Statistics Center [44]. GIS data were obtained from the National Statistics Office (e-Stat) for the boundaries of the subregions in the census of all Kyoto City administrative districts (released in 2018) and the boundaries of the DID for the entire Kyoto Prefecture (released in 2017). In addition, map information data for the boundaries of use districts (released in 2019) for the entire Kyoto Prefecture was obtained from digital national land information from the Ministry of Land, Infrastructure, Transport and Tourism [45]. Subsequently, the three acquired GIS data were combined using sf package on R language as the process in the estimation of GVI. The subregions encompassing the DID boundaries of the entire Kyoto Prefecture were extracted from the subregion boundaries in the census of all Kyoto City administrative districts. The layer was further divided into subregional units, each of which created a layer that cut through the boundaries of the Kyoto Prefecture-wide zoning district. Consequently, a zoning layer was created for each subregion encompassed by the DID in Kyoto City with the boundaries of each category. Finally, the total area of each district within these layers was divided by the total area of the subregion to which they belonged, and the percentage of the area of each zoning district within the subject area was calculated. The percentages of areas that were not classified into any category of use districts were calculated as "non-use districts." However, the case where a subregion had any enclave was excluded from the following analysis because it lacked geographic integration when viewed as a neighborhood, making it difficult to interpret the percentage of green space within the subregion. Consequently, 3,989 subregions remained valid for analysis.

Items of residents' feelings toward their neighborhood from the resident survey

As an indicator of residents' feelings toward their neighborhood, including social capital, in the target area, we used the survey on neighborhood associations (hereinafter referred to as the 'resident survey') conducted by Kyoto City for analysis. The survey was conducted in Kyoto City to understand the current situation and issues of neighborhood associations regarding policymaking to support local community building [46]. Permission to use the data for academic research was obtained with the cooperation of the officials in charge of Kyoto City's greening policies. Kyoto City asked those responsible for the neighborhood associations in each subregion to respond to the survey because they were residents who had frequent daily contact with local residents and a holistic perspective on their subregion through the activities of their associations. Therefore, though not a random sampling, the responses could be expected to be fairly representative with regard to the situation of each subregion and the social relations of its residents. A total of 6,477 questionnaires were distributed and 3,345 (51.6 %) were collected through The survey was conducted from September 6 to December 31, 2018 [46].

The questionnaire contained 58 items, including basic information about the neighborhood association to which the respondent belonged (name of the administrative and school district, the association, the subregion, and the number of member households), additional questions about membership status (three items), and association management (one item).

Of the above, 45 items in five categories were employed in the analysis, which asked about conditions within the community, residents' relationships, and community participation using a five-point Likert scale. The internal consistency was evaluated by principal component analysis (PCA) for each of the categories originally set up on the questionnaire, and then each was scored as an average to form a single scale: undesirable conditions in the neighborhood ($\alpha = 0.71$, $\omega = 0.81$); interaction between neighbors ($\alpha = 0.87$, $\omega = 0.90$); security concerns in the neighborhood ($\alpha = 0.89$, $\omega = 0.92$); relationships of the neighbors ($\alpha = 0.81$, $\omega = 0.85$); and community participation ($\alpha = 0.92$, $\omega = 0.94$). The relationship between residents and community participation was treated as an item related to social capital. The specific items are shown in Supplemental Table 2.

[4] Items whose categories were nearly equal, albeit with tiny deviations, such as the combination of "total" and "relatives only" in "general household with person(s) under 6 years old", were detected. In addition, complemental combinations, such as the rates of "general households living in a house" and "general households living in a non-residential building" in "number of general households" were also detected. Meanwhile, there were seven pairs of census item combinations with correlation coefficients with absolute values between 0.990 and 0.999. However, those combinations were pairs by categories that were either inclusively related but not nearly equal (e.g., rates of "only married couple" and "nuclear family" in "number of household") or not categorically fully complementary (e.g., rates of "number of general household (one person)" and "number of household (only relatives)"). Hence, they were left as candidates for variable selection by the elastic net (described below).

[5] There were two categories of household in the census: "general" and "principal household". Meanwhile "General household" meant all units of person(s) who shared a livelihood, whether they were living with another household or not, "principal household" meant the representative household of a house.

Three of the five variables created—interaction between neighbors, relationships of the neighbors, and community participation—were regarded social networks as elements of social capital [7]. Similar examples of subjective report items being treated as elements of social capital seem common to many previous studies (e.g., [18–21,24,27]).

Names of the administrative district, the school district ("moto-gakku"), and the subregion in the basic information responses were used to link the variables to the other data. However, cases in which the respondent's neighborhood association did not uniquely correspond to one of the subregions were excluded from the analysis. Thus, 1,047 subregion responses (one from each subregion) to the resident survey were combined with the demographic, zoning, and greening indicators obtained through the above process.

Statistical analysis

To explore the association between greening, social capital, and other social factors in the target areas, we estimated models of the items through a data-driven approach, which had statistical explanatory power for each greening evaluation indicator from the census, area percentages of zoning classifications, and resident survey scores. When a large number of candidate explanatory variables are analyzed, as in the present study (120 items), methods such as classical stepwise regression are computationally expensive and may omit the optimal model. To deal with this, least absolute shrinkage and selection operator (LASSO) regression is a method for variable selection and model estimation using regularization [47]. However, it has been pointed out that the regularization method in LASSO regression alone can destabilize the estimation of models for variables containing items that are strongly correlated with each other, as in the present data (i.e., some census items). Therefore, the elastic net—an advanced method of LASSO regression that combines two types of regularization methods to achieve stable variable selection and model estimation even when including highly correlated items as candidate explanatory variables—was implemented [48]. In this analysis, variables that might have explanatory power for the target variables were suggested, and overfitting of the model was avoided by regularization in the estimation of coefficients in the linear regression models. Before conducting the elastic net, nine subregions with fewer than 10 GSV images were excluded from the overall analysis because they did not have a sufficient number of images to estimate the GVI. As for the target variables, GCR and GVI, violations of normality were detected in the Lilliefors test ($ps < 0.001$; histograms are shown in Supplemental Figs. 3 and 4); therefore, each was log-transformed for the analysis. Supplemental Figs. 5 and 6 show the histograms of the log-transformed GCR and GVI. The final variables were the two target variables and 120 explanatory variables, totaling 121 for each model. Fig. 6 describes the overview of the analysis process.

The programming language R 3.4.4 [40] and its package, glmnet [49], were used to implement the analysis. The optimal value of λ was determined by cross-validation, and the corresponding coefficients were output. We compared the corresponding standardized coefficients for the regression models with GCR and GVI as objective variables (the results of the regression coefficients are presented in the Results section). Supplemental Figs. 7 and 8 show the results of the cross-validation. Supplemental Fig. 9 and 10 show the estimated coefficients according to log(λ). Those with the optimal λ are given at the vertical dotted line.

Results

Descriptive statistics

Supplemental Table 3 shows the descriptive statistics of the explanatory variables, including the target variables, for the 1,038 subregions included in the analysis. There were variations in the sample size of valid data in the four variable categories of the evaluation of greening, census, use districts and resident survey. The categories for which data were available for all target subregions were the evaluation of greening and use districts, related to geographical data. Meanwhile, the valid responses for the resident survey items ranged from 866 to 974 with a mean of 925. In addition, 103 census items had a higher available sample size variance (ranging from 531 to 1029, with a mean of 926), but 72 % of the items had more than 90 % of available samples.

Results of the elastic net

The results of the elastic net identified 28 out of 120 items in the two models with explanatory power for GCR or GVI as a horizontal and

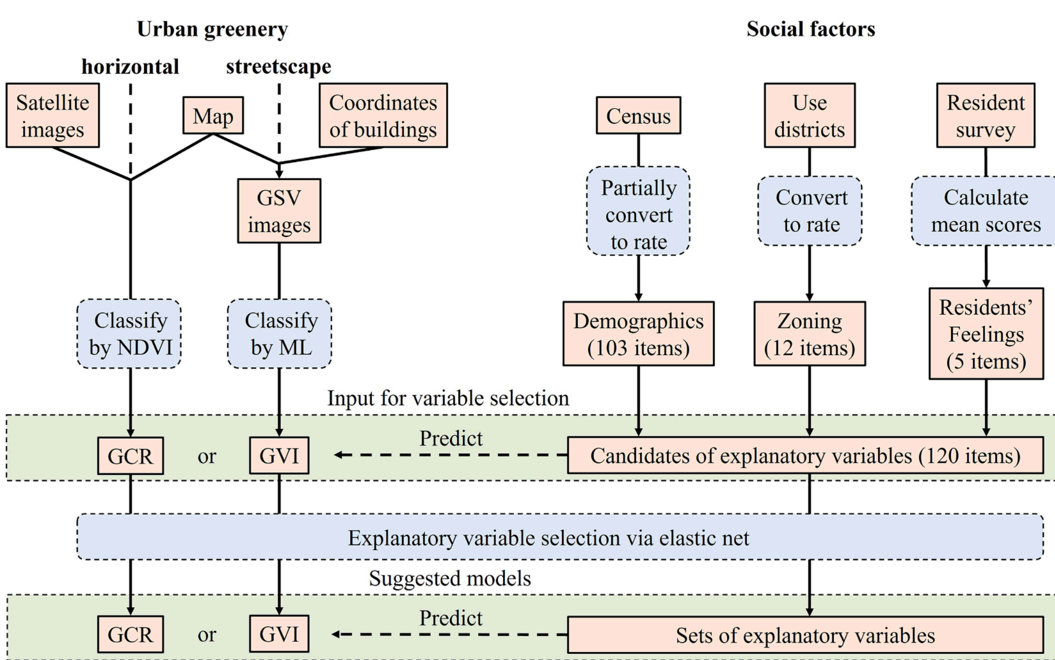

Fig. 6. Overview of the analysis *Note*. GCR: green coverage rate, GSV: Google Street View, GVI: Green View Index, ML: machine learning, NDVI: Normalized Difference Vegetation Index. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

streetscape greenery indicator, respectively. Table 1 lists the items and their standardized regression coefficients (variables for which the corresponding coefficients were zero, namely those that were not selected, were excluded).

First, 16 out of 120 items with explanatory power were selected as variables in the model, with GCR as the objective variable. For the census items, 10 of the 103 variables were selected. Seven items were found to have positive coefficients: number of households, headcount per household (apartment), headcount per household (issued house), female population over 85 years old (rate), number of principal household (apartment) (rate), general household with person(s) under 6 years old (total) (rate), and general household with person(s) under 18 years old (three generations) (rate). However, three items were selected with negative coefficients: average age of males, headcount per household (nuclear family), and general household headcount (general households living in a house). Next, for the item on use districts, six items out of the 12 variables were selected. Three items, category 1 low-rise exclusive residential districts, category 2 residential districts, and not use district, were found to have positive coefficients. However, three items, commercial district, quasi-industrial district, and industrial districts were selected with negative coefficients. Finally, no items were selected from the five scales of the resident surveys.

For the GVI, 20 out of 120 items were selected as variables with explanatory power. Of the 107 variables, 12 were selected as census items. Eight items with positive coefficients were selected: average age of females, headcount per household (3–5 stories of the building), headcount per household (issued house), headcount per household (containing non-relatives), female population over 85 years old (rate), general household headcount (only married couple) (rate), number of general household (three generations) (rate), and general household with person(s) under 6 years old (total) (rate). However, four items were selected with negative coefficients: average age of males, female population between 15–64 years old (rate), general household headcount (general households living in a house) (rate), and number of general households (rented room) (rate). Seven of the twelve use variables were selected for use districts. Four items were found to have positive coefficients: category 1 low-rise exclusive residential district, category 1 medium-to-high-rise exclusive residential district, category 2 medium-to-high-rise exclusive residential district, and not use district. Three items were selected with negative coefficients: quasi-residential district, neighborhood commercial district, and quasi-industrial district. Finally, interaction between neighbors was selected with a negative coefficient in the five scales of the resident survey.

Synthesizing the results of both models, first, among the census items related to demographics, the combination of gender and age (e.g., the percentage of the female population aged over 85 years) showed explanatory power for either or both GCR and GVI. For items related to households, the composition of households and type of residence (e.g., only married couple and rented room) showed explanatory power. Second, the coefficients for use district categories, which have less restrictive commercial and industrial zoning than the residential zones, were negative for either or both green coverage and green visibility, such as quasi-residential districts, commercial districts, and quasi-industrial districts. In contrast, the coefficients for the four exclusive residential district categories and not use district were positive. Lastly, regarding the items of the resident survey, the interaction between neighbors showed a negative coefficient for GVI, and no items were selected with explanatory power for GCR.

Table 1
Variables selected in the elastic net.

Variables	Standardized coefficient	
	GCR	GVI
Demographics (census)		
Average age of males	−0.128	−0.127
Average age of females	–	0.056
Number of households	0.056	–
Headcount per household (apartment)	0.038	–
Headcount per household (3–5 stories of the building)	–	0.009
Headcount per household (issued house)	0.003	0.002
Headcount per household (nuclear family)	−0.296	–
Headcount per household (containing non-relatives)	–	0.023
Female population of 15–64 years old	–	−0.021
Female population of 85 years old	0.140	0.016
General household headcount (general households living in a house)	−0.111	−0.013
General household headcount (only married couple)	–	0.139
Number of principal household (apartment)	0.107	–
Number of general household (rented room)	–	−0.153
Number of general household (three generations)	–	0.074
General household with person(s) under 6 years old (total)	0.197	0.012
General household with person(s) under 18 years old (three generations)	0.015	–
Zoning (use districts)		
Category 1 low-rise exclusive residential districts	0.113	0.050
Category 1 medium-to-high-rise exclusive residential districts	–	0.027
Category 2 medium-to-high-rise exclusive residential districts	–	0.011
Category 2 residential districts	0.005	–
Quasi-residential districts	–	−0.037
Neighborhood commercial districts	–	−0.072
Commercial districts	−0.170	–
Quasi-industrial districts	−0.340	−0.129
Industrial districts	−0.059	–
Not use district	0.168	0.041
Residents' feelings toward their neighborhood (resident survey)		
Interaction between neighbors	–	−0.010
(Intercept)	1.493	−3.134

Note: GVI = Green View Index, GCR = green coverage rate.

Discussion

To understand the mutual interaction between urban greening and social capital while concerning different aspects of greenery and the contextual elements of the area, this study used neighborhoods as the unit of analysis and estimated the explanatory power of population composition, area classification in urban planning, and residents' feelings toward their neighborhoods for two types of greening evaluation indicators to compare. These two indicators were GCR for the horizontal urban greening and GVI for the urban greening in streetscape, respectively. The target area was an urban area in Kyoto City, Japan, which has a long tradition of landscape policies and neighborhood associations.

Findings

In this study, the elastic net regression was conducted to estimate the associations between GCR or GVI and 120 explanatory variables for 1,038 subregions within the DID of Kyoto City. The results indicated 16 variables with explanatory power for GCR and 20 variables for GVI. Notably, because the random numbers were used in the process of elastic net, subtle variations could appear in the variable selection. The following discussion is based on the premise that the effect of it is insufficient to change the core conclusions.

Through the two models, the most notable result was found in the patterns of variable selection of the resident survey items: an item, interaction between neighbors was selected only in the GVI model as it had negative explanatory power. This explanatory variable suggests the presence or absence of social capital, especially social networks, within a subregion. These results seem to contrast with the empirical results in previous studies (e.g., [26,27,30]). This gap can be explained by the difference in perspectives between these studies and this study. Concerning both results, the elastic net models contained the variables of demographics and zoning, which were not necessarily considered in the analysis in prior studies. As for the negative correlation between GVI and social capital, whereas prior studies evaluated greenery primarily as an element that increased walkability and local social interaction, such as parks, the facet of greenery as a streetscape element, such as roadside trees and house plants, was a focus here. This also relates to the difference in the results of two models of GVI and GCR, because GVI is closer to pedestrians' awareness of streetscape greenery and thus has a more direct connection to social capital than GCR, as indicated by Samsudin et al. [27]. Moreover, cultural contexts can also change the role of greening in streetscapes. Liu et al. [50] showed that competitive situations could make neighbors more vigilant of each other in collectivistic regions, such as Japan, than individualistic regions. As discussed by Uchida et al. [28] in farm and fishing villages, planting in the target area might have functioned as a conspicuous consumption by which economic competition is visualized within the subregion, contributing to a vicious cycle of greening and social capital. In this scenario, GVI and the social capital item can have a negative correlation, as the result showed.

Second, the patterns of selected variables of demographics in both models imply that areas with a relative abundance of plant greenery may be preferred by residents with certain attributes and living arrangements, and that such factors may be associated with residents planting plants in their homes. Interestingly, of the 17 demographic variables selected in both models, only five were common. One reason for this could be that small-scale plantings (e.g., flowerpots, flowerbeds, and hedges), which are difficult to detect from the sky but contribute to GVI, can be influenced by residents' leisure time availability and the presence of a garden, whereas trees and fields contribute to both indicators.

Lastly, the patterns of the selected variables of zoning in the models showed a reasonable correspondence between urban planning and greenery, though the sets of the selected variables were not totally same between the models. In general, residential subregions have relatively more plants and parks, whereas the opposite is true for commercial and industrial subregions, and the subregions without designation of use districts are far from the city center area. Therefore, the amount of vegetation appears to reflect the extent of urban planning. The difference of the selected variables in the two models might be explained by the types of planting that each indicator of greening (i.e., GCR and GVI) is more likely to capture, as mentioned above.

Implications

The study findings suggest the need to consider aspects of greenery and the local context in understanding the mutual interaction between greening and social capital. Whereas horizontal greenery would need to be focused on to discuss benefits of urban greening in terms of mitigating extremely high temperatures and physical and mental health, streetscape greenery would be a rather important greenery aspect to contemplate the perspective of community building in urban greening. Additionally, as Hong et al. [19] also indicated, perceived types of plant greenery would differently influence its effect on social capital; some categories of greening that visualize economic competition among neighbors can have a negative relationship with social capital. The meaning and function of the amount of streetscape greenery, as measured by the GVI, would differ depending on the local context, which is shaped by the demographics, zoning, and the dominant cultural mindset. As these trends are revealed and theorized through methodological development and the accumulation of knowledge, understanding of the interaction between greening and social capital will become sophisticated. In turn, this may contribute to effective greening policies and expand their role in urban planning by connecting them to community buildings. Furthermore, this may provide practical implications in the discourse of building social capital.

Limitations and future studies

This study has a few limitations. First, while the census data and data for use districts were generally comprehensive and consistent in terms of areas and dates, the community association survey and GSV images were not the same. Available data from the community association survey were limited to samples that unambiguously corresponded to census tracts. Furthermore, as the respondent was the head of each community association or neighborhood association, the analysis did not necessarily represent public opinion of the targeted subregions. This makes it impossible to consider the hierarchical nature of the data in a multilevel analysis. However, there are only a limited number of surveys of residents who have received broad responses from the subregions of Kyoto City's urban area, other than the data employed in this study. The limitations of GSV images include the fact that coverage varied by subregion (potential for systematic errors), the seasons in which the images were taken were not uniform, and there was a maximum range of approximately 14 years in the timing of the images (cf., [51]). This is a common limitation of similar studies using GSV image datasets. Additionally, regional trends in the socio-economic status (SES) and health status of residents are also potential explanatory variables to be considered. However, currently, there do not seem to be any data available in Japan that correspond to the units of the present analysis. The resident survey used in this study did not include enough items relating to the SES and health status of the respondents. In the future, publicly available data is expected to be developed and the feasibility of using data such as land prices needs to be examined.

Second, regarding the validity of the machine learning model, the precision was relatively low, indicating that false positives may occur slightly more often than false negatives. However, this bias was not large enough to undermine the utility of the model. As a result, the GVI estimated in this study had a certain degree of validity, not only because of its correspondence with the actual streetscape identified in Fig. 5, but also because the analysis showed a valid correspondence with the zoning classification of urban planning. The limitations regarding the use of GSV images are the same as those mentioned by Uchida et al. [28]; thus, it is important to consider data sources other than GSV.

Third, variable selection via elastic net using R package glmnet [49] depends on the choice of validation data in the cross-validation, which can cause subtle differences in the results with it. Additionally, it has been pointed out that p-values of the coefficients of the multiple regression models with variables selected by methods such as elastic net can be inappropriate [52]. Therefore, in this study, the discussion was limited to tendencies in the combination of selected variables and based on the positivity or negativity of the coefficients, rather than evaluating the coefficients of the explanatory variables as in a multiple regression model using the ordinary least squares regression. Furthermore, the geographical relationships between target areas remain an issue to be considered in the analysis. Methods to consider spatial autocorrelation in analyses have traditionally been discussed, while advances in elastic net for this purpose have been explored (e.g., [53,54]). Thus, future research is expected to develop more detailed discussions based on the findings of this study by implementing available solutions to this technical challenge. Fourth, the representativeness of the targeted areas in this study to other urban areas is unknown, and similar surveys in other target areas are required to examine the generalizability of the findings.

Finally, regarding the limitations of the analytical approach, the present study results only suggest variables that may be associated with GRC and GVI and do not provide convincing evidence for a causal relationship. Based on the mutual interaction between urban greening and social capital suggested in previous studies (e.g., [17,22]), future studies that consider a time series are expected to address this point.

Conclusion

This study explored relationships between two aspects of greenery and social capital in an urban area, considering demographics and zoning. In contrast to previous studies, the results showed that streetscape greenery, evaluated by combining GSV images and a machine learning model, had a negative correlation with social capital, while horizontal green coverage evaluated using NDVI had no correlation with it. This suggests the necessity to contemplate greenery aspects and the local context in understanding the interaction between urban greening and social capital. Future research on this topic is expected to expand the scope of effective implementation of urban greening and contribute to the theory and practice of building social capital.

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CRediT authorship contribution statement

Atsuhiko Uchida: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Taishin Kameoka:** Writing – review & editing, Validation, Software, Methodology. **Takeshi Ise:** Writing – review & editing, Supervision, Software, Resources, Funding acquisition. **Hidetoshi Matsui:** Writing – review & editing, Software, Methodology. **Yukiko Uchida:** Writing – review & editing, Supervision.

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.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cacint.2024.100160.

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