Urban greenspaces benefit both human utility and biodiversity

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Abstract

Urban greenspaces are essential for both human well-being and biodiversity, with their importance continually growing in the face of increasing urbanization. The dual role of these spaces raises questions about how their planning and management can best serve the diverse needs of both people and biodiversity. Our goal was to quantify the synergies and tradeoffs between human utility and biodiversity benefits in urban greenspaces. Through a detailed inventory, we mapped 639 urban greenspaces throughout Broward County, Florida — one of the most populous counties in the United States. We identified and categorized various physical attributes (N=8 in total), including playgrounds, athletic facilities, and picnic areas and derived a 'human utility index'. Concurrently, we assessed biodiversity by estimating species richness within an urban greenspace. We found little relationship between our human utility index and biodiversity. More specifically, when the index was broken down to its parts, we found a positive correlation between some attributes such as playgrounds, bodies of water, nature preserves, and dog parks with biodiversity, indicating potential synergies rather than tradeoffs. This alignment between our human utility index and biodiversity suggests that urban parks can effectively serve multiple values without necessarily sacrificing one for the other. Both the human utility index and biodiversity correlate with greenspace size, emphasizing the significance of larger greenspaces in accommodating diverse values. Our results offer insights for optimizing planning and management of urban greenspaces to simultaneously benefit local communities and ecosystems, highlighting the potential for harmonizing human and biodiversity needs to foster sustainable cities.

Keywords: urban greenspace; biodiversity; human use; human-natural systems; urbanization; recreation

1. Introduction

Rapid growth in urbanization (United Nations, 2018; Trivedi, Sareen, & Dhyani, 2008) has transformed cities worldwide. This rapid urban expansion reshapes the daily lives of people living within cities as well as how ecosystems, and associated biodiversity, operate within urban areas. One component of cities that is critical to both humans and biodiversity are urban greenspaces. Urban greenspaces (i.e., broadly defined as open-space areas within cities for parks and recreational purposes) play a pivotal role in urban environments due to their role in providing essential habitats to various forms of life and sustaining vital urban ecosystem services (Li et al., 2019; Tzoulas et al., 2007). Urban greenspaces can provide substantial ecosystem services, encompassing air and water purification, climate regulation, carbon sequestration, landscape aesthetics and recreational benefits, and supporting biodiversity (Aronson et al., 2017; Mexia et al., 2018). Understanding how urbanization influences greenspace availability, structure, and function is key to ensuring that cities can meet the needs of both humans and biodiversity.

Biodiversity in urban greenspaces is essential for maintaining healthy ecosystems and supporting ecosystem services such as pollination, pest control, and climate regulation (Aronson et al., 2017). High levels of biodiversity enhance the resilience of urban ecosystems, allowing them to better withstand environmental stressors (Beninde et al., 2015). Furthermore, biodiversity-rich greenspaces provide opportunities for people to connect with nature, which can have profound effects on physical and mental health (Veen et al., 2020). To promote such benefits, strategies developed in the context of supporting biodiversity in urban greenspaces include increasing tree canopy with native species (Shackleton et al., 2015), expanding greenspaces near one another to increase connectivity (Beninde et al., 2015), and restoring habitats where diverse species can thrive (Blaustein, 2013). Human preference for the planning of greenspaces has shown to be driven by their ability to maximize health benefits (Veen et al., 2020). Preferences for attributes in greenspaces include experiencing and interacting with nature (Lafrenz, 2022), athletic and sport facilities (Mahmoudi Farahani & Maller, 2018), and play zones (Almanza et al., 2012). Beyond recreation and health, urban greenspaces also provide utilitarian benefits such as urban foraging (Adeyemi and Shackleton 2023) or other cultural ecosystem services (Sultana and Selim 2021), both of which are related to anthropogenic uses. As a result, common greenspace management techniques are not always strategically and explicitly aimed at enhancing biodiversity. Standard management procedures, such as turf grass lawns, pesticide and herbicide usage, and the introduction of non-native plant species, could minimize the potential of urban biodiversity (Aronson et al., 2017).

Biodiversity benefits and human utility represent the functions of urban greenspace that could potentially lie at opposite ends of the social-ecological spectrum. The design and planning of urban greenspaces differ based on human preferences for how users interact with, and perceive, a greenspace (Mahmoudi Farahani & Maller, 2018). In some instances, a greenspace can be designed with ‘biodiversity benefits’ in mind, for example, a greenspace can be created and designed to duplicate a natural system (e.g., a nature preserve). In contrast, an urban greenspace can be designed with ‘human benefits’ in mind, and organized primarily to serve human activities (e.g., athletic facilities, playgrounds, walking paths), driven primarily by utilitarian benefits (Lafrenz, 2022; Veen et al., 2020).

Depending on the focus of the planning for urban greenspaces, there can be contrasting benefits for biodiversity and humans, leading to potential tradeoffs with urban greenspaces impacting biodiversity and human utility separately (Brown & Grant 2005; Sadler et al. 2010; Belaire et al. 2022). As an example, light installations might be installed for safety purposes after dark which can benefit human safety; but also lead to light pollution, negatively impacting biodiversity such as nocturnal insects, birds, and bats (Eisenbeis et al., 2009; Stone et al., 2015; Lao et al. 2020). Or, frequent mowing might be conducted to meet human aesthetic preferences but this can have negative impacts on native pollinator diversity (Proske, Lokatis, & Rolff, 2022). Contrarily, park visitation is influenced by a desire to visit nature, and while biodiversity is not often directly considered by park visitors, it is a secondary benefit that visitors derive from their visit to urban parks (Taylor et al., 2020; Raymond et al., 2017). While some studies explore these contrasting objectives (Semeraro et al. 2021; Belaire et al. 2022), many have yet to comprehensively integrate both biodiversity and human utility in one study (Proske et al., 2022; Song et al., 2022). Rather, existing research which assesses urban greenspaces tends to focus on biodiversity and human utility in isolation, without adequately addressing how greenspaces may be managed to support both biodiversity and human utility simultaneously (Taylor & Hochuli, 2017). This division has led to gaps in our understanding of how design strategies can harmonize both goals. There is still a gap in empirical research investigating how specific greenspace attributes impact biodiversity and human use in one framework, particularly in urbanized subtropical cities, where biodiversity faces unique pressures over the past decades (Crouzeilles et al., 2021; Lee et al., 2021).

Data to produce a comprehensive understanding of biodiversity and human utility among urban greenspaces from traditional fieldwork-intensive methods can be difficult to scale up, posing a challenge to an empirical understanding of the human-biodiversity dynamic in urban greenspaces. Leveraging big data platforms, such as iNaturalist, can expedite the collection of ecological data, providing biodiversity data and offering a scalable solution for understanding biodiversity patterns on a broader scale (Callaghan et al., 2021a). Further, this dataset provides insight into how people interact with biodiversity. Human utility—the overall usefulness of a greenspace for humans—encompasses various functions of greenspaces, including recreational opportunities, social interaction spaces, aesthetic enjoyment, and ecosystem services that contribute to human well-being (McLain et al., 2012; Shackleton et al., 2015). Visitor facilities significantly influence visitation levels (Grilli et al., 2020), which is why the overall usefulness of an urban greenspace for humans can be directly and indirectly correlated with the presence of specific physical attributes within greenspaces (Chuang et al. 2022). This is evidenced by previous frameworks that categorize greenspace usage into utilitarian, recreational, sport, and play functions (Tzoulas & James, 2010; Ives et al., 2017; see Methods). Additionally, incorporating the physical attributes of a greenspace can provide an understanding of how greenspace attributes can influence biodiversity.

We perform a large-scale assessment which examines the relationship between human utility and biodiversity across over 600 urban greenspaces within a subtropical system. This large dataset, made possible by citizen science, allows for a comprehensive comparison of how human utility, defined as the sum of eight identified physical attributes, correlates with biodiversity across diverse urban greenspaces. Our overall objective was to investigate the synergies and tradeoffs between human utility and biodiversity among urban greenspaces. Specifically, we first quantified the distribution of human utility within these greenspaces, and then assessed how it relates to biodiversity and how both attributes relate to greenspace size. Our study addresses key gaps in the literature by focusing on both biodiversity and human utility simultaneously. This research provides an empirical framework to optimize urban greenspaces for both biodiversity conservation and human well-being.

2. Methods

2.1. Study Area

Our research was conducted throughout Broward County, Florida, United States. Broward County is Florida's second most populated county and ranked among the top 20 largest counties in the U.S. with roughly 1.9 million residents (U.S. Census Bureau, 2021). The majority of Broward County's expanse is the Everglades Wildlife Management Area that extends to the western border, but with a sharp demarcation that delineates the urban boundary within the county which is represented by a mostly developed land cover (Fig. 1; Volk et al., 2017). The county encompasses a total area of 342,655 hectares, with 8.5% of the total area consisting of water. Broward county contains 31 municipalities, with urbanized areas occupying 110,799 hectares of land (U.S. Census Bureau, 2021). The Broward County Parks and Recreation division consists of nearly 2,630 hectares of land (Broward County Parks and Recreation, 2023). Our selection of Broward County was based on the following reasons: (1) its representation of highly urbanized landscapes (Volk et al., 2017); (2) where urban greenspaces are much needed but also face threats from ongoing development (Volk et al., 2017); and (3) it represents a subtropical and tropical urban system that remain less understood in the literature but has the potential to harbor substantial levels of urban biodiversity.

2.2. Defining and delineating urban greenspaces

In this study, our focus was on defining urban greenspace predominantly in the context of urban parks and similar green areas within urbanized regions. Urban greenspace refers to green zones predominantly surrounded by urban development, distinct from contiguous natural vegetation, and generally accessible to the public (Taylor & Hochuli, 2017). These spaces exhibit qualitative disparities from adjoining green areas, emphasizing their unique character within an urban landscape. We adapted the definition by Callaghan et. al (2020) of urban spaces as ‘managed and designated’ parks or recreational spaces accessible to the community that are adjacent to built-up landcover. A key guiding principle in our definition was that a given urban greenspace had a high likelihood of being a contingent management unit, therefore neglecting vacant lots and other similar types of green areas that are less likely to have management interventions.

Based on the above definition, we stratified our delineation of urban greenspaces throughout Broward County by municipality. Broward County consists of 31 municipalities, however, two of them (Village of Lazy Lake and Village of Sea Ranch Lakes) did not contain any greenspaces based on the definition we are using in this study (see Table A.1. for a full table of greenspaces per municipality). To map urban greenspaces, each municipality’s official Parks and Recreation website was reviewed to compile a list of urban parks and greenspaces. OpenStreet maps and Google Maps were used to create, verify, and delineate the boundaries of each identified greenspaces, individually in GEOJSON format. OpenStreet maps was utilized for their open source, user contributed, up-to-date geographic information, which allowed for precise identification and mapping of greenspaces, and was accessed through geojson.io. Additionally, Broward County managed parks were mapped separately as its own municipality, rather than incorporating them into their respective municipality based on location. Exclusions were made for types of parks that did not qualify as a greenspace for the purpose of this study, such as marinas or small beach areas (N = 40), standalone indoor recreation centers (N = 5), and greenways (i.e., long contiguous strips of vegetation; N = 8). We also excluded cemeteries (N = 15) and golf courses (N = 40) due to their infrequency, specificity, and lack of range in human utility characteristics. Finally, we excluded large wildlife management areas that are not surround by built area such as Everglades and Francis S. Taylor Wildlife Management Area and the Everglades Wildlife Management Area. In total, 749 greenspaces were identified, of which 110 were excluded based on the aforementioned criteria, resulting in 639 urban greenspaces that were mapped and included in our final analyses (Fig. 1). All geographical analyses used the World Geodetic System 1984 (WGS 84) datum.

2.3. Quantifying physical attributes of urban greenspaces and a human utility index

The characteristics of greenspaces used in this analysis were adapted from prior studies that investigate the human perception of value in a greenspace that groups greenspace usage into four broad categories: utilitarian, recreation, sport, and play (Tzoulas & James, 2010). Ives et al. (2017) created a final typology of values including nature, activity/physical exercise, and social interaction. Building upon these conceptual frameworks, we generated and defined a list of eight distinct physical attributes that represent common forms of human utility (see Table 1). These attributes were chosen to balance ease of annotation and generalizability to be relatively employable throughout all urban greenspaces, following some exploratory analyses of individually searching each urban greenspace for different types of physical attributes. For example, while some urban greenspaces have additional types of characteristics that can serve human utility (e.g., disc golf course), these were excluded because they do not broadly represent multiple human utilities of urban greenspaces based on our literature review and were often uncommon, only appearing in a handful of urban greenspaces during our preliminary scoping analyses. The primary author, with input from co-authors, determined the presence or absence of each type of physical human attribute per individual greenspace (i.e., binary annotation). We chose this methodology based on previous research, which found that the presence of human utility attributes, such as number of trees, playgrounds, and other facilities, influence people's preferences for urban parks (Vliet et al., 2021). To assign the presence or absence of each type, the primary author used a combination of aerial imagery, content from Google Reviews accessed through the internet, and the municipality's parks and recreation website as sources to gather the data. Table 1 provides a detailed overview of each characteristic and their corresponding definition. After we annotated each urban greenspace with the physical attributes, we calculated a human utility attribute index. Hereafter, referred to as "human utility." To do this, we counted the number of physical attributes for each greenspace and scaled the count between 0 to 1 using the "rescale" function in the R package Scales (Wickham & Seidel, 2022). We found this data to be normally distributed. This rescaling process provided a relative index of potential human use based on features present to compare among greenspaces and to biodiversity (see next section).

2.4. Estimating biodiversity

To quantify the use of greenspaces for biodiversity benefits, we calculated a standardized species richness value for each greenspace that served as a proxy for biodiversity. To obtain a measure of biodiversity, we used citizen science data from the platform iNaturalist (www.inaturalist.org), an online social network for sharing observations of organisms and obtaining crowdsourced species identifications (Callaghan et al., 2022). In Broward County alone, there are approximately 140,000 observations from more than 9,000 users on iNaturalist (iNaturalist, 2023), indicating the potential robustness of available data to quantify biodiversity. Citizen science data are prevalent in urban areas, even more so than professionally collected biodiversity data, making this data source ideal for quantifying biodiversity in urban greenspaces (Li et al., 2019). We downloaded all iNaturalist data from Broward County, Florida, United States directly from the iNaturalist website so we could obtain all non-research grade and research grade observations (i.e., observations with two thirds agreement on species identification) to increase the sample size of the dataset (iNaturalist Community, 2023). While the inclusion of non-research grade observations may introduce falsely identified species, Hochmair et al. (2020) found that the use of non-research grade observations can successfully be used to map species presence. Additionally, our focus was not on the absolute species richness value (i.e., how many species per urban greenspace), but rather a relative measure of user submitted biodiversity across different urban greenspaces. However, we did remove observations of captive organisms, which are occasionally shared with iNaturalist for casual documentation but are not appropriate for biodiversity calculation. We did not account for native versus non-native species because of the diverse public perceptions of non-native species and native pest species (Van Eeden et al., 2020). Because our measure of biodiversity is taxon agnostic, we do not present on the raw species richness values, but the data downloaded are available in our data repository accompanying the paper (see below). Additionally, in Appendix A, we present a table (Table A.2.) summarizing the number of observations by taxon group and listing the top five species within each taxon group, along with their observation counts.

To predict a relative value of species richness across all greenspaces, we first obtained habitat data for all greenspaces. The habitat variables were obtained from raster data on percentage of tree cover (DiMinceli et al. 2017), non-tree vegetation (DiMinceli et al., 2017), water (Global Inland Water, 2015), and impervious surface coverage (Dewitz and US. Geological Survey, 2021), accessed from within the Google Earth Engine Data Catalog. From the raster files, we calculated average percentage of tree cover per 250 m^2 (resolution of raster), average percentage of non-tree vegetation cover per 250 m^2 (resolution of raster), the percentage of area that contained water (at 30 m resolution), and average percentage of impervious surface cover per 30 m^2 (minimum resolution of raster).

To understand the relationship between species richness and our predictor variables, we used a random forest analysis to model species richness in greenspaces with iNaturalist data using the randomForest R package (Liaw & Wiener, 2002). The model included log10 transformed species richness (number of observed species) as the response variable and number of iNaturalist observations, number of iNaturalist users, average percentage of tree cover (%), water cover area (%), average percentage of impervious surface (%), and average percentage of non-tree vegetation cover (%) as the predictor variables. To test the predictive ability of the random forest analysis from our dataset, we created a model from a training dataset (80% of data) and used it to calculate species richness values from a test dataset (20% of the data). We found a linear association between the predicted richness and observed richness in the test dataset (R^2 = 0.99), meaning the random forest model is reliable for predicting richness. Next, we ran the random forest model for the entire dataset, and found this model explained 96.39% of variance in the data.

To make species richness comparable across greenspaces, we chose a constant value for number of observations and used this to predict species richness for each park. We chose a constant value of 1,000 to allow for trends in the data, and subsequently scaled the number of observers (number of observers * (1000/number of observations)) based on this value. The other predictor variables are percentage of habitat coverage for each park, so these values were not scaled. From this new dataset, we used the predict function in the randomForest package (Liaw & Wiener, 2002) to predict species richness for the scaled values based on the previously calculated random forest model.

Finally, to calculate species richness values for greenspaces with no iNaturalist data (N=355), we used a random forest imputation algorithm from the R package missForest (Stekhoven, 2022). For the greenspaces with missing iNaturalist data, we set the total number of observations to 1,000. We combined the data with the predicted species richness, scaled covariates, and habitat variables dataset calculated previously, and ran the random forest imputation to fill in missing values. To test the predictive ability of this analysis, we conducted a leave-one-out cross validation analysis and found a linear association between predicted and observed values (R^2 = 0.93), meaning this method is valid for predicting species richness. We additionally compared the relationship of the imputed richness values to the richness values calculated from the real data, and found that the imputed values align well with trends in the real data (Fig. A.1) signifying that our predictions were within bounds of the training data. Lastly, we scaled the predicted bio-use to values between 0 to 1 using the "rescale" function in the R package Scales (Wickham & Seidel, 2022) to get a relative measure of biodiversity that is comparable to the human utility attribute index. Because imputation requires a solid understanding of the ecological system (Bowler et al. 2024) and becomes less reliable with larger data gaps, we tested four alternative approaches for calculating biodiversity and how these varying measures influenced our overall understanding of the relationship between biodiversity and the human utility index. These included different methods for estimation, as well as different sample sizes for urban greenspaces, including no imputation at all. The full methods and results from the comparison of these methods to the imputation method detailed in this paper are presented in Appendix B. Because we found that our random forest model captured 93% of the variation in species richness, and to retain all the information on human utility values in the analyses involving biodiversity, we chose to use random forest models to scale the data and impute missing values, as described in detail above.

2.5. Statistical analyses

We first empirically summarized the correlations between human utility by calculating correlation coefficients and visualizing the data as a correlogram using the "corrplot" function in R package corrplot (Wei & Simko, 2021). From the correlation matrix, we report the degree of correlation (r), and the lower and upper 95% confidence interval (CI). To quantify the relationships between human utility and biodiversity we first ran a linear model using the "lm" function in R. This model included scaled biodiversity as the response variable and scaled human utility as a predictor variable. In addition, because greenspace size was positively correlated with human utility and biodiversity (Fig. A.2), we also included log10-transformed greenspace size (m^2), due to the positively skewed distribution, as a predictor variable. We ran three models, one with human utility and greenspace area as the predictor variables, one with just human utility as the predictor variable, and one with just greenspace area as the predictor variable. We did this to account for all combinations of variables and compared models using the Akaike Information Criterion (AIC). To assess whether specific physical attributes (i.e., Table 1) were related to biodiversity, we used a linear model with biodiversity as the response variable and a binary categorical variable for each of the eight physical attributes and log10-transformed greenspace size (m^2) as the predictor variables. For all models (N=8), we examined the relationship between residuals and fitted values and the QQ plot to ensure model assumptions were met.

2.6. Data analysis and availability

Unless otherwise stated, all analyses were conducted in R statistical software (R Core Team, 2023). We report statistical significance following the convention suggested by Muff et al. (2022), where *p*-values between 0.1 – 1 indicate little or no evidence, 0.05 – 0.1 indicate weak evidence, 0.01 – 0.05 indicate moderate evidence, 0.001 – 0.01 indicate strong evidence, and less than 0.001 indicate very strong evidence of a relationship between variables of interest. Data from iNaturalist are openly available (see inaturalist.org), but summarized versions as well as our data on human utility attributes are available at this GitHub repository (https://github.com/coreytcallaghan/greenspaces_broward) and will be archived in Zenodo following acceptance. We additionally share a supplementary table containing the greenspace area, number of iNaturalist observations, number of iNaturalist users, biodiversity value, and human utility index values for every park.

3. Results

We analyzed 639 greenspaces in Broward County with an average size of 8.0 ha (range = 0.03 to 376 ha; Fig. 1). On average, there were about 22 greenspaces included per municipality. The number of physical attributes in urban greenspaces is approximately normally distributed (Fig. 2a), with the median number of 3 attributes per urban greenspace, few having 1 physical attribute and few having 7 (the maximum observed). The most frequent physical attributes were pavilion/picnic area (23.08%), followed by kid's playground (21.72%), jogging/walking path (18.50%), athletic facility (16.06%), indoor/outdoor fitness center (6.67%), body of water (8.48%), dog park (2.94%), and nature preserve (2.54%) as illustrated by Fig. 2b.

When assessing the relationships between physical attributes in urban greenspaces we found a mix of positive and negative associations (Fig. A.3). The strongest positive pairs with a strong correlation ($p < 0.001$) include pavilion/picnic area and kid's playground (r = 0.36, CI = 0.29 – 0.42), kid's playground and athletic facility (r = 0.44, CI = 0.37 – 0.50). There was a strong correlation ($p < 0.001$) between nature preserve and body of water (r = 0.09, CI = 0.02 – 0.17); pavilion/picnic area and body of water (r = 0.12, CI = 0.05 – 0.20); athletic facility and pavilion/picnic area (r = 0.21, CI = 0.14 – 0.29); jog/walk path and body of water (r = 0.21, CI = 0.14 – 0.29), nature preserve (r = 0.17, CI = 0.09 – 0.25), and pavilion/picnic area (r = 0.22, CI = 0.14 – 0.29); and indoor/outdoor fitness center and pavilion/picnic area (r = 0.15, CI = 0.07 – 0.22), kid's playground (r = 0.21, CI = 0.13 – 0.28), athletic facility (r = 0.22, CI = 0.15 – 0.30), dog park (r = 0.11, CI = 0.03 – 0.19), and jog/walk path (r = 0.25, CI = 0.17 – 0.32). There is a near neutral trend between nature preserve and picnic area ($p < 0.001$, r = 0.02, CI = -0.06 –

0.09), and near neutral trend between dog park and pavilion/picnic area (p = 0.041, r = 0.08, CI = 0.00 – 0.16). Conversely, strong evidence (p < 0.001) points to a negative correlation between kid's playground and body of water (r = -0.14, CI = -0.21 – -0.06), kid's playground and nature preserve (r = -0.21, CI = -0.29 – -0.14), athletic facility and body of water (r = -0.14, CI = -0.21 – -0.06), and athletic facility and nature preserve (r = -0.18, CI = -0.26 – -0.11).

3.1. Association between human utility attributes and biodiversity

We found very strong evidence of a positive, logarithmic relationship between biodiversity and greenspace size (β = 0.048, SE = 0.004, p < 0.001) and human utility and greenspace size (β = 0.076, SE = 0.005, p < 0.001; Table 2; Fig. A.2.). However, at the aggregated level, we found no evidence of a relationship between biodiversity and human utility (β = -0.018, SE = 0.030, p = 0.546; Table 2; Fig. 3). Our linear model with just greenspace size as the predictor variable performed slightly better than the full model (ΔAIC = 1.633). When we modeled biodiversity in relation to human utility and greenspace area using the four alternative methods of calculating biodiversity, we consistently observed the same trends (Appendix B).

However, for the different physical attributes, we did find significant relationships between certain physical attributes and biodiversity (Table 2; Fig. 4). There was moderate evidence of a positive relationship between body of water (β = 0.034, SE = 0.012, p = 0.07) and biodiversity; strong evidence of a positive relationship between the presence of kid's playground (β = 0.035, SE = 0.012, p = 0.004) and biodiversity; and very strong evidence of a positive relationship between presence nature preserve (β = 0.168, SE = 0.024, p < 0.001) and biodiversity. Additionally, we found moderate evidence of a negative relationship between pavilion/picnic area (β = -0.021, SE = 0.011, p = 0.065) and biodiversity, and very strong evidence of a negative relationship between presence of an athletic facility (β = -0.069, SE = 0.012, p < 0.001) and biodiversity. We found little to no evidence of a relationship between the presence of jog/walk path (β = 0.011, SE = 0.011, p = 0.325) and indoor/outdoor fitness center (β = -0.013, SE = 0.014, p = 0.326) and biodiversity. The trends were consistent across different methods of calculating biodiversity (Appendix B).

4. Discussion

By mapping more than 600 urban greenspaces and quantifying human utility attributes we found that our human utility index is approximately normally distributed among greenspaces and that there was no evidence of tradeoffs in overall human utility and biodiversity benefits at the aggregated level. Our findings suggest that there are notable synergies between certain physical attributes and biodiversity in urban greenspaces, illustrating the potential of urban greenspaces to be designed and managed to simultaneously benefit both human populations and local biodiversity (Connop et al., 2016; van Leeuwen et al., 2010). The positive associations between certain physical attributes — such as kid's playgrounds, dog parks, bodies of water, and nature preserves — and biodiversity underscore the potential of thoughtful urban greenspace design (Daniels et al., 2018) to foster biodiversity alongside recreational and social activities.

The absence of a direct tradeoff between human utility attributes and biodiversity in our analysis challenges a commonly held assumption that urban development inevitably leads to minimizing ecological integrity (Balfors et al., 2016). Potential benefits derived from urban greenspaces for human populations does not necessarily conflict with the maintenance of biodiversity, supporting previous work by Engemann et al. (2024) who found that residents use greenspaces and benefit from greenspaces which have high biodiversity value. Our results suggest that with careful planning and consideration of ecological principles, urban greenspaces can be optimized to serve dual purposes effectively, specifically supporting ecosystem services from a multifunctionality perspective (Semeraro et al. 2021). This outcome is particularly relevant in the context of rapid urbanization and the increasing need for spaces that support human well-being while preserving and enhancing urban biodiversity (Tzoulas et al., 2007). However, overall greenspace size appears to be an important factor in urban greenspace utility, positively influencing both human utility attributes and biodiversity. This phenomenon makes sense as larger greenspaces accommodate a larger range of human activities and provide more varied habitats for biodiversity (Callaghan et al., 2018), backing the idea that size matters in optimizing the multifunctionality potential of urban greenspaces. This result contrasts with others who have found that the marginal value per hectare of urban greenspace decreases with increasing size of the urban greenspace (Roberts et al. 2022b). One thing we did not account for is the number of visitors that are attracted to an urban greenspace — another potential measure of human utility that could be explored in future work (e.g., Taylor et al. 2020).

From an urban planning perspective, our findings highlight the importance of considering multiple benefits derived from both humans and biodiversity, challenging the division between prioritizing human utility or biodiversity solely. Our results extend the literature of understanding the contributions of biodiversity to ecosystem services (Haines-Young & Potschin, 2010; Le Provost et al., 2023; Mitchell et al., 2024) to the potential use and benefits of urban greenspaces to humans' welfare. For instance, the specific design and management of greenspaces — such as the maintenance of native plant species, the provision of water features, and the limitation of light pollution — are critical factors that can encourage park visitation and influence the biodiversity of these areas (Song et al., 2022; Threlfall et al., 2017). Further, active facilitation of community stewardship to improve visitor interactions with nature can further increase the biodiversity of greenspaces (Garrad, 2017). Additionally, although dog parks, kid's playgrounds, and pavilion/picnic area cater more towards 'human benefit,' we found that they also are associated with higher biodiversity. This relationship is likely due to these features encouraging park visitation and use of other features, such as walking trails, which are valued by both dog owners and children (Lee, Shepley, & Huang, 2009; Song et al., 2022; Veitch et al., 2020). Contrarily, fitness centers do not tend to significantly increase or decrease biodiversity likely due to their limited impact on long-term park visitation (Song et al., 2022). Pavilion and picnic areas and athletic facilities, which significantly decrease biodiversity, are primarily designed for structured human activities, and often if in a large greenspace do not occupy a large area, and if in a small greenspace might occupy a significant proportion of the greenspace. As such, they are unlikely to offer sufficient habitat or resources to support biodiversity.

4.1 Limitations and future research directions

Our analysis illustrates the importance of integrating biodiversity and human utility, but nevertheless takes a macroecological scale approach, looking across many urban greenspaces at once. While we performed a comprehensive search of all urban greenspaces throughout Broward County, it is possible that not every urban greenspace is included as some gated communities, for example, have privately managed greenspaces, or municipality websites could be out-of-date. Additionally, we did not examine the extent of physical attributes in each park, which could provide more insight into potential human utility. Nevertheless, our methodologies, specifically the use of big data platforms like iNaturalist for biodiversity analysis, provide a scalable solution to understand urban biodiversity patterns.

The iNaturalist data has been widely used to calculate species richness across a range of spatial scales (e.g., Roberts et al. 2022a; Zhu and Newman 2025), and here in this study allowed us to analyze a large sample of greenspaces. However, there are some potential biases in this data that worth mentioning. Namely, observations require photo or audio evidence of an organism, making large bodied and less mobile organisms more likely to be captured on iNaturalist (Callaghan et al., 2021b). We focused on species richness as a proxy for biodiversity, and it is important to acknowledge that species richness alone does not fully capture the complexity of biodiversity. For example, we considered all non-native and native species as equal due to the diverse values that people hold for these species (Van Eeden et al., 2013). Future studies could incorporate metrics such as functional or phylogenetic diversity to help distinguish areas with high ecological value from those that may simply support many species, many of which could be generalists or non-native. Additionally, many greenspaces included in this study lacked iNaturalist data, which we addressed by imputing missing values (Bowler et al. 2024). However, collecting additional data from these greenspaces would help improve model certainty.

Our work focused on publicly accessible urban greenspaces, which could lead to a bias of human activity in urban greenspaces where biodiversity tends to be more frequently observed. Although physical attributes have a strong influence on greenspace visitation levels (Grilli et al., 2020), we recommend future studies could use in situ counts of visitors using various attributes at each greenspace to directly assess human utility and disentangle potential confounding bias between where humans are more likely to frequent. While this study provides valuable insights into the relationship between human utility and biodiversity, it is focused on a specific region—Broward County, Florida. While this region represents the populous and rapidly urbanizing coastal metropolitans, this regional focus may limit the generalizability of our findings to other subtropical or tropical cities with different ecological and urban planning contexts. Indeed, others have found that the relationship between ecosystem services and green infrastructure are variable and highly context-dependent (Zhang et al. 2024). However, our inclusion of over 600 urban greenspaces represents a significant advantage over previous studies, allowing for a robust analysis of these relationships at a large scale. Future research should conduct cross-regional comparisons to determine whether similar synergies between human utility and biodiversity are observed across varied socio-ecological conditions.

Big data and AI can be leveraged to obtain human utility data on a larger scale to provide further information on the human experience of greenspaces through online reviews and aerial imagery. Future research should explore incorporating other big data platforms for a more refined understanding of human utility, incorporating online reviews, social media, and citizen engagement for broader and more nuanced insights of the human and biodiversity dynamics (e.g., actual human uses of greenspaces). This methodology contrasts with the laborious task of searching through each individual urban greenspace manually to annotate physical attributes (see Methods). We also did not assess individual management actions, for example, our approach estimates biodiversity from a holistic perspective. However, within an urban greenspace, management actions can have a significant influence (positively or negatively) on biodiversity, either for individual taxa or at aggregated levels, as well as on extent to which greenspaces can better serve human needs and utilities (Threlfall et al., 2017). And further from this, staff, funding levels, and the population that an urban greenspace serves could all be informative avenues to explore in future work. Understanding the effects of scale and urban greenspace management (Borgström et al., 2006), for example how actions within one urban greenspace correlate and correspond with actions among all urban greenspaces, remains an important avenue for future research.

5. Conclusions

While there are many calls to integrate urban biodiversity and human use within urban planning (e.g., Sadler et al., 2010), we have provided empirical data showing that indeed, there is a lack of evidence of inherent tradeoffs between biodiversity and human utility attributes. Our results also illustrated multiple synergies between urban biodiversity and certain physical attributes, highlighting the potential to achieve 'win-win' outcomes for sustainable urban greenspace management. As cities continue to grow, our study highlights the importance of considering multifunctional benefits in urban greenspaces. Urban greenspaces are important components of cities for both people and nature.

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Tables

Table 1. Human utility characteristics found in greenspaces and definitions.

Attribute type	**Definition**	**Uses**	**Examples**
Pavilion/Picnic Area	A sheltered area within a park that provides seating and tables.	Outdoor dining, special events, socializing.	Benches, picnic tables, pavilions, gazebos.
Kids Playground	An area specifically designed with play equipment and features tailored to children.	Physical exercise, playing, and social interaction among children.	Slides, swings, climbing structures, splash pads, water parks.
Body of water	A natural or man-made water feature within or surrounding a park.	Boating, fishing, swimming, water view.	Ponds, rivers, lakes, canals, beaches.
Jog/Walk Path	A designated route or trail typically paved or surfaced with materials suitable for foot traffic. May be marked with signage or directional indicators.	Walking, jogging, running activities.	Nature trail, exercise path.
Athletic Facility	An area designed with infrastructure and amenities for various organized sports.	Soccer, basketball, tennis, volleyball, swimming, etc.	Sports fields, courts, tracks, swimming pools.
Nature Preserve	A designated area that is actively managed and protected to serve natural ecosystems and biodiversity.	Bird watching, scientific research, education, nature-based recreation.	Contain native plants, animal species, and preserved natural features.

Dog Park	An area or open field that provides a controlled environment for dogs to exercise and play off leash.	Recreational activities for dogs and dog owners.	Fenced boundaries, waste disposal stations, water stations, agility equipment.
Indoor/Outdoor Fitness Center	An enclosed or open air space with equipment to promote physical fitness through exercise.	Individual or group fitness, yoga, calisthenics, strength training.	Exercise machines, weights, cardio equipment, allocated spaces for physical activities.

Table 2. Linear models (lm) to compare the relationship between (1 – 3) scaled biodiversity to scaled human utility values and log transformed greenspace area (m^2), (4) scaled human utility values to greenspace area, and (5) scaled bio-use values to eight physical attributes and log transformed area (m^2). The human utility attributes are binary, and the model estimates are for attribute presence. For each model, we report the adjusted R^2 value.

Model specification	**Estimate**	**SE**	**t value**	**p-value**
lm(biodiversity ~ human_utility + log(area))				
Human Utility	-0.018	0.030	-0.604	0.546
Area	0.050	0.004	11.766	<0.001
Adj R^2 = 0.22				
lm(biodiversity ~ human_utility)				
Human Utility	0.168	0.028	6.069	<0.001
Adj R^2 = 0.05				
lm(biodiversity ~ log(area))				
Area	0.048	0.004	13.530	<0.001
Adj R^2 = 0.22				
lm(human_utility ~ log(area))				
Area	0.076	0.005	15.885	<0.001
Adj R^2 = 0.28				
lm(biodiversity ~ pp + kp + w + path + af + np + dp + fc + log(area))				
Pavilion/Picnic Area (pp)	-0.021	0.011	-1.847	0.065

Kids Playground (kp)	0.035	0.012	2.860	0.004
Body of Water (w)	0.034	0.012	2.728	0.07
Jog/Walk Path (path)	0.011	0.011	0.985	0.325
Athletic Facility (af)	-0.069	0.012	-5.644	<0.001
Nature Preserve (np)	0.092	0.021	4.301	<0.001
Dog Park (dp)	0.034	0.018	1.864	0.063
Indoor/Outdoor Fitness Center (fc)	-0.013	0.014	-0.982	0.326
Area	0.045	0.004	11.225	<0.001
Adj R^2 = 0.16				

Figures

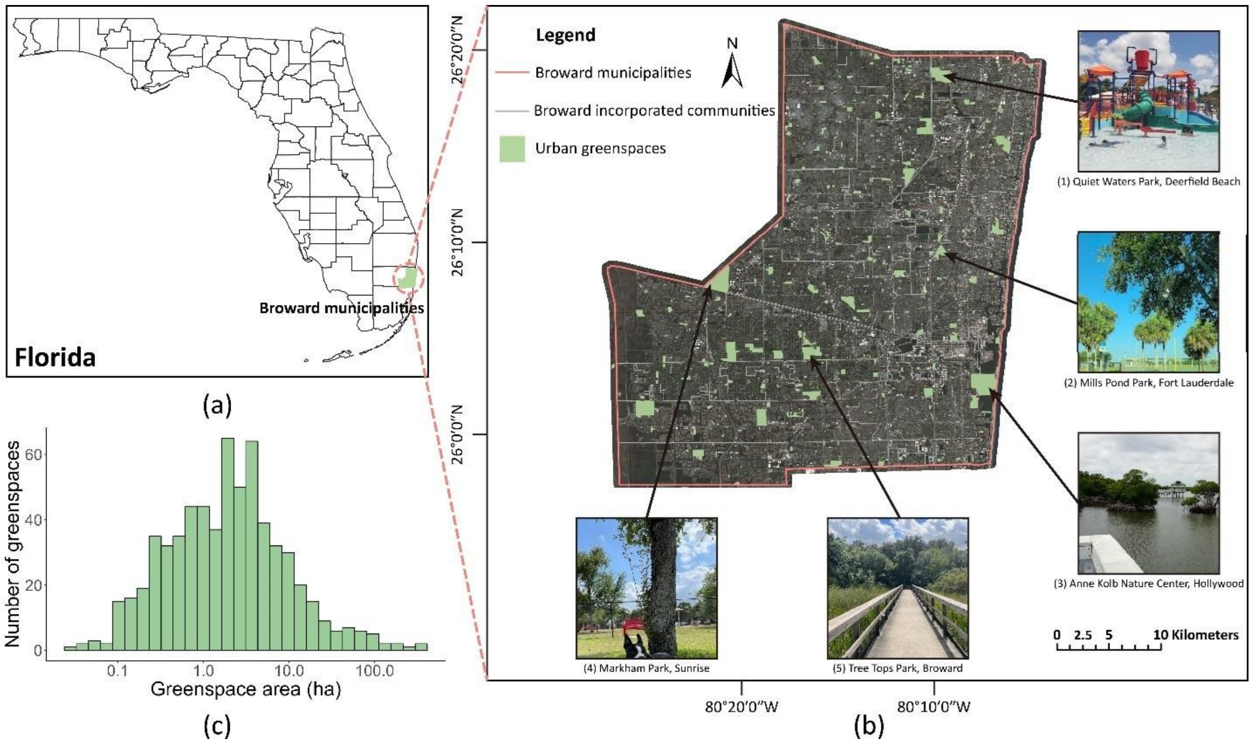

Fig. 1. (a) Location of Broward County, Florida, USA. (b) Map of study area and the 639 delineated urban greenspaces. (c) The histogram displays the distribution of greenspace area on the log10 scale for ease of interpretation.

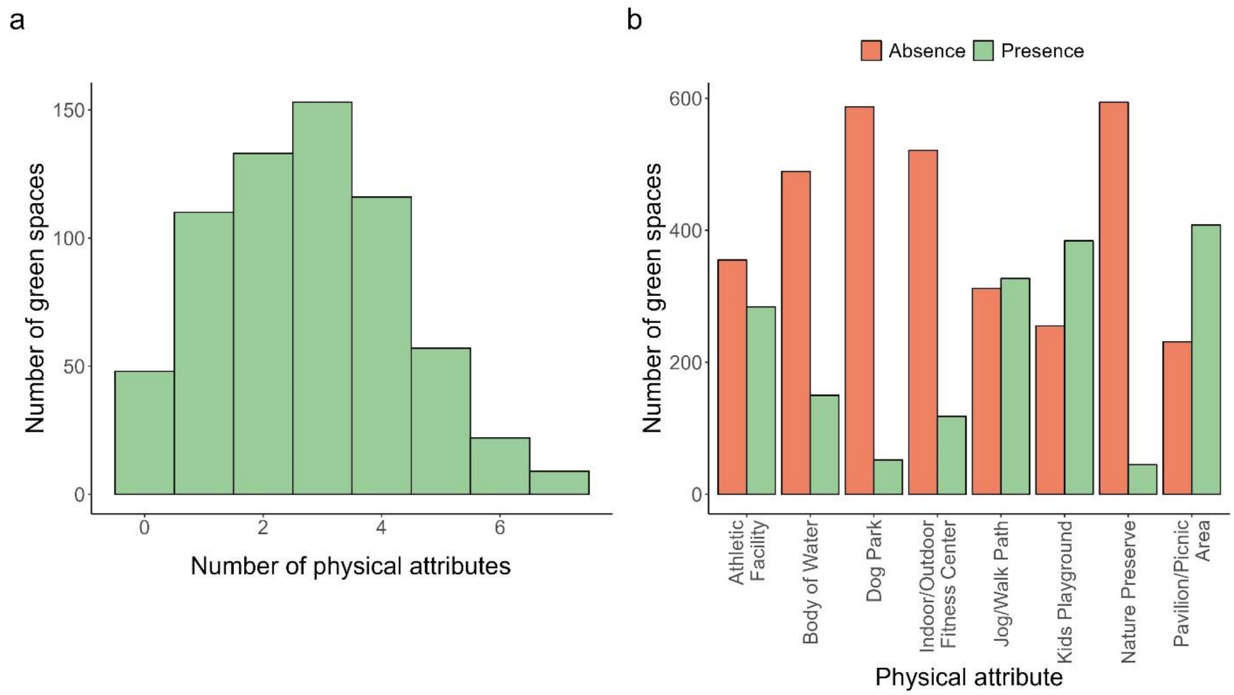

Fig. 2. The (a) distribution of number of physical attributes per greenspace and (b) the count of presence and absence of each physical attribute for all greenspaces.

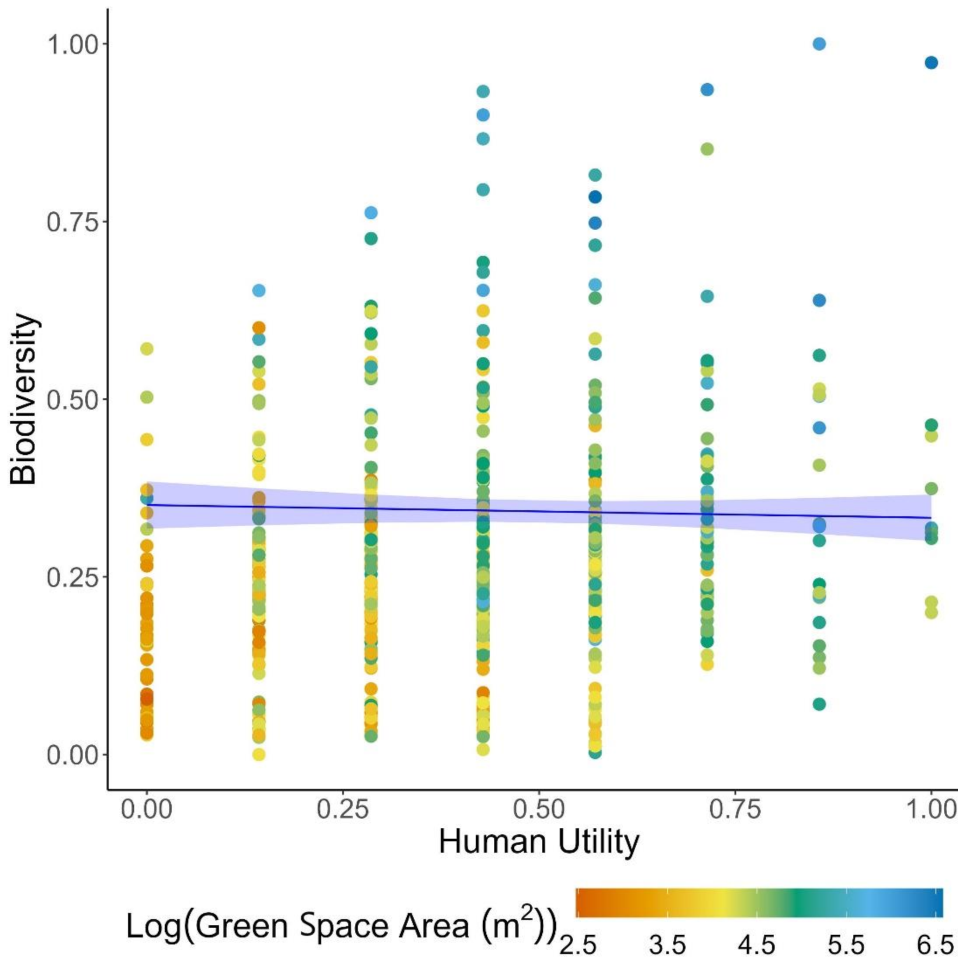

Fig. 3. Comparison of human utility attributes and biodiversity value by log10 transformed greenspace area. The blue slope line and 95% confidence interval is from a linear model that compared biodiversity to human utility and greenspace area (see Table 2).

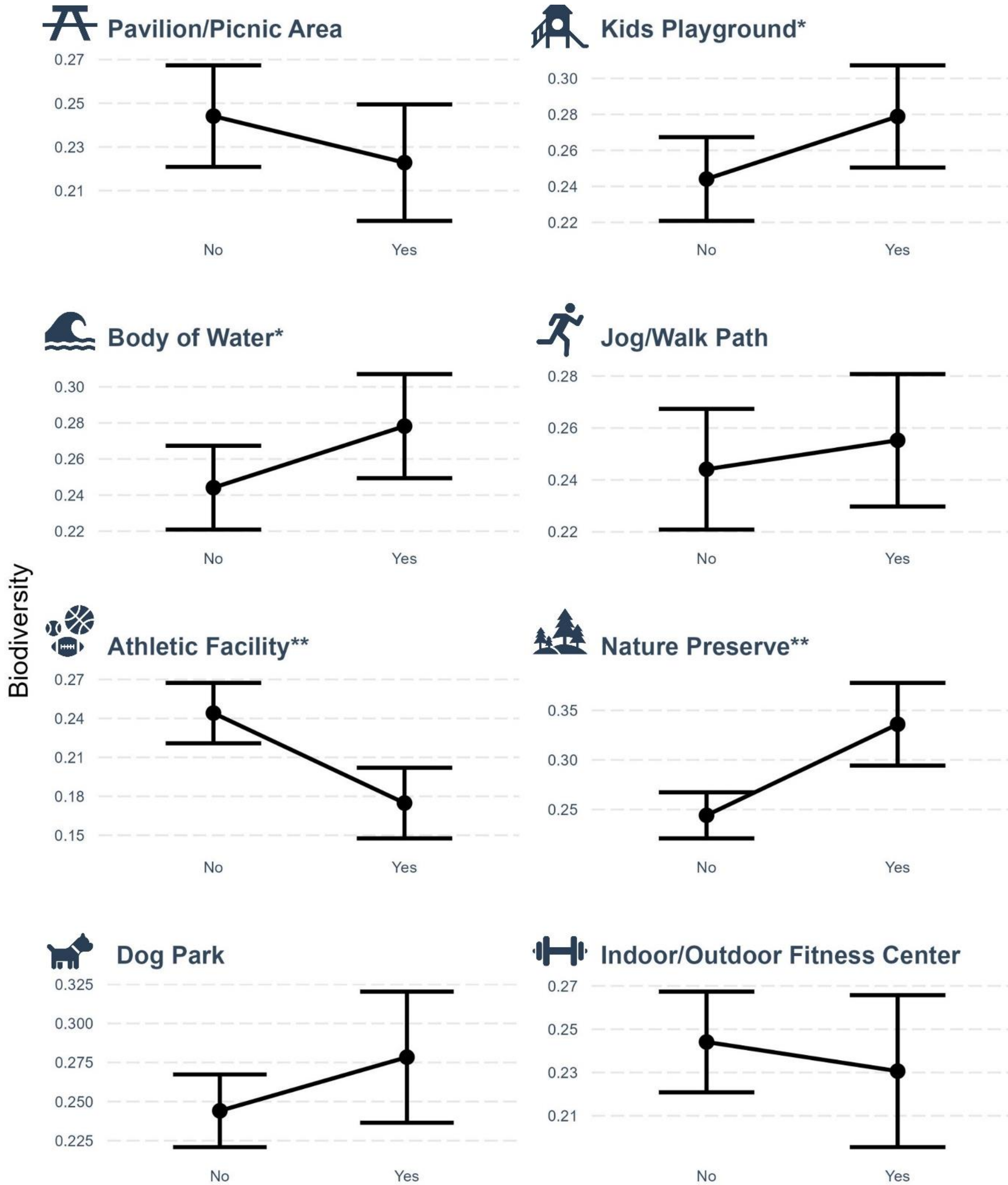

Fig. 4. Linear model predictions of human utility attributes by bio-use value (see Table 2). The linear model included scaled bio-use values as the response variable and log10 transformed greenspace area (m^2) and each human utility attribute (binary) as predictor variables. *p-value <0.05 and ≥ 0.001 **p-value < 0.001

Appendix A: Supporting Information

Table A.1. Number of greenspaces that were used in analysis by municipality.

Municipality	Number of greenspaces	Municipality	Number of greenspaces
Coconut Creek	24	North Lauderdale	16
Cooper City	23	Oakland Park	15
Coral Springs	43	Parkland	9
Dania Beach	17	Pembroke Park	2
Davie	36	Pembroke Pines	34
Deerfield Beach	32	Plantation	38
Fort Lauderdale	109	Pompano Beach	40
Hallandale Beach	12	Southwest Ranches	7
Hollywood	42	Sunrise	18
Lauderdale Lakes	5	Tamarac	11
Lauderdale by the Sea	3	West Park	3
Lauderhill	23	Weston	15
Lighthouse Point	3	Wilton Manors	7
Margate	19	Village of Lazy Lake	0
Miramar	35	Village of Sea Ranch Lakes	0

Table A.2. Summary of taxa observed in Broward County, Florida greenspaces. The first column displays the total number of observations under each described taxon. For taxon groups with over 20 observations, the "Species" and "Count" columns highlight the top five most frequently reported species, along with their respective observation counts. Species names are presented as the common name followed by the scientific name in parentheses. If no common name is available, only the scientific name is provided.

Taxon name	Species	Count
Plantae (N = 11,039)	Shiny-leaved wild coffee (*Psychotria nervosa*)	349
	White beggarticks (*Bidens alba*)	231
	American beautyberry (*Callicarpa americana*)	225
	Largeflower Mexican clover (*Richardia grandiflora*)	212
	Cabbage palmetto (*Sabal palmetto*)	184
Insecta (N = 5,756)	Zebra longwing (*Heliconius charithonia*)	260
	White peacock (*Anartia jatrophae*)	209
	Monarch (*Danaus plexippus*)	188
	Gulf fritillary (*Dione vanillae*)	181
	Band-winged dragonlet (*Erythrodiplax umbrata*)	167
Aves (N = 3,960)	Burrowing owl (*Athene cunicularia*)	202
	Boat-tailed grackle (*Quiscalus major*)	192
	Domestic muscovy duck (*Cairina moschata*)	183
	White ibis (*Eudocimus albus*)	166
	North American common gallinule (*Gallinula galeata*)	150
Reptilia (N = 1,918)	Green iguana (*Iguana iguana*)	343
	Brown anole (*Anolis sagrei*)	334
	Brown basilisk (*Basiliscus vittatus*)	207
	Northern curly-tailed lizard (*Leiocephalus carinatus*)	138
	Green anole (*Anolis carolinensis*)	128
Arachnida (N = 597)	Golden silk spider (*Trichonephila clavipes*)	155
	Spinybacked orbweaver (*Gasteracantha cancriformis*)	110
	Leucauge argyra	52
	Mabel orchard orbweaver (*Leucauge argyrobapta*)	41
	Magnolia green jumping spider (*Lyssomanes viridis*)	35
Mammalia (N = 545)	Eastern gray squirrel (*Sciurus carolinensis*)	231
	Common raccoon (*Procyon lotor*)	121
	Marsh rabbit (*Sylvilagus palustris*)	78
	Coyote (*Canis latrans*)	24
	Nine-banded armadillo (*Dasypus novemcinctus*)	20

Fungi (N = 398)	Hairy hexagonia (*Hexagonia hydnoides*)	57
	Clathrus crispus	25
	Cinnabar bracket (*Trametes sanguinea*)	22
	Favolus brasiliensis	12
	green-spored parasol (*Chlorophyllum molybdites*)	11
Actinopterygii (N = 312)	Mayan cichlid (*Mayaheros urophthalmus*)	53
	Spotted tilapia (*Pelmatolapia mariae*)	25
	Checkered puffer (*Sphoeroides testudineus*)	25
	Sailfin molly (*Poecilia latipinna*)	15
	Florida gar (*Lepisosteus platyrhincus*)	14
Animalia - Other (N = 295)	Mangrove tree crab (*Aratus pisonii*)	88
	Blue land crab (*Cardisoma guanhumi*)	36
	Bumblebee millipede (*Anadenobolus monilicornis*)	24
	Atlantic sand fiddler crab (*Leptuca pugilator*)	21
	New Guinea flatworm (*Platydemus manokwari*)	19
Amphibia (N = 206)	Cuban tree frog (*Osteopilus septentrionalis*)	141
	Greenhouse frog (*Eleutherodactylus planirostris*)	17
	Cane toad (*Rhinella marina*)	17
	Eastern narrow-mouthed toad (*Gastrophryne carolinensis*)	9
	Pig frog (*Lithobates grylio*)	7
Mollusca (N = 201)	Mangrove periwinkle (*Littoraria angulifera*)	29
	Island apple snail (*Pomacea maculata*)	20
	West Indian bulimulus (*Bulimulus guadalupensis*)	15
	Cuban brown snail (*Zachrysia provisoria*)	15
	Lined treesnail (*Drymaeus multilineatus*)	12

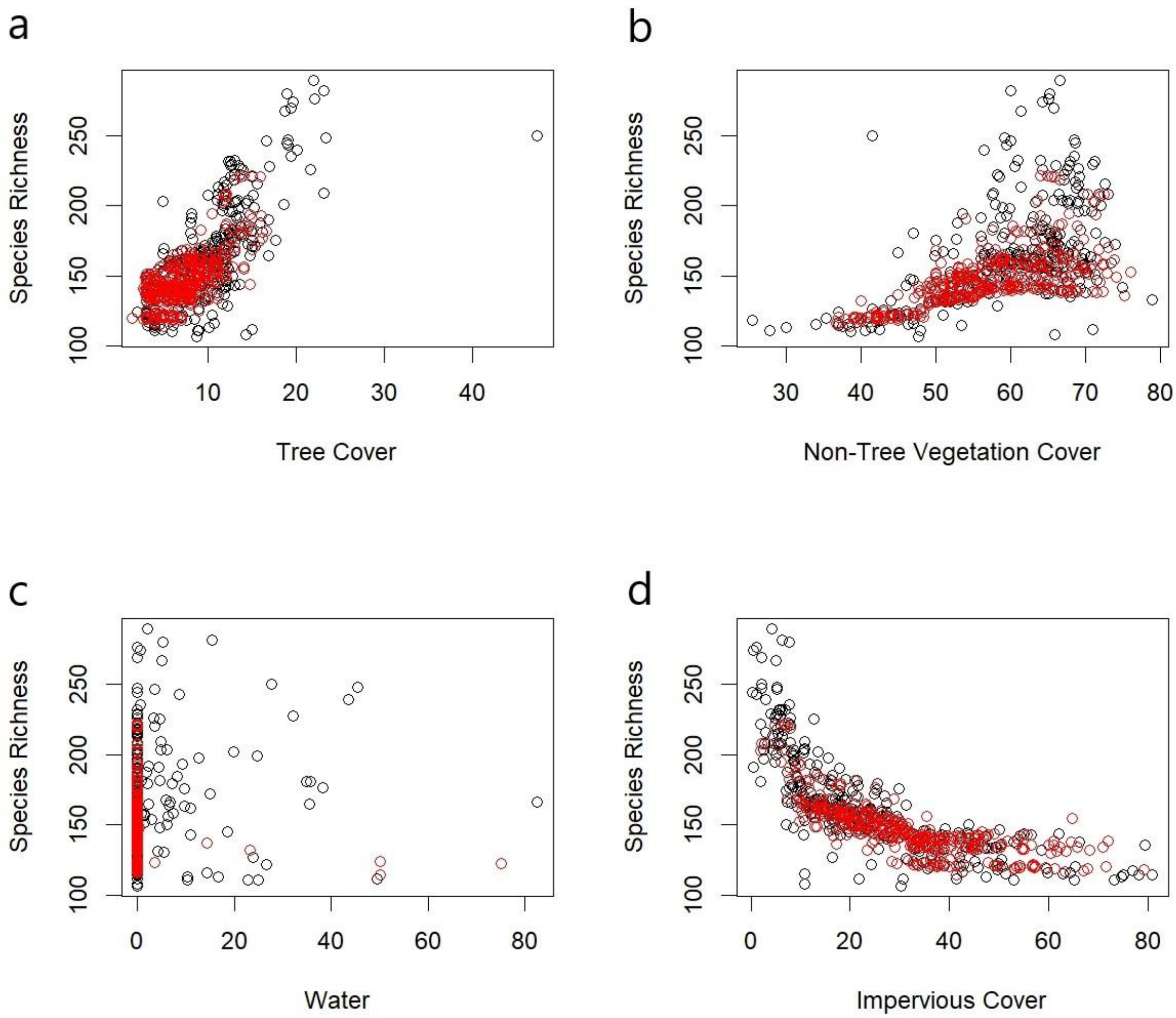

Fig. A.1. Comparison of imputed values (red) to real values that were scaled to 1,000 total observations (black). This plot shows that the imputation correctly followed the trends in the real data.

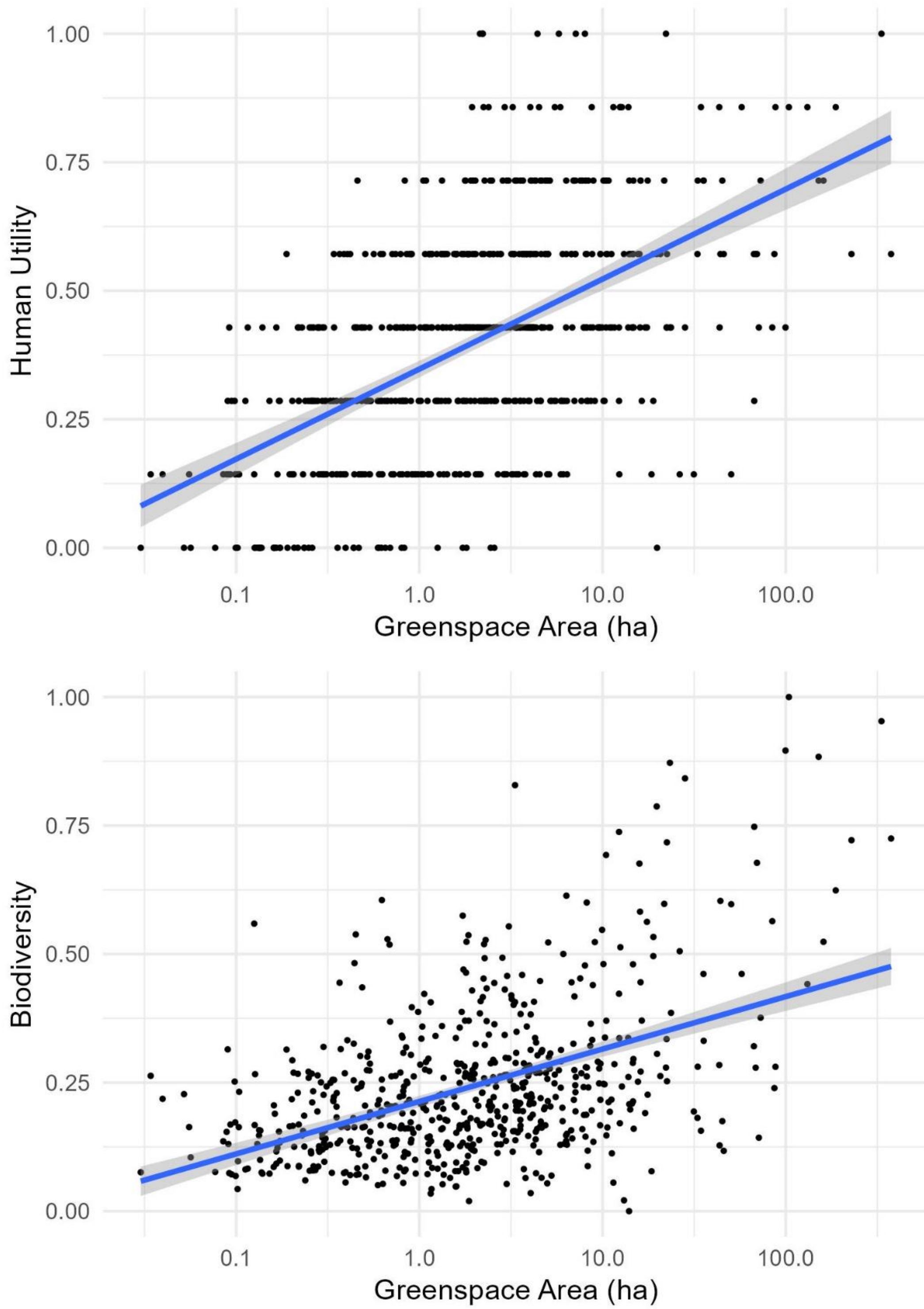

Fig. A.2. The relationship between human utility value and greenspace area (top) and biodiversity and greenspace area (bottom). The x-axis is displayed on the log10-scale. The blue line represents the linear model trend line using geom_smooth() and the grey shading is the 95% confidence interval.

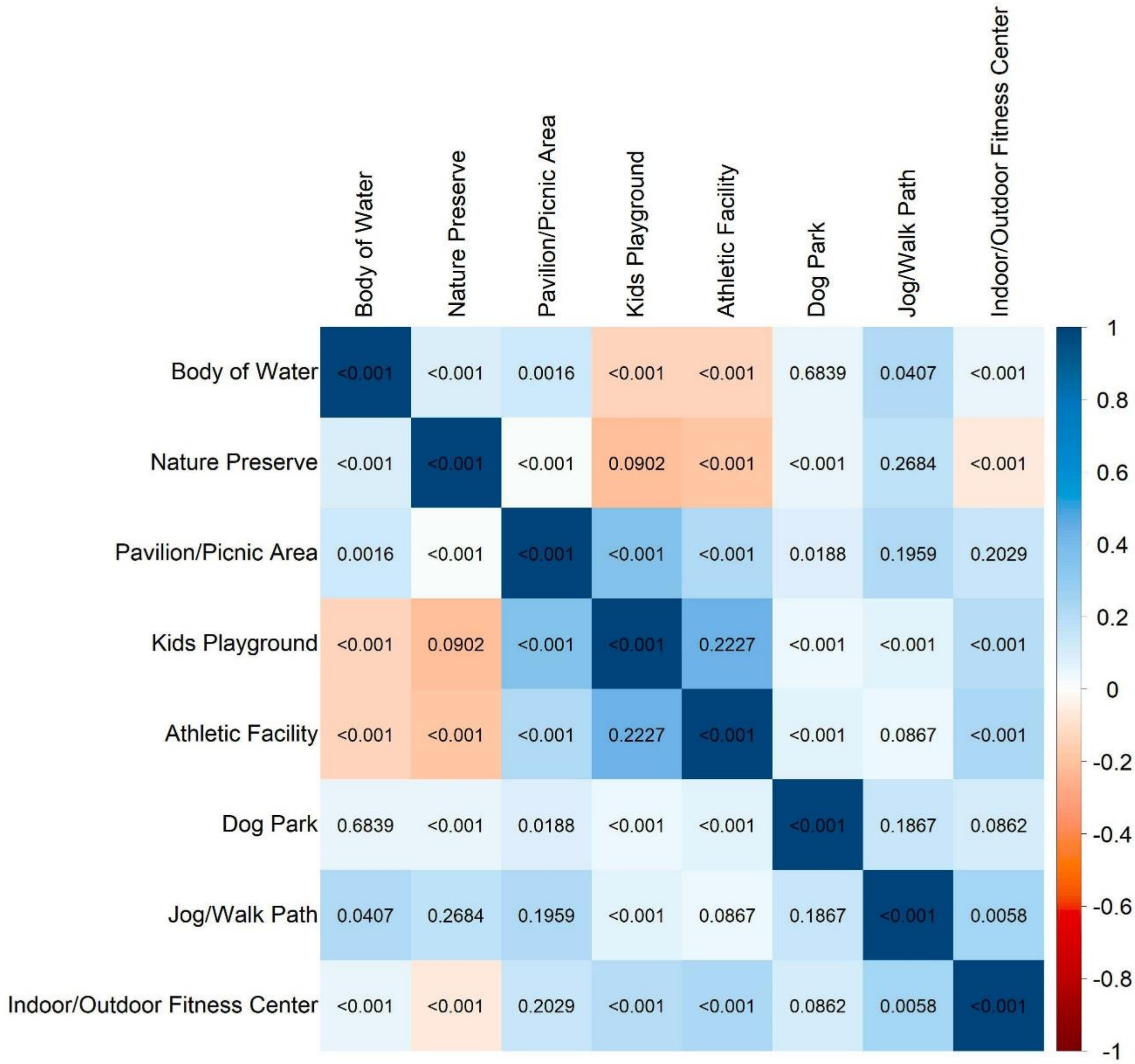

Fig. A.3. Correlogram of physical attributes, displayed as clusters from hierarchical clustering. Colors represent the correlation coefficient and values in the boxes represent *p*-values.

Appendix B: Method comparison for calculating a measure of relative biodiversity

Our dataset includes 639 parks, with 288 having iNaturalist observations to predict biodiversity. To address this limitation and increase data availability, we used a random forest imputation to estimate biodiversity utility for parks that do not have observations (see paper for full methods). However, imputing missing data can potentially influence model outputs. Therefore, we compared different methods to calculate biodiversity utility to assess the impact of our approach on the results. We conducted all analyses presented in the paper using five different methods for calculating biodiversity. The methods are described below (Table B.1):

- **Method 1:** We created a random forest model and used this to predict species richness at a constant value of 1,000 observations for each park. Afterwards, we used a random forest imputation algorithm to impute species richness for parks without iNaturalist observations. The resulting predicting is species richness for parks with and without iNaturalist data. This method was used in the main paper (*N* = 639).
- **Method 2:** We created a random forest model and used this to predict species richness at a constant value of 1,000 observations for each park. The resulting prediction is species richness for parks that have iNaturalist data (*N* = 288).
- **Method 3:** We used a Generalized Additive Model to predict richness for 1,000 total observations. The resulting prediction is species richness values for parks that have iNaturalist data (*N* = 288).
- **Method 4:** Because many parks have a small amount of iNaturalist observations, we filtered the data to parks that have at least 50 iNaturalist observations. Then we created a

random forest model and predicted species richness at 1,000 observations for each park. The resulting prediction is species richness for parks that have greater than 50 iNaturalist observations (N = 72).

- **Method 5**: We filtered the data to parks that have at least 50 iNaturalist observations. Then, used a generalized additive model to scale richness for 1,000 total observations for parks that have iNaturalist data (N = 72).

In each method, we used the log10 transformed species richness as the response variable and number of iNaturalist observations, number of iNaturalist users, average percentage of tree cover (%), water cover area (%), average percentage of impervious surface (%), and average percentage of non-tree vegetation cover (%) as the predictor variables. The methods for the random forest models and imputation are described in detail in the main paper. For the generalized additive models (GAM), the predictor variables were modeled as smooth terms using cubic regression splines. To determine the appropriate number of basis functions (k), we tested various values and used the gam.check() function to ensure the model fit was suitable. Specifically, we ensured that the residuals were not significant and that the effective degrees of freedom were not overly constrained.

Results

Overall, we observed consistent trends across all methods; however, the sample size influenced the strength of these trends. When we compared biodiversity utility to human utility while controlling greenspace area, we found that all models indicated a non-significant trend between biodiversity utility and human utility and a significant positive trend between biodiversity utility and greenspace area (Table B.2, Figure B.1). The random forest model demonstrated better fit, as indicated by the adjusted R^2. As expected, methods that reduced the sample size of parks led to higher standard errors.

The method to calculate biodiversity utility influenced the linear model comparing biodiversity utility to binary human utility attributes (Table B.3, Figure B.2). While all significant trends identified using the primary method present in the main paper were also present in the other methods, the significance of these relationships varied. The first method found a significant, positive relationship between biodiversity utility and kid's playground ($\beta = 0.035$, SE = 0.012, $p = 0.004$), body of water ($\beta = 0.034$, SE = 0.012, $p = 0.007$), and nature preserve ($\beta = 0.092$, SE = 0.021, $p < 0.001$), and a significant, negative relationship between biodiversity utility and athletic facility ($\beta = -0.069$, SE = 0.012, $p < 0.001$). Method 2 found a significant negative relationship between biodiversity utility and athletic facility ($\beta = -0.098$, SE = 0.023, $p < 0.001$). Method 3 found a significant, positive trend between biodiversity utility and nature preserve ($\beta = 0.118$, SE = 0.052, $p = 0.025$). Method 4 found no significant trends. Finally, Method 5 found a significant positive trend between biodiversity utility and indoor/outdoor fitness centers ($\beta = 0.141$, SE = 0.019, $p = 0.050$). These results highlight that the sample size does impact the quantitative results slightly, but the qualitative patterns and overall relative effect sizes remain comparable. Nevertheless, we provide all 'methods' of calculating biodiversity for transparency here.

Table B.1. Description of the five different methods we tested to calculate biodiversity utility.

Method	Data filtering	Sample Size	Model	Imputation
Method 1	All data	639	Random Forest Model	Yes
Method 2	Parks with iNaturalist observations	288	Random Forest Model	No
Method 3	Parks with iNaturalist observations	288	Generalized Additive Model	No
Method 4	Parks with >50 iNaturalist observations	72	Random Forest Model	No
Method 5	Parks with >50 iNaturalist observations	72	Generalized Additive Model	No

Table B.2. Comparison of linear model outputs to compare the relationship between five methods to calculate biodiversity utility and scaled human utility values and log transformed greenspace area (m^2).

Method	Variable	Estimate	SE	t value	P-value	Adj R^2
Method 1	Human utility	-0.024	0.027	-0.871	0.384	0.218
	Greenspace area	0.046	0.004	11.80	<0.001	
Method 2	Human utility	-0.041	0.051	-0.820	0.413	0.238
	Greenspace area	0.064	0.007	8.77	<0.001	
Method 3	Human utility	-0.076	0.80	-0.952	0.342	0.143
	Greenspace area	0.07566	0.012	6.558	<0.01	
Method 4	Human utility	-0.028	0.132	-0.214	0.831	0.261
	Greenspace area	0.097	0.022	4.434	<0.001	
Method 5	Human utility	0.157	0.110	1.425	0.159	0.187
	Greenspace area	0.047	0.018	2.572	0.012	

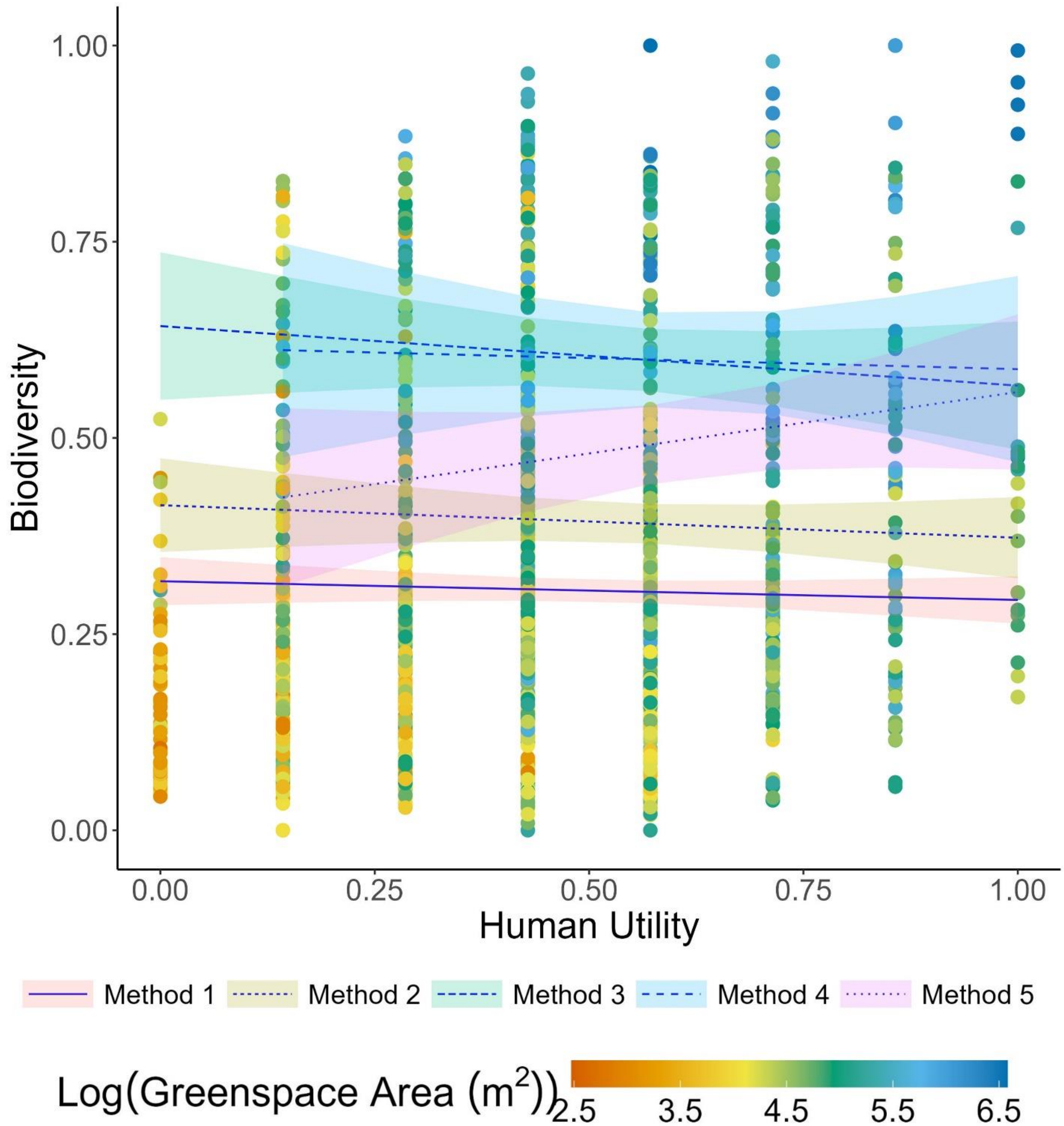

Fig. B.1. Comparison of human utility attributes and biodiversity value, calculated from five methods, by log10 transformed greenspace area. The blue slope line and the shaded 95% confidence interval is from the linear model that compared biodiversity to human utility and greenspace area (see Tabe B2). In every model, human utility was not a significant predictor of biodiversity.

Table B.3. Comparison of model outputs from linear models comparing the relationship between biodiversity utility values, calculated using five different methods, to eight physical attributes and log transformed area (m^2).

Method	Variable	Estimate	SE	t value	p-value
Method 1	Pavilion/Picnic Area	-0.021	0.011	-1.847	0.065
	Kids Playground	0.035	0.012	2.860	0.004
	Body of Water	0.034	0.012	2.728	0.007
	Jog/Walk Path	0.011	0.011	0.985	0.325
	Athletic Facility	-0.069	0.012	-5.644	<0.001
	Nature Preserve	0.092	0.021	4.301	<0.001
	Dog Park	0.034	0.018	1.864	0.063
	Indoor/Outdoor fitness Center	-0.013	0.014	-0.982	0.326
	Area	0.045	0.004	11.225	<0.001
	Adj R^2 = 0.312				
Method 2	Pavilion/Picnic Area	-0.038	0.022	-1.717	0.087
	Kids Playground	0.044	0.023	1.883	0.061
	Body of Water	0.021	0.020	1.026	0.306
	Jog/Walk Path	0.036	0.022	1.645	0.101
	Athletic Facility	-0.098	0.023	-4.193	<0.001
	Nature Preserve	0.048	0.032	1.512	0.132
	Dog Park	0.050	0.031	1.618	0.107
	Indoor/Outdoor fitness Center	-0.012	0.025	-0.442	0.659
	Area	0.062	0.007	8.446	<0.001
	Adj R^2 = 0.314				
Method 3	Pavilion/Picnic Area	-0.063	0.036	-1.727	0.085
	Kids Playground	-0.004	0.038	-0.111	0.912
	Body of Water	0.021	0.033	0.639	0.523
	Jog/Walk Path	0.061	0.036	1.712	0.088

	Athletic Facility	-0.038	0.038	-1.004	0.316
	Nature Preserve	0.118	0.052	2.253	0.025
	Dog Park	0.007	0.050	0.113	0.910
	Indoor/Outdoor fitness Center	-0.008	0.040	-0.208	0.835
	Area	0.064	0.012	5.339	<0.001
	Adj R^2 = 0.177				
Method 4	Pavilion/Picnic Area	-0.016	0.073	-0.222	0.825
	Kids Playground	0.030	0.074	0.407	0.685
	Body of Water	0.019	0.063	0.301	0.764
	Jog/Walk Path	0.052	0.084	0.616	0.540
	Athletic Facility	-0.101	0.069	-1.449	0.152
	Nature Preserve	0.076	0.069	1.096	0.277
	Dog Park	-0.018	0.108	-0.170	0.865
	Indoor/Outdoor fitness Center	0.083	0.071	1.165	0.248
	Area	0.088	0.023	3.776	<0.001
	Adj R^2 = 0.244				
Method 5	Pavilion/Picnic Area	-0.013	0.061	-0.209	0.835
	Kids Playground	0.041	0.061	0.674	0.503
	Body of Water	0.083	0.053	1.566	0.122
	Jog/Walk Path	0.000	0.030	-0.004	0.997
	Athletic Facility	-0.052	0.058	-0.906	0.368
	Nature Preserve	0.035	0.058	0.600	0.550
	Dog Park	-0.072	0.090	-0.801	0.426
	Indoor/Outdoor fitness Center	0.141	0.059	2.367	0.021
	Area	0.039	0.019	2.014	0.050
	Adj R^2 0.17				

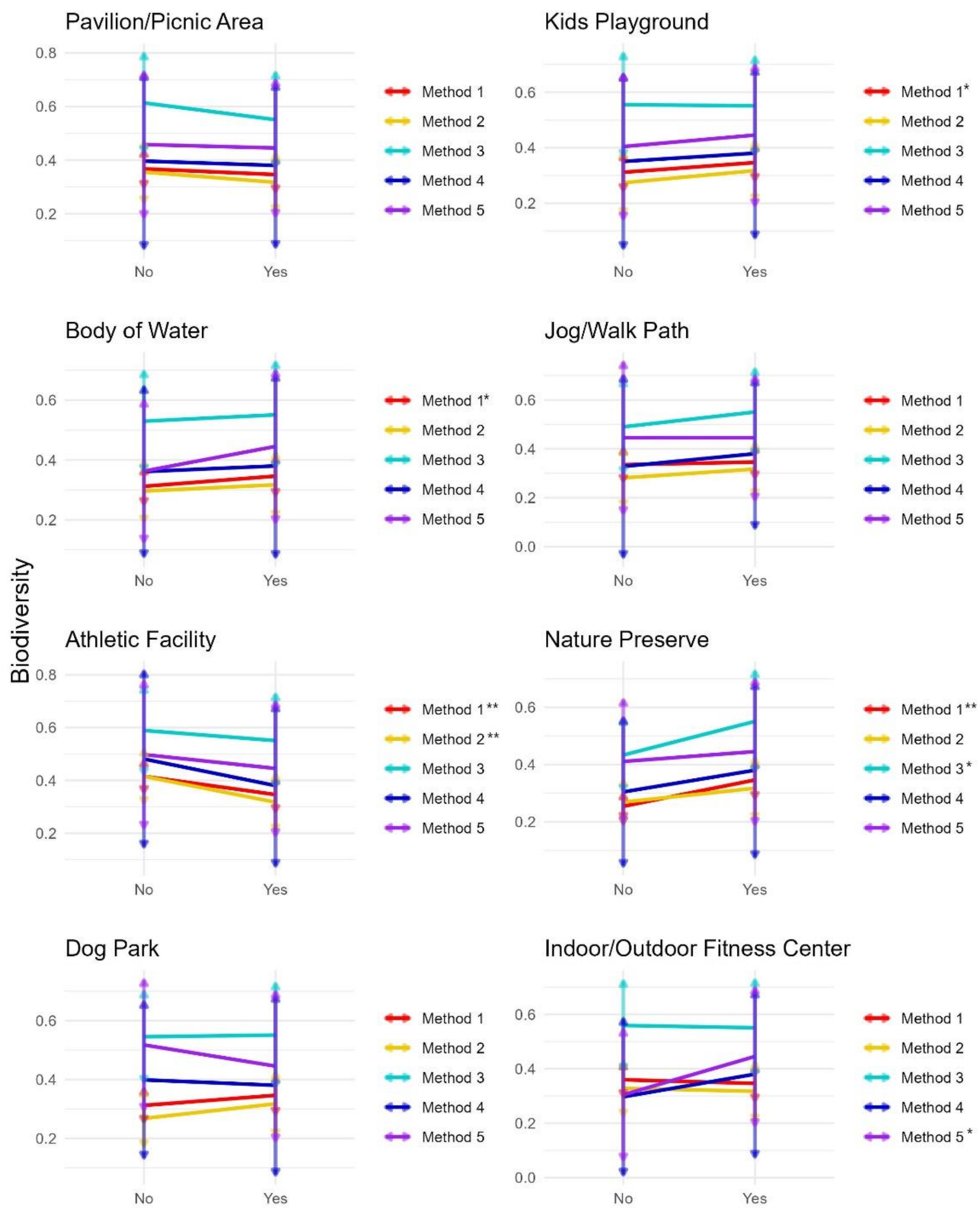

Fig. B.2. Linear model predictions of human utility attributes by biodiversity utility values, calculated using five methods. The linear model included scaled biodiversity utility as the response variable and each human utility attribute and log10 transformed greenspace area (m^2) as the predicator variable. *p-value <0.05 and ≥ 0.001 **p-value < 0.001