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Global patterns in urban green space are strongly linked to human development and population density

Rasmus Attrup Bille [a], Kristine Engemann Jensen [a], Robert Buitenwerf [a,b,*]

[a] Section for Ecoinformatics and Biodiversity, Department of Biology, Aarhus University, Ny Munkegade 114, 8000 Aarhus C, Denmark
[b] Center for Ecological Dynamics in a Novel Biosphere (ECONOVO) & Center for Biodiversity Dynamics in a Changing World (BIOCHANGE), Department of Biology, Aarhus University, Ny Munkegade 114, 8000 Aarhus C, Denmark

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ABSTRACT

Urban green space is important for alleviating high temperatures, pollution, and flooding in cities. Furthermore, it is becoming increasingly clear that urban green space is important for the mental and physical health of humans residing in cities and that urban green space may harbor unique biodiversity. Understanding the extent and drivers of urban green space is thus important. While urban green space has been mapped and studied at local to national scales, the global patterns and drivers of urban green space remain unknown, potentially hampering effective planning and allocation of resources toward reaching sustainable development goals. Here, we quantified the effect of environmental and socio-economic drivers (temperature, precipitation, human development, and population density) on urban green space globally by focusing on national capital cities. We used satellite imagery to map urban green space using two measures: the Normalized Difference Vegetation Index (NDVI), and the fractional cover of "green" land cover classes. NDVI is useful as it includes all vegetated surfaces, also small ones like gardens. However, land cover classes allow the exclusion of certain classes such as sports fields or cropland. We used boosted regression trees to show that climatic variables accounted for 75 % of the relative influence in urban green space, with a positive effect of precipitation and a negative effect of temperature. Importantly, socioeconomic variables accounted for 25 % of the influence on global urban green space, with a positive effect of human development index (HDI) and a negative effect of population density. HDI in relation to urban green space has not previously been tested globally, and our study shows that significantly affects urban greenspace. The results demonstrate that cities where development status is low and population densities are high, typically in the Global South, have less urban green space than the climate would predict. The results therefore suggest that human wellbeing does not only benefit directly from increasing human development and decreasing population densities in urban areas, but that these effects may be compounded by also improving nature's contribution to people.

1. Introduction

The Anthropocene is characterized by environmental and societal challenges. Among these are the fast increase in global urban populations, the loss of natural areas and biodiversity, as well as global warming caused by greenhouse gas emissions (United Nations, 2015; IPBES, 2019; IPCC, 2021). In 2007, the global urban population exceeded the global rural population for the first time in history, and by 2050 it is expected that two thirds of the world population will be urban (United Nations, 2015). As more people live in urban areas, it becomes increasingly important to consider the wellbeing of urban dwellers in city planning (Galea and Vlahov, 2005).

For cities undergoing urbanization the exposure to "green space" such as gardens, urban parks and forests is a major and often overlooked aspect of urban wellbeing (van den Bosch and Nieuwenhuijsen 2017), as lacking green space provision is associated with poor mental health (Engemann et al. 2019). Higher levels of green space have been associated with increased cognitive development of children (Dadvand et al., 2015), reduced rumination and brain activity linked to stress (Bratman et al., 2015), and lower risk of developing psychiatric disorders (Engemann et al. 2019). The proposed mechanisms linking green space to mental health includes mitigation of air pollution and noise,

* Corresponding author at: Section for Ecoinformatics and Biodiversity, Department of Biology, Aarhus University, Ny Munkegade 114, 8000 Aarhus C, Denmark.
E-mail address: buitenwerf@bio.au.dk (R. Buitenwerf).

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encouraging physical activity and social interactions, restoring cognitive functioning and alleviating stress (Hartig et al. 2014). Growing urban populations may therefore be problematic, as densification leads to less per capita urban green space putting urban residents at risk (Fuller and Gaston, 2009).

Physical wellbeing of urban dwellers may also benefit from green space, both directly and indirectly, especially as ongoing climate change will result in hotter conditions and more extreme weather events (Rocque et al. 2021). By providing shade, lowering heat retention and increasing evaporative cooling, urban green space can reduce ambient temperatures and is therefore an important tool to combat the urban heat island effect, which can raise temperatures by more 2,8 °C above surrounding areas (Oliveiraet al., 2011; Mohajerani et al., 2017; Frumkin, 2002). Avoiding additional warming in urban areas is not just a luxury as more than one-third of the global population will likely be exposed to Sahara-like temperatures within the next 50 years (Xu et al. 2020). Urban green space may also improve physical health of urban dwellers by increasing water infiltration and reducing storm flood runoff, which is becoming increasingly important as climate change is expected to increase the frequency of extreme rainfall events (Easterling et al., 2000). Urban green space has also been linked to improved physical health through lower cardiovascular disease risk, diabetes risk and overall mortality by lowering concentrations of aerial pollutants and promoting physical activity (Hartig et al., 2014).

Finally, as urban areas continue to expand it becomes increasingly important to consider how urban densification and expansion contributes to biodiversity loss and how biodiversity in urban areas can be restored or potentially redesigned. Creating urban green spaces can create new habitats and promote biodiversity in cities (Beninde et al., 2015), where vegetation is typically scarce and biodiversity low. In more natural ecosystems greater biodiversity can increase the resilience of ecosystem functioning in changing and fluctuating environments, e.g. the capacity to maintain primary production (Malhi et al. 2020). It may therefore be hypothesized that increasing biodiversity of urban green space may also increase resilience of ecosystem services such as city cooling and storm flood mitigation, and potentially increase mental health benefits. Urban habitats can thus be seen as a nature-based solution to address biodiversity loss, health and restore ecosystem functioning but these links remain to be studied in detail (Rega et al. 2022).

Since urban green space can improve physical and mental wellbeing of people and provide a nature-based solution to biodiversity loss and climate change adaptation, it is key to understand the drivers and limitations to urban green space. While research on urban green space has increased strongly in recent years, the literature remains biased toward North America and Europe and the role of local patterns and drivers of urban green space are still unknown (Haaland and van den Bosch, 2015; Richards et al., 2017). The distribution of urban green space in much of the southern hemisphere remains undocumented, while local drivers and limitations that explain between-city variation in urban green space remain poorly understood.

Since climate is the main driver of global variation in vegetation productivity and activity (Buitenwerf et al. 2015; Nemani et al. 2003), climate can also be expected to influence urban green space. Recently, greening has been observed globally driven by a combination of warming and CO_2 fertilization, but with locally diverging patterns linked to human activities and negative climate effects on vegetation in the tropics (Piao et al., 2020). Consequently, vegetation patterns are influenced by global change through various processes, but their relative importance at the local (city) scale remains unclear. Hence, an investigation of how climatic and sociodemographic factors influence vegetation patterns is important, as a better understanding of drivers of urban green space will allow better planning toward increased green space.

Urban green spaces are due to their location likely strongly impacted by both climate and sociodemographic factors. Several studies have found that provision of green space is highly unequal within cities around the world as affluent neighborhoods are often greener than poorer areas, illustrating the role of socioeconomic variables (Fergusona et al., 2018; Nesbitt et al., 2019). For example, one study found GDP growth and population growth to be two main drivers behind global scale temporal urban vegetation trends and document that positive vegetation trends, to some extent, are predominant in Europe and North America (Zhang et al., 2021). Furthermore, their study indicates GDP per capita is positively linked to NDVI trends, while population density has a strong negative correlation (Zhang et al., 2021). Similarly Dobbs et al., (2017) found human population density to correlate negatively with urban green space, while others have documented a positive effect from GDP and negative from population density, on urban green space ratio (Li et al., 2018). However, most studies on this topic are constrained to the regional scale (Zhang et al., 2021) and thus limited to a subset of global climatic and sociodemographic gradients, potentially hindering inference to understudied parts of the world.

To capture global gradients in key drivers of urban green space we use a globally distributed sample of cities to 1) map global patterns of urban green space and 2) to test whether climate and socioeconomic variables determine differences in urban green space between cities. Since the definition used to calculate measures of green space may affect the hypothesized relationships, we use two alternative (and potentially complementary) measures of urban green space. The first measure is the "greenness" of terrestrial surfaces quantified using satellite imagery which is positively related to the amount and productivity of vegetation and may therefore be strongly affected by the climatic potential for vegetation growth. The second measure is the (proportional) cover of "green" spaces in a city which may be more directly impacted by urban planning and therefore by socioeconomic variables.

2. Methods

2.1. Study area

To test the impacts of climate and country-level socioeconomic status on urban green space we required a global sample spanning geographic and climatic gradients. We therefore selected the capital city from each country for the analysis. Capital cities were identified using the Esri world cities feature layer (Esri et al., 2021) and to delineate city boundaries we used spatial polygon data derived from the European Commission Joint Research Center, which is based on a population and built-up dataset (Florczyk et al., 2019). We visually inspected the city boundaries by overlaying them onto recent high resolution satellite imagery, which revealed that the boundary polygons were inaccurate for small capital cities with < 50,000 inhabitants, which may be due to the relatively coarse resolution of city boundary polygons (1 km) relative to the total size of smaller cities. A further 11 cities were excluded as predictor variables were not available, resulting in a final sample of 159 capital cities (Table. S1).

2.2. Climate and socioeconomic data

To capture the potential impact of climate on urban green space, we selected temperature and precipitation, which are the main limitations to vegetation productivity. Mean annual temperature and precipitation for 1970–2000 were downloaded from WorldClim 2.1 in 1 km^2 resolution (Fick and Hijmans, 2017). To capture socioeconomic status we used the Human Development Index (HDI) and human population density. HDI calculated for 2020 was downloaded from the United Nations Development Program (Undp, 2020). HDI is a widely-used country-level summary measure of human development based on life expectancy at birth, expected years of schooling, mean years of schooling and gross national income (GNI) per capita (Undp, 2020). These input variables are transformed into three indices on life expectancy, education, standard of living and HDI is then calculated as the geometric mean of the three indices (Undp, 2021). Finally, we included human population density. The most recent population density data from 2015 was downloaded from the European Joint Research Center in Mollweide projection with 250-meter resolution (JRC, 2015). We selected only these variables to represent the broad environmental and socio-economic categories to keep the analysis tractable, but we recognize that further detail could be added to each category, e.g. climate seasonality, or direct measurements of poverty, or implementation of rule of law, etc.

2.3. Urban green space

We measured urban green space with two different remotely sensed variables. First, we quantify the '*greenness*' of cities using Normalized Difference Vegetation Index (NDVI) at 10 m resolution from Sentinel 2 data. We also quantify urban green space as '*green land cover*', which we calculated using a new global land cover classification at 10-meter resolution (Karra et al., 2021). We use two independent measurements of urban green space as they capture and highlight different aspects of urban vegetation cover and seasonal dynamics, which we hypothesize can help to better understand the role of potential drivers of urban green space and facilitate cross-study comparisons.

2.3.1. Greenness

Land surface greenness can vary substantially throughout the year depending on rainfall and temperature seasonality. Since we want to compare cities with very different climates and seasonalities, we chose to use the maximum annual greenness, which should give a better estimate of available urban green space than e.g. the mean. We used 10-m Sentinel 2 data in Google Earth Engine (GEE) (Gorelick et al., 2017) to first remove pixels with > 30 % cloud cover and then calculate the maximum NDVI value for every pixel in a city over the year 2020. We then averaged across all pixels within a city to calculate greenness for each city. Water was not excluded in this calculation.

2.3.2. Green land cover

We calculated green land cover in GEE using the ESRI 2020 Global land cover (Karra et al., 2021). The dataset is global with 10 land cover classes at a 10-meter resolution, derived from Sentinel 2 satellite data using a deep learning approach (Karra et al., 2021). The frequency of each land cover class was extracted for each city polygon and proportional cover "green" land covers was then calculated as

$$Green\ land\ cover = \frac{TREES + GRASS + FLOODED\ VEGETATION + SHRUB}{TREES + GRASS + FLOODED\ VEGETATION + SHRUB + BUILD\ AREA + CROPS + BARE\ GROUND}$$

Water was excluded as were cloud-covered pixels although very few pixels were cloudy. All GEE code is available through the link in Appendix 2.

Based on these methods we provided a full list of green land cover and greenness for all capitals in our study (Table S1).

2.4. Statistical analysis

We used boosted regression trees to investigate relationships between climatic and socioeconomic variables and urban green space as regression trees can model complex and non-linear relationships and we had no a-priori hypothesis that relationships should be linear. Boosted regression trees is a machine learning method with many advantages such as insensitivity to outliers, good visualization and ability to deal with missing data (Elith et al., 2008). It is necessary to define and tune a set of hyperparameters which impact the learning process. Here, we tuned tree complexity (more complex trees allow higher levels of interaction), learning rate (fast learning rates shrink the contribution of each tree), number of trees (more trees requires longer computation time), minimum number of observations in terminal nodes, and bag fraction (a stochasticity parameter) (Elith et al., 2008; University of Cincinati, 2018). We performed hyperparameter tuning by grid search to find the best combination of settings to optimize overall accuracy of the model (Duarte and Wainer, 2017; Schratz et al., 2019). Separate models were tuned for greenness and green land cover.

Hyper tuning was to attain the smallest possible root mean square error (RMSE) through a 5-fold cross validation (Table S2).

The combination of hyperparameters with the lowest RMSE resulted in 27 and 56 trees for green land cover and greenness respectively (Table 1). Learning rates should be slow enough to result in at least 1000 trees for small sample sizes (<250 sites) (Elith et al., 2008). We therefore also trained models with slow enough learning rates to result in > 1000 trees, which provided qualitatively identical results to our final models with 27 and 56 trees (Fig. S1). Both the models with < 100 and > 1000 trees were trained with tree complexity > 1 allowing first order interactions (De'ath, 2007), however, for green land cover, using model stumps (tree complexity = 1) resulted in almost a similar RMSE, indicating that interactions may not be very important. To test for interactions, we calculated Freidman's H (Friedman and Popescu, 2008) which showed that no two variables had a Freidman's H of more than ~ 0,12. Each model contains 5 and 7 minimum observations in each terminal node which increases generalizability. For this analysis we used the gbm function in the gbm package for R (Greenwell et al., 2020).

Once the optimal set of hyperparameters was identified the model was trained with these parameters. All data points were used in the training step as the sample was relatively small for a boosted regression tree approach. To avoid overfitting the RMSE of both models were estimated from 5-fold internal cross validation, which indicates the model's ability to predict on unseen data. Moran's I was calculated on the residuals, as spatial autocorrelation can yield overoptimistic predictive performances (Schratz et al., 2019), but the results showed no spatial autocorrelation. As the model was not used to predict urban green space, e.g. in unseen cities or under future climates, we consider the risk that overfitting impacts the results as low.

To visualize the effect of each predictor variable on the response, we used partial dependence plots and relative influence plots of each predictor. Partial dependence plots (PDP) show how a specific predictor variable is assumed to influence the predicted outcome of the response when the remaining predictors are held constant. Another important element of the PDPs, when based on a boosted regression tree model, is the lack of a significance parameter (Elith et al., 2008). Instead, the relative importance of each predictor variable was calculated for interpreting the PDPs (Friedman, 2001).

We estimated model performance for both models using the predict function from the gbm package in R. This outputs a vector of predicted values, by using the same number of iterations as the original model was trained with (Greenwell et al., 2020). The predicted values were then compared to the observed values and R^2 was calculated as a measure of model accuracy. Lastly, we performed an ANNOVA to test significant differences in urban green space between continents (Table S3).

Table 1
Hyperparameter tuning. The table shows the combinations of hyperparameters that attain the lowest minimum root mean squared error by cross validation.

Model response	Learning rate	Tree complexity	Minimum observations in terminal node	Bag fraction	Optimal number of trees	Root mean squared error (RMSE)
Green land cover	0,05	2	7	0,80	27	0,0581
Greenness	0,05	3	5	0,65	56	0,0702

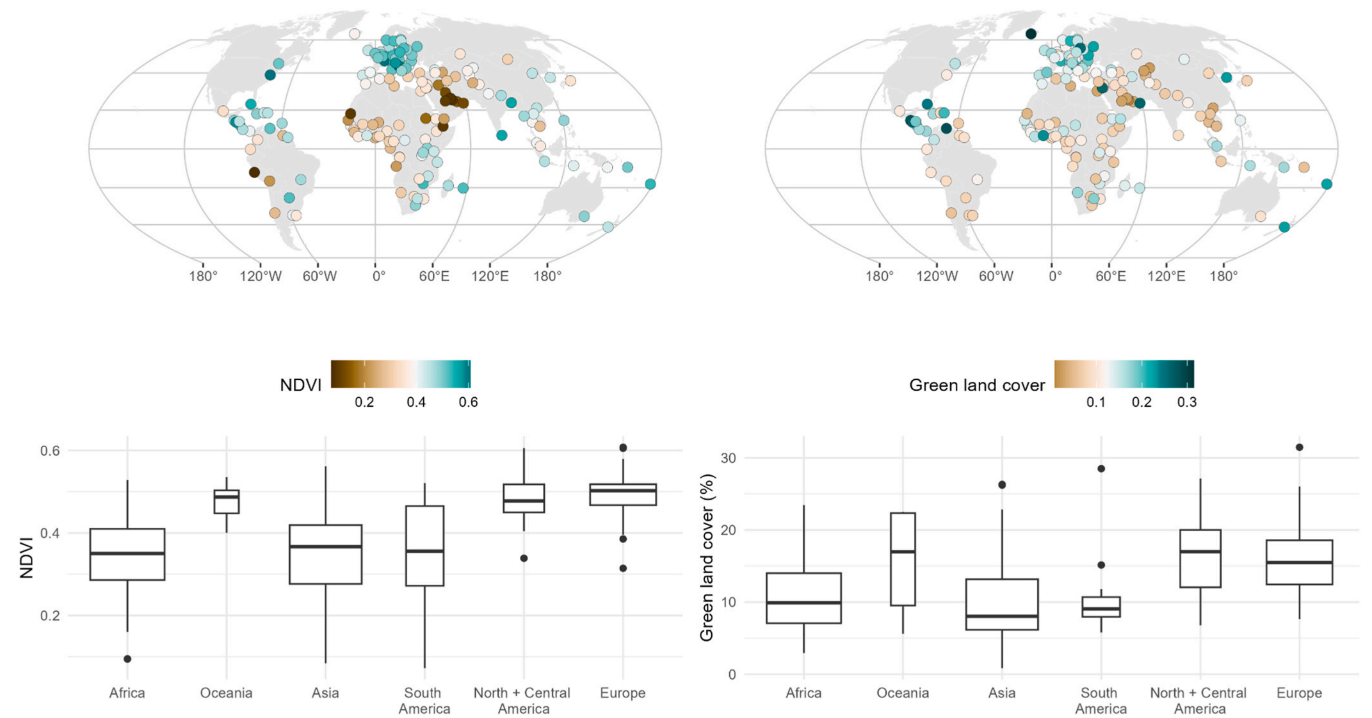

Fig. 1. Global distribution of a) greenness (NDVI) and b) green land cover in capital cities around the world. Summaries by continent are shown in boxplots c-d), where box width reflects the number of cities per continent. The map scales are centered on the mean, i.e. browns mean below-average and greens mean above-average. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Results

3.1. Global distribution of urban green space

Urban green space measured as greenness and green land cover was non-randomly distributed across the globe. Many cities in Europe, Central America, Southeast Africa and Southeast Asia had high greenness values, while West African, Middle Eastern, and Central Asian cities had low values (Fig. 1). Similar patterns were observed for green land cover where Asian, African and South American cities showed low values while Central American and European cities generally scored higher.

Only the grouped data with green land cover passed the '*Levene Test*' for homogeneity of variance. Cities in Europe had significantly more green land cover than cities in Africa ($p = 0.0003$) and Asia ($p = 0.00008$). Likewise North American cities also showed significantly

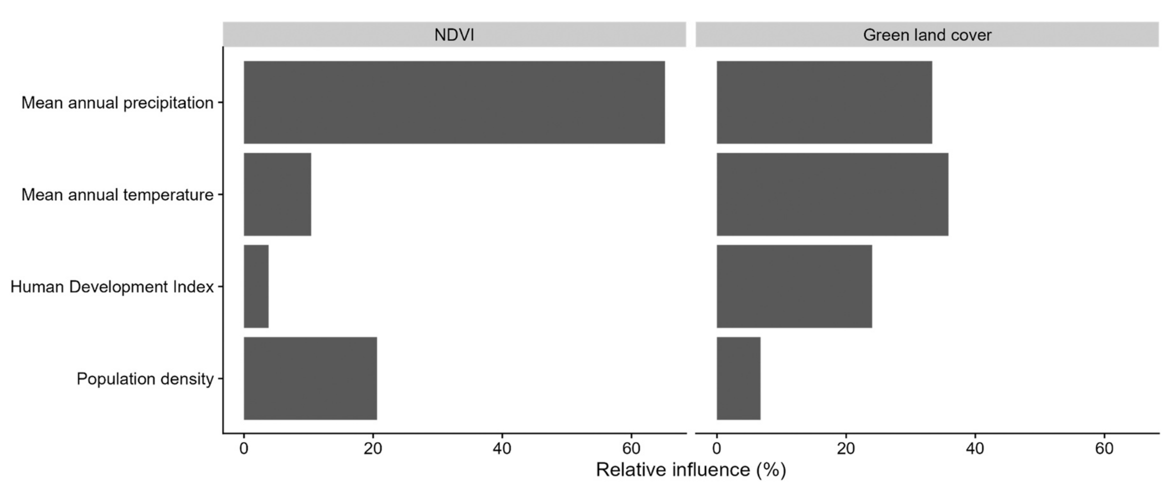

Fig. 2. Relative influence of each predictor variable on a) greenness (NDVI) and b) green land cover the two responses. MAP:Mean annual precipitation, MAT: Mean annual temperature, POP: Population Density, HDI: Human development index.

more green land cover compared to both Africa ($p = 0.002$) and Asia ($p = 0.0007$, Fig. 1). Oceanian cities also seemed to have more green land cover than African, Asian and South American cities, but this difference was not significant. The patterns looked very similar for urban green space measured as land surface greenness with higher greenness in Europe, North America and Oceania than in Africa, Asia and South America, but since greenness did not meet the assumption of homogeneity of variance (Levene test $p = 0.00154$) this could not be tested statistically with ANOVA.

3.2. Urban green space explained by climatic and socioeconomic drivers

Tuned boosted regression tree models performed well and could explain urban green space using climate (temperature, rainfall), human population density and human development index (HDI) for both greenness ($R2 = 0.79$, $RMSE = 0.07$ and green land cover ($R2 = 0.22$, $RMSE = 5.8$ %) (Fig. S2).

The partial dependence plots show the relative influence of each predictor, while the effect of the remaining predictors are accounted for in the model. Here, climate variables accounted for around 75 % of variable importance in explaining urban green space, for both greenness (75.58 %) and green land cover (69.19 %) (Fig. 2). Precipitation had the strongest influence on the greenness of cities - with 65,2 % relative influence whereas temperature had a relatively small influence on greenness with 10,1 % relative influence. For green land the importance of precipitation (35.86 %) and temperature (33.33 %) were more balanced.

Partial dependence plots for temperature and precipitation were similar for both measures of urban green space, with more urban green space in cool and wet areas (Fig. 3 a-d).

Both greenness and green land cover increase steeply between 0 and 1000 mm mean annual precipitation and level off at > 1000 mm, suggesting that vegetation growth is not limited by moisture above 1000 mm per annum. For temperature the response curves had different shapes for greenness and green land cover, with the steepest decline in greenness around 10 °C whereas the steepest decline in green land cover occurred at 25 °C, suggesting different temperature limitations of greenness and green land cover.

HDI was positively related to both measures of urban green space, suggesting that more developed countries have more urban green space after accounting for differences in climate and human population density. Greenness increased between HDI 0.5–0.7, after which it leveled off. Absolute increases in greenness were small along the HDI gradient. Green land cover increased at slightly higher HDI values than greenness did, between 0.6 and 0.8, with larger absolute increases of up to 1.5 % (i.e. from 12 % to 13.5 %). This suggests that human development status may have a larger impact on green land cover than on land surface greenness in cities around the world.

Testing for interactions was done for the greenness model and revealed no significant interactions as no two variables had a Freidman's H of more than ~ 0.12.

Urban green space was negatively related to population density, with a steep decline of both greenness and green land cover around 300–400 people pr. 250 × 250 m, although the absolute declines of green land cover with increasing population density were small.

4. Discussion

To our knowledge, this is the first study that maps patterns and explores the combined effect of climatic and socioeconomic drivers of urban green space at the global scale. We found that urban green space is highly non-randomly distributed around the globe, that climate explains a substantial part of variation in urban green space between cities, but that human-controllable variables such as human population density and human development status also have a significant impact on the amount of urban green space, with more green space in less densely populated and more developed cities. Knowing how climate and socioeconomic factors may promote or limit urban green space potential in cities may aid the global green transition and guide city planning over the coming decades, as urban areas and populations continue to expand and densify.

4.1. Geographic variation in urban green space

The results showed that green land cover and greenness varied between continents. European, North American, and Oceanic cities had high green land cover and greenness values compared to the remaining continents (Fig. 1). Testing differences between continents verified these observations as Europe and North America had significantly more green land cover than Africa and Asia (Table S3). The sample size of Oceanian capitals was low ($n = 5$), which might explain why no significant difference between Oceania and the remaining continents was detected. Although this analysis does not yet take climate and other potential drivers or co-variates into account, it suggests that cities in the Global South on average have less urban green space than the Global North, which may have negative implications for human wellbeing, urban biodiversity and nature-based solutions to climate change adaptation in the Global South.

The relationship between population density, HDI and urban green space may partially explain why Africa and Asia contain less green land cover compared to Europe and North America, as Africa and Asia are experiencing rapid urbanization (Grullon, 2016). These findings are in accordance with findings from Sun, et al. (2020), who investigated urbanization trends in 841 cities globally. They found low-income countries to have the highest urban growth, but the lowest greenness in the sample. Similarly, Zhang et al. (2021) found positive vegetation trends for Europe and North America. Furthermore, these trends are linked to negative correlations between population density and urban green space in addition to a positive correlation between GDP growth and urban green space (Zhang et al., 2021; Dobbs et al.,. 2017), supporting our results.

The rapid increase in urban population density, which is projected to continue, has resulted in low provision of urban green spaces for various reasons including economic limitations, capacity, policies and planning based on different priorities and corruption (Fuller and Gaston, 2009; McDonald et al., 2010; Adhikari et al., 2019; Fuwape and Onyekwelu, 2011; Mensah, 2014). These observations are also consistent with the highly unequal distribution of gross national product per capita, where Africa, Asia, and South America fall far below other continents (The World Bank, 2022; WorldAtlas, 2022). Therefore, having resources to control and plan urbanization and densification may partly explain the global green land cover patterns observed, an observation which is similar to findings focused on Southeast Asian cities (Richards et al., 2017). Climate likely also contributes to the uneven distribution, as the climate variables accounted for a large part of the influence. However, using boosted regression trees allowed us to detect the effect of socioeconomic variables, after accounting for the influence from climate.

4.2. Determinants of urban greenspace

4.2.1. Climate

Mean annual precipitation and mean annual temperature accounted for approximately 75 % of the influence of predictor variables on both green land cover and greenness (see 2.3). This suggests that hot and arid cities can support less urban green space consistent with previous findings (Huang et al., 2017; Dobbs et al., 2017). This result was expected for greenness, as vegetation is typically limited by temperature, moisture or both (Nicholson and Farrar, 1994; Hatfield and Prueger, 2015). However, in our definition of green land cover, urban green space is not necessarily green as it includes e.g. shrublands and grasslands regardless of the seasonality of vegetation growth. It therefore seems that in hot and dry cities less space may be allocated to green land

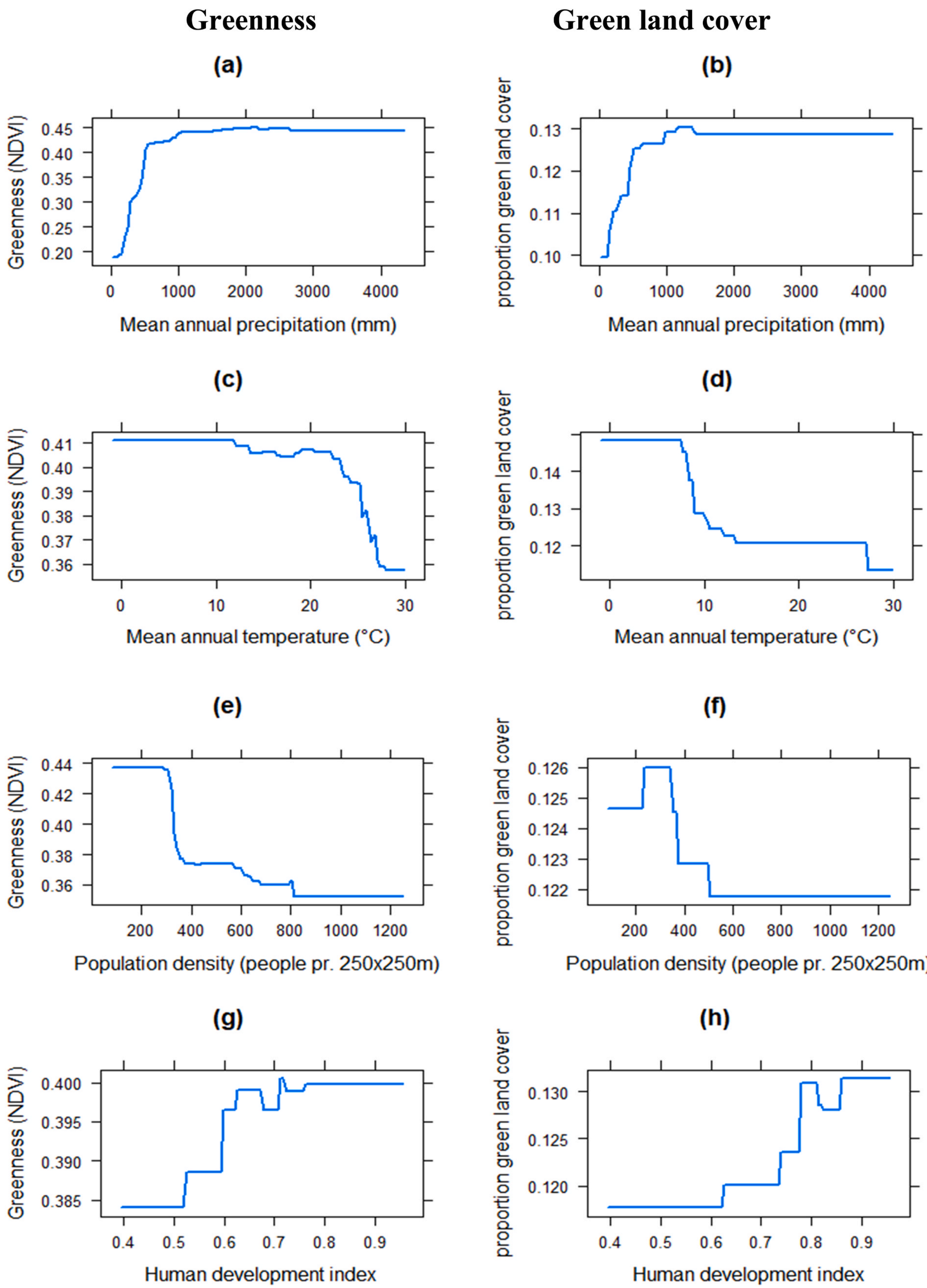

Fig. 3. Boosted regression tree partial dependence plots of predictor variables for a) greenness and b) green land cover to show how each predictor variable is expected to affect urban greening when all other predictors are accounted for.

covers. This may be because in hot and dry climates these green land covers are not actually green for much of the year, potentially limiting their functionality and therefore their prioritization in city planning. To test this idea additional studies would be required.

Our finding that urban green space is limited by climate is important as without targeted action global warming and the derived urban heat island effect may further restrict urban green space (Chen and Wong, 2006; Norton et al., 2015; Oliveira et al., 2011). A positive feedback through replacing impervious surfaces with vegetation may therefore work as a solution to increase human wellbeing by keeping temperatures low, and may also create a more suitable microclimate for expansion of urban green spaces. Furthermore, all continents (except Antarctica) have experienced increases in ecological drought due to climate change (IPCC, 2021), which may negatively affect urban green space in areas where urban green space is water limited (<1000 mm yr^{-1}). At the same time extreme rainfall events are predicted to increase in frequency and intensity, stressing the need for maintenance or expansion of urban green space to increase infiltration and reduce storm floods (Oliveira et al., 2011; Semeraro et al., 2021). Without further action, climate change is thus likely to reduce urban green space in cities around the world, while maintenance and expansion of urban green space may mitigate impacts of climate change on human wellbeing. However, since socioeconomic variables explain part of the variation in urban green space, there are opportunities to take action and increase urban green space within current and future climate limitations.

4.2.2. Socioeconomic drivers

Socioeconomic drivers collectively account for approximately 25 % of the influence of predictor variables on urban green space patterns. Green land cover was particularly influenced by HDI (24.04 %), while population density had greater influence on greenness (20.61 %, Fig. 2).

The fact that population density has a large influence on greenness might indicate that it captures a different element of urban green space compared to green land cover. For example, individual garden size has been shown to strongly predict land cover composition (Tratalos et al., 2007). This means that small green spots, like gardens, may be captured by greenness, but are not classified as green land cover. These small green areas are expected to decline with increasing population densities, unless cities are wealthy enough to invest in architectural solutions such as high-density housing (Richards et al., 2017). Besides gardens, cropland (which are not included in the green land cover) also score high greenness values. These urban farmlands are expected to contain low population densities, which might further explain why population density is more important for predicting greenness, compared to green land cover, and why increasing population density will decrease expected greenness of a city.

Our results show a strong relationship between development status, population density and urban green space at the global scale, which is consistent with previous findings (Escobedo et al., 2006; Kinzig et al., 2005; Richards et al., 2017; Tian et al., 2011). The result is in contrast to another study on 28 mega cities, which did not find an effect of socioeconomic factors (Huang and Yang 2017) implying that different mechanism may influence specific types of cities. The influence of HDI and population density on urban green space is important as unequal access to urban green space and the associated benefits to human wellbeing creates social inequality and environmental injustice (Dahmann et al., 2010; Johnson-Gaither, 2011; Wolch et al., 2014). To increase urban green space in low HDI cities and countries it is thus important to better understand the mechanisms by which human development and population density affect urban green space.

Since one of three input indices to HDI is based on per capita income, economic capacity and HDI is closely linked to wealth of cities (Richards et al., 2019). Our results suggest that a certain level of economic capacity is needed before increases in urban green space can be expected. Underfunded city governance may instead be focused on fulfilling more basic needs such as infrastructure, housing or health, and a lack of resources for city planning can result in dense settlements with little green space (Fuller and Gaston, 2009; McDonald et al., 2010; Richards et al., 2017). Similar findings have been documented in China, where economic growth of cities only resulted in additional allocation to urban green space after a certain economic threshold was reached (Chen and Wang, 2013).

However, decision makers must also be willing to allocate resources to urban greening (See Box 1). Managing population densities, which was shown to have a large negative effect on greenness of cities, by planning housing is an important part of city planning and policies favoring strategic densification of cities have shown to substantially decrease urban green space (Dallimer et al., 2011). For example, the relatively large amount of urban green space per capita in Europe is explained by packing more people into built areas, leaving space for green areas (Fuller and Gaston, 2009). Within climatic and socioeconomic limits, strategic planning to accommodate higher population densities can thus favor urban green space in compact and green cities (Artmann et al. 2019).

While available funds and the vision of policy makers can control the "supply" of urban green space, the influence of HDI may also function through increasing the "demand" for urban green space. HDI also describes the access to and level of education for people (Undp, 2020). A more educated population may demand access to urban green space more strongly, e.g. education has been linked to perceived importance of

Box 1
Ljubljana – a case study to explore the mechanisms behind urban greening.

Ljubljana, the capital of Slovenia, has previously been awarded the Green Capital Award (EU, 2016; Adhikari et al., 2019) and has been highlighted as an example of how a city can be transformed by the right policy and urban planning framework (Gotovac and Kerbler, 2019). This achievement is consistent with our results, as the city had some of the highest levels of urban green space in any capital (Table S1).

The high urban green space in Ljubljana may be related to the relatively high human development index, which captures economic capacity. For example, city-council decisions to increase ecosystem resilience by restoring and maintaining degraded areas such as establishing new urban green spaces on abandoned industrial areas may be related to available funds and possibly to the demand for urban green space by an educated and economically developed population (Nastran and Regina, 2016; Gotovac and Kerbler, 2019). In addition to local government decisions, decisions by private land owners on garden management may also partly explain the success of greening Ljubljana, as lack of information on is a key challenge in increasing vegetation complexity through residential efforts (Goddard et al., 2010).

Finally, Ljubljana has sought to increase green space connectivity by integrating green corridors (City of Ljubljana, 2022, Fig. 4), to increase biodiversity levels both within the city limits and in the natural areas around the city. These green corridors are likely more easily implemented in cities with low population densities, such as Ljubljana. Although the relatively low population density in Ljubljana is likely determined by macro-sale processes, not efforts made by policy makers, other countries with high population densities and growing urban areas may benefit from actively managing urban densification and apply green interventions to create denser and greener cities (McDonald et al. 2023).

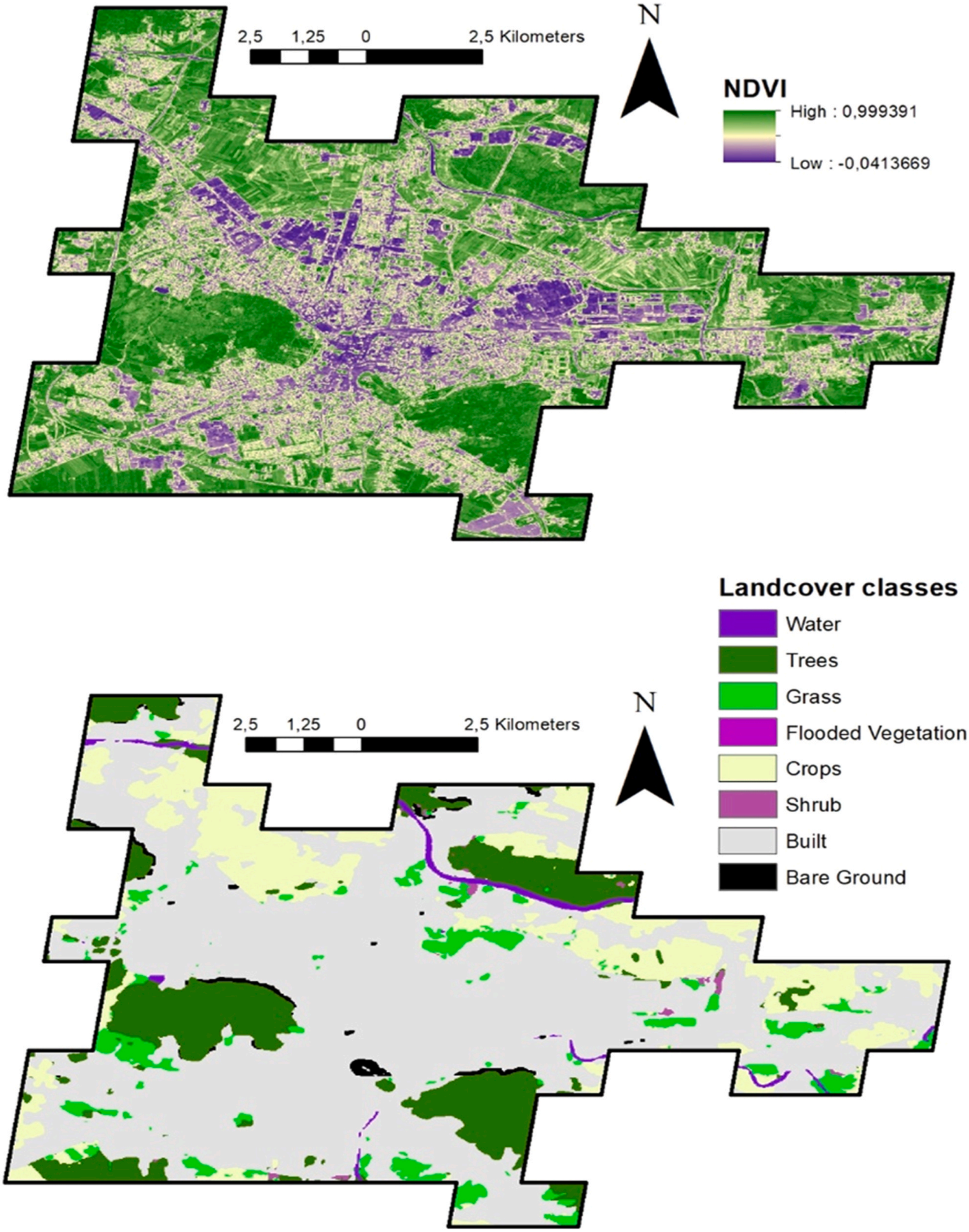

Fig. 4. Ljubljana polygon from the analysis. Top: Yearly maximum greenness (NDVI) value for each pixel at 10-meter resolution. Bottom: Land cover classes of each pixel. Image shows how Ljubljana has several green wedges penetrating far into the city. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ecosystem services (Lau et al., 2019) and described as a tool to reach sustainability (Hopkins and McKeown, 2002). Although interactions with economic status are likely to be strong, knowledge about the importance of urban green space could facilitate projects by local residents, such as the famous urban green space 'The High Line' in New York City (The High Line, 2022). Knowledge on the value of biodiversity may also facilitate initiatives to create habitats in private gardens, which can increase urban biodiversity (Aronson et al., 2017). Expanding such initiatives to developing countries may benefit both human health (Hartig et al., 2014; Beninde et al., 2015; Aronson et al., 2017) and biodiversity as some of the least developed and highly populated cities like Port-au-Prince, Haiti or Lomé , Togo, are situated in biodiversity hotspots, with high numbers of threatened endemic species (Blowes et al., 2019, Aronson et al., 2017).

4.3. Urban green space definitions - implications of green space metrics

We showed that two different measures of urban green space (greenness vs green land cover) gave qualitatively similar results on the directionality and relative influence of climate vs socioeconomic predictors (Figs. 2–3), but the relative roles of individual predictor variables differed. Similarly, the predictor variables explained more variance in greenness (NDVI) than in green land cover. Potential explanations for differences between greenness and green land cover models may partially reveal and help untangle mechanistic relationship between predictor variables and the alternative measures of urban green space. For example, NDVI in terrestrial ecosystems is an indicator of vegetation productivity, which is strongly driven by climatic variables, providing a mechanistic explanation for why our predictor variables may better explain greenness than green land cover (Nicholson and Farrar, 1994; Wang et al., 2003). Similarly, crop fields are common in some cities, e.g. around 35 % of Hanoi, but crop fields were excluded from green land cover while they were implicitly included in greenness measurements. Since crop NDVI is largely controlled by precipitation and temperature (Hollinger and Angel, 2009) this may also partially explain why the greenness model explained more of the total variance in urban green space.

However, attributes of the green space data may also play a role. Green land cover included shrubland which was defined very broadly in the land cover product: *"Mix of small clusters of plants or single plants dispersed on a landscape that shows exposed soil or rock; scrub-filled clearings within dense forests that are clearly not taller than trees; examples: moderate to sparse cover of bushes, shrubs and tufts of grass, savannas with very sparse grasses, trees or other plants"* (Karra et al., 2021). Removing shrubs from the urban green space category greatly increased model performance (from $R^2 = 0.22$ with shrubs to $R^2 = 0.79$ without shrubs, Fig. S3*)*. Another explanation for differences between greenness and green land cover may be indicated by the large negative influence of population density on greenness. For example, individual garden size has been shown to strongly predict land cover composition (Tratalos et al., 2007). However, many (parts of) residential gardens are smaller than the land cover pixels size (10×10 m) and may thus be excluded from the green land cover analysis.

The relatively high importance of HDI in explaining green land cover (25 %), but not greenness (5 %), is an interesting result that requires further testing. A potential explanation may be that green land cover as defined in this study largely captures intentional urban green spaces, while the greenness signal also includes e.g. urban croplands or abandoned areas. The deliberate design and planning for urban green space for e.g. recreation or other ecosystem services is likely to emerge at high HDI, when city budgets may be less constrained and the demand for urban green space from a more educated population may increase. This may be consistent with the increase in green land cover at HDI 0.70–0.85 (Fig. 3), while greenness increases at lower HDI (~0.6).

We thus conclude that analyzing greenness and green land cover in parallel provides a complementary and meaningful view on urban green space. While greenness is an effective metric that is agnostic to the type of vegetation that contributes urban green space (Dzhambov et al., 2018; Nesbitt et al., 2019; Sun et al., 2011), green land cover can capture additional detail on different types of urban green spaces such as semi-barren areas with sparse or seasonally dormant vegetation that scores low on greenness. These areas can have similar benefits to green areas as they are also habitats for wildlife, remove air pollutants, promote physical activities and are cool compared to built-up areas (Chaparro and Terrasdas, 2009; Puga-Caballero et al., 2014; Villeneuve et al., 2018; Zhang, 2020). Land cover classifications also allow researchers and city planners to exclude areas such as cropland that may not contribute to biodiversity or allow recreational activities by urban residents.

4.4. Management implications

Our results have implications for urban planners and policy makers who are challenged by the combined challenges from rapidly changing climate and urban densification and rapid population growth. Resilient plant species should be chosen based on locally relevant climate scenarios to survive extreme events such as flooding and droughts, and to thrive long term given the future climatic conditions. To accommodate increased competition for space, it will be necessary to increasingly utilize innovative urban green space solutions such as green roofs and walls, and protect existing green space as the city expands. Unmanaged green space and brown fields can have high biodiversity value that is difficult to replace if lost. Lastly, greening of cities may lead to gentrification thereby displacing marginalized communities creating social justice issues through unequal access the green space benefits. Taking a holistic approach to urban green space planning collaborating across disciplines and stakeholders will ensure that urban green spaces provide a variety of benefits and are adapted to future conditions.

4.5. Outlook

We acknowledge that capital cities may be less representative for some countries than for others. For example, São Paulo may be more representative of Brazilian cities than Brasilia, or Melbourne may be more representative of Australian cities than Canberra. However, when working with a large global sample objective criteria are key to avoid (implicit) biases in selecting samples, so we chose to refrain from making manual adjustments to a subset of countries with which we are more familiar. Nevertheless, in future work it will be important to increase the overall number and types of cities to test whether the relationships between urban green space and sociodemographic drivers that we identified hold and can be used for predicting urban green space in unmeasured areas, e.g. to generate nation-wide estimates of urban green space. Similarly, these relationships will be important to forecast future (potential) urban green space given rapid global climate and sociodemographic change.

5. Conclusion

This study provides novel knowledge on spatial patterns and the potential underlying drivers of urban green space globally. We conclude that urban green space is unequally distributed around the globe, and that even after accounting for differences in climate and the potential for vegetation growth, urban dwellers in the Global South have a lower availability of urban green space. While climate had a dominant influence on global patterns of urban green space, we showed that anthropogenic variables, such as human development status and population density also have a large influence. Global-scale studies that make use of the increasingly rich archive from Earth observation satellites and derived data products can play an important role unravelling the mechanisms that determine the availability of urban green space across geographic, socioeconomic and climatic gradients, which is an important step in developing strategies to plan sustainable, healthy and biodiverse cities. This includes maintaining and expanding urban green space globally to boost climate change adaptions, secure human physical and mental wellbeing, and provide habitats for biodiversity. Future studies should focus on investigating within-country heterogeneity, examining within-city landscape metrics for e.g. green space fragmentation, how the different components of the human development index, such as education and income, are linked mechanistically to the amount and spatial configuration of different green land covers in order to work toward greener and more functional urban areas.

CRediT authorship contribution statement

Rasmus Attrup Bille: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Kristine Engemann Jensen:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Robert Buitenwerf:** Conceptualization, Methodology, Supervision, Visualization, Writing – review & editing.

Declaration of Competing Interest

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

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.127980.

References

Adhikari, B., Pokharel, S., Mishra, S.R., 2019. Shrinking urban greenspace and the rise in non-communicable diseases in south asia: an urgent need for an advocacy. Front. Sustain. Cities 1, 1–5. https://doi.org/10.3389/frsc.2019.00005.

Aronson, M.F.J., et al., 2017. Bodiversity in the city: key challenges for urban green space management. Front. Ecol. Environ. 15 (4), 189–196. https://doi.org/10.1002/fee.1480.

Artmann, Martina, Manon Kohler, Gotthard Meinel, Jing Gan, Ioan-cristian, Ioja, 2019. How smart growth and green infrastructure can mutually support each other — a conceptual framework for compact and green cities. Ecol. Indic. 96, 10–22.

Beninde, J., Veith, M., Hochkirch, A., 2015. Biodiversity in cities needs space: a meta-analysis of factors determining intra-urban biodiversity variation. Ecol. Lett. 18 (6), 581–592. https://doi.org/10.1111/ele.12427.

Blowes, S.A., et al., 2019. The geography of biodiversity change in marine and terrestrial assemblages. Science 366 (6463), 339–345. https://doi.org/10.1126/science.aaw1620.

Bratman, G.N., et al., 2015. Nature experience reduces rumination and subgenual prefrontal cortex activation. Proc. Natl. Acad. Sci. USA 112, 8567–8572. https://doi.org/10.1073/pnas.1510459112.

Buitenwerf, R., Rose, L., Higgins, S.I., 2015. Three decades of multi-dimensional change in global leaf phenology. Nat. Cim. Change 5.

Chaparro, L., Terrasdas, J., 2009. Ecological services of urban forest in Barcelona. Acta Ecol. Sin. 29, 103. https://doi.org/10.13140/RG.2.1.4013.9604. Shengtai Xuebao, 29(August).

Chen, W., Wang, D., 2013. Economic development and natural amenity: an econometric analysis of urban green spaces in China. Urban For. Urban Green 12 (4), 435–442. https://doi.org/10.1016/j.ufug.2013.08.004.

Chen, Y., Wong, N.H., 2006. Thermal benefits of city parks. Energy Build. 38 (2), 105–120. https://doi.org/10.1016/j.enbuild.2005.04.003.

City of Ljubljana , 2022. City of Ljubljana. https://www.ljubljana.si/. (Accessed 13 May 2022).

Dadvand, P., et al., 2015. Green Spaces and Cognitive Development in Primary Schoolchildren. Proc. Natl. Acad. Sci. USA 112, 7937–7942.

Dahmann, N., et al., 2010. The active city? Disparities in provision of urban public recreation resources. Health Place 16 (3), 431–445. https://doi.org/10.1016/j.healthplace.2009.11.005.

Dallimer, M., et al., 2011. Temporal changes in greenspace in a highly urbanized region. Biol. Lett. 7 (5), 763–766. https://doi.org/10.1098/rsbl.2011.0025.

De'ath, G., 2007. Boosted trees for ecological modeling and prediction. Ecology 88 (1), 243–251. https://doi.org/10.1890/0012–9658(2007)88[243:BTFEMA]2.0.CO;2.

Dobbs, C., Nitschke, C., Kendal, D., 2017. Assessing the drivers shaping global patterns of urban vegetation landscape structure. Sci. Total Environ. 592, 171–177. https://doi.org/10.1016/j.scitotenv.2017.03.058.

Duarte, E., Wainer, J., 2017. Empirical comparison of cross-validation and internal metrics for tuning SVM hyperparameters. Pattern Recognit. Lett. 88, 6–11. https://doi.org/10.1016/j.patrec.2017.01.007.

Dzhambov, A., et al., 2018. Urban residential greenspace and mental health in youth: different approaches to testing multiple pathways yield different conclusions. Environ. Res. 160, 47–59. https://doi.org/10.1016/j.envres.2017.09.015.

Easterling, D.R., et al., 2000. Climate extremes: observations, modeling, and impacts. Science 289, 2068–2074. https://doi.org/10.1126/science.289.5487.2068.

Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol. 77 (4), 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x.

Engemann, K., et al., 2019. Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence into adulthood. PNAS 116, 5188–5193.

Escobedo, F.J., et al., 2006. The socioeconomics and management of Santiago de Chile's public urban forests. Urban For. Urban Green 4 (3–4), 105–114. https://doi.org/10.1016/j.ufug.2005.12.002.

Esri et al., 2021. World Cities - Oversigt. https://www.arcgis.com/home/item.html?id=6996f03a1b364dbab4008d99380370ed#overview. (Accessed 13 May 2022).

EU , 2016. ljubljana 2016 Leaflet, 1, 1–12. https://ec.europa.eu/environment/european-green-capital-award/winning-cities/previous-winning-cities_en.

Fergusona, M., Roberts, H.E., McEachanc, R.R.C., Dallimer, M., 2018. Contrasting distributions of urban green infrastructure across social and ethno-racial groups. Landsc. Urban Plan. 175, 136–148.

Fick, S. , Hijmans, R. , 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. International Journal of Climatology, 37 (12), 4302–4315. https://www.worldclim.org/. (Accessed 13 May 2022).

Florczyk, A. J. et al., 2019. GHSL Data Package 2019 Public Release. doi: 10.2760/0726. Florczyk, A.J. et al. (2019) GHSL Data Package 2019 Public release. doi: 10.2760/0726.

Friedman, J.H., Popescu, B.E., 2008. Predictive learning via rule ensembles. Ann. Appl. Stat. 2 (3), 916–954. https://doi.org/10.1214/07-AOAS148.

Friedman, J. , 2001. Greedy Function Approximation: A Gradient Boosting Machine Author (s): Jerome H. Friedman Source: The Annals of Statistics, Published by: Institute of Mathematical Statistics Stable, 29(5) Oct., 2001,1189–1232; The Annals of Statistics, 29(5), 1189–1232. http://www; https://www.jstor.org/stable/2699986.

Frumkin, Howard, 2002. Urban Sprawl and Public Health, 117(June), 201–17.

Fuller, R.A., Gaston, K.J., 2009. The scaling of green space coverage in European cities. Biol. Lett. 5 (3), 352–355. https://doi.org/10.1098/rsbl.2009.0010.

Fuwape, J.A., Onyekwelu, J.C., 2011. Urban forest development in West Africa: benefits and challenges. J. Biodivers. Ecol. Sci. 1 (1), 77–94.

Galea, S., Vlahov, D., 2005. URBAN HEALTH: Evidence, Challenges, and Directions. Annu. Rev. Public Health 26, 341–365.

Goddard, M.A., Dougill, A.J., Benton, T.G., 2010. Scaling up from gardens: biodiversity conservation in urban environments. Trends Ecol. Evol. 25 (2), 90–98. https://doi.org/10.1016/j.tree.2009.07.016.

Gorelick, N., et al., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. (Accessed 13 May 2022) https://earthengine.google.com/.

Gotovac, A.S., Kerbler, B., 2019. From post-socialist to sustainable: the city of Ljubljana. Sustainability 11 (24). https://doi.org/10.3390/su11247126.

Greenwell, B. , Boehmke, B. , Cunningham, J. , 2020. Package "gbm" - Generalized boosted regression models, CRAN Repository, 39. https://cran.r-project.org/web/packages/gbm/gbm.pdf%0Ahttps://github.com/gbm-developers/gbm.

Grullon, G., 2016. Rise of the city. Science 352 (6288), 80–88.

Haaland, C., van den Bosch, C.K., 2015. Challenges and strategies for urban green-space planning in cities undergoing densification: a review. Urban For. Urban Green 14 (4), 760–771. https://doi.org/10.1016/j.ufug.2015.07.009.

Hartig, T., et al., 2014. Nature and health. Annu. Rev. Public Health 35, 207–228. https://doi.org/10.1146/annurev-publhealth-032013-182443.

Hatfield, J.L., Prueger, J.H., 2015. Temperature extremes: effect on plant growth and development. Weather Clim. Extrem. 10, 4–10. https://doi.org/10.1016/j.wace.2015.08.001.

Hollinger, S.E., Angel, J.R., 2009. Weather and crops. Ill. Agron. Handb. 66 (285), 155–166. https://doi.org/10.1002/qj.49706628504.

Hopkins, C. , McKeown, R. , 2002. Education and Sustainability: Responding to the Global Challenge - Chapter 2. https://books.google.dk/books?hl=da&lr=&id=q18nBgAAQBAJ&oi=fnd&pg=PA13&dq=Hopkins+%26+McKeown,+2002).&ots=Koe8N5jbRB&sig=u-xAijgsA-gXQuUaBSszksRZO8I&redir_esc=y#v=onepage&q=Hopkins %26 McKeown%2C 2002).&f=false. (Accessed 28 May 2022).

Huang, C., et al., 2017. Green spaces as an indicator of urban health: evaluating its changes in 28 mega-cities. Remote Sens. 9 (12), 1–15. https://doi.org/10.3390/rs9121266.

IPBES , 2019. Summary for policymakers of the global assessment report on biodiversity and ecosystem services, Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. https://zenodo.org/record/3553579#.YfmYTerMI2w.

IPCC , 2021. IPCC: Climate Change 2021: the Physical Science Basis', Cambridge University Press. In Press.,42. https://www.ipcc.ch/report/ar6/wg1/.

Johnson-Gaither, C. , 2011. Latino park access: examining environmental equity in a " New destination " county in the South, Journal of Park and Recreation Administration Winter, 29(4), 37–52. https://www.srs.fs.usda.gov/pubs/ja/2011/ja_2011_gaither_002.pdf.

JRC , 2015. Global Human Settlement - Download - European Commission. https://ghsl.jrc.ec.europa.eu/download.php. (Accessed 30 August 2022).

Karra, K. et al., 2021. Global Land Use / Land Cover With Sentinel 2 and Deep Learning, 4704–4707. doi: 10.1109/igarss47720.2021.9553499.
Kinzig, A.P. et al., 2005. The effects of human socioeconomic status and cultural characteristics on urban patterns of biodiversity. Ecology and Society, 10(1). doi: 10.5751/ES-01264–100123.
Lau, J.D., et al., 2019. What matters to whom and why? Understanding the importance of coastal ecosystem services in developing coastal communities. Ecosyst. Serv. 35, 219–230. https://doi.org/10.1016/j.ecoser.2018.12.012.
Li, F., Wang, X., Liu, H., Li, X., Zhang, X., Sun, Y., Wang, Y., 2018. Does economic development improve urban greening? Evidence from 289 cities in China using spatial regression models. Environ. Monit. Assess. 190. https://doi.org/10.1007/s10661-018-6871-4.
Malhi, Y., et al., 2020. Climate change and ecosystems: threats, opportunities and solutions. Philos. Trans. R. Soc. B Biol. Sci. 375 (1794) https://doi.org/10.1098/rstb.2019.0104.
McDonald, et al., 2023. Denser and greener cities: green interventions to achieve both urban density and nature. People Nat. 5, 84–102. https://doi.org/10.1002/PAN3.10423.
McDonald, R.I., Forman, R.T.T., Kareiva, P., 2010. Open space loss and land inequality in United States' cities, 1990-2000. PLoS One 5 (3). https://doi.org/10.1371/journal.pone.0009509.
Mensah, C.A., 2014. Urban green spaces in Africa: nature and challenges. Int. J. Ecosyst. 2014 (1), 1–11. https://doi.org/10.5923/j.ije.20140401.01.
Mohajerani, A., Bakaric, J., Jeffrey-Bailey, T., 2017. The urban heat island effect, its causes, and mitigation, with reference to the thermal properties of asphalt concrete. J. Environ. Manag. 197, 522–538. https://doi.org/10.1016/j.jenvman.2017.03.095.
Nastran, M., Regina, H., 2016. Advancing urban ecosystem governance in Ljubljana. Environ. Sci. Policy 62, 123–126. https://doi.org/10.1016/j.envsci.2015.06.003.
Nemani , et al., 2003. Climate-Driven Increases in Global Terrestrial Net Primary Production from 1982 to 1999, 300(June), 1560–1563.
Nesbitt, L., et al., 2019. Who has access to urban vegetation? A spatial analysis of distributional green equity in 10 US cities. Landsc. Urban Plan. 181, 51–79. https://doi.org/10.1016/j.landurbplan.2018.08.007.
Nicholson, S.E., Farrar, T.J., 1994. The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana. I. NDVI response to rainfall. Remote Sens. Environ. 50 (2), 107–120. https://doi.org/10.1016/0034-4257(94)90038-8.
Norton, B.A., et al., 2015. Planning for cooler cities: a framework to prioritise green infrastructure to mitigate high temperatures in urban landscapes. Landsc. Urban Plan. 134, 127–138. https://doi.org/10.1016/j.landurbplan.2014.10.018.
Oliveira, S., Andrade, H., Vaz, T., 2011. The cooling effect of green spaces as a contribution to the mitigation of urban heat: a case study in Lisbon. Build. Environ. 46 (11), 2186–2194. https://doi.org/10.1016/j.buildenv.2011.04.034.
Piao, S., et al., 2020. Characteristics, drivers and feedbacks of global greening. Nat. Rev. Earth Environ. 1, 14–27.
Puga-Caballero, A., MacGregor-Fors, I., Ortega-Álvarez, R., 2014. Birds at the urban fringe: avian community shifts in different peri-urban ecotones of a megacity. Ecol. Res. 29 (4), 619–628. https://doi.org/10.1007/s11284-014-1145-2.
Rega, Christine C., Brodsky Myla, F.J., Aronson Max, R.Piana, Ela, Sita, Carpenter, Amy, K.Hahs, 2022. Urban biodiversity: state of the science and future directions. Urban Ecosyst. 1083–1096, 1083–96.
Richards, D., et al., 2019. Global variation in climate, human development, and population density has implications for urban ecosystem services. Sustainability 11 (22). https://doi.org/10.3390/su11226200.
Richards, D.R., Passy, P., Oh, R.R.Y., 2017. Impacts of population density and wealth on the quantity and structure of urban green space in tropical Southeast Asia. Landsc. Urban Plan. 157, 553–560. https://doi.org/10.1016/j.landurbplan.2016.09.005.
Rocque, Rhea J. , Caroline Beaudoin , Ruth Ndjaboue , Laura Cameron ,Louann Poirier-Bergeron , Rose-Alice Poulin- Rheault , Catherine Fallon , Andrea C. . Tricco , Holly O. . Witteman . 2021. Health Effects of Climate Change: an Overview of Systematic Reviews.
Schratz, P., et al., 2019. Hyperparameter tuning and performance assessment of statistical and machine-learning algorithms using spatial data. Ecol. Model. 406, 109–120. https://doi.org/10.1016/j.ecolmodel.2019.06.002.
Semeraro, T., et al., 2021. Planning of urban green spaces: an ecological perspective on human benefits. Land 10 (2), 1–26. https://doi.org/10.3390/land10020105.
Sun, J., et al., 2011. NDVI indicated characteristics of vegetation cover change in China's metropolises over the last three decades. Environ. Monit. Assess. 179 (1–4), 1–14. https://doi.org/10.1007/s10661-010-1715-x.
Sun, L., Chen, J., Li, Q., Huang, D., 2020. Dramatic uneven urbanization of large cities throughout the world in recent decades. Nat. Commun. 11, 1–9. https://doi.org/10.1038/s41467-020-19158-1.
The High Line , 2022. The High Line. https://www.thehighline.org/. (Accessed 13 May 2022).
The World Bank , 2022. The World Bank GDP Per Capita.https://data.worldbank.org/indicator/NY.GDP.PCAP.CD. (Accessed 13 May 2022).
Tian, Y. , Jim, C. , Tao, Y. , 2011. Factors on the spatial pattern of green cover in the compact city of Hong Kong. In: Proceedings of the International Conference on Computer Distributed Control and Intelligent Environmental Monitoring, CDCIEM 2011, 1527–1531. doi: 10.1109/CDCIEM.2011.424.
Tratalos, J., et al., 2007. Urban form, biodiversity potential and ecosystem services. Landsc. Urban Plan. 83 (4), 308–317. https://doi.org/10.1016/j.landurbplan.2007.05.003.
Undp , 2020. Human development index (HDI), Human Development Reports. https://hdr.undp.org/en/content/human-development-index-hdi. (Accessed 13 May 2022).
Undp , 2021. Technical Notes Calculating Human Development Indices.https://hdr.undp.org/en/content/human-development-index-hdi.
United Nations , 2015. World Urbanization Prospects The 2014 Revision.
University of Cincinati , 2018. Gradient Boosting Machines·UC Business Analytics R Programming Guide. http://uc-r.github.io/gbm_regression. (Accessed 13 May 2022).
van den Bosch, Matilda, Nieuwenhuijsen, Mark., 2017. No time to lose – Green the cities now. Environ. Int. 99, 343–350.
Villeneuve, P.J., et al., 2018. Association of residential greenness with obesity and physical activity in a US cohort of women. Environ. Res. 160, 372–384. https://doi.org/10.1016/j.envres.2017.10.005.
Wang, J., Rich, P.M., Price, K.P., 2003. Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int. J. Remote Sens. 24 (11), 2345–2364. https://doi.org/10.1080/01431160210154812.
Wolch, J.R., Byrne, J., Newell, J.P., 2014. Urban green space, public health, and environmental justice: the challenge of making cities "just green enough". Landsc. Urban Plan. 125, 234–244. https://doi.org/10.1016/j.landurbplan.2014.01.017.
WorldAtlas , 2022. The Continents of the World Per Capita GDP - WorldAtlas. https://www.worldatlas.com/articles/the-continents-of-the-world-by-gdp-per-capita.html. (Accessed 13 May 2022).
Xu, C. et al., 2020. Future of the human climate niche. Proceedings of the National Academy of Sciences of the United States of America, 117(21). doi: 10.1073/pnas.1910114117.
Zhang, R., 2020. Cooling effect and control factors of common shrubs on the urban heat island effect in a southern city in China. Sci. Rep. 10 (1), 1–8. https://doi.org/10.1038/s41598-020-74559-y.
Zhang, W., et al., 2021. Socio-economic and climatic changes lead to contrasting global urban vegetation trends. Glob. Environ. Change 71, 102385.