Airborne assessment uncovers socioeconomic stratification of urban nature in England

Andrés Zúñiga-González[1,2*], Anil Madhavapeddy[2†] and Ronita Bardhan[1†]

[1*]Department of Architecture, University of Cambridge, Street, Cambridge, 100190, Cambridgeshire, United Kingdom.
[2]Department of Computer Science and Technology, University of Cambridge, Street, Cambridge, 100190, Cambridgeshire, United Kingdom.

*Corresponding author(s). E-mail(s): acz25@cam.ac.uk;
Contributing authors: avsm2@cam.ac.uk; rb867@cam.ac.uk;
[†]These authors contributed equally to this work.

Abstract

Urban green infrastructure is essential for climate resilience, public health, and environmental justice. Yet, the absence of standardised methods to quantify urban nature hinders the development of equitable greening policies. In this study, we present the first national, building-level assessment of the 3-30-300 urban greening rule, a policy framework proposing that every citizen should see three trees from their home, live in a neighbourhood with 30% canopy cover, and reside within 300 m of a public green space. Using high-resolution LiDAR (Vegetation Object Model), Sentinel 2 imagery, and open geospatial datasets for over 28 million buildings across England, we integrate raster, vector, and socioeconomic data within a scalable computational framework. Tree segmentation was performed using adaptive local-maximum filtering, canopy cover estimated at 1 m resolution, and park accessibility derived from network-based walking distances. Inequality in access to nature was quantified via Gini coefficients and modelled with spatial error regressions against socioeconomic deprivation. Our results reveal that while most urban areas meet the 3-tree proximity rule, fewer than 3% achieve 30% canopy cover, and only a minority satisfy all three components simultaneously. Crucially, ambient greenness (trees and canopy) is concentrated in affluent areas, whereas proximity to parks is greatest in dense, often deprived urban centres, exposing a multidimensional nature gap. This framework establishes a reproducible, open, and computationally efficient blueprint for evaluating urban nature equity at scale, supporting the integration of environmental justice metrics into national urban planning agendas.

Keywords: urban green infrastructure, deprivation, 3-30-300, green equity, environmental deprivation

1 Introduction

Urban green infrastructure is crucial for urban resilience and public health, providing a vital nature-based solution to the pressures posed by climate change and urbanisation. This becomes a crucial factor in ever-growing cities, since approximately 70% of the global population is projected to live in urban areas [1]. Multiple studies have highlighted the role of urban greenery in mitigating air pollution, reducing urban heat island effects (higher temperatures in urban areas due absorption of heat by built-up surfaces), and fostering social cohesion [2]. Moreover, accessible green spaces are linked to improved physical and mental well-being, positioning them as a pillar of sustainable urban planning with human health as a focus [3].

Effective urban greening policies depend on reliable and consistent measurement, yet no standard process exists. Methodologies, spatial scales, and time frames for analysis differ widely between studies, making it impossible to compare cities accurately or establish global benchmarks. This inconsistency is particularly damaging for research that connects green infrastructure to social and health outcomes, as the lack of a standard metric for “greenness” undermines the findings. A standardised method is therefore crucial for building effective, evidence-based greening policies worldwide [4–6].

Existing efforts to quantify urban green infrastructure are typically conducted at two distinct scales: granular analyses within individual cities [7–10] or broad continental comparisons. The latter have revealed large-scale patterns, such as a North-South divide in green space accessibility across Europe, where northern cities are generally greener [11]. Zooming into the British context, research has confirmed a strong link between urban form and inequality, finding that populous, deprived urban centres tend to have less canopy cover [12]. What remains absent, however, is a consistent, high-resolution analysis at the national scale capable of moving beyond city-specific findings or regional averages to systematically map the nuanced geography of environmental inequality.

In response to this need for simplified and actionable metrics, the “3-30-300 rule” has recently been proposed and is gaining significant traction in urban policy circles around Europe and North America [13]. This ”rule of thumb” offers an intuitive framework for what a sufficiently green city should look like: every citizen should see at least 3 trees from their home, school, and workplace; every neighbourhood should have at least 30% canopy cover; and every resident should live within 300 metres of a quality public green space. Together, these components aim to quantify the visibility, availability, and accessibility of urban nature, respectively [14].

Despite its growing adoption in cities such as Singapore, Amsterdam (Netherlands), Buenos Aires (Argentina), Sydney, Melbourne (Australia), New York, Seattle, Denver (USA)[15, 16] and in the entire Italian territory[17], the 3-30-300 rule currently lacks a standardised methodological foundation for assessment at scale. Current approaches are fragmented, ranging from satellite-derived vegetation indices, such as NDVI, to labour-intensive street-level photograph analysis [4, 14], and even survey-based methods. This methodological void prevents a systematic and comparable evaluation and makes it difficult to ascertain whether the rule truly captures the nuances of nature exposure and accessibility.

In response to the lack of a standard methodology, we develop and apply a novel computational framework to conduct the first national-scale, building-level assessment of the 3-30-300 rule, using England as our case study. The methodology presented applies high-performance computing on publicly available LiDAR and geospatial data to overcome previous limitations of scale and resolution. Specifically, we: 1) develop and validate novel, high-resolution proxies for the rule. For the '3 visible trees' component, we move beyond simple tree counts to a regression-based metric that captures the density of the surrounding tree canopy from each building's perspective. For the '300m to a park' component, we use a detailed national road network to model realistic walking distances, a significant improvement over simpler distance-based estimations; 2) directly quantify environmental inequality by calculating Gini coefficients [18] from this building-level data on residential units, revealing disparities within local areas and regions; and 3) critically evaluate how these human-centric 3-30-300 metrics correlate and integrate with traditional remote-sensing-derived indices.

By providing a methodological framework, this research facilitates the standardised application of the 3-30-300 rule in other countries with comparable data. Ultimately, we aim to determine if this increasingly influential rule, when combined with remote sensing data, provides a robust framework for guiding evidence-based urban planning and promoting equitable access to urban nature in other countries. Finally, our results highlight that most citizens live in areas where the 30 and 300 components thresholds are not met, while the 3-component is largely fulfilled by most areas. Specifically, our inequality analysis further signals a nature deprivation difference by regions, revealing that disparities in nature access align with and potentially exacerbate existing regional socio-economic inequalities, indicating that nature accessibility is a new layer of inequality to be considered.

2 Results

2.1 Data Synthesis and Scale of Analysis

To conduct the first national-scale assessment of the 3-30-300 rule, we gathered multiple high-resolution geospatial datasets. This process created a comprehensive building-level record of potential nature exposure for the entirety of England, representing an analysis of unprecedented scale and granularity. The core components of this synthesised dataset are summarised in Table 1, quantifying the millions of individual features processed to derive our findings.

Table 1: Data Synthesis and Scale of the National 3-30-300 Assessment. This table outlines the primary datasets, unit of analysis, and overall scale for each analytical component quantified across England.

Analytical Component	**Core Datasets Used**	**Initial Unit of Measurement**	**Scale of Analysis (No. of Features)**
3 (Tree Proximity)	VOM, Buildings	Individual Building	˜190 million trees; 28,944,175 buildings
30 (Availability)	VOM, LSOA Boundaries	1m^2 Raster Grid Cell	33,755 LSOAs
300 (Accessibility)	OS Roads, Green Spaces, Verisk Buildings	Individual Building	3,919,444 road segments; 157,274 green spaces 28,944,175 buildings
Socio-Economic Context	Deprivation Score	LSOA Polygon	32,742 LSOAs
Spectral Indices	NDVI, NDWI, NDBI	100m^2 Raster Grid Cell	Full coverage of England

2.2 How many trees are there in English cities?

Our national LiDAR segmentation identified approximately 190 million trees across England. A key finding is the stark urban-rural divide: only 26.9% of these trees are located within urban areas as defined by the ONS. For the subsequent analysis of the "3-30-300" rule, we used a filtered dataset of 156 million significant trees (those with a height >3 m and crown area >10 m^2; see Methods). This entire analysis was performed across 32,742 Lower Layer Super Output Areas (LSOAs), which represent the geographies for which consistent 2019 Index of Multiple Deprivation (IMD) data were available, explaining minor discrepancies with the total number of official 2021 LSOAs. A map of all the areas covered by the segmentation algorithm is shown in Figure A1

2.3 Tree Distribution: Per Capita vs. Absolute Density

Our analysis of tree distribution across England reveals a fundamental dichotomy: the greenest parts of the country can be identified as either its most rural expanses or its most densely populated urban regions, depending entirely on the metric used. This finding (Figure 1) presents a critical measurement contradiction for urban planners and policymakers, as the choice of metric can lead to dramatically different conclusions about where greening interventions are most needed (Figure 1).

When viewed through a per capita lens—a measure of how many trees are available per person—resources appear most plentiful in rural, sparsely populated regions. Local Authority Districts (LADs) in the North of England (e.g., Northumberland, Cumbria) and the South West exhibit the highest values, often exceeding 40 trees per person (Figure 1A). From this perspective, a clear urban-rural divide emerges, suggesting that residents of major metropolitan areas like London and Manchester have the least access to tree resources.

However, this narrative is completely inverted when considering absolute density (trees per km²), which measures the concentration of trees in a given area (Figure 1B). Here, the highest concentrations are found not in the countryside, but in the densely populated and affluent South East. The commuter belt surrounding Greater London, along with parts of London itself, shows the highest densities, with many areas containing over 3,000 trees per km². This finding challenges the simplistic view of cities as concrete jungles, revealing that many urban and suburban areas contain an exceptionally high overall stock of trees, even if they are shared among more people.

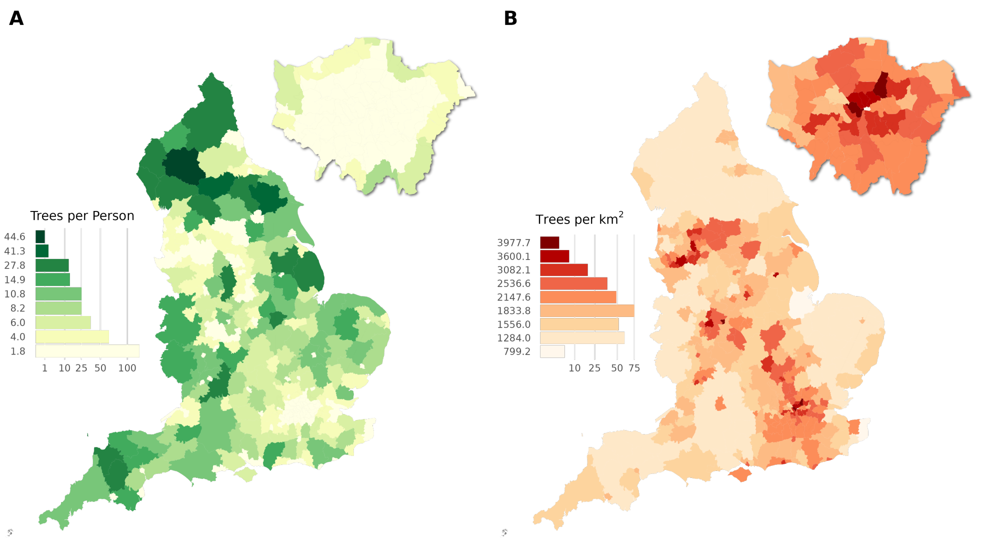

Fig. 1: Contrasting spatial distributions of per capita and absolute tree density in England. Choropleth maps illustrate two metrics of tree distribution at the Local Authority District level. **(A)** Trees per person, a measure of per capita tree availability. **(B)** Trees per km², a measure of absolute tree density. Map insets depict the Greater London area.

2.4 Quantification and Attainment of the 3-30-300

When accounting for the areas with high access to trees and other forms of green infrastructure, we only considered those in LSOAs classified as urban by the ONS, which further reduced the number of areas, as seen in Table A1. Most areas complied with having an average of more than 3 visible trees with no significant differences between regions, while canopy cover presented the lowest percentage of high cover, with the South West considerably outclassing the other regions. Moreover, access to parks was significantly higher in London than in other regions, with the Eastern regions presenting higher average values in walking distances. In total, only 0.1% of the urban

LSOAs fulfilled the three rules, with the North East having the highest number of regions that passed the rule.

Our national assessment reveals a profound disparity in the attainment rates for the three distinct components of the 3-30-300 rule across all regions of England (Figure 2).

The “3-tree proximity” rule is the most widely achieved guideline. In London, for example, almost 40% of the region’s 8.2 million residents are estimated to live within 25 m of at least 3 trees from their homes, with no clear difference between inner and outer parts of the city. This pattern of high attainment holds true across the country, from the North West, where most of its 6.5 million people meet the standard, to the South West, indicating widespread success in integrating individual trees within highly urbanised areas. Nonetheless, approximately only one quarter of the inhabitants of Yorkshire and the Humber and the North East accomplish the goal.

The most significant national deficit is for the “30%-canopy cover” rule, which is met by the smallest number of people. In every region, only a minority of the population lives in a neighbourhood with an adequate tree coverage, with the South East showing the largest proportion of urban inhabitants, followed by the North East, East of England, South West and Outer London.

The “300-metre park accessibility” rule demonstrates the second-highest level of attainment. While a substantial number of people meet this standard, the total is considerably less than for the 3-tree rule. London again has the largest number of residents where a public park is within walking distance, particularly in the central boroughs, whereas the East Midlands, East of England and South East show the largest number of inhabitants with low accessibility to green spaces.

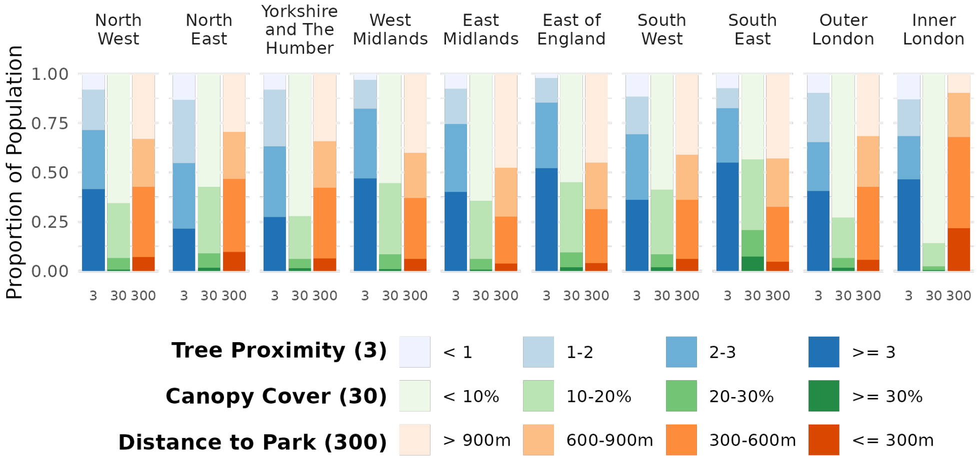

Fig. 2: Population meeting each component of the 3-30-300 rule across the regions of England. The chart displays the proportion of the population in each region that fulfil each one of the rules (dark colours) and how close they are to achieving them (light colours): proximity to at least 3 trees in a 25 m-radius from a residence (3, blue), living in a neighbourhood with at least 30% tree canopy cover (30, green), and living within 300 metres of a public park (300, orange).

2.5 Systemic Environmental Inequality Gradients in Green Infrastructure

To dissect the relationship between socioeconomic status and green infrastructure, we analysed the distribution of each 3-30-300 component across Index of Multiple Deprivation (IMD) deciles for every region in England (Figure 3). The analysis reveals a clear, systematic, and contrasting pattern of environmental inequality for different types of green space.

For vegetation-based metrics, we observe a consistent green gap: canopy cover and tree proximity are strongly positively correlated with socioeconomic advantage. Within every single region, from the North West to London, LSOAs in the least deprived deciles have more trees in proximity (Figure 3A) and higher canopy cover (Figure 3B) than those in the most deprived deciles. For the London case, there is no clear difference in canopy cover, but there is more variability in proximity to trees.

In contrast, park accessibility exhibits a reverse green gap (Figure 3C). The most deprived LSOAs are, on average, located closer to a public park than the least deprived LSOAs. This trend is visible across most regions and suggests that the dense urban environments typically associated with higher deprivation have better proximity to public parks than more affluent suburban areas. Interestingly, inner boroughs in London have better access to parks. These findings expose a fundamental divergence in the distribution of urban green infrastructure: while formal public parks are highly accessible in dense, often deprived areas, ambient greenness like street trees and garden canopy is systematically skewed towards wealthier communities.

In addition to the 3-30-300, water was also contrasted regionally (Figure 3D). Although it didn't show a strong correlation with deprivation, in some regions, such as the North West and the East Midlands, residents of affluent areas live closer to water sources, while in the rest of the regions, access to water is more uniform.

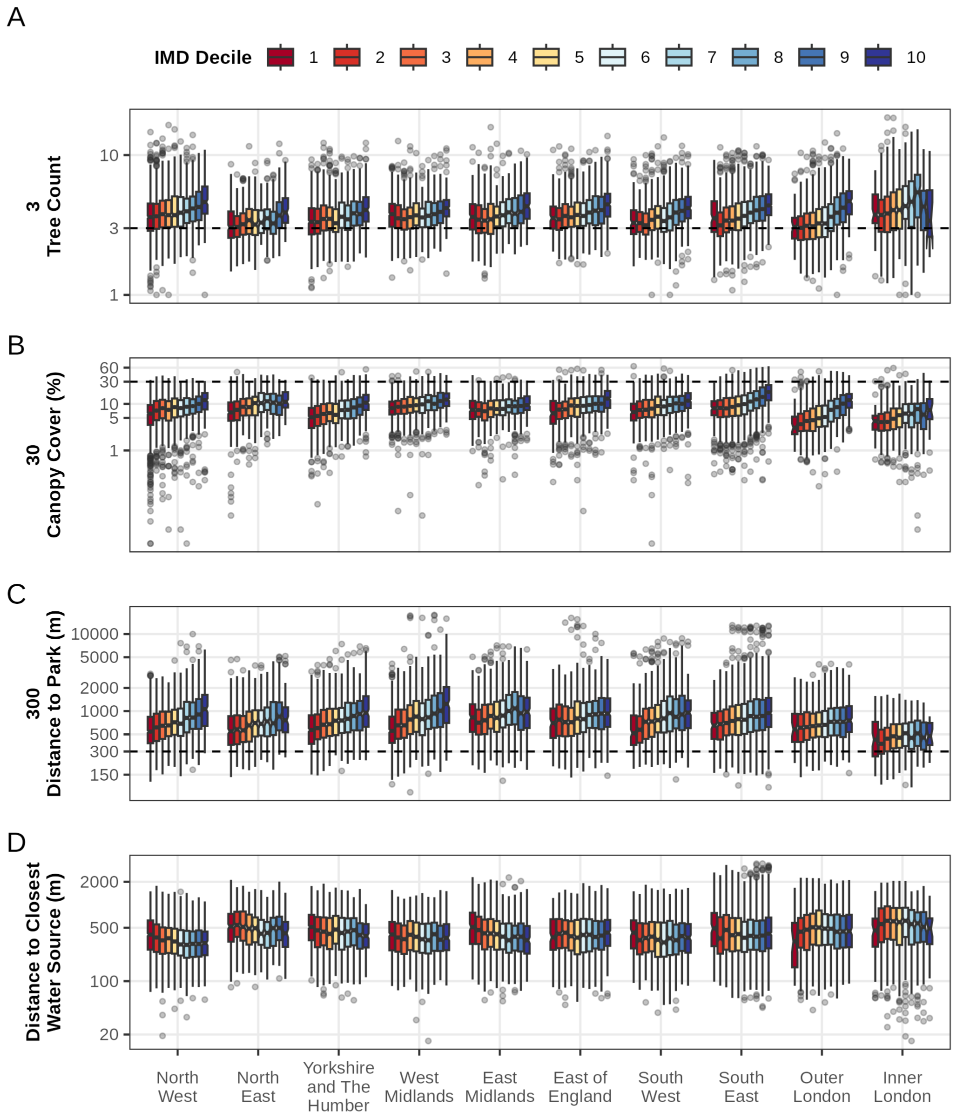

Fig. 3: Environmental inequality in access to green infrastructure across England. The distribution of the three 3-30-300 rule components at the Lower Layer Super Output Area (LSOA) level is shown, grouped by region. **(A)** Tree Count at 25 m radius. **(B)** Canopy cover percentage. **(C)** Walking distance to the nearest park. **(D)** Distance to the nearest water source. Dashed horizontal lines indicate the respective guideline thresholds for the 3-30-300. Each boxplot summarises the distribution for LSOAs within a given Index of Multiple Deprivation (IMD) decile, coloured from most deprived (Decile 1, red) to least deprived (Decile 10, blue); y-axes are log-scaled.

2.6 The Geography of Greenness versus Inequality

To understand the relationship between the quantity of green infrastructure and the equity of its distribution, we mapped both average canopy cover and the intra-regional inequality in access to nature across England (Figure 4). The analysis of average canopy cover confirms that the South East of England is the nation's greenest region in absolute terms (Figure 4A). Local Authorities in and around the London commuter belt, such as Surrey, consistently show the highest percentages of canopy cover, often approaching the 30% guideline, while many districts in the Midlands and the North have lower average cover.

However, this picture of a green South East is fundamentally challenged by the geography of inequality (Figure 4B). The bivariate analysis of Gini coefficients reveals that the most severe inequalities in green infrastructure access are often concentrated within these same leafy regions. Major urban centres—especially Inner London (see inset), Birmingham, and Manchester—emerge as dark hotspots, indicating high inequality in the distribution of both nearby trees (blue tones) and walking distance to parks (red tones) among their respective residents.

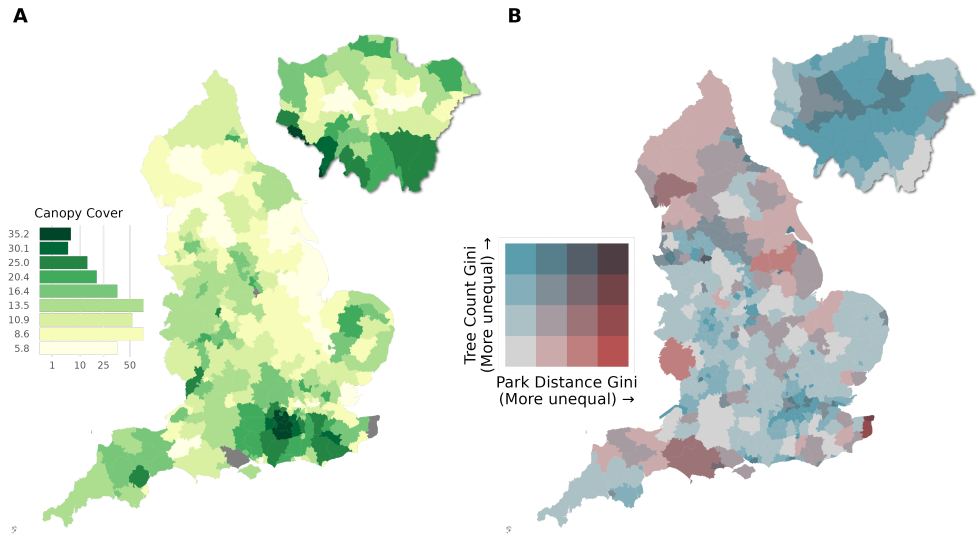

Fig. 4: Spatial Distribution of Canopy Cover and Environmental Inequality in England. **(A)** Average percentage of tree canopy cover at the Local Authority District (LAD) level. Darker green indicates higher canopy cover, with the highest values concentrated in the South East of England. The inset displays the significant variation across London's boroughs. **(B)** Bivariate map showing two measures of environmental inequality, calculated as a Gini coefficient at the LAD level. The colour scale indicates the degree of inequality in the distribution of nearby trees among buildings (blue y-axis) and inequality in walking distance to a park (red x-axis). Darker, mixed colours (e.g., purple) signify high inequality in both metrics.

2.7 Socioeconomic Stratification of Urban Environmental Metrics

To understand how the relationships between different environmental metrics are shaped by socioeconomic status, we visualised their pairwise correlations, with each Lower Layer Super Output Area (LSOA) coloured by its Index of Multiple Deprivation (IMD) decile (Figure 5). The analysis reveals a powerful, intertwined relationship between vegetation, built-up density, and deprivation. We observe a strong positive correlation between our vegetation-based rule components ('3' and '30') and satellite-derived Normalized Difference Built-up Index (NDVI) (Figure A2). Critically, these plots show a clear socioeconomic stratification: LSOAs with high NDVI and high canopy cover are almost exclusively the least deprived, while those with low vegetation and high Normalized Difference Built-up Index (NDBI) (Figure A3) scores are predominantly the most deprived.

The thresholds of the 3-30-300 rule further illustrate these disparities. A large number of the most deprived LSOAs fall below the 30% canopy cover guideline, while a majority of the least deprived LSOAs meet or exceed it, confirming that failure to meet the vegetation-based components of the rule is systematically linked to socioeconomic deprivation, as demonstrated in the previous sections. This pattern is inverted when considering park accessibility. The plot of park distance ('300') versus NDBI shows that the most deprived LSOAs, which have the highest built-up density, are also clustered at shorter distances to parks. This corroborates the finding from the distributional analysis that park provision is often better in dense urban areas, even as ambient greenness is lower. Overall, the matrix demonstrates that environmental variables are not independent but form a nexus where deprivation is co-located with low ambient vegetation and high built-up density, despite often having good proximity to formal parks.

The analysis further reveals that proximity to blue space, as measured by water distance, represents a distinct dimension of environmental character with a low correlation to the green infrastructure metrics assessed. This suggests that the spatial distribution of blue infrastructure is driven by different factors than that of parks and tree canopy, and its relationship with deprivation is less direct. In contrast, the Normalized Difference Water Index (NDWI) (Figure A4) exhibited a positive correlation with NDVI, underscoring the frequent co-location of blue and green spaces within features like vegetated riparian zones. Finally, NDBI showed a strong negative correlation with both the '3' and '30' components. This powerful inverse relationship highlights how dense, grey urban infrastructure fundamentally constrains the available space for trees and canopy, quantitatively linking the most heavily built-up LSOAs with the lowest levels of ambient greenness.

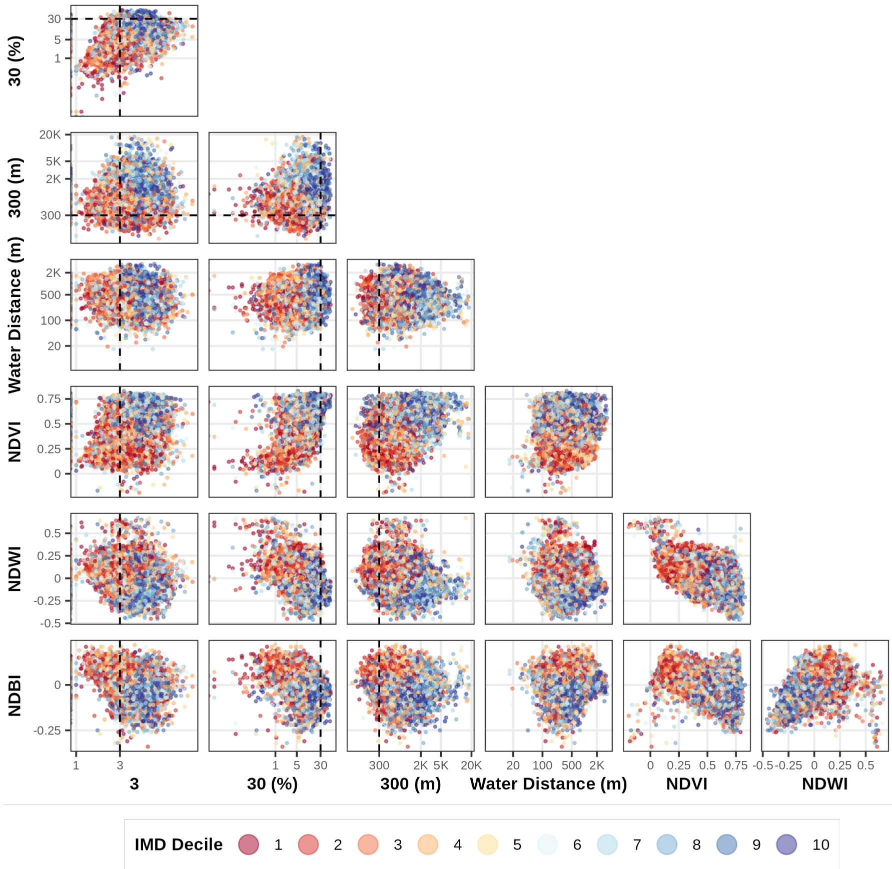

Fig. 5: Socioeconomic stratification of correlations between environmental metrics. The scatter plot matrix shows the pairwise relationships between the 3-30-300 rule components (3: Tree Count Index, 30: Canopy Cover, 300: Park Distance), distance to water, and satellite-derived spectral indices (NDVI, NDWI, NDBI). Each point is a Lower Layer Super Output Area (LSOA) in England, coloured by its Index of Multiple Deprivation (IMD) decile, from most deprived (Decile 1, red) to least deprived (Decile 10, blue). Dashed lines indicate the guideline thresholds for the 3-30-300 rule. Note that the axes for Park Distance and Water Distance are on a logarithmic scale.

In order to evaluate the relationship between remote sensing indices and the 3-30-300 variables, as well as water access, we fitted three spatial error models to identify the drivers of inequity for tree count, park distance, and water distance at the LSOA level. The significance of the spatial error term (λ) in all models ($p < 2.210^{-16}$) confirmed strong spatial clustering (Table A2).

We found that more deprived areas, as measured by IMD suffer from greater inequity in tree distribution ($\beta = 0.0004, p = 0.003$). However, this effect is mainly a rural phenomenon. In urban areas, the relationship between deprivation and tree inequity is significantly weaker ($p = 0.009$ for the interaction term). Inequity is also worse in highly built-up areas (NDBI) and places with less overall greenness (NDVI), while it's surprisingly lower in more densely populated LSOAs.

For park access, the trend reverses: higher IMD scores are linked to lower inequity ($\beta = -0.0005, p = 0.010$). This suggests a pattern of uniformly poor access in more deprived areas rather than selective access. Urban areas generally have more equitable park access than rural ones. The strongest predictors were environmental, with inequity rising with population density and falling in greener areas (NDVI). The relationship was especially pronounced in London, where high deprivation was linked to even more equitable access.

The link between deprivation and access to water depends entirely on location. A powerful interaction ($p = 1.310^{-9}$) shows two opposing trends: In rural areas, more deprivation is linked to lower inequity, while in urban areas, the relationship flips, and more deprivation is strongly associated with higher inequity. Overall, urban LSOAs have much higher baseline inequity in water access. This inequity is worsened by high population density and built-up land, and reduced by the presence of vegetation (NDVI) and water bodies (NDWI). Our findings highlight a critical urban-rural divide in environmental justice concerning blue spaces (Figure A5).

3 Discussion

In this study, we developed and implemented the first standardised national assessment of the 3-30-300 urban greening rule for England. Our findings reveal a profound disconnect between different forms of nature access, challenging traditional narratives of environmental provision. Although England is highly successful in meeting the '3' visible trees guideline, understood as proximity to trees, it systematically fails to provide adequate neighbourhood canopy cover (30) and a walkable park (300) for the majority of its population. More critically, we uncovered a stark socioeconomic gradient to this disparity: ambient greenness, such as tree canopy, is a feature of affluence, whereas proximity to public parks is often greatest in denser, more deprived urban centres. This work provides not just a novel dataset, but a scalable methodological blueprint for other nations to diagnose their own geographies of environmental inequality for further comparison between territories.

Our analysis reveals a profound heterogeneity in the distribution of environmental amenities across England, defined by three intersecting gradients: North-South, urban-rural, and socioeconomic. A pronounced North-South divide is evident in absolute green infrastructure, with southern regions, particularly the South East, possessing significantly greater tree density and canopy cover. This geographical disparity, however, is moderated by a stark urban-rural split in per-capita provision, where low population densities in both northern and southern rural areas result in a greater number of trees per person. This highlights that simple geographical comparisons of greenness are insufficient, as the experience of environmental provision is fundamentally shaped by the demographic context of the landscape.

Beyond these broad geographical patterns, a steep socioeconomic gradient governs the equitable distribution of these amenities, especially within urbanised areas where the majority of the population resides. For arboreal green space, increased provision in affluent urban areas correlates with more equitable distribution, suggesting that investment in greening may yield a co-benefit of reduced inequality. In stark contrast, access to blue space constitutes a clear environmental justice issue. We find a consistent and strong positive correlation between socioeconomic deprivation and both the distance to and inequality of access to water. This pattern, which persists across all urban regions, demonstrates a systemic environmental disamenity, where the most deprived communities are disproportionately disconnected from blue-space resources. These findings underscore the necessity for policy interventions that not only address the North-South deficit in green infrastructure but also tackle the pervasive intra-urban inequities that are sharply stratified by wealth.

Our findings demonstrate that the primary value of the 3-30-300 rule is not as a simple pass/fail checklist, but as a multi-dimensional diagnostic tool. By disaggregating proximity, availability, and accessibility, the rule allows policymakers to identify specific deficits that would be obscured by a single metric like NDVI or total park area. We argue that a city -or neighbourhood- failing the 30% canopy rule but passing the 300 m park rule has a fundamentally different challenge than a city in the opposite situation. Therefore, rather than focusing on universal attainment of all three numbers—which may be unrealistic in diverse local contexts—the power lies in using the quantification of each component, in combination with socioeconomic indicators like the IMD, to create tailored, evidence-based greening strategies. This multidimensional approach is essential for addressing SDG 11 and ensuring urban policies are designed for the equitable betterment of all citizens.

The primary challenge in urban planning has been establishing a standardised methodology for comparative studies. Our work demonstrates the feasibility of a national-scale, building-level analysis by integrating open LiDAR data with a high-performance computational framework using Apache Sedona and Google Earth Engine. While requiring geospatial expertise, this approach creates a scalable and replicable blueprint.

To validate our findings and understand their place within the UK's green infrastructure data landscape, we compared our results to the authoritative Trees Outside Woodland (TOW) dataset from Forest Research. Our segmentation method identifies a significantly higher number of individual tree features across all regions than the TOW dataset (Table A3). This is a methodological difference, as the TOW approach clusters nearby trees into single features of several sizes, whereas our algorithm aimed to delineate individual crowns, but our approach detects larger areas as trees in total, albeit, Forest Research excludes non-TOW from their data release, since those records are part of the National Forest Inventory (NFI) dataset.

Despite this higher feature count, our national tree tally likely represents a conservative estimate of the true number of trees. For instance, while London is estimated to be home to over eight million trees[19], our method identified just over three million. This underestimation is an inherent trade-off of any top-down aerial-based approach. Key challenges include the occlusion of smaller, understory trees by taller canopies and the difficulty in distinguishing large shrubs from small trees, which can lead to both omissions and misclassifications. While alternative methods combining aerial imagery with street-view photographs can improve precision[20], they are constrained by the spatial bias of road networks and cannot effectively capture trees within parks or private gardens. Therefore, our methodology represents a robust and scalable compromise, providing a consistent, albeit conservative, assessment of tree distribution suitable for national-level comparative analysis.

This study is a stepping stone. Future work must build upon this framework by incorporating more nuanced variables. For instance, our proxy for first component of the rule could be enhanced with true 3D view-shed analysis using street-level imagery, to correctly evaluate visibility. Furthermore, metrics of green space quality—such as biodiversity, safety, and maintenance levels—must be integrated to understand the true value of these resources.

4 Methods

Our study employs a multi-stage methodology to quantify the 3-30-300 rule at a national scale, assess its relationship with socioeconomic deprivation, and compare its components to traditional remote sensing indices. The workflow encompasses data acquisition, high-resolution geospatial processing, and statistical analysis of environmental inequality.

4.1 Definition of Study Area

Most geographic statistics released by public agencies, particularly for census-related studies in Great Britain, are done using the Lower Layer Super Output Areas (LSOAs) as a measurement unit, which is what we used in our study. However, only those that were in England according to the official December 2021 release by the Office for National Statistics (ONS) were considered.

4.2 Socio-Economic and Demographic Indicators

The Index of Multiple Deprivation (IMD) is a metric last produced in 2019 by the Ministry of Housing, Communities and Local Government for every LSOA in England. The index summarises seven main domains of inequality: Income, Employment, Education, Health, Crime, Housing and Environment. The scores for each component were downloaded from the Consumer Data Research Centre (CDRC) online platform.

In addition, the mid-2022 edition of population estimates by the ONS, including age groups and gender counts, are included in the analysis. These variables are available at the LSOA level as well.

4.3 3-30-300 Metrics

Most country-wide datasets for tree cover or individual tree locations are proprietary; therefore, our approach to measuring the '3-30-300' rule was based on using the publicly available 1-m-resolution Vegetation Object Model (VOM), gathered by the

Environment Agency and published by Department for Environment, Food & Rural Affairs (Defra) as part of their Light Detection and Ranging (LiDAR) programme.

4.3.1 Tree Segmentation

We first segmented individual trees on the VOM using the *lidR* package in *R* [21]. To segment the crown shape, the height was used with the Dalponte and & Coomes algorithm [22] and a customised formula for the Local Maximum Filter (LMF), as seen in Equation 1, where z is the height in metres for a given pixel, and the result is the window size to check for minimum and maximum values to model the crown shape. This approach is more adaptive than a fixed-size filter, as it enables the algorithm to search for smaller crowns in areas with dense, young trees and larger crowns in mature, isolated trees, thereby better reflecting the real-world forest structure. While methods with higher geometric fidelity exist for single-tree analysis, our approach is optimised for large-scale quantification. Its use of a simplified crown model, combined with the dataset's broad spatial range, offers a consistent methodology for quantifying trees without introducing systematic bias to the overall findings.

$$\mathrm{LMF}(z) = \begin{cases} \text{min\_size}, & \text{if } s < \text{min\_size} \\ s, & \text{if } \text{min\_size} \leq s \leq \text{max\_size} \\ \text{max\_size}, & \text{if } s > \text{max\_size} \end{cases} \tag{1}$$

Where:

$$s = \left\lfloor 6 + 18 \cdot \exp\left(-\frac{(z-\mu)^2}{2\sigma^2}\right)\right\rfloor$$

With:
- z = canopy height at a given location
- $\mu = 18$ (mean of the Gaussian function)
- $\sigma = 7$ (spread of the Gaussian function)
- min_size = 7 (minimum search window size)
- max_size = $0.7 \times P_{95}(z)$ (maximum search window based on the 95th percentile)

The resulting trees were vectorised as points and grouped together into the 50x50-km tiles, following the definition in the British National Grid released by the Ordnance Survey (OS), which were then saved as geoparquet files.

4.3.2 3 Component

We define the first component of the rule (3) as tree proximity. We created buffers of different sizes (10, 25, 50, 75 and 100 m) around each feature in the Verisk buildings dataset and counted the number of trees inside that area. This dataset includes features such as height, number of floors and distance to water, which this study uses to quantify water access. Due to the number of polygons in the buildings layer, this step was performed using *Apache Sedona* RDD API in *Python* alongside a vectorised and point-based version of the VOM-derived tree product. This spatial join operation was performed using QuadTree spatial indexing and KDBTree partitioning to optimise computation times.

4.3.3 30 Component

Canopy cover or green space availability (30) was obtained by creating a binary layer of the VOM raster where pixels between 3 and 60 m were considered 1. Then, using the LSOA boundaries, we calculated the tree coverage at 1 m resolution.

4.3.4 300 Component

Finally, for park accessibility (300), we filtered the OS Green Space Layer to include only public parks and calculated the walking distance (network-based) from each building to the closest green space access point. To accomplish this, a road network was built from the OS Roads dataset, and Dijkstra's algorithm was used to measure the shortest path along the graph between each building and its corresponding park. Moreover, the "crow flies" distance (Euclidean-based) was measured for each building and their closest park boundary as well.

Due to the size of the datasets, particularly of the buildings and VOM-derived trees, the results of the three components were calculated using Local Authority District (LAD) geometries, where the datasets were clipped using the LAD to reduce the number of iterations. Finally, the 3 and 300 components, measured at the building level, were aggregated at the LSAO level to match the IMD spatial unit of measurement as that of the 30-component. In addition to this, a total count of trees was done at the same geographic level.

4.4 Spectral Indices

Three main (normalised) spectral indices were considered in this study. These indicators were calculated using Sentinel 2 scenes from 2024 with values under 10% cloud coverage through the Google Earth Engine *Python* API [23]. These were estimated as the maximum for the entire year for the study region. To aggregate the values at the LSOA level, we used the median value for all pixels falling into the polygon.

Index	Name	Formula	Reference
NDBI	Normalized Difference Built-Up Index	$\frac{B11-B8}{B11+B8}$	[24, 25]
NDVI	Normalized Difference Vegetation Index	$\frac{B8-B4}{B8+B4}$	[26, 27]
NDWI	Normalized Difference Water Index	$\frac{B3-B8}{B3+B8}$	[25, 28]

4.5 Inequality Measurement

The 3 and 300 components measured in the study, as well as the distance to water variable in the Verisk buildings dataset, were used to calculate the Gini Index at the LSOA level. To do so, the unaggregated measurements for each building categorised as a residential unit were considered in the analysis. The Gini coefficient was calculated using the DescTools package in R using the unbiased parameter, which corrects for differences in sample size, as shown in 2. This correction makes the coefficient to have a range between 0 and $\sqrt{\frac{n-1}{n}}$, unlike regular Gini metrics that can only be between 0 and 1.

$$G_{\text{unbiased}} = \left(\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n \sum_{i=1}^{n} x_i} \right) \times \frac{n}{n-1} \tag{2}$$

With:
- n = number of buildings in a given LSOA
- x_i and x_j = environmental metric for two buildings

To create a single, robust metric for the '3 visible trees' component, we moved beyond a simple count at a single distance. For each building, we counted the VOM-derived trees within five concentric buffers (10, 25, 50, 75, 100 m). We then fitted an exponential regression to these counts against the buffer radius (Figure A6). The slope of this regression was used as our final metric. This approach offers a more nuanced measure of tree availability than a simple count; a steeper slope indicates not just the presence of trees, but a rapid increase in their number as one's view expands outwards, proxying for a richer, denser tree-dominated area.

4.6 Statistical Modelling

To analyse the socio-demographic drivers of environmental inequality, we addressed the inherent spatial autocorrelation in our LSOA-level data using a Spatial Error Model (SEM), which models spatial dependence in the error term, to account for unobserved, spatially structured covariates. Separate models were fitted for each of our three inequality outcome variables: the Gini coefficients for tree distribution (slope of the exponential regression), park access (walking distance to closest park), and blue space access (straight-line distance to closest water source).

The predictor variables for each model included population density, urban-rural classification, region, the Index of Multiple Deprivation (IMD) score, and mean spectral indices (NDVI, NDWI, NDBI). To investigate how the relationship between deprivation and green/blue space inequality varies across different contexts, we incorporated interaction terms between the IMD score and both urban-rural classification and region. The generalised model is formalised in Equation 3.

$$\begin{gathered} G_{unbiased} \sim \text{PopDensity} + \text{NDVI} + \text{NDWI} + \text{NDBI} + \\ \text{IMD} * \text{UrbanRural} + \text{IMD} * \text{Region} \end{gathered} \tag{3}$$

4.7 Limitations

While our methodology is capable of measuring each individual component of the 3-30-300 for all the buildings, it does so using a general assumption of tree shapes from the VOM, which creates square-shaped polygons that don't represent the real shape of trees. Moreover, this is calculated from a mosaic of LiDAR reads collected from 2018 to 2023; hence, changes in urban canopy due to tree removal might not be accounted for.

Measurement of tree visibility requires view-shed modelling, which involves a 3D representation of each building and its surroundings. This method is unfeasible for the number of buildings and trees used, thus why we defined the 3 metric as tree proximity instead of visibility.

Canopy cover was estimated using the VOM, which represented the highest-resolution and openly available vegetation product at the national level at the time of this study. However, it is worth noting that privately owned datasets of trees that include crown area and height exist, which could be used as a more accurate representation of urban trees.

In addition, some tiles from the original source were corrupted or missing, which limited the calculation for certain areas, affecting both 3- and 30-component models that relied on the VOM product (Figure A1).

In a similar fashion, the 300 calculation was impacted by the spatial extent of the processing, meaning that for a given LAD with no public green spaces, the estimate for all buildings would be null, or if there is no direct path from a building to a park in the road network, the aggregated value would not be determined. Vehicle roads were used to measure the distance to the closest access point to an open public park; however, walking paths might differ in length from those used by vehicles.

Finally, although the Verisk dataset we used is proprietary, an open version with the same building polygons is available through the EDINA platform, which academic institution members can access fully for research purposes.

A graphical summary of the methodology is presented in Figure 6

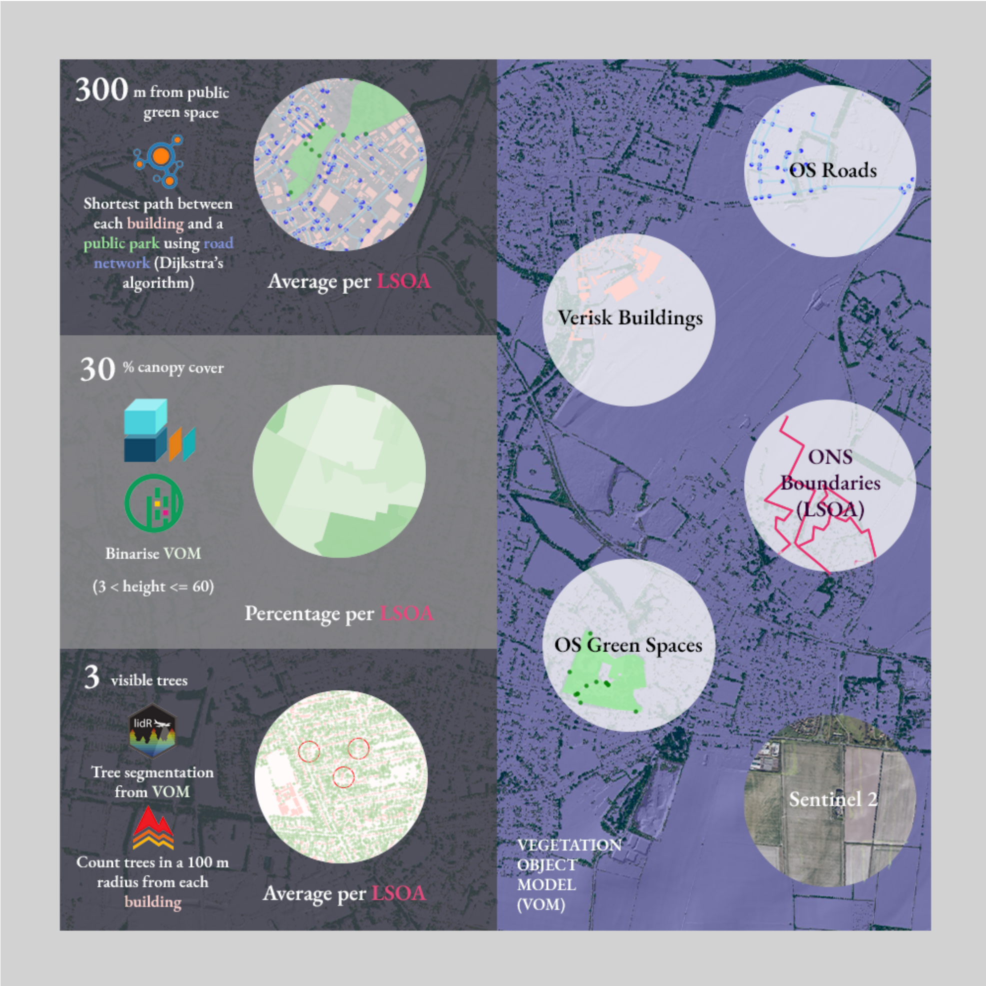

Fig. 6: Overview of the data integration and processing workflow. The methodology synthesises multiple national datasets (right), including the Vegetation Object Model (VOM) and Ordnance Survey (OS) layers for roads, buildings, and green spaces. These inputs are used to calculate the three components of the 3-30-300 rule (left): park accessibility (300m) via network analysis, canopy cover availability (30%) from the binarised VOM, and visible tree counts (3) from LiDAR-based tree segmentation.

5 Code and Data Availability

The Python and R code used to measure the 3-30-300 rule and extract data from Sentinel 2 images is available in the GitHub repository https://github.com/ancazugo/3-30-300-analysis. The aggregated data at LSOA and LAD levels are available in the Zenodo repository (https://doi.org/10.5281/zenodo.16911970). Tree segmentation tiles are available upon request. Two visualisation applications are available on the website for the code repository: the first one with the aggregated data at the LSOA level and the second one with the location of all trees in England.

Appendix A Supplementary Material

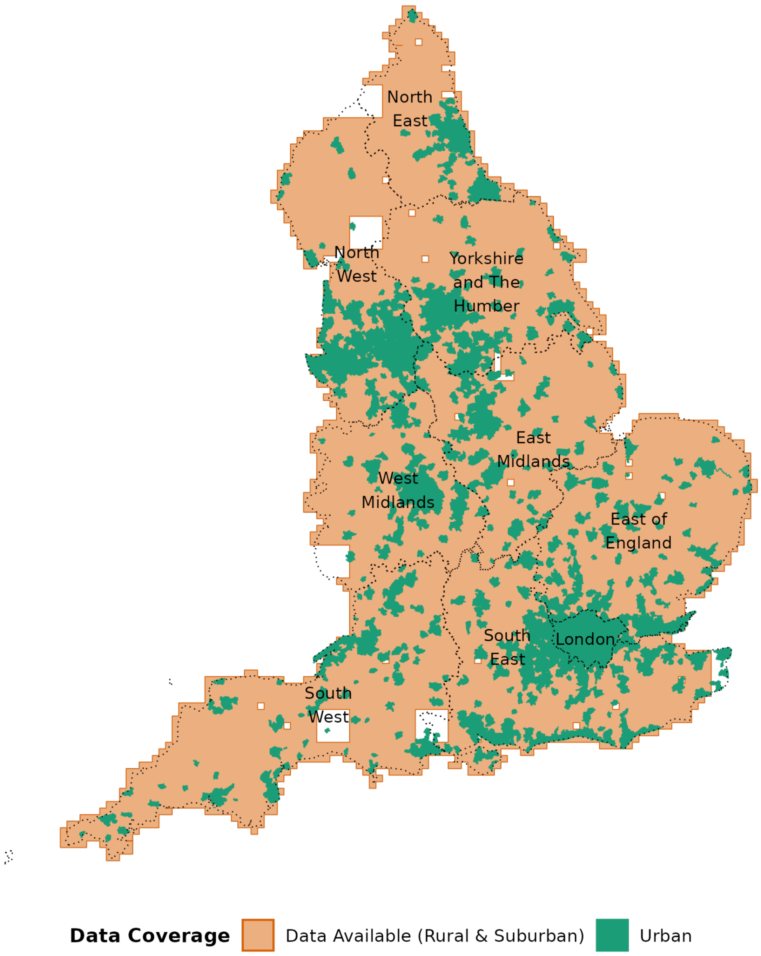

Fig. A1: Coverage of the tree segmentation process in all of England, including rural and urban areas. Blank patches represent areas where data was missing or corrupted.

Table A1: Summary of the number of urban Lower Layer Super Output Areas (LSOAs) per region that fulfil each component of the 3-30-300 rule and all of them combined. The values for the components (3, 30, 300) are percentages of the total urban LSOAs in that region, while the 3-30-300 column represents the percentage of LSOAs fulfilling all criteria simultaneously.

Region	No. Urban LSOAs	3 (%)	30 (%)	300 (%)	3-30-300 (%)
North West	4135	41.0	0.7	7.4	0.0
North East	1393	21.4	1.7	10.1	0.1
Yorkshire and The Humber	2802	27.5	1.4	6.7	0.0
West Midlands	3062	45.7	1.3	7.1	0.1
East Midlands	2122	39.6	0.8	4.3	0.0
East of England	2740	51.5	2.1	4.4	0.0
South West	2411	35.8	2.0	6.4	0.2
South East	4542	53.9	7.4	5.4	0.1
London	4994	43.3	1.3	12.7	0.0
England	28 201	42.2	2.3	7.4	0.1

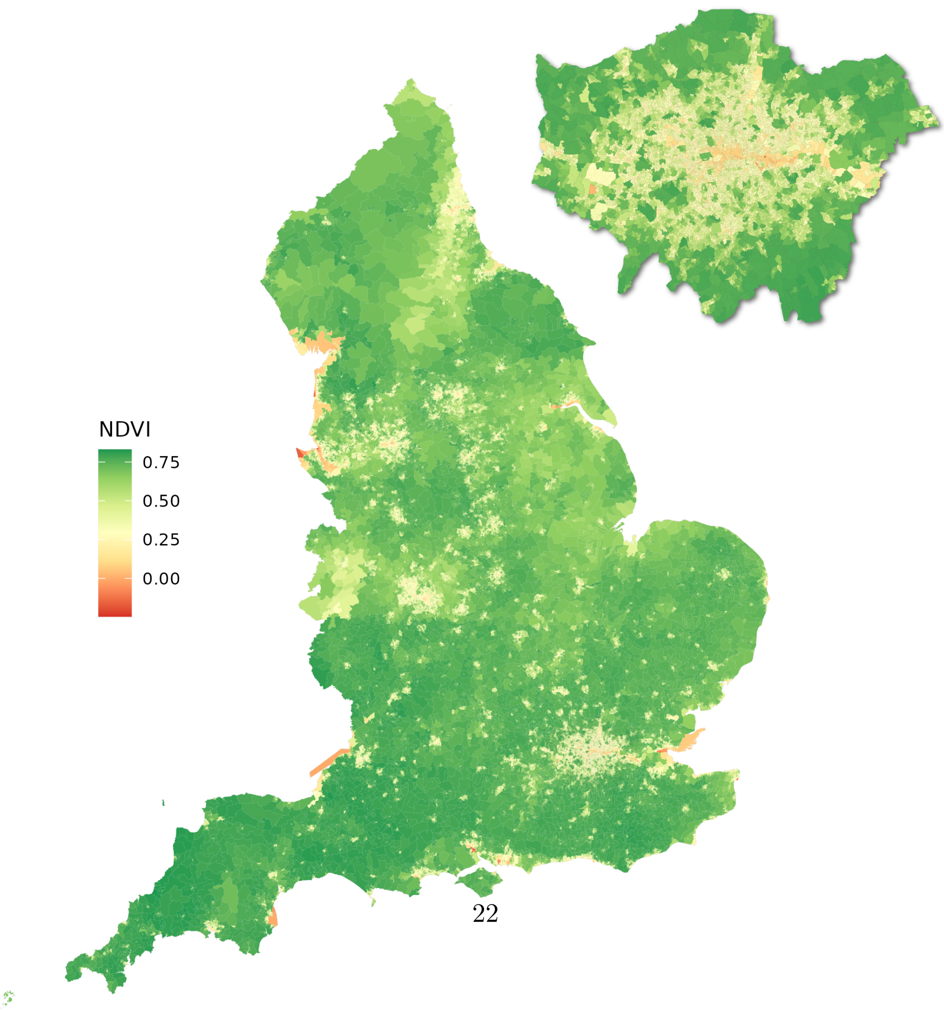

Fig. A2: NDVI for each LSOA in England

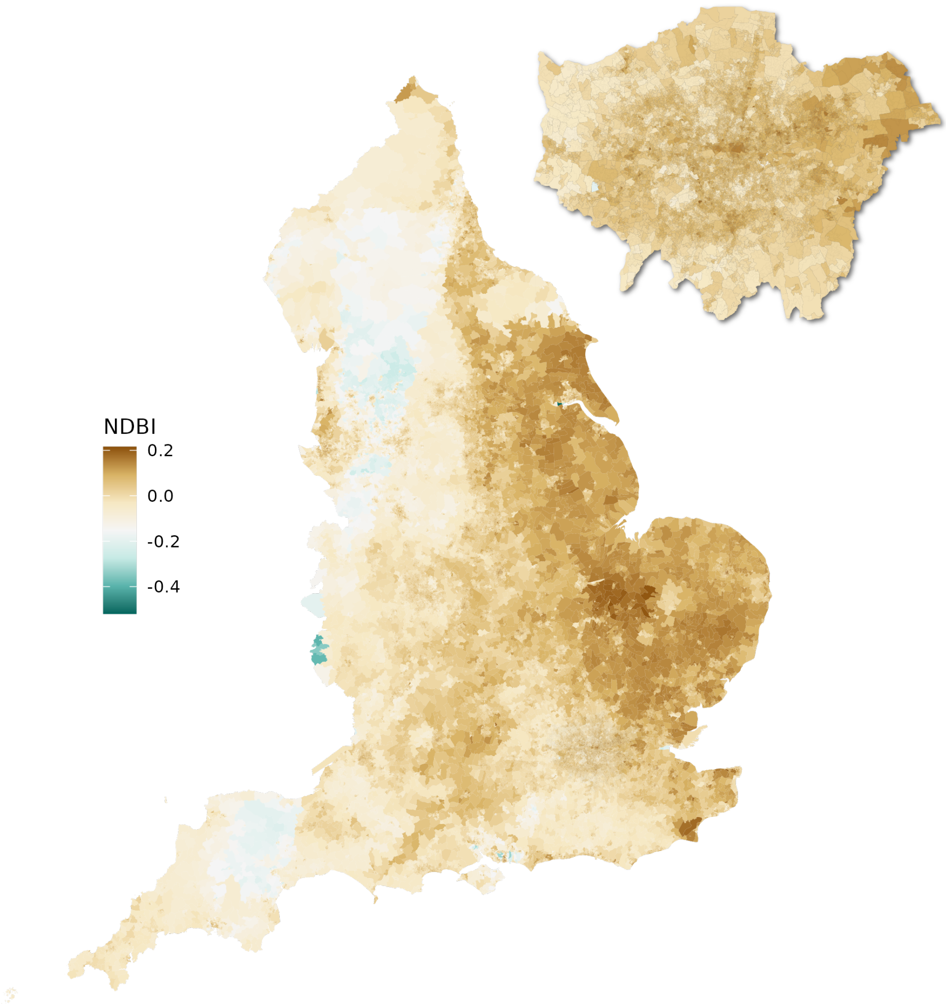

Fig. A3: NDBI for each LSOA in England

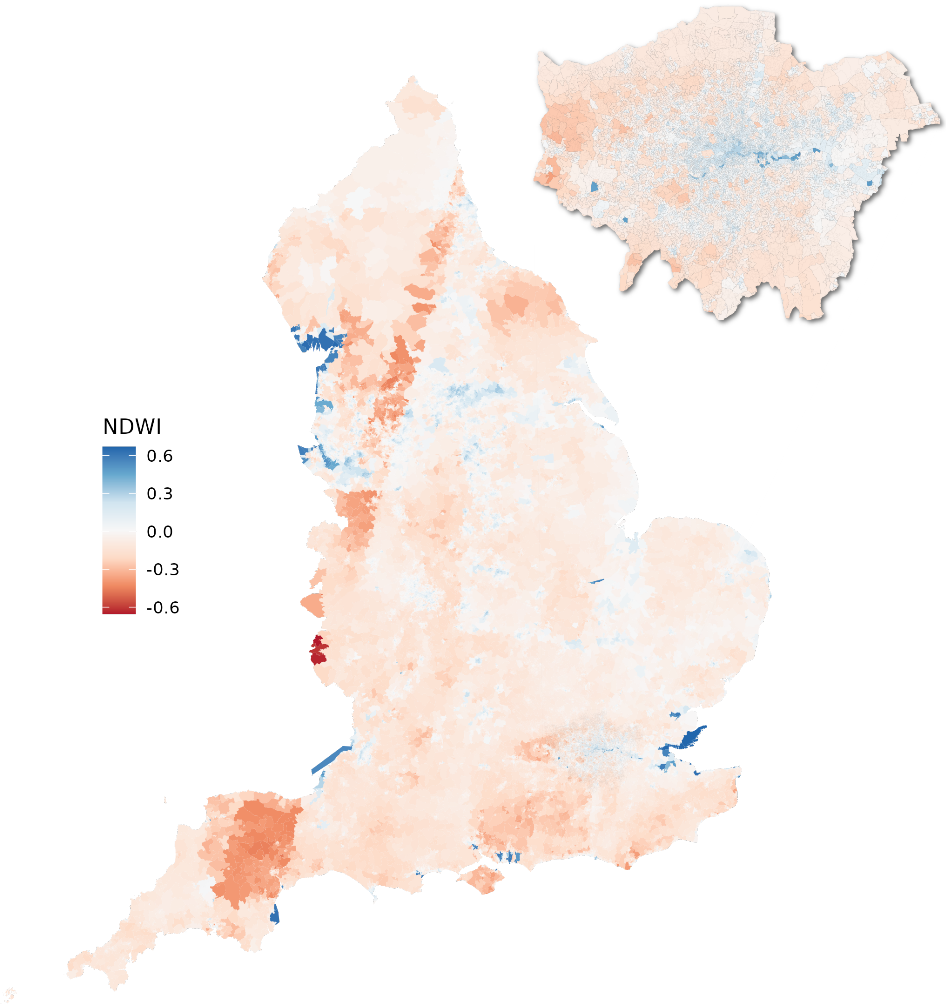

Fig. A4: NDWI for each LSOA in England

Table A2: Spatial error model results for inequality (Gini coefficients) in tree count, park distance, and water distance at the LSOA level in England. Standard errors in parentheses. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Tree Count Gini		Park Distance Gini		Water Distance Gini	
Variable	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	0.13293***	(0.00464)	0.84046***	(0.00622)	0.72883***	(0.00607)
IMDScore	0.00041**	(0.00014)	-0.00052*	(0.00020)	-0.00053**	(0.00019)
UrbanUrban	-0.00168	(0.00245)	-0.01647***	(0.00350)	0.04937***	(0.00333)
RegionNorth East	-0.00389	(0.00604)	-0.02246**	(0.00717)	0.03714***	(0.00739)
RegionYorkshire and The Humber	-0.00694	(0.00483)	0.00046	(0.00576)	0.01955**	(0.00594)
RegionWest Midlands	-0.03296***	(0.00478)	0.01479**	(0.00570)	0.00527	(0.00588)
RegionEast Midlands	-0.02556***	(0.00500)	0.01338*	(0.00601)	0.00995	(0.00617)
RegionEast of England	-0.04834***	(0.00478)	0.00405	(0.00577)	0.01542**	(0.00591)
RegionSouth West	-0.00706	(0.00486)	0.00918	(0.00577)	-0.00241	(0.00596)
RegionSouth East	-0.04572***	(0.00425)	0.00627	(0.00505)	0.01465**	(0.00521)
RegionLondon	-0.04834***	(0.00475)	0.00471	(0.00581)	0.02851***	(0.00592)
population_density	-0.00000**	(0.00000)	0.00000***	(0.00000)	0.00001***	(0.00000)
NDVI	-0.03152***	(0.00450)	-0.06172***	(0.00642)	-0.06950***	(0.00612)
NDWI	0.02578***	(0.00577)	-0.01505	(0.00794)	-0.06503***	(0.00771)
NDBI	0.14228***	(0.01086)	0.00453	(0.01504)	0.05381***	(0.01458)
IMDScore:UrbanUrban	-0.00032**	(0.00012)	0.00023	(0.00018)	0.00103***	(0.00017)
IMDScore:RegionNorth East	0.00011	(0.00013)	0.00029	(0.00018)	0.00002	(0.00017)
IMDScore:RegionYorkshire and The Humber	-0.00010	(0.00011)	-0.00010	(0.00015)	0.00010	(0.00015)
IMDScore:RegionWest Midlands	-0.00035**	(0.00011)	-0.00035*	(0.00016)	-0.00029	(0.00015)
IMDScore:RegionEast Midlands	-0.00025	(0.00013)	0.00026	(0.00018)	0.00011	(0.00017)
IMDScore:RegionEast of England	-0.00000	(0.00013)	0.00013	(0.00019)	-0.00034	(0.00018)
IMDScore:RegionSouth West	-0.00030*	(0.00013)	-0.00021	(0.00019)	-0.00029	(0.00018)
IMDScore:RegionSouth East	0.00002	(0.00012)	-0.00005	(0.00017)	-0.00035*	(0.00017)
IMDScore:RegionLondon	0.00011	(0.00014)	-0.00079***	(0.00019)	-0.00089***	(0.00018)
Model diagnostics						
λ	0.64497		0.45495		0.55726	
Asymptotic SE (λ)	0.00515		0.00652		0.00583	
Wald statistic (λ)	15701.00		4863.30		9120.60	
Log likelihood	42760.54		29928.67		32469.97	
ML residual variance	0.00343		0.00827		0.00683	
AIC	-85469.00		-59805.00		-64888.00	

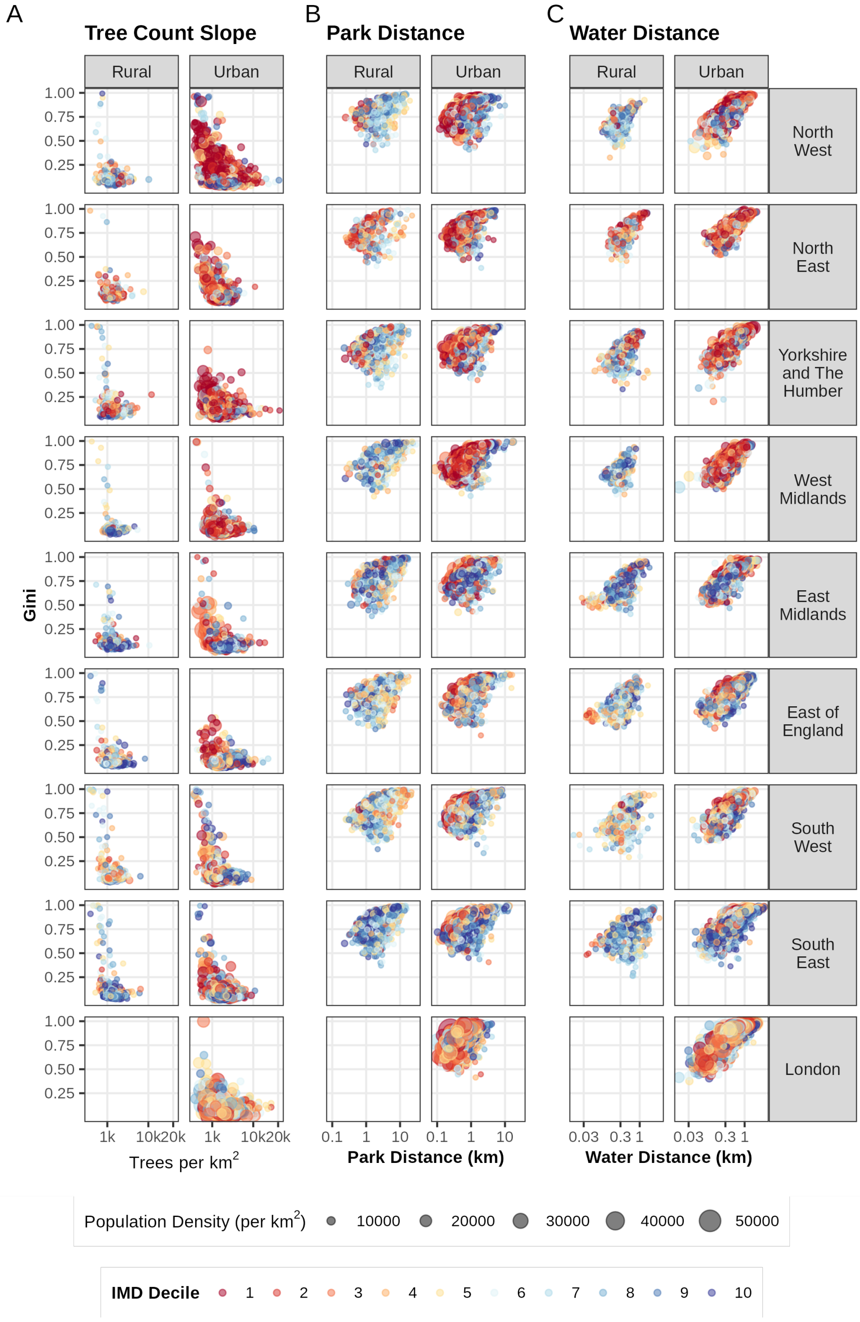

Fig. A5: Scatter plot between the three Gini coefficients and their corresponding environmental metric for each region in England. Size depicts population density, while colours point to IMD classification. A: Tree count slope, B: Walking distance to closest park, and C: Distance to closest water source.

Table A3: Comparison of tree geometry counts and total area between the Forest Research Trees Outside Woodland (TOW) dataset and this study's segmentation approach, by region.

Region	**TOW Dataset**		**This Study**	
	Count	**Total Area (m^2)**	**Count**	**Total Area (m^2)**
North West	4,155,143	613,505,095	8,205,613	1,005,555,299
North East	1,571,966	229,361,711	2,263,592	699,848,693
Yorkshire and the Humber	3,444,172	534,527,559	6,425,401	1,040,430,826
West Midlands	4,252,559	833,297,949	5,164,030	1,223,817,794
East Midlands	3,778,562	653,799,830	4,897,732	1,060,999,126
East of England	4,941,670	959,028,854	6,166,459	1,718,896,157
South West	6,583,686	1,474,924,354	4,911,044	2,512,667,899
South East	6,157,704	1,370,145,617	9,419,679	2,718,374,849
London	1,418,131	167,073,513	3,689,884	128,330,021

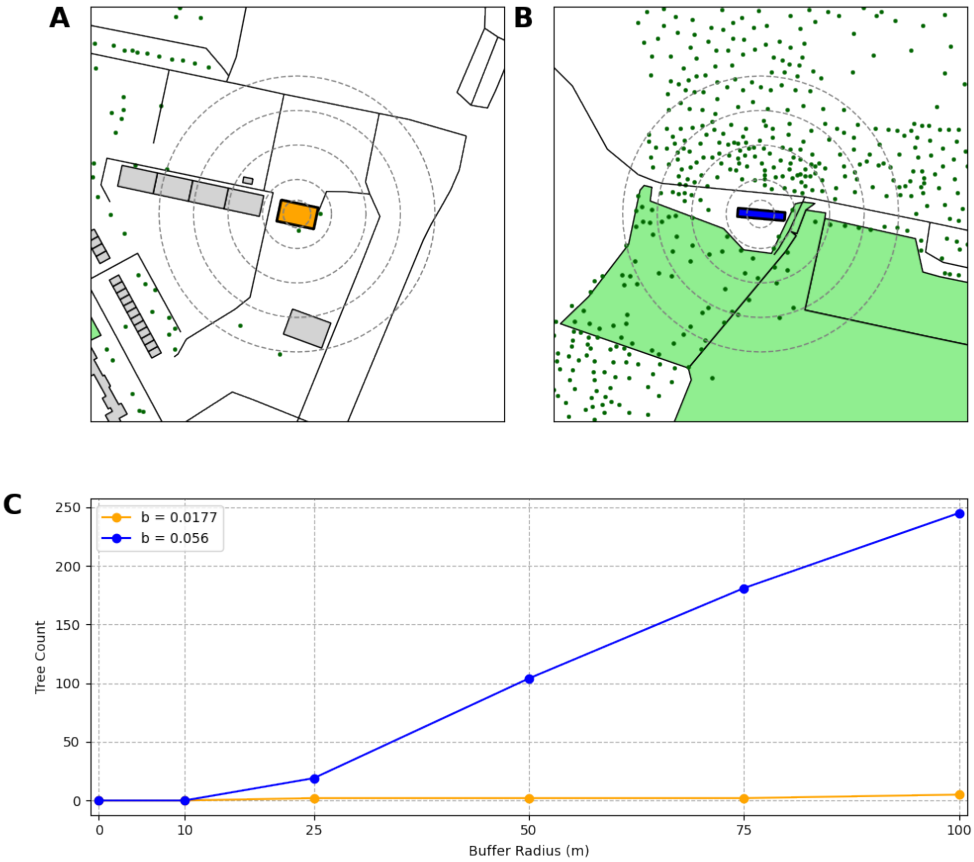

Fig. A6: Calculation of the tree index using the buffered count. A depicts a residential unit with a low slope in the regression, while B represents a house with a high slope. C shows the regression for both buildings.

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