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Research Paper

The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning

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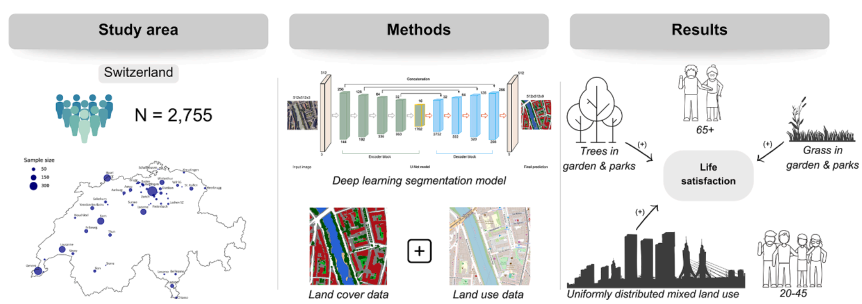
HIGHLIGHTS

- With regard to life satisfaction in Switzerland, only residents aged above 65 appear to benefit from urban greenery.
- Trees and grass situated in parks and gardens are the main drivers of this positive relationship.
- A greater land use mix is positively associated with life satisfaction solely for younger individuals.

GRAPHICAL ABSTRACT



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ABSTRACT

Most Europeans reside in urban areas. Due to anthropogenic air and noise pollution, as well as crowdedness, urban residents experience lower levels of well-being and life satisfaction. The literature indicates that greening urban spaces can help to mitigate these negative effects on life satisfaction. This study employs a deep learning approach in conjunction with high-resolution satellite imagery and land use data to obtain the distribution of different green space types in the residents' neighborhood and examine their effect on life satisfaction. Furthermore, the study sheds light on the indeterminate relationship between mixed urban land use and life satisfaction. In both cases, the study considers heterogeneous age group effects. The empirical results reveal that in Switzerland, (1) solely older residents' life satisfaction is positively affected by a greener neighborhood; (2) trees and grass located in gardens and parks are the primary drivers of this effect; and (3) the positive association between land use mixture and life satisfaction decreases with age, with no association found for older individuals. These findings provide practical implications for future city planning in Switzerland and other European countries and highlight the importance of considering the neighborhood's age distribution in this process to maximize the positive impact of urban greenery and mixed land use on residents' life satisfaction.

1. Introduction

The global rise in population has led to a substantial increase in the urban population. In 1960, only 34 % of the world's population resided in cities, whereas by 2022, this number had almost doubled to 57 %. The World Bank (2023) projects that this trend will continue, with an estimated urban population of 70 % by 2050. The European Union has already reached this level, as evidenced by the fact that 75 % of its population resided in urbanized areas in 2022. Studies suggest that urban areas have become the epicenters of mental distress (Dye, 2008;

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Sundquist, Frank, & Sundquist, 2004) and that this is partly due to the detachment from the natural environments in which humans evolved (Kaplan & Kaplan, 1989; Wilson, 1984). Due to the growing population in urban areas and the negative effects of these areas on humans, urban planning has become increasingly vital in maintaining residents' mental and physical health. This is acknowledged by the European Commission (2020) and its EU Biodiversity Strategy 2030, which aims to promote investments in green infrastructure as well as the systematic integration of healthy ecosystems, green infrastructure, and nature-based solutions into urban planning. These efforts are supported by a substantial body of literature, which suggests that people living in greener urban environments tend to have better health and higher levels of well-being (e.g., see Hartig, Mitchell, De Vries, & Frumkin, 2014; Reyes-Riveros et al., 2021; Yang et al., 2021 for reviews). However, limited space in cities, along with a range of stakeholders with divergent land usage objectives, complicates urban planning decisions and puts strain on the limited green urban areas.

Besides various other urban planning objectives, such as reducing air and water pollution, traffic noise, and congestion, building human-oriented smart cities has been increasingly promoted in the past. Consequently, they have become an essential dimension of planning livable cities alongside greening urban landscapes. As advocated by the new urbanism movement (Garde, 2020), this concept promotes neighborhoods that comprise a high mix of different land use classes. The proximity of residential areas to workplaces, grocery stores, public transportation, commercial, educational, health, leisure, sports, and cultural facilities creates a multitude of amenities, reduces the necessity for residents to commute, and tends to result in a higher satisfaction among residents. (Dong & Qin, 2017; Mouratidis, 2018).

Nowadays, urban greenery and mixed land use neighborhoods play a major role in designing livable and smart growing cities. While many studies have examined the relationship between urban greenery and well-being, there is little consensus about measuring urban green spaces. Although multiple approaches have been used to do so, a thorough operationalization of green spaces is inevitable to correctly estimate its effect on residents' well-being. Earlier studies (Ambrey & Fleming, 2014; Bertram & Rehdanz, 2015; Krekel, Kolbe, & Wüstemann, 2016; White, Alcock, Wheeler, & Depledge, 2013) relied on land usage data, whereas more recent studies (Kwon et al., 2021; Taylor, Hahs, & Hochuli, 2018; Tsurumi, Imauji, & Managi, 2018) shifted to using remote sensing imagery and measured green space by calculating the Normalized Difference Vegetation Index (NDVI), which measures the amount and vigor of vegetation. The emergence of deep learning and the facilitated access to street-level imagery led to a rising number of studies using street-level imagery in combination with segmentation models to quantify urban greenness (e.g., see Seiferling, Naik, Ratti, & Proulx, 2017; Stubbings, Peskett, Rowe, & Arribas-Bel, 2019) and some of them used it to examine the relationship with residents' life satisfaction (Wu, Chen, Yun, Wang, & Gong, 2022; Wu, Tan, Wang, & Chen, 2023). I argue that the mentioned approaches have significant limitations and suggest a procedure that combines deep learning with publicly available high-resolution satellite images and land use data. This produces a very detailed and spatially fine-grained measurement of the distribution of urban green space types.

The contribution of the article is fourfold. First, it contributes to the field of urban planning by presenting a novel measurement of urban greenery. It enables scholars and urban planners to select from an extensive set of green space types and use them in examinations. Second, it contributes to the literature by using the proposed measurement and disentangling the association between urban greenery and residents' life satisfaction in a case study in Switzerland, by examining nine different green space types in the analysis. As the suggested approach allows it to easily obtain the proportion of green space types in any selected area, all densely populated areas in Switzerland, a country where 2/3 of its population live in urbanized areas, but comprehensive evidence is lacking, are analyzed. Third, some studies suggest that the preferences for urban greenery components differ by age. They showed that younger individuals value green spaces more if they can be used for physical activities or meeting others, whereas older people value them more if they can relax, stay with children, and enjoy nature (Chiesura, 2004; Kabisch & Haase, 2014). The article acknowledges these findings by considering heterogeneous age subgroup effects in the association between urban greenery and life satisfaction. The provided evidence indicates to urban planners which types of green spaces are most promising to be promoted in a neighborhood, given its age distribution, to enhance residents' life satisfaction. Fourth, while human-oriented smart neighborhoods are an essential pillar of a livable and sustainable city, only a limited number of studies examine the relationship between mixed land use neighborhoods and residents' life satisfaction. This study aims to contribute further evidence on this relationship.

2. Literature review

2.1. Life satisfaction and urban green space

Self-reported subjective well-being is a comprehensive tool to assess the impact of green spaces on respondents' lives and is used in a growing number of studies as a proxy for well-being (e.g., see Bertram & Rehdanz, 2015; MacKerron & Mourato, 2013; Tsurumi, Imauji, & Managi, 2018; White et al., 2013). Since it indicates overall satisfaction with one's life, it is often considered to be synonymous with happiness or life satisfaction (Diener, Oishi, & Lucas, 2003).

Previous research has identified three main mechanisms with regard to how urban greenery is linked to well-being. First, green spaces result in environmental benefits such as reductions of anthropogenic noise (Gaudon, McTavish, Hamberg, Cray, & Murphy, 2022), air pollution (Nowak, Hirabayashi, Doyle, McGovern, & Pasher, 2018; Selmi et al., 2016), and heat islands (Aram, Higueras García, Solgi, & Mansournia, 2019) which contribute to a better life experience and better well-being. Second, public green spaces such as parks or recreation areas encourage residents to pursue physical activities and social interactions (Akpinar, 2016). Evidence from Hong Kong suggests that even street greenery fosters physical activities and cycling behavior (Lu, 2019; Lu, Yang, Sun, & Gou, 2019). This can lead to better health and higher levels of well-being. Third, natural environments can help with relaxation by providing a mental escape and thereby reducing mental distress, as evidenced by studies in Australia (Shanahan et al., 2016), England (White et al., 2013), and the Netherlands (De Vries, Verheij, Groenewegen, & Spreeuwenberg, 2003; Maas et al., 2009; Van Den Berg, Maas, Verheij, & Groenewegen, 2010).

Existing research mainly examines the relationship between availability (e.g., see Ambrey & Fleming, 2014; Bertram & Rehdanz, 2015; Kley & Dovbishchuk, 2021; Krekel et al., 2016; White et al., 2013; Wu, Tan, Wang, & Chen, 2023), or proximity (e.g., see Bertram & Rehdanz, 2015; Fleming, Manning, & Ambrey, 2016; Krekel et al., 2016; Wu, Chen, Yun, Wang, & Gong, 2022) of green space and residents' subjective well-being in a predefined buffer zone created around the residents' home. The majority of these studies find a positive relationship between green space and subjective well-being in the urban context. However, in Beijing, a number of studies found no evidence that the distance to urban parks is associated with higher life satisfaction (Ma, Dong, Chen, & Zhang, 2018; Wu et al., 2022), and an analysis of 33 cities located in six countries did not reveal any association between green land cover and residents' subjective well-being (Brown, Oueslati, & Silva, 2016).

Previous research has applied different approaches to measure urban greenery. However, I argue that they suffer from significant limitations. Bertram and Rehdanz (2015), Olsen et al. (2019), and Krekel et al. (2016) used the European Urban Atlas, which contains land usage data for all European urbanized areas with more than 50,000 inhabitants and with a minimum mapping unit size of 0.25 ha. It has the disadvantage that data on densely populated areas with less than 50,000 inhabitants are not available, and due to the moderate resolution, the data does not contain information on private or small green areas such as gardens, playgrounds, or tree canopies. However, it is plausible that these small green spaces create amenities and can influence well-being positively. Hence, they are an essential part of the analysis and should not be neglected. Assessing green cover using the NDVI is simple; however, it comes at the cost that the input images need to contain a near-infrared band. Most studies (e.g., Kwon et al., 2021; Taylor et al., 2018) use Landsat 8 satellite imagery because it includes all the necessary color bands for calculating the NDVI. However, the data is only available at a 30-meter per pixel resolution. Li, Saphores, and Gillespie (2015) provided evidence that the resolution matters and the economic benefits of tree canopy cover and grass measured with medium- (30 m) and high- (0.6 m) resolution satellite images only correlate weakly. Tsurumi et al. (2018) expanded the literature by utilizing QuickBird satellite images to assess the NDVI in high resolution (0.61 m per pixel). They combined the NDVI score of an image pixel with the land use type it is located in, e.g., residential area, park, or roadside. This measure is subsequently used to examine the association between green spaces and well-being in Tokyo. They found that only urban green in residential areas and along roads was positively associated with well-being, but not green space in parks or public facilities, which is surprising. The main limitation of using the NDVI to assess urban green spaces is that it is measured at a low resolution, which can be overcome by using QuickBird images. However, the mission ended in 2015, and no recent high-resolution data is available. In addition, the NDVI measures the amount and vigor of plants but cannot differentiate between different vegetation types, such as grass, meadows, or trees. This issue can only be partly addressed by adding information on the land use type in which an image pixel is located. For instance, it cannot be distinguished if a pixel with a high NDVI score inside a park belongs to a tree or a grass field.

However, a strain of literature indicates that these nuances matter when it comes to the effect of urban greenery on residents' life satisfaction (Ayala-Azcárraga, Diaz, & Zambrano, 2019; Syrbe et al., 2021; Wu et al., 2023). Evidence for Mexico City suggests that the prevalence of trees is a significant factor influencing the utilization of parks. Additionally, the height of trees and the melodies of birds inhabiting them are associated with the well-being of park visitors (Ayala-Azcárraga et al., 2019). An examination in two Czech cities and one German city revealed that residents prefer natural (less intensively maintained) green spaces with safe, clean, and accessible pathways (Syrbe et al., 2021). These findings underscore the importance of considering not only the proportion and proximity of urban green spaces when investigating their effect on residents' well-being but also their composition. The composition of urban greenery is often measured by survey data, which has the disadvantage of being costly to generate, resulting in a small study area, and being prone to survey bias. A more recent case study conducted in Beijing (Wu et al., 2023) revealed that the quantity (availability, accessibility) and quality (attractiveness, natural aesthetics) of urban greenery exert heterogeneous effects on well-being. The relationship between attractiveness and natural aesthetics was found to be more pronounced compared to the quantitative dimensions, indicating that the quality of urban green spaces is of great importance when assessing its relationship with life satisfaction. The study employed a manual rating system to determine the attractiveness and natural aesthetics of green spaces. This involved rating 200 street-view images, after which a deep learning segmentation model was trained to predict these characteristics on the remaining street-view images. Differentiating urban greenery into their components, such as trees, hedges, and grass fields, and rating their quality by applying segmentation models is a promising approach. However, it should be noted that street-view data has some limitations over high-resolution satellite data. This is because street-view data is limited to areas adjacent to streets and mostly neglects green spaces in residential areas. Moreover, buildings or other vegetation, such as tree canopies or hedges, may obscure green space located behind them, particularly in urban settings. Tong et al. (2020) support this by demonstrating a weak correlation between greenery measured through street-level imagery and satellite imagery in residential and industrial neighborhoods. Furthermore, street imagery does not provide information on the size of the vegetated area, which is an essential determinant of the relationship between urban greenery and subjective well-being (Krekel et al., 2016; Tsurumi et al., 2018).

This study proposes a novel approach to measure the various components of urban green spaces and their association with residents' life satisfaction. It builds on evidence (Ayala-Azcárraga et al., 2019; Syrbe et al., 2021; Wu et al., 2023) indicating varying assessment and usage of these components, which may result in heterogeneous effects on life satisfaction. It employs high-resolution and publicly available satellite imagery combined with a deep learning semantic segmentation model to derive nine distinct urban green space components. This procedure allows the study to consider the proportion and type of green spaces and comprehensively answers the question (Q1) if different types of urban green spaces located in the walkable neighborhood have heterogeneous effects on residents' life satisfaction in urban areas in Switzerland.

2.2. Life satisfaction and mixed land use

The urban environment affects residents' subjective well-being not solely through urban greenery; the access to various goods and amenities in the neighborhood is also critical. A mixed land use neighborhood is defined by the presence of different stores, businesses, and services in the area of interest. From a theoretical perspective, a neighborhood environment that provides a large variety of services such as education, the provision of daily goods and public services, cultural and culinary activities, sports, and recreation should increase the livability of that area and positively affect residents' subjective well-being. This is due to greater social cohesion, more social engagement, economic vibrancy, and better accessibility, which is especially relevant for older people. While the examination of the relationship between urban green spaces and subjective well-being has been given a lot of attention in the literature, there are just a limited number of studies (Cao, 2016; Dong & Qin, 2017; Guo et al., 2021; McCarthy & Habib, 2018; Mouratidis, 2018; Olsen, Nicholls, & Mitchell, 2019; Wu et al., 2022) focusing on the relationship between mixed land use and residents' subjective well-being. Case studies examining the direct effect of mixed land use on residents' well-being conducted in Beijing (Dong & Qin, 2017) and Nova Scotia, Canada (McCarthy & Habib, 2018) could not find any effect. In contrast, evidence from Minneapolis-St. Paul, Minnesota, indicates that a greater mix of land use types leads to better accessibility but also to increased nuisance due to crowdedness, noise, and pollution. Accessibility was positively associated, and nuisance was negatively associated with life satisfaction, resulting in an insignificant total effect (Cao, 2016). Guo et al. (2021) found no direct effect of land use mix on subjective well-being. However, a mediation analysis revealed that the neighborhood's perceived age-friendliness and sense of community in Hong Kong mediates the relationship. Further evidence from China (Beijing) that operationalizes mixed land use by calculating the land use entropy in an area indicates that a higher mixture is not only positively associated with residents' life satisfaction but that this relationship is more substantial in areas with more green space (Wu et al., 2022). Evidence from Europe is somewhat mixed. A study conducted in 66 European cities revealed a weak negative effect of the area covered by continuous urban fabric (at least 80 % building coverage) and residents' subjective well-being. However, they found no evidence that land cover diversity or evenness is related to subjective well-being (Olsen et al., 2019). Contrarily, results from Oslo (Norway) suggest that the number of cafés, restaurants, and bars in an area positively affects residents' satisfaction with their relationships, by enabling them to have larger social networks and more frequent social interactions (Mouratidis, 2018). Since the effect of mixed land use on residents' subjective well-being is empirically indeterminate, this study aims to shed further light on this relationship by answering the question (Q2) whether in Switzerland residents' life satisfaction is positively associated with a higher mix of land use types in the walkable neighborhood.

2.3. Heterogeneous age effects

People's preferences change over their life course, as do the residents' preferences for urban green spaces. Syrbe et al. (2021) discovered that older individuals residing in Dresden, Germany, and two Czech cities tend to hold a more favorable opinion of parks than forests. Conversely, middle-aged residents in these cities express greater appreciation for forests and playgrounds. This aligns with previous findings from Berlin (Kabisch & Haase, 2014) and Amsterdam (Chiesura, 2004), which indicate that younger age groups primarily visit green spaces for recreational purposes, including sports, sunbathing, and social gatherings. In contrast, older individuals sought out environments that offered opportunities for relaxation and appreciation of nature. The utilization of green spaces for social gatherings is of greater significance to younger individuals in Denmark as well. Nevertheless, the most prevalent reason for visiting green spaces across all age groups was "enjoy the weather and get fresh air". In contrast to other studies, relaxation and stress relief were more prevalent reasons for visiting urban greenery among younger age groups (Schipperijn et al., 2010). A series of studies conducted in Germany and Basel, Switzerland, examined the interaction effect of urban greenery and age groups on residents' life satisfaction. Both studies yielded evidence that green spaces have a more substantial effect on life satisfaction among older age groups. (Jeong et al., 2022; Krekel et al., 2016). This work contributes to the existing body of literature by investigating the interaction between age and different urban green spaces and addressing the question (Q3) whether there are heterogeneous effects in the association between various types of urban greenery and life satisfaction by age group.

3. Methodology

3.1. Study area

Switzerland lies in the center of Europe, and the Alps and the Jura Mountains cover 70 % of its area. The remaining 30 % is covered by the Swiss Plateau region, which reaches from Lake Geneva to St. Gallen and Lake Constance, and holds 2/3 of the country's population. This area is characterized by a medium to high population density of 400 inhabitants per km^2 and, due to federalism, many small to medium-sized municipalities (Federal Department of Foreign Affairs, 2023). The DEGURA typology developed by Eurostat (2018) and adopted by the Swiss Federal Statistical Office classifies areas as urban centers when they have a population density of at least 1500 inhabitants per km^2 and a minimum population of 50,000. However, as only ten Swiss cities have more than 50,000 inhabitants, using this classification would limit the study area and hamper the study's generalizability. Since the study aims to examine the effect of urban greenery and mixed land use on life satisfaction in a densely built and urbanized context, I argue that high population density is the main distinct feature of these areas and less so population size. Therefore, an adapted version of the DEGURA typology is used, and the analysis is restricted to postcodes with a population density of 1500 people per km^2.

3.2. Data

3.2.1. Residents' life satisfaction

The subjective well-being approach is used in this study to ensure comparability with previous research and to assess the effect the built environment has on the resident's overall life. As in other studies, the terms subjective well-being and life satisfaction are used interchangeably. The residents' life satisfaction data was obtained from the Swiss Household Panel Wave 23 conducted in 2021 and 2022 (individual level response rate = 77%). In the survey, life satisfaction was measured on an 11-point Likert scale by asking the respondents, "In general, how satisfied are you with your life if 0 means not at all satisfied and 10 means completely satisfied". The households were selected using stratified random sampling, and where possible, all individuals of a household aged 16 years and over were interviewed. A total of 11,890 individuals aged between 20 and 85 years, clustering in 7,816 households, answered the life satisfaction question. After restricting the sample to highly urbanized postcodes and excluding records with missing values on any control variable, a total of 2,755 individuals based in 1,867 households located in 206 postcodes, which are part of 57 cities, remained and formed the final sample. The spatial distribution of the interviewed households is depicted in Fig. 1. As expected, most surveyed households reside in the densely populated Swiss Plateau. The respondents indicated an average life satisfaction value of 7.94 (SD = 1.46). To obtain the neighborhood characteristics related to greenery and mixed land use the exact geo-location of the household is added to the data.

3.2.2. Urban green space

To measure green land cover, this study uses satellite images of the households' neighborhood environment in combination with a deep learning semantic segmentation model. A 1260 m × 1260 m tile was created for every household, with the household at the center. This corresponds to an approximate 10-minute walking distance. Each tile represented the area (neighborhood) of interest and was split into nine sub-tiles, as can be seen in Fig. 2A. For every sub-tile, a satellite image with a size of 1024 × 1024 pixels (0.42 m per pixel) was scraped from the Google Static Maps API (see Fig. 2B). Semantic segmentation models offer the unique opportunity to separate an image into different categories. For the case at hand, this method allows the detection of up to eight different land cover classes on a satellite image (see Fig. 2C), enabling the study to differentiate between different green land cover types. One advantage of semantic segmentation models is that their prediction is mostly based on the structure and shape of an object and less on its color. This makes the model robust to changes in the saturation and luminosity of colors, as it could be due to changing lighting conditions or seasons at which the satellite imagery was collected. The model was trained on the publicly available OpenEarthMap (Xia, Yokoya, Adriano, & Broni-Bediako, 2022) dataset. It contains around 5,000 high-resolution satellite images with manually annotated 8-class land cover labels, covering 97 regions from 44 countries across 6 continents. Due to its high generalizability, it can be applied to tasks worldwide. All images were split into sub-images of 512 × 512 pixels to reduce the computational load. As annotations were absent in the dataset for some images, this procedure resulted in 9,278 images, 39 % from developed and 61 % from developing countries. The data was randomly split into five folds (Fig. 2E). This allows the evaluation of the performance of the model on different data and gives a better understanding of how the performance can vary on different datasets. In the first step, the semantic segmentation model consisting of a U-Net architecture (Ronneberger, Fischer, & Brox, 2015) with an Efficient Net B4 (Tan & Le, 2020) encoder was trained on an NVIDIA GeForce RTX 3090. In the encoder part, the U-Net compresses the information contained in the input image by reducing height and width and increasing the depth of the feature map. The decoder tries to upsample and rebuild the input image based on that information. However, instead of outputting the RGB values of a pixel, it predicts the segmentation class it belongs to (see Fig. 2D). In the training process, the model learned to assign the following eight land cover classes to the input satellite image: bareland, rangeland (grass, shrubs, gardens, and parks), trees, agricultural land, roads, developed space (pavements, parking lots or other paved areas), buildings, and water. Test time augmentation (TTA) is used to enhance the generalization performance of the model. Since the model is used for predictions in Switzerland, it is evaluated solely on images from developed countries. As Fig. 2E depicts, the optimal hyperparameters of the model were assessed on dataset 1. This set of hyperparameters was used to train four separate U-Nets on the four remaining datasets (2–5). Each

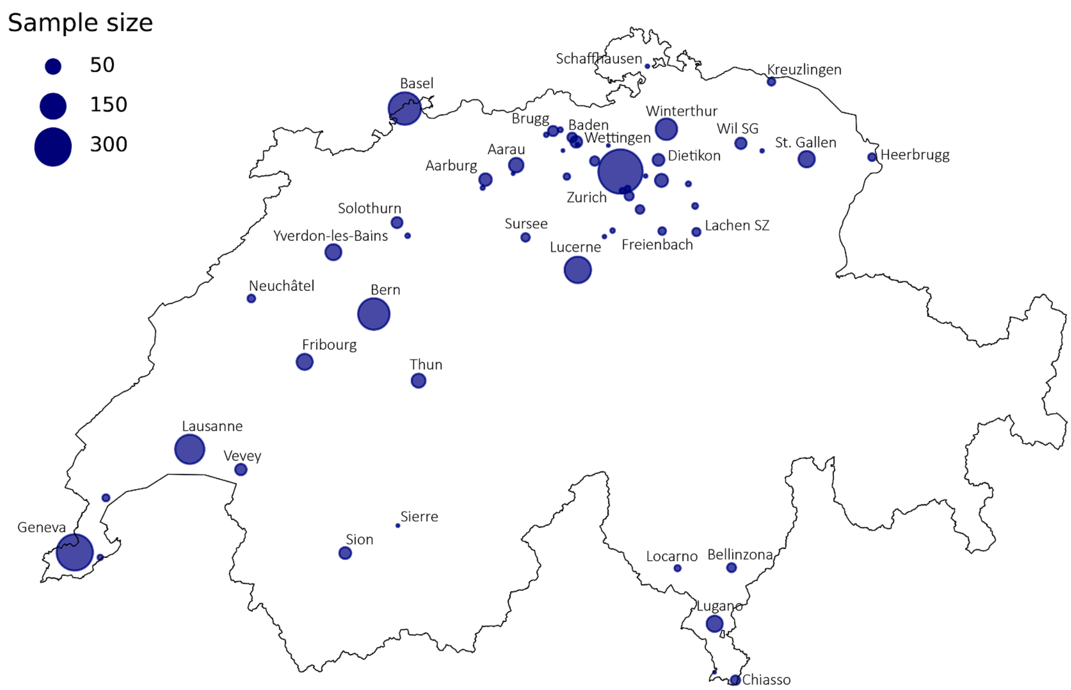

Fig. 1. Map of sample locations. The circle size is proportional to the sample size. The sample size varies from 2 in Sierre to 569 in Zurich, with a mean of 48. A circle represents either a single postcode if it is considered an independent municipality or multiple postcodes if they belong to one city. All postcodes have a population density of at least 1,500 inhabitants per km^2.

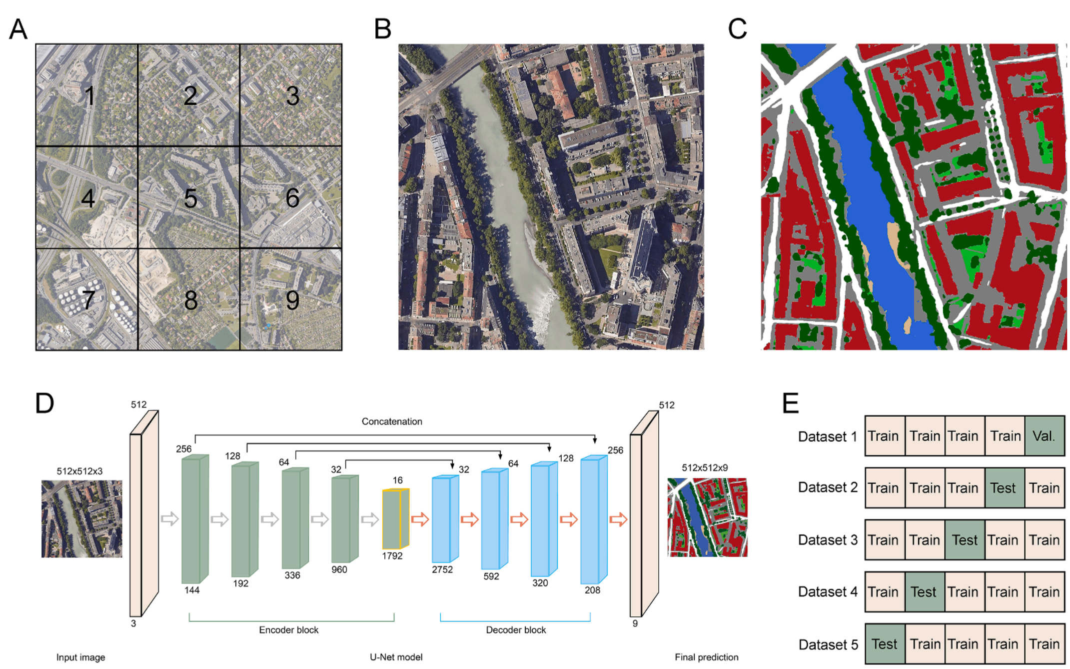

Fig. 2. Satellite image sampling process, example input and output image, model architecture, and training procedure. A Depicts a neighborhood of 1260 m × 1260 m, split into 9 sub-tiles, each representing 420 m × 420 m and consisting of 1024 × 1024 pixels. B Example satellite image of size 512 × 512 pixels is provided as input to the segmentation model. C Land cover classes predicted by the model, based on the input image. Red depicts buildings, gray developed space, white roads, light green grass, dark green trees, and blue water. D Overview of the U-Net architecture and the size of the feature maps. The green parts represent the encoder that compresses the input image into a lower dimensional space ($512 \times 512 \times 3 \rightarrow 16 \times 16 \times 1792$). The decoder is colored in blue. It up-samples the compressed image to the size of the input, and predicts the segmentation classes instead of the RGB values. E Overview of the training, validation, and test procedure. The model is trained on 4/5 of the data and validated or tested on the remaining part. This gives better insights into the generalization capability of the model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

model was trained on 4/5 of the data and evaluated on 1/5. The models achieved an average pixel accuracy of 95 % ± 1 %. However, some land cover classes are more frequent than others, and accuracy as a performance metric is biased towards the performance of the frequent classes. Metrics like the intersection over union (IoU) or the F1-score are less affected by class imbalance. Nevertheless, the good model performance is confirmed by an F1-score of 0.766 $\pm$ 0.01 (ranges from 0 to 1, the higher, the better) and an IoU of 0.691 $\pm$ 0.01 (ranges from 0 to 1, a value of 0.5 is considered good). A more in-depth overview of the model performance is depicted in Table S1 (supplement). As all five models were trained on slightly different data, they may have learned different patterns, and combining them into a model ensemble should increase the generalizability of the predictions. Accordingly, to the previously learned patterns, the model ensemble assigned each pixel of the satellite image to one of the eight land cover classes. This approach would only allow for the differentiation between three urban green space types (trees, grass, and agricultural land). However, the effect of grass or trees in a park or garden differs from that of a wild meadow or a tree canopy next to a road. Hence, the three green land cover types are matched with freely available land usage data from OpenStreetMap (OSM) for detailed separation. This allows a more sophisticated answer to the first research question (Q1). Out of the three existing, nine new classes are built by differentiating land cover based on its land usage. E. g., trees located in forests are recoded as *trees forest,* and trees in parks or gardens as *trees garden & park*. The nine following categories were created: trees forest, trees garden & park, trees other, grass garden & park, grass recreation, grass playground, grass other, allotments, agriculture other (see Table 1 for an overview of their composition). These classes are referred to as *green land types* in the following to avoid confusion with the terms land cover and land use. Because the area of analysis is identical in size for all observed households, the coverage of each neighborhood tile by a *green land type* can be compared between neighborhoods. The coverage C_i for *green land type i* is calculated by dividing the total number of pixels in the neighborhood tile by the number of pixels belonging to *green land type i* (Eq. (1)). The coverage ranges from 0 to 1. It is used as an exogenous variable in the analysis. Table S2 (supplement) contains a description of the distribution of all *green land type* variables.

$$C_i = \frac{N_i}{\sum_{i=1}^{n} N_i} \tag{1}$$

3.2.3. Mixed land use

To examine the effect of mixed land use on residents' life satisfaction an extensive set of 172 land use classes in the resident's neighborhood are obtained from OSM. They are assigned to five broader categories, based on the service or amenity they are creating for the residents, namely *residential, commercial or groceries*, *recreation*, *public services*, and the class *culinary, culture, and events (CCE)*. As a result, the created land use categories consist of green as well as build-up areas. A detailed overview of the assignment procedure can be found in Table S3 (supplement). The literature suggests multiple approaches to measure mixed land use (Song, Merlin, & Rodriguez, 2013), such as the proportion of a particular land use type, the relative proportion of different land use types (entropy), the interaction between two land use types (exposure index), the land use diversity (Atkinson or Herfindahl-Hirschman index) or the evenness of two different land use classes (Gini index). Each of the measures provides a distinct perspective on the land use mixture. However, this study opts for the entropy measure as with this approach, multiple land use classes can be considered simultaneously. Further, it is symmetrical to the proportion of land use types. Therefore, the distribution 50/30/20 and the distribution 30/20/50 result in the same entropy score. In addition, entropy can measure the evenness and diversity of land use classes concurrently and reaches its maximum value 1 only if all k classes are evenly distributed (Song et al., 2013). Entropy is calculated as denoted in Eq. (2), whereas P_j is the percentage or proportion of a land use category j in the neighborhood of a surveyed household. The proportion is measured as the number of pixels in a resident's neighborhood covered by a specific land use category. This is done for all five land use types (residential, commercial or groceries, recreation, public services, and CCE). $k = 5$ as it is the number of considered land use classes.

$$Entropy = \frac{-\left[\sum_{j=1}^{k} P_j \ln(P_j)\right]}{\ln(k)} \tag{2}$$

The surveyed individuals live in neighborhoods with an average entropy of 0.7 (SD = 0.15). For simplicity, entropy is referred to as mixed land use in the following sections.

3.2.4. Confounding covariates

The relationship between urban greenery, land use mixture and life satisfaction is directly and indirectly affected by various factors at the individual, household, and neighborhood levels. As households were not assigned randomly to their neighborhoods but directly or indirectly selected themselves into them, self-selection into the treatment is an issue and would cause spurious correlations. This issue can be solved by including the confounding variables in the statistical model and controlling for them, assuming no unobserved heterogeneity remains. For instance, wealthier households have the financial ability to move to greener and more vibrant neighborhoods. Further, the preferences of individuals and households for their neighborhood environment differ. Younger individuals prefer a vibrant and built-up environment, whereas public services such as schools and playgrounds matter more for families with children. Older people, on the other hand, can be limited in their freedom of movement due to health issues and might prefer to live in areas with nearby green spaces. The different preferences and financial constraints likely cause self-selection of specific individuals into greener and more vibrant neighborhoods. Because household income and the presence of children are also related to life satisfaction (Ambrey & Fleming, 2014; Krekel et al., 2016; Wu et al., 2022), they act as confounders and must be controlled for. As the literature suggests heterogeneous effects of urban greener on life satisfaction by age groups, the age variable is split into four categories. Each group represents different life courses and should theoretically result in similar green space preferences. These categories are young adults (20–29 years), middle-aged adults possibly sharing a household with their children (30–49), older adults where possible children recently moved out (50–65), and older people (65+). Covariates like the residence type (apartment or detached house), the ownership of the accommodation, the population density of the resident's postcode, the distance to the city center, and the language region (French, Italian, or German) the accommodation is located in are likely related to the amount of green space or the land use mix in the resident's neighborhood. Theoretically, these covariates also affect life satisfaction, which the literature could confirm for some of them (Ambrey & Fleming, 2014; Krekel et al., 2016; Wu et al., 2022). Therefore, the analysis controls for these confounding variables. Further control variables that are considered are sex, civil status, education, and

Table 1
Composition of land types.

Land type	Land cover	Land use
Trees forest	Trees	Forest
Trees garden & park		Park, public, or private garden
Trees other		Single trees, canopies, or not available
Grass garden & park	Rangeland	Park, pavilion, flowerbed, public or private garden
Grass recreation		Recreation area and sports ground
Grass playground		Playground
Grass other		Meadows, greenfields, shrubs, hedges, or not available
Allotments	Agricultural land	Allotments
Agriculture other		Farmland, vineyard, greenhouse, farm, orchard, or not available

occupation.

3.2.5. Statistical modeling approach

The units of analysis are individuals, and they cluster in households. Therefore, cluster robust standard errors on the household level are applied to all analyses. However, one could argue that households are nested in cities and life satisfaction varies strongly between cities, which would favor using a multilevel model. However, the data does not confirm this. Only 2 % of the total variance can be explained at the city level, and using an ordinary least-squares regression approach with cluster robust standard errors is therefore appropriate. By applying this approach, the direct effect of greenery and mixed land use variables (exogenous) on life satisfaction (endogenous) can be estimated considering confounding variables. The model can be formulated as shown in Eq. (3). LS_i is the stated level of life satisfaction, LT_i the proportion of a *green land type* or the land use entropy in the neighborhood, X_i includes all individual-level characteristics of the respondent, Z_i contains all households and V_i all neighborhood characteristics. Equation (4) depicts the modeling approach of an interaction effect between a *green land type* or the land use entropy (LT_i) and age (Age_i). Since the *green land type* trees garden & park is strongly correlated with grass garden & park ($r = 0.93$) the *green land type* categories related to trees, grass and agriculture are analyzed independently to avoid multicollinearity.

$$LS_i = \beta_0 + \beta_{lt}LT_i + \beta_x X_i + \beta_z Z_i + \beta_v V_i + \varepsilon_i \quad (3)$$

$$LS_i = \beta_0 + \beta_{lt}LT_i + \beta_{age}Age_i + \beta_{lt*age}LT_i{*}Age_i + \beta_x X_i + \beta_z Z_i + \beta_v V_i + \varepsilon_i \quad (4)$$

To illustrate the interaction effect of mixed land use and age on life satisfaction (Fig. 4) a random forest machine learning model (Breiman, 2001) is trained on the data using the same variables as included in Model 6 (Table 2). The advantage of using a random forest over a linear regression is its ability to model non-linear patterns without overfitting the data. Similar to obtaining conditional expected values from a regression model, the fitted random forest model can be used to predict the endogenous variable $\widehat{Y}_i$ conditional on selected X_i values and control variables C_i. A random forest is an ensemble of uncorrelated decision trees. A decision tree tries to split the data on variable values that result in the most homogeneous subgroups, groups that have similar Y-values. This process is repeated until a certain level of homogeneity is reached.

All files are available at the GitHub repository: https://github.com/sebastianbahr/urban-environment-CH.

4. Results

Model 1 (Table 2) aims to answer the question of whether there is an association between green spaces in general and life satisfaction. Therefore, an additive index of all tree and grass-related *land types* is created. However, Model 1 suggests no relationship between urban greenery within the walkable neighborhood and residents' life satisfaction. As indicated in the literature, age groups value different amenities of urban green spaces. Therefore, an interaction effect is introduced in Model 2 (Table 2) to model heterogeneous age group effects. The analysis indicates that the association between urban greenery and life satisfaction differs between age groups. Nevertheless, only for

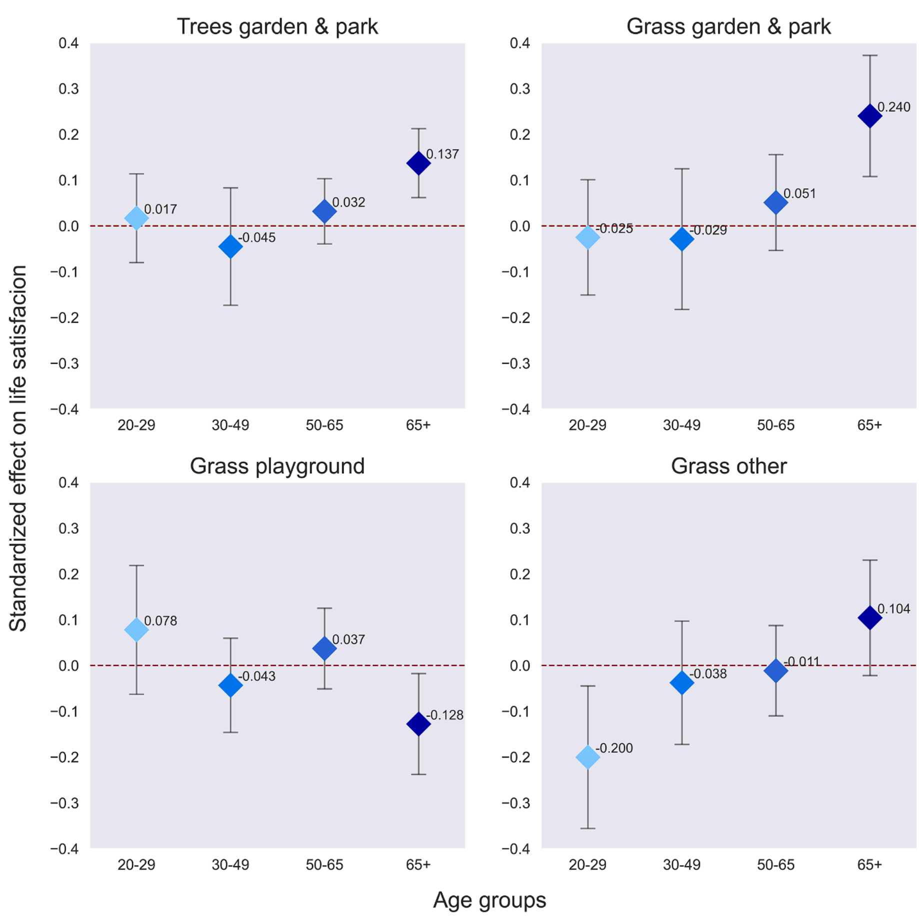

Fig. 3. Standardized effect of different urban green types on residents' life satisfaction by age category (buffer 1260 m). The rhombus depicts the change in life satisfaction in standard deviations if the green space type increases by one standard deviation. The displayed values are the main effect of the interaction between the green space type and the categorized age variable when the corresponding age group is set as the reference category. Similar to Model 3 and Model 4 in Table 2, a linear OLS model is used for estimation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

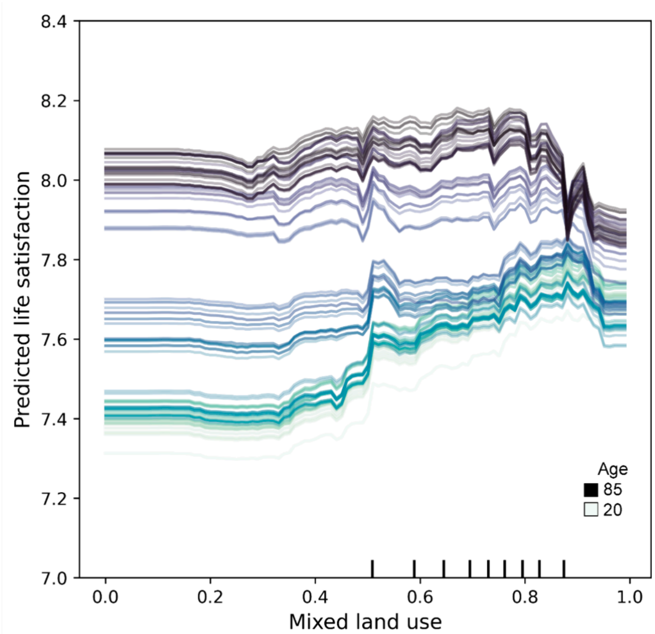

Fig. 4. Predicted life satisfaction value based on the interaction effect of mixed land use and age. Light green lines depict younger and black older age groups. The bars on the x-axis depict the distribution of mixed land use in quantiles. Predictions were performed by using a random forest machine learning model (hyperparameters: estimators = 1,000, max depth = 10). The depicted predicted life satisfaction values are based on 1,000 different ages and mixed land use combinations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

individuals aged above 65 the effect is significantly more positive than for the reference category (20–29 years). To better understand which components of urban green spaces matter for life satisfaction and to answer research question Q1, tree-, grass-, and agricultural-related *land types* are separately examined in Models 3 to 5 (Table 2). Notably, none of the green space types located in the walkable neighborhood are significantly associated with the life satisfaction of residents aged between 20 and 29. An exception is grass located in land use categories other than the specified ones, which exhibits an inverse relationship with life satisfaction among this age group. In contrast, for individuals aged above 65, trees and grass located in gardens and parks are positively associated with life satisfaction (Models 3 and 4). Fig. 3 provides a more intuitive understanding of the total effects (main + interaction effect). It shows that only in the age group 65+ an increase of trees located in gardens and parks by one standard deviation is associated with a significant increase in life satisfaction by 0.137 standard deviations. The same is true for grass located in gardens and parks. For the oldest age category, a one-standard-deviation increase in this *green land type* is associated with a 0.240-standard-deviation increase in life satisfaction. In contrast, a rise in grass located on playgrounds reduces the life satisfaction of older individuals. Model 4 (Table 2) suggests that the negative effect ($\beta = -0.200$) of grass located in any other than the specified *green land types*, is less negative or even positive for the age categories 50–65 and 65+ compared to the reference category (aged 20–29). However, as depicted in Fig. 3, the total effect does not differ significantly from zero. A rise in agricultural land other than allotments in the age group 30–49 is associated with a positive rather than a negative association with life satisfaction when compared to the age reference category (Model 5 Table 2). Nevertheless, the total effect for this group of residents does not differ from zero. ($\beta = 0.043, SE = 0.032$).

The next step evaluates the association between mixed land use and life satisfaction. Mixed land use is not related to life satisfaction if heterogeneous age group effects are not modeled ($\beta = 0.012, SE = 0.021$). The same holds if the previously utilized age categories are used. It appears that the information loss imposed by the categorization of age prevents the accurate capturing of the interaction between age and mixed land use. Consequently, a continuous age variable is employed in the interaction. The coefficient of mixed land use indicates the impact of mixed land use on life satisfaction at an age of zero. As no observations in the sample have an age of zero and to allow a more meaningful and robust estimation and interpretation of the effect, age is centered at 25 years. Correspondingly, an increase in mixed land use in the walkable neighborhood by one standard deviation increases life satisfaction by 0.079 standard deviations among the residents aged 25 (Model 6 Table 2). Estimating this effect is repeated by splitting age into 5-year and 10-year buckets, which did not substantially alter the previous findings. The negative interaction effect of mixed land use and age indicates that the positive association between the two variables diminishes with increasing age. This interaction is graphically represented in Fig. 4. The colored lines illustrate the predicted values for life satisfaction at a specified age, contingent upon the degree of mixed land use. The light green lines represent the predicted values for younger individuals, while the dark black lines represent those for older individuals. It can be demonstrated that an increase in mixed land use is associated with higher predicted life satisfaction values for younger residents. Conversely, the predicted life satisfaction remains unchanged for varying mixed land use values at older ages.

Recent evidence from Beijing shows a positive interaction effect between mixed land use and urban greenery, suggesting that promoting both concurrently has beneficial effects on residents' life satisfaction (Wu et al., 2022). To acknowledge these findings, the previous interaction between mixed land use and age is extended by an interaction with an additive index of all tree- and grass-related *land types*. Model 7 (Table 2) indicates that at age 25, an increase in greenery reduces the positive effect of mixed land use on life satisfaction. However, since a three-way interaction is not straightforward to interpret, the colored rhombus in Fig. 5 depicts the association between mixed land use in the resident's walkable neighborhood and life satisfaction conditioned on the greenness level of the neighborhood and different age values. A positive relationship between mixed land use and life satisfaction is observed at ages 25 and 35. This relationship is most pronounced among individuals residing in urban areas with limited access to green spaces and diminishes in neighborhoods with more extensive green infrastructure. A comparable tendency can be observed in residents aged 45. Nevertheless, the effects are not statistically significant. In accordance with the findings of Model 6 (Table 2), there is no correlation between mixed land use and life satisfaction at older ages (55, 65, and 75). It appears neither deprivation nor abundance of urban greenery can alter this unrelatedness. A notable exception is the 75-year-old cohort, where mixed land use is negatively associated with life satisfaction in areas with limited green space (10 % and 20 % percentile). It can be observed that an increase in green space tends to reduce this negative effect.

The results are tested for robustness. First, some *green land type* variables contain up to 1/3 of zero values. Because the effect of not-having to *having* a land type class in the neighborhood might differ from the effect a one-unit increase has, a control dummy is added to the model. None of the dummies were significant, and the linear effects did not change. Second, for around 300 respondents, the household equivalence income is missing. To avoid a bias that could have occurred due to the exclusion of these observations, the household equivalence income is imputed using a machine learning approach (Breiman, 2001). The re-analysis did not lead to a substantial difference in the coefficients. The only exception is the interaction effect of pooled green spaces with the age group 65+ (Model 2 Table 2). Third, all models are estimated using multilevel models with city random intercepts, which did not change the results. Fourth, instead of examining the neighborhood environment within 10 min' walking distance (1260 m × 1260 m), just the immediate environment, located in a tile of size 420 m × 420 m, is

Table 2
OLS model of land types and life satisfaction (buffer 1260 m).

Life satisfaction	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Control variables [a]	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Age groups: 20–29		*Ref.*	*Ref.*	*Ref.*	*Ref.*		
30–49		−0.034 (0.079)	−0.042 (0.079)	−0.049 (0.120)	−0.027 (0.078)		
50–65		0.015 (0.082)	0.013 (0.083)	0.030 (0.125)	0.017 (0.083)		
65+		0.171 (0.124)	0.163 (0.124)	0.261 (0.187)	0.175 (0.124)		
Age continuous [b]	0.004 (0.002)					0.004 (0.002)	0.008* (0.003)
Environmental variables							
Green (trees & grass, age 20–29) [c, d]	−0.001 (0.022)	−0.082 (0.049)					−0.013 (0.066)
× age group (30–49)		0.092 (0.059)					
× age group (50–65)		0.071 (0.055)					
× age group (65+)		**0.125*** (0.062)					
Trees (forest, age 20–29)			−0.021 (0.041)				
× age group (30–49)			−0.029 (0.054)				
× age group (50–65)			0.090 (0.053)				
× age group (65+)			0.049 (0.049)				
Trees (garden & park, age 20–29)			0.017 (0.049)				
× age group (30–49)			−0.062 (0.080)				
× age group (50–65)			0.015 (0.053)				
× age group (65+)			**0.120*** (0.060)				
Trees (other, age 20–29)			−0.034 (0.051)				
× age group (30–49)			0.096 (0.060)				
× age group (50–65)			−0.005 (0.057)				
× age group (65+)			0.003 (0.064)				
Grass (garden & park, age 20–29)				−0.025 (0.064)			
× age group (30–49)				−0.004 (0.101)			
× age group (50–65)				0.076 (0.075)			
× age group (65+)				**0.265*** (0.089)			
Grass (recreation, age 20–29)				−0.097 (0.092)			
× age group (30–49)				0.099 (0.096)			
× age group (50–65)				0.078 (0.099)			
× age group (65+)				0.045 (0.126)			
Grass (playground, age 20–29)				0.078 (0.072)			
× age group (30–49)				−0.121 (0.090)			
× age group (50–65)				−0.041 (0.084)			
× age group (65+)				**−0.206*** (0.092)			
Grass (other, age 20–29)				**−0.200*** (0.079)			
× age group (30–49)				0.163 (0.097)			
× age group (50–65)				**0.189*** (0.088)			
× age group (65+)				**0.304**** (0.096)			
Allotments (age 20–29)					−0.007 (0.072)		
× age group (30–49)					0.063 (0.098)		
× age group (50–65)					0.020 (0.082)		
× age group (65+)					−0.032 (0.084)		
Other agricultural land (age 20–29)					−0.118 (0.067)		
× age group (30–49)					**0.161*** (0.072)		
× age group (50–65)					0.122 (0.067)		
× age group (65+)					0.109 (0.076)		
Mixed land use						**0.079*** (0.039)	**0.148*** (0.069)
Mixed land use × age [b]						**−0.002*** (0.001)	**−0.004*** (0.002)
Green (trees & grass) × age [b]							0.001 (0.001)
Green (trees & grass) × Mixed land use							**−0.106*** (0.046)
Mixed land use × Green (forest & grass) × age [b]							**0.004*** (0.002)

(*continued on next page*)

Table 2 (*continued*)

Life satisfaction	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
N	2755	2755	2755	2755	2755	2755	2755
Adj. R2	0.10	0.10	0.11	0.11	0.10	0.10	0.10

Note: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. [a] The coefficients of the control variables are depicted in Table S4 of the supplement. [b] Age is centered at 25 years to enhance the interpretability of the main effect of mixed land use in Models 6 and 7. [c] In Model 1, the Green (trees & grass) effect incorporates all age groups and is not restricted to individuals aged 20–29. [d] Green effect at age 25 in Model 7. Life satisfaction, population density, distance to the city center, mixed land use, and all tree-, grass- and agriculture-related variables are z-standardized. For these variables, the coefficient depicts the change of the endogenous variable in standard deviations if the exogenous variable increases by one standard deviation. Household cluster robust and heteroscedasticity robust standard errors in parenthesis. Source: Swiss Household Panel (SHP) and author's data.

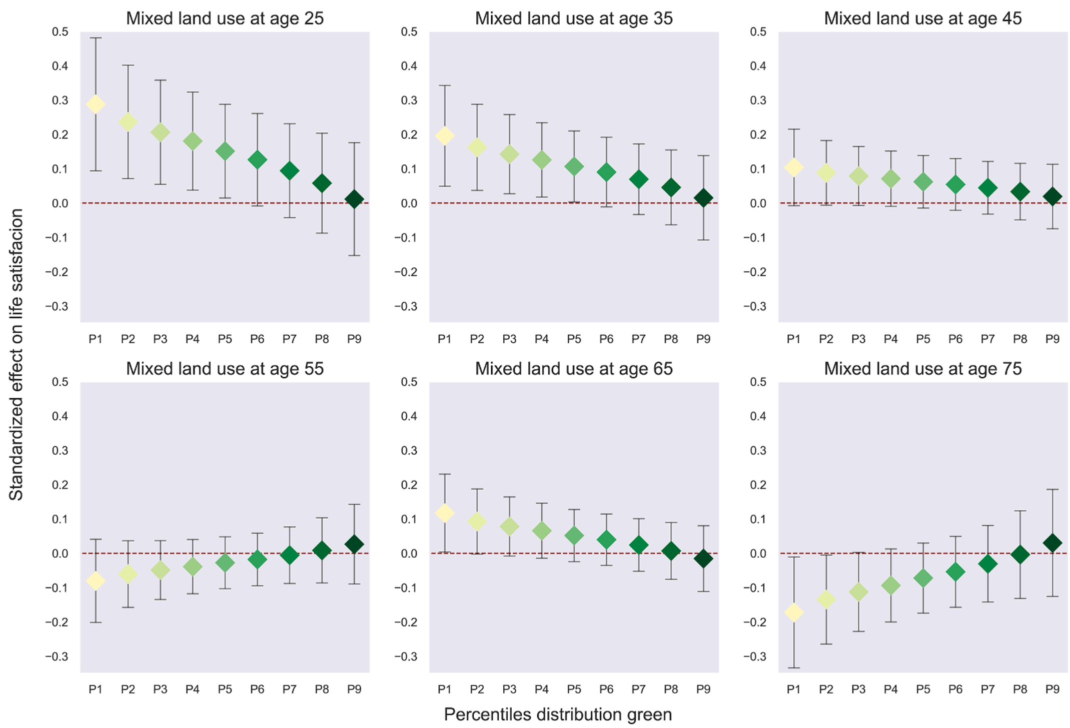

Fig. 5. Standardized effect of mixed land use on residents' life satisfaction at specified urban greenery percentiles and ages (buffer 1260 m). Urban greenery is an additive index of all tree- and grass-related green space types. The rhombus depicts the change in life satisfaction in standard deviations if mixed land use increases by one standard deviation conditioned on the stated urban greenery percentile and age. The displayed values are the main effect of the interaction between mixed land use, age, and urban greenery when the corresponding urban greenery percentile and age are set as the reference category. The same control variables as in Model 7 in Table 2 are introduced, and a linear OLS model is used for estimation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

analyzed. Changing the area of analysis reduces the effect size of *grass garden & park* but does not alter the main findings (Fig. 6).

5. Discussion

This study examined how different urban green space types and the land use mixture in the walkable neighborhood are related to residents' life satisfaction in Switzerland, with a particular focus on age-related differences in these relationships. Previous research indicates heterogeneous preferences and usage patterns of urban green spaces by different age groups (Chiesura, 2004; Kabisch & Haase, 2014; Schipperijn et al., 2010; Syrbe et al., 2021). Additionally, a stronger positive relationship was found between urban greenery and life satisfaction among older individuals (Jeong et al., 2022; Krekel et al., 2016). In light of the third research question (Q3), the study finds varying effects of urban greenery on residents' life satisfaction by age and corroborates evidence from Basel, Switzerland (Jeong et al., 2022). There it was found that greenery has a negative effect on the youngest age group (20–29), but the effect diminishes and becomes positive for older age cohorts. A similar pattern emerges in this study when examining all urban areas in Switzerland. However, the negative effect of the youngest age cohort is not significant, and only for residents over the age of 65 is greenery positively associated with their life satisfaction. Differences in preferences and spatial mobility can explain this. As the literature suggests, younger individuals use urban green spaces predominantly for social interactions and physical activities (Chiesura, 2004; Kabisch & Haase, 2014). Pursuing sports requires larger green areas covered with groomed lawns, markings, and equipment such as goals. Given the high cost of maintaining such areas, they are typically situated in close proximity to leisure centers and rarely in the vicinity of residential areas. Similarly, social gatherings can only be held in green areas with cut and groomed lawns, which must also be located away from busy and noisy roads. Consequently, it is probable that younger individuals are compelled to leave their neighborhood in order to engage in these activities. Their good health and high mobility allow them to easily access these green spaces, reducing their reliance on such areas in their vicinity. In contrast, older people visit urban green spaces to relax and appreciate nature (Chiesura, 2004; Kabisch & Haase, 2014). Green areas

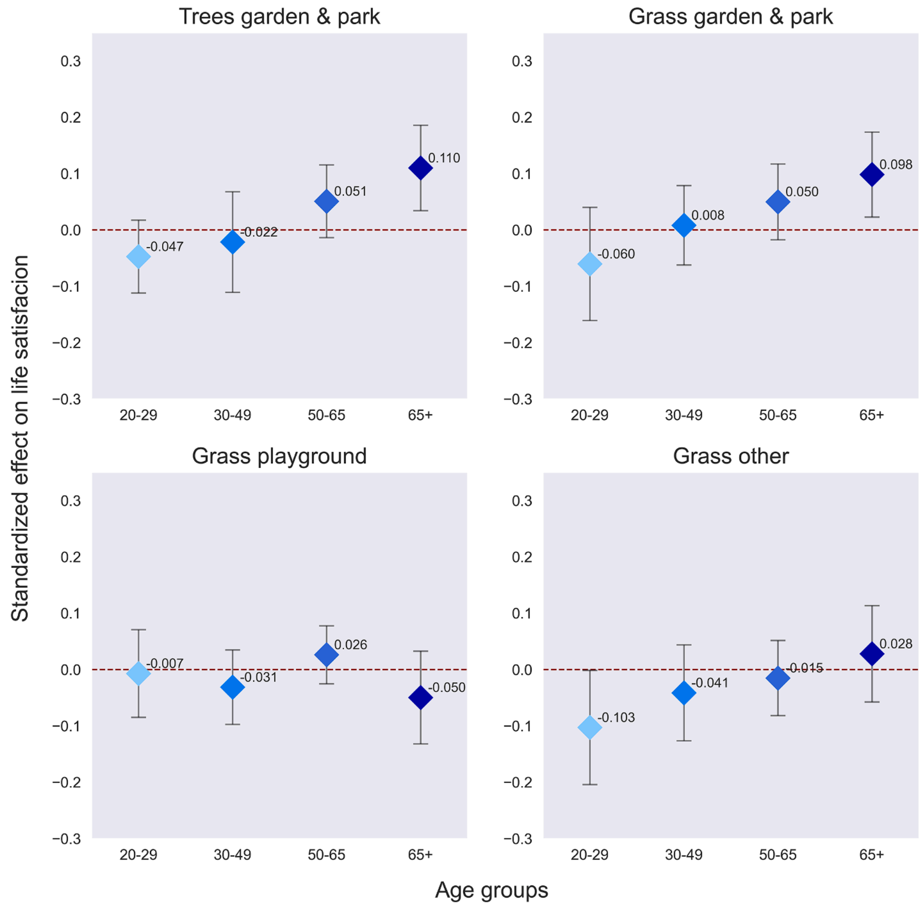

Fig. 6. Standardized effect of different urban green types on residents' life satisfaction by age category (buffer 420 m). The rhombus depicts the change in life satisfaction in standard deviations if the green space type increases by one standard deviation. The displayed values are the main effect of the interaction between the green space type and the categorized age variable when the corresponding age group is set as the reference category. Similar to Model 3 and Model 4 in Table 2, a linear OLS model is used for estimation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that are smaller, less well-maintained, or private, such as tree canopies, small parks, or private gardens, can provide these amenities. Hence, urban greenery in their immediate neighborhood likely satisfies these needs. Accordingly, due to their constrained area of movement, caused by their health condition, a lack of sufficient green spaces in the vicinity can result in reduced life satisfaction.

The partitioning of green spaces within a resident's neighborhood into subgroups allows urban planners to gain a more nuanced understanding of the types of urban greenery that should be prioritized in future city planning to improve dwellers' life satisfaction. The heterogeneous findings for different green urban areas in the analysis support these claims empirically (Q1). Solely trees and grass fields located in gardens and parks are positively associated with the life satisfaction of older residents. Whereas, the effect of grass is almost twice as much as the effect of trees. In contrast, trees situated in forests or other land use categories are not correlated. This suggests that trees should be incorporated into a more diverse and versatile green area, such as parks or gardens, to be associated with life satisfaction. Theoretically, forests would fulfill this requirement. However, they usually lack seating possibilities and paved paths, which makes them less appealing to older individuals (Syrbe et al., 2021). Grass located on recreation sides is not related to life satisfaction at all, which is especially surprising for younger individuals, as older tend to pursue fewer physical activities in general. This discrepancy may be attributed to the heterogeneous interest in pursuing physical activities and their type. Some residents may engage in no sports at all, while others may participate in a specific sport that is not permitted on the recreation grounds in their neighborhood. These varying preferences may result in a lack of perceived value for some residents. On the contrary, playgrounds equipped with larger grass fields reduce the life satisfaction of people aged over 65. Their association with noise might be an explanation. Grass situated in unspecified land use types of a neighborhood is negatively associated with the life satisfaction of younger adults. As this *green land type* encompasses a variety of urban green spaces it is hard to provide an explanation for this relationship. Possibly, greener neighborhoods are located in smaller and less vibrant cities, with limited nightlife and social and cultural events.

In both the European case (Mouratidis, 2018; Olsen et al., 2019) and the global case (Cao, 2016; Dong & Qin, 2017; McCarthy & Habib, 2018; Wu et al., 2022), the evidence of the relationship between mixed land use and life satisfaction is indeterminate. Mouratidis (2018) shows a positive association between mixed land use and life satisfaction in Oslo (Norway). This study tends to corroborate these findings, but the results in Switzerland are more nuanced, and the positive relationship only exists among younger individuals (Q2). The land use entropy provides insight into the uniformity of the distribution of the five analyzed land use categories within a resident's neighborhood. Due to their limited mobility, older individuals tend to utilize a greater range of services in their local area, including shopping, health care, social services, and culture (between variety). Nonetheless, it is probable that they are already satisfied with a lower number of the same service, and younger individuals might value the versatility of the same service (within variety), e.g., one bar vs. five bars. Hence, the needs of younger residents are better met if services are uniformly distributed. Further, in contrast to younger individuals, older individuals tend to value fewer services from the land use category *culture, culinary, and events (CCE)* and *recreation* as they visit fewer bars, pubs, nightclubs, sports venues, sports centers, fitness centers, water parks, swimming pools, or bowling alleys. Consequently, despite the presence of these land use categories in their neighborhood, resulting in a higher entropy score, it is more probable that older individuals derive less benefit from their existence. Furthermore, the noise and pollution generated by a vibrant nightlife can, in fact, diminish the positive impact of the amenities created by a neighborhood with a high land use mixture. This phenomenon is indeed observed in the sample, as an increase in the land use category *CCE* is associated with an increase in life satisfaction among younger residents but a decrease among older residents. In contrast to the findings of Wu et al. (2022), higher green coverage does not amplify the positive effect of mixed land use on life satisfaction in Swiss urban areas. Instead, it decreases the positive mixed land use effect at younger ages. The reason might be that the residents' life satisfaction is influenced by a myriad of factors, one of which is the living environment. However, this particular factor exerts only a limited influence on life satisfaction. Hence, it is probable that the marginal utility resulting from improvements in the neighborhood environment diminishes in more livable areas. This could explain why mixed land use has a more pronounced influence on life satisfaction among young residents deprived of green. Conversely, in greener areas, urban greenery and the amenities it provides have already increased life satisfaction attributed to the neighborhood environment, and the influence of other environmental factors, such as mixed land use, diminish. Moreover, green spaces like parks or sports fields can provide amenities comparable to those offered by certain land use classes, e.g., bars, pubs, or sports centers. This substitution is likely to weaken the influence of mixed land use. As noted, older residents tend not to benefit from a more uniformly distributed land use mix due to their specific set of needs, which can be satisfied at lower entropy levels. Therefore, it is reasonable that a rise in urban greenery does not affect the amenities provided by different land use classes and consequently does not alter the zero effect of mixed land use. Furthermore, the results from the megacity Beijing, with 21 million inhabitants, can hardly be compared with the findings of a country where the largest city has 1 million inhabitants, and residents' neighborhoods tend to be rather green on average ($\overline{x} = 39\%; \widetilde{x} = 38\%$ green coverage) compared to Beijing with an average green coverage of 29 % in 2020 (Cao, Li, & Huang, 2023). Nevertheless, the theoretical rationale for this phenomenon is not yet fully identified, and further research is required to better explain the underlying mechanisms.

The contributions of this work are multifold. First, it implements a new approach to measure the distribution of urban greenery in a more detailed and unbiased way. The fine-grained measurement ensures that all components of urban green spaces are considered when analyzing their impact on residents' life satisfaction. Second, the applied measurement approach not only guarantees a more fine-grained measurement but also allows splitting urban green spaces into nine subcategories. This provides urban planners with new empirical evidence on what green space types to focus on to influence residents' life satisfaction positively. Third, by acknowledging a strain of literature that suggests heterogeneous preferences for urban green space types based on residents' age, this work generates new evidence on how these different preferences affect the relationship between urban greenery and life satisfaction. Lastly, the work sheds light on a relatively new research field inspired by the claims of the new urbanism movement to build human-oriented smart neighborhoods (Garde, 2020). This field examines the effect of mixed land use on residents' life satisfaction; however, current evidence is indeterminate. The empirical results of this work propose that an equal mix of different land use types can enhance residents' life satisfaction in tendency and support the claims of the new urbanism movement and findings from Oslo (Mouratidis, 2018). Nevertheless, the association is more nuanced in Switzerland and only holds for younger individuals and vanishes at higher ages. This is precious information for Swiss city planners when determining the mixture of land use types in newly built urban areas. Additionally, these findings should encourage future research in other countries to account for heterogeneous age group effects. Regarding urban green spaces, the empirical results are much more subtle than those of former studies (e.g., see Bertram & Rehdanz, 2015; Krekel et al., 2016; White et al., 2013). They suggest that greener neighborhoods are not, per se, associated with higher life satisfaction in Switzerland. Instead, they underline the importance of considering heterogeneous age effects when examining the relationship between urban greenery and life satisfaction. These findings expand prior work that suggests varying preferences for urban green spaces among age groups by showcasing how these preferences influence the effect of urban greenery on residents' life satisfaction. Finally, to the best of the author's knowledge, no other study analyzes urban green spaces in such detail and incorporates the vegetation type and the land usage class in which it is located. The heterogeneous effects of different *green land types* on life satisfaction highlight the importance of this disentanglement. For the first time, this provides city planners with comprehensive information on what urban green types to focus on, given the neighborhoods' age distribution, to positively influence residents' life satisfaction. As urbanization continues unabated, these findings might become even more valuable for planning livable urban neighborhoods in the future.

It is important to highlight that the study solely examines the association of urban greenery, mixed land use, and their interaction with age on life satisfaction in the walkable neighborhood of residents in Switzerland. Consequently, claims outside the study area and generalizations to other countries must be made with caution. The study faces some limitations. First, the individuals were surveyed between September 2021 and March 2022. In the warmer season, residents profit more from amenities offered by green spaces, which could lead to an underestimation of the effect of greenery in winter. However, a *t*-test ($t = 0.32, N = 2755$) did not reveal any difference in life satisfaction between individuals surveyed in fall and winter. Second, the segmentation model performs well but still misclassifies pixels, potentially leading to biased results. Third, land usage types are assigned by volunteers at OpenStreetMap, and they need to follow a predefined classification methodology. Plausibility checks were performed for some analyzed neighborhoods, but there is still a margin of error. Fourth, by controlling for variables that cause self-selection, the study tries to alleviate this issue. However, only the usage of panel data would fully prevent self-selection.

6. Conclusion

This study examined how different urban green space types and the neighborhood's land use mixture are related to residents' life satisfaction in Switzerland. Thereby, it particularly focuses on age-related differences in these relationships. The study employed a deep learning approach to assess urban green spaces at a granular level and to identify a comprehensive set of green space types. The findings indicate that age groups value green spaces differently. For residents aged above 65, trees and grass located in parks and gardens are positively associated with life satisfaction. In contrast, green areas on playgrounds are negatively associated with this age group. A more uniform distribution of land use types appears to be more valuable for younger individuals and its positive association with life satisfaction decreases at higher ages. Insights gained from this research provide valuable information to city planners in Switzerland and expand prior findings in the literature.

CRediT authorship contribution statement

Sebastian Bahr: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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 Swiss Household Panel data is upon request at FORS. Land cover and usage data can be obtained from the GitHub repository: https://github.com/sebastianbahr/urban-environment-CH

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2024.105174.

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