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Urban blue and green spaces in the UK: Distribution, equity and ecological implications

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Abstract

Cities are closely linked to the 'triple planetary crisis', climate change, pollution, and biodiversity loss, and urbanisation affects human physical and psychological health. Urban blue-green spaces can lessen impacts by regulating temperature and water, purifying air, and supporting biodiversity, but research remains focused on green spaces. We investigate blue space cover across 500 towns and cities in Great Britain by including high-resolution blue spaces into existing land cover maps. We then assessed how blue and green cover, and land-cover diversity vary across socioeconomic deprivation gradients. Blue space covers less area than green space but is more evenly distributed across socioeconomic gradients. Higher land-cover diversity in deprived areas suggests urban regeneration may contribute to habitat homogenisation. These findings provide the first nationwide comparison of blue space cover, providing a holistic assessment of their ecosystem service distribution. In addition, we highlight the social relevance of overall land-cover diversity for sustainable urban development.

Introduction

Urban areas, characterised by high population densities and built infrastructure (hereafter also referred to as cities), are home to more than 55% of the global population[1] and play a critical role in driving the 'triple planetary crisis', climate change, pollution, and biodiversity loss[2,3]. Urban expansion contributes significantly to greenhouse gas emissions and habitat loss[4,5], while extensive impervious surfaces and reduced natural cover create urban-specific challenges, including the 'urban heat island effect'[6], increased flood risk[7], and poor air quality[8]. Limited access to natural outdoor spaces also increases the prevalence of physical and mental health conditions, particularly in deprived areas where environmental inequalities are greatest[9,10]. Research into sustainable urban design is required to create cities that hold adaptive, absorptive, and transformative capacity[11]. One of the most effective approaches for meeting these demands is through nature-based solutions, which provide critical ecosystem services, such as temperature moderation, water regulation, and air purification, supporting human health and well-being[12–17].

Natural outdoor environments within cities can be grouped into two broad categories: blue spaces, natural or man-made environments containing water[18] and green spaces, land characterised by vegetation, such as parks, gardens, and unused marginal land (road verges and railway sidings). Green spaces have been well studied across geospatial, ecological, and social contexts[19–21], whereas blue spaces have received less attention, despite their potential to advance urban sustainability[22,23]. Research has often treated blue spaces as a subset of green space[20,24], limiting recognition of their specific ecosystem services and biodiversity value in planning and policy. Blue spaces provide distinct ecological functions, such as supporting aquatic and riparian biodiversity[25–28], and delivering unique social and cultural benefits linked to recreation, relaxation, and sense of place[29–31]. Understanding how these functions are distributed across spatial and social contexts, and how urban pressures affect them, is therefore crucial for achieving urban sustainability.

Human development has long been shaped by access to water, with many major cities established along coasts, rivers, and canals that support industry, transport, and food provision[32–34]. As a result, urban residents commonly have opportunities for blue space exposure[35], whether through proximity (e.g., riverside walks, viewpoints) or direct contact (e.g., swimming, kayaking), which can promote physical and psychological health[22]. Urban blue spaces are also valuable for biodiversity, providing refuge for endangered species[36]. However, urban development poses significant risks to blue spaces[37], which include highly productive and regionally restricted habitats such as estuaries[38]. Examples include heavy modification through culverting, straightening, and reclamation[39,40]. These urban patterns reflect a wider global trend of wetland loss, with global coverage declining sharply due to anthropogenic disturbance and climatic pressures[37], with estimated losses of 21–87% over the past 300 years[37,41]. Consequently, a quarter of freshwater fauna now faces extinction[42]. In Great Britain (GB; England, Scotland, and Wales), wetland extent has decreased by approximately 90% over the last century[43], underscoring the urgent need to integrate urban blue spaces into conservation planning and public health research.

In GB, more than 80% of people live in urban areas[44], and it is recognised as one of the most nature-depleted nations globally[45]. Levels of human-nature connection are likewise relatively low compared to other European countries[46]. However, most urban environmental research in GB has focused on green spaces[21], overlooking the distinct characteristics and spatial patterns of blue spaces. To our knowledge, no large-scale study in GB has examined both the ecological and social dimensions of blue space cover, as has been done for green spaces[21]. Establishing baseline data and understanding spatial patterns of urban blue spaces are essential for ensuring they are valued and managed as effectively as their green counterparts, and for identifying inequities in ecosystem services that can inform sustainable urban planning. Existing assessments of blue spaces in GB remain limited in scope and consistency. For example, Natural England's Green Infrastructure Map[47] defines blue space exclusively as inland waterbodies identified in land-use datasets, excluding major features such as intertidal zones, beaches, foreshores, and wetland habitats (e.g., fens, bogs, and salt marshes). Similarly, an assessment by the Canal & Rivers Trust[48], which measured blue space accessibility using land use data within a 20 m buffer of public rights of way, excluded relevant environments beyond this distance and overlooked the fact that blue spaces can also be experienced indirectly, such as from coastal paths or viewpoints. As a result, their broader potential is often overlooked and important blue habitats are underrepresented in national-scale datasets. Such data gaps contribute to the systematic undervaluation of blue space in both research and policy contexts.

In this study, we investigate spatial and social patterns of blue space and other land-cover types across 500 urban areas in GB, selected to capture the full range of built-up environments from small towns to major conurbations. To do so, we: (1) develop a method to incorporate high-resolution blue space cover into existing land cover maps; (2) using this method we explore how land cover patterns, in particular blue spaces, are influenced by geographic setting (coastal, inland, estuarine); (3) evaluate how geographic setting and urban features influence blue space extent; and (4) examine how blue, green and grey cover, and overall land-cover diversity vary across socioeconomic deprivation gradients (see Fig. 1 and Fig. 2 for details).

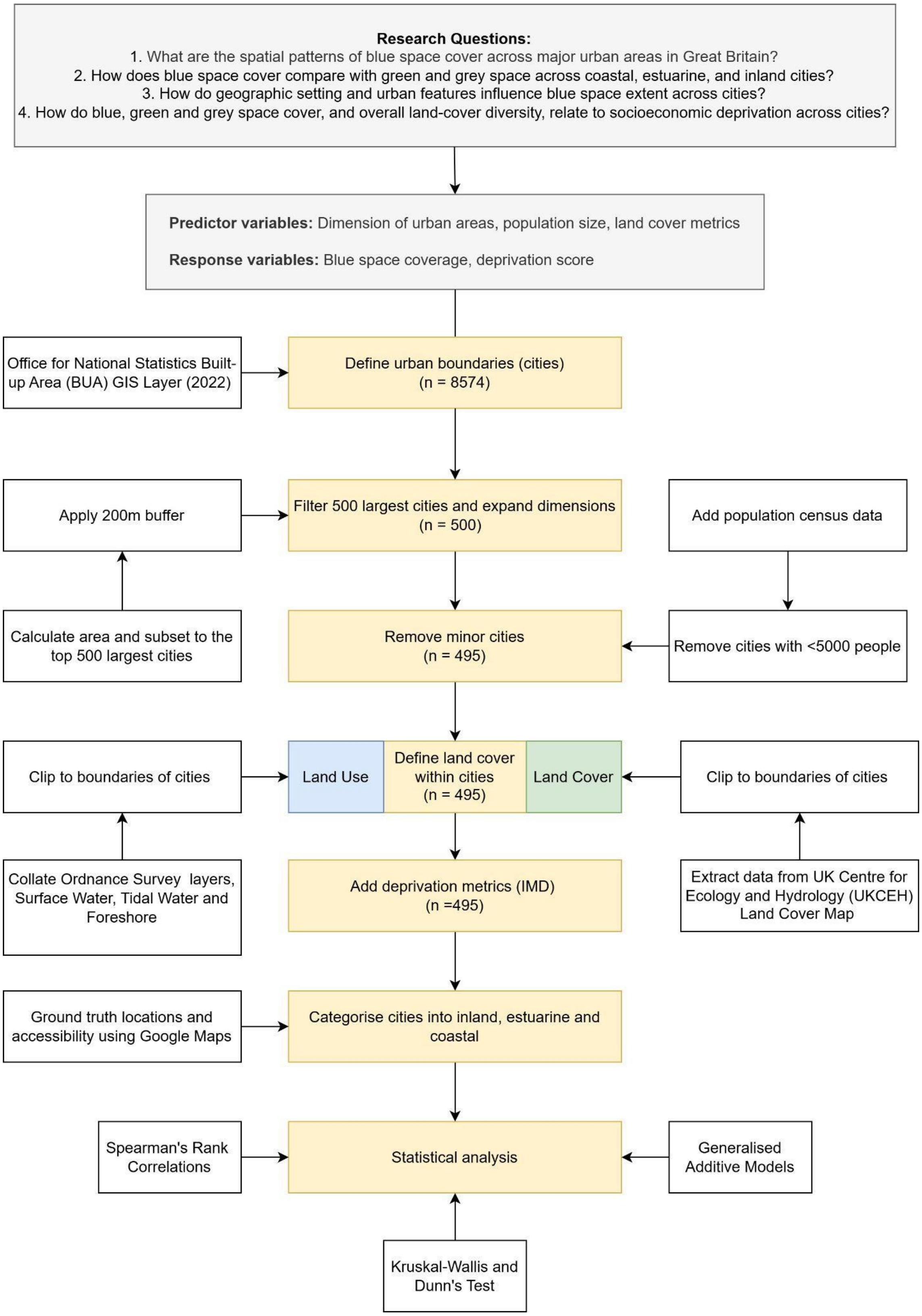
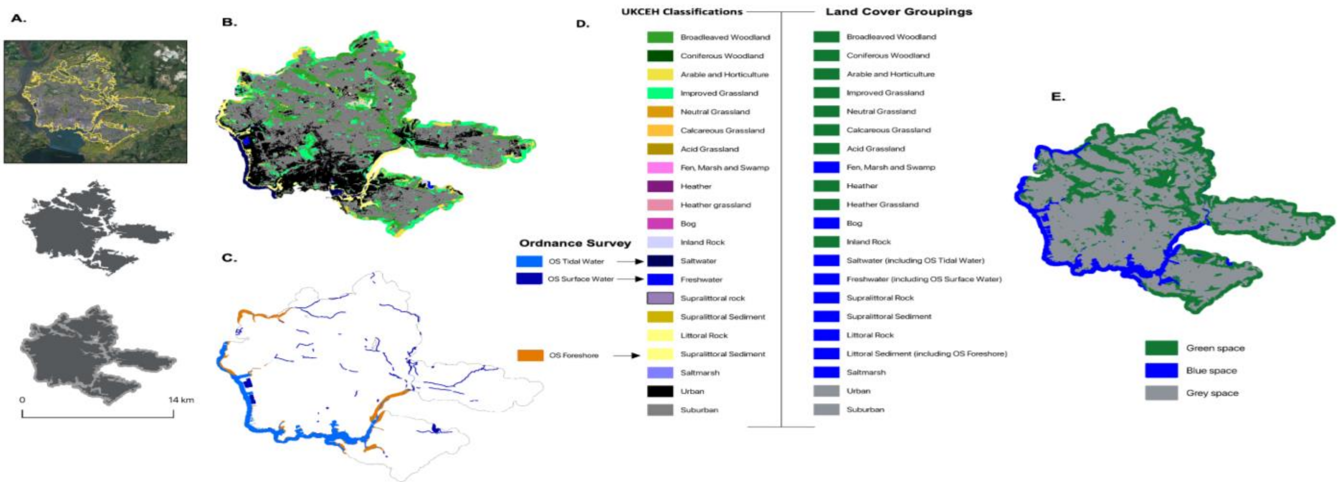


Fig. 1: Schematic overview of the study design, showing the main research focus, data sources, and analytical methods.

Fig. 2: Figure showing how land coverage was quantified and grouped across each urban area. **A.** Original BUA boundaries for Plymouth (top and middle) and the same area after the 200 m extension (bottom). **B.** UKCEH land cover data (legend shown in section D). **C**. Blue space land use data from Ordnance Survey (OS). **D.** Visualisation of how land use and land cover data were combined for the composite map and analysis. **E.** Composite map after combining datasets, colour-coded by grey, green, and blue classifications.



Results

Quantifying Urban Land Cover

Across Great Britain, the 500 largest urban areas, identified with built-up area shapefiles, were extended by 200 m and classified into 21 land cover types. Quality checks, comparing classified areas against unclassified areas, confirmed that, on average, 100% of the land in each area was accounted for (range: 99.58–100.51%). *Urban* and *Suburban land* cover were the most abundant, accounting for 46.3% and 20.5% of the summed classified area, respectively (Fig. 3a). This was followed by *Improved grassland* (13.5%), *Deciduous woodland* (7.2%), *Arable land* (6.5%), *Freshwater* (1.4%), and *Neutral grassland* (1.4%). The remaining 14 land cover types, of which eight were blue and six were grey, all had < 1% coverage each and were unevenly distributed across locations (Fig. 3b). Following classification, five areas were excluded from the study due to having populations of less than 5000 people, making them minor urban areas. This resulted in a final sample of 495 cities for the remainder of the study.

After grouping land-cover types into categories based on shared characteristics: blue spaces (n = 9), green spaces (n = 10), and grey space (n = 2), blue spaces had the lowest overall mean cover at 3.56% (Min: 0.06, Max: 25.49, SD: 3.98). As expected, grey space was the most dominant component of urban cover, with an overall mean of 64.61% (Min: 38.94, Max: 97.87, SD: 8.99), followed by green space at 31.82% (Min: 25.06, Max: 36.77, SD: 8.08), see Supplementary Table 1 for full results.

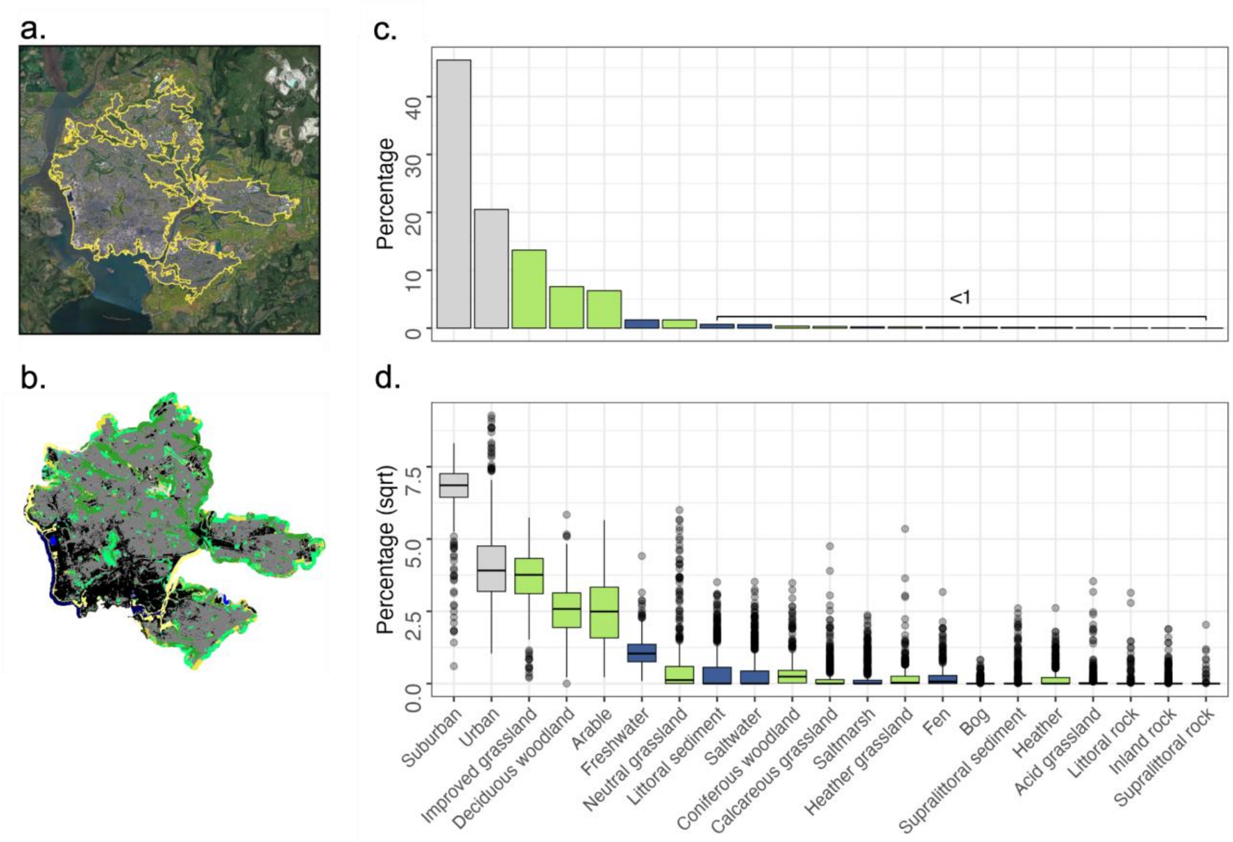


Fig. 3: Land cover in urban areas, colour-coded by grey, green, and blue land-cover groupings (see Supplementary Table 3). **a**. Satellite image showing one of the 500 urban geometries (outlined in yellow) before classification. **b**. Urban geometry after classification with land cover and land use data (100% coverage). **c.** Total coverage (y-axis) of each land cover type (x-axis, n = 21) across all urban areas (n = 495), with overlap removed. **d***.* Box plot showing the percentage (y-axis) of each land cover type (x-axis) per urban area.

Urban areas ranked by blue space cover

Urban areas were categorised into coastal (*n* = 71), estuarine (*n* = 27), and inland (*n* = 397) based on their location (Fig. 4a) and ranked by blue space cover using a decile scale (Fig. 4b, top panel). Coastal areas had the highest proportionate blue space overall, comprising 75% (38/50) and 50% (25/50) of decile one (ranks 1–50) and decile two (ranks 51–100), respectively (Fig. 4b). Estuarine areas ranked second for blue space with consistently high blue space values placing them within deciles one to four, as with coastal areas. Inland urban areas were the least blue overall, making up 100% of deciles five to ten, indicating 75% of inland areas had less blue space than any coastal or estuarine areas included in the study. However, some inland areas were present in deciles one to four, highlighting the variability of blue space within this category.

From the bluest decile (1) to the least blue (10), grey space remained relatively constant (Min: 62.06, Max: 67.57, SD: 1.58) with a mean of 64.60% (Fig. 4c). In contrast, blue space was highly variable (Min: 0.28, Max: 12.95, SD: 3.56) with a mean of 3.56%, as was green space (Min: 24.99, Max: 36.50, SD: 3.99) with a mean of 31.84% (see Supplementary Table 2 for full results). Average blue space cover decreased from a high of 12.9% in decile one to 2.3% by decile five, and 0.3% by decile ten; it was mostly replaced by green space, which increased from 25% in decile one to 35.6% by decile ten. This either-or pattern between green and blue space allowed grey space to remain comparatively stable (see Fig. 4c).

As shown in Fig. 4d, the bluest cities overall were all located on the coast, which included Great Yarmouth, Peterhead and Fleetwood, ranked 1st, 2nd and 3rd, respectively. However, some inland and estuarine areas also had high proportions of blue space, such as Staines-upon-Thames (ranked 4th) and Canvey Island (ranked 6th). A full list of ranked cities is provided in Supplementary Table 7.

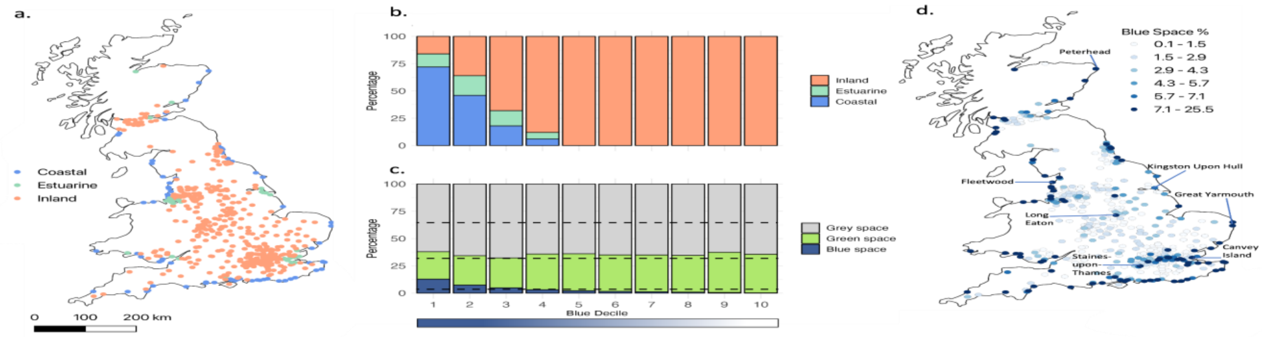


Fig. 4: Urban areas ranked by blue space cover **a.** Distribution of inland (*n* = 397), estuarine (*n* = 27), and coastal (*n* = 71) urban areas. **b.** Composition of inland, estuarine and coastal urban areas within each decile (ranked by blue space). **c.** Average cover of grey space, green space, and blue space per decile. Dashed lines represent overall means: grey space 64.6% (top line), green space 31.8% (middle line), and blue space 3.6% (bottom line). **d.** Urban areas colour-coded by their blue space (%).

Land cover differences across coastal, estuarine, and inland urban areas

The relative proportions of grey, green, and blue space were compared across coastal, estuarine, and inland urban areas (see Fig. 5). Blue space cover was significantly higher in coastal areas than in inland ($Z = 12.68$, adj. $p < 0.001$) and estuarine areas ($Z = 2.17$, adj. $p = 0.045$), and estuarine areas had more blue space cover than inland areas ($Z = 6.00$, adj. $p < 0.001$). Green space cover was significantly higher across inland areas, when compared to coastal ($Z = -6.24$, adj. $p < 0.001$) and estuarine areas ($Z = -3.65$, $p < 0.001$), but there was no difference between coastal and estuarine areas ($Z = -0.45$, adj. $p = 0.976$). Grey space cover was not significantly different across any comparisons ($p = 0.31$), although estuarine areas exhibited a slight trend toward higher grey space cover. Full test results are listed in Supplementary Table 4.

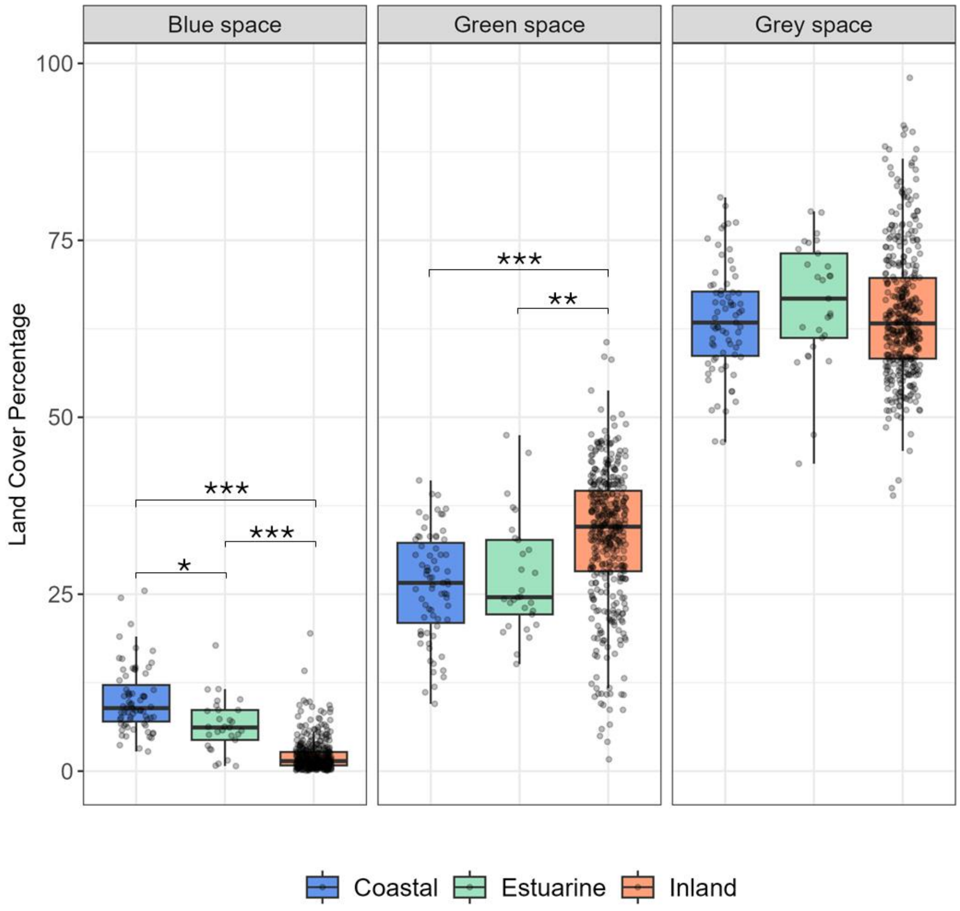


Fig. 5: Land cover composition across coastal, estuarine, and inland urban areas. Percentages of blue space (left), green space (middle), and grey space (right) are shown for all urban areas, grouped by region: coastal (n = 71), estuarine (n = 27), and inland (n = 397). Significant differences identified by Dunn's test are indicated (*$p < 0.05$, **$p < 0.001$, ***$p < 0.0001$).

Associations between blue space cover and city size, population density, green space cover, and grey space cover

Bivariate associations between blue space (%), city size (m^2), grey space (%), green space (%), and population size were tested using Spearman's rank correlation across each geographic category (see Table 1 and Fig. 6). In coastal cities, blue space had a moderate negative correlation with size (ρ = -0.328, p = 0.005), grey space (ρ = -0.227, p = 0.012) and population size (ρ = -0.132, p = 0.009). In inland cities, blue space showed a weak positive correlation with city size (ρ = 0.154, p = 0.002) and population size (ρ = 0.156, p = 0.002) but a negative correlation with green space (ρ = -0.250, p < 0.001). In estuarine cities, we found no significant associations between blue space and any of the variables tested.

Table 1: Spearman's rank correlations (ρ) between blue space cover (%) and city size, green space cover (%), grey space cover (%), and population size across coastal, estuarine, and inland cities.

Variable 1	Variable 2	Rho (ρ)	P-Value
Coastal Blue space (%)	Size (m^2)	-0.328	**0.005**
	Green Space (%)	-0.227	0.056
	Grey Space (%)	-0.295	**0.012**
	Population Size	-0.307	**0.009**
Inland Blue space (%)	Size (m^2)	0.154	**0.002**
	Green Space (%)	-0.250	**<0.001**
	Grey Space (%)	0.049	0.328
	Population Size	0.156	**0.002**
Estuarine Blue space (%)	Size (m^2)	-0.124	0.517
	Green Space (%)	-0.866	0.653

	Grey Space (%)	-0.300	0.114
	Population Size	-0.231	0.905

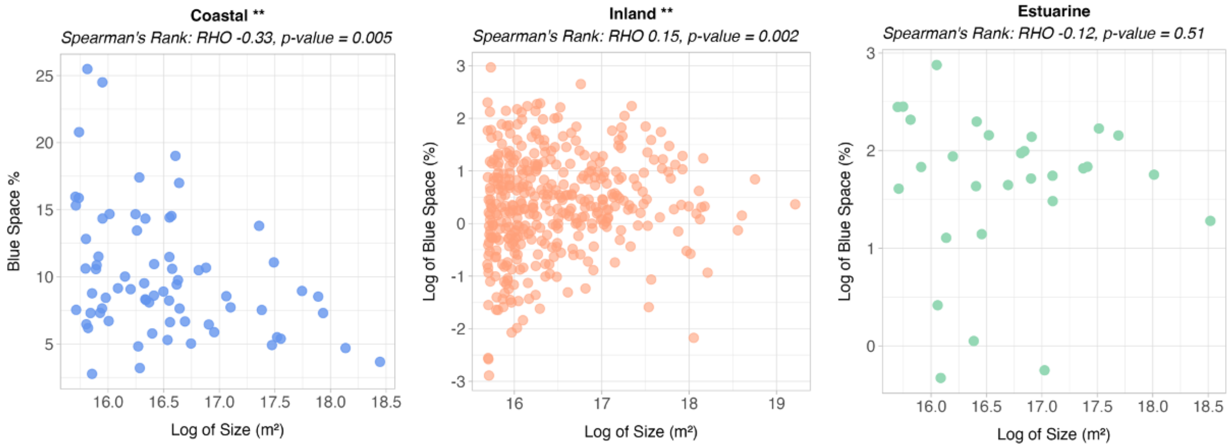


Fig. 6. Scatter plots showing associations between blue space cover (%) and city area (m^2) across coastal (left), inland (middle), and estuarine cities (right). Spearman's rank correlation coefficients (RHO) and *p*-values are shown above each plot. Inland and estuarine data are displayed on a log scale.

Environmental predictors of deprivation

Generalised Additive Models (GAMs) were used to explore the predictive power of environmental variables for deprivation indices, represented by the Index of Multiple Deprivation (IMD) deciles, based on relative socioeconomic disadvantage. Models controlled for latitude, longitude, geographic classification (coastal, estuarine, inland), population counts, and city size (see Supplementary Table 6 for permutations). The best-fitting GAM, indicated that green space, blue space, Simpson's Index, and latitude were the only significant predictors of socioeconomic deprivation (Adj. R^2 = 0.52, GCV = 1.82, n = 435), best described using smooth terms (thin plate regression splines) due to their varying degrees of linearity (see Fig. 7 and Table 2 for full summary). Using 10-fold cross-validation, the model achieved an average RMSE of 1.37, indicating a moderate prediction error (~16%) with the dependent variable ranging from 1.56 to 9.95 with a mean of 5.75. Green space showed a positive, linear relationship (edf = 1.280) with deprivation decreasing as green space cover increased ($p < 0.001$). Blue space had a non-linear trend with deprivation (edf = 1.909) with negligible effects at lower values, but slightly positive effects at higher values ($p < 0.001$). Simpson's diversity had a complex non-linear relationship with deprivation (edf = 7.184), which was consistently negative across the majority of data points ($p < 0.001$). Latitude had a non-linear effect with deprivation (edf = 4.380,

$p < 0.001$), with area between 51° and 52° being the least deprived (including London, Cambridge and Oxford). Overall, the results indicate that total natural cover increases with decreasing deprivation, whereas overall land-cover diversity declines.

Table 2: General Additive Model summary table.

Family	**Link Function**	**Formula**	**Adjusted R-squared**	**Deviance explained (%)**	
Gaussian	identity	imdd_weight_av ~ s(total_green, k = 9, bs = "tp", fx = FALSE) + s(log(total_blue), bs = "tp", k = 9, fx = FALSE) + s(simpsons, k = 9, bs = "tp", fx = FALSE) + s(lat, k = 9, bs = "tp", fx = FALSE)	0.523	53.9	
A. Parametric coefficients	**Term**	**Estimate**	**Std Error**	**t-value**	**p-value**
	(Intercept)	5.75331	0.06343	90.7	<0.001
B. Smooth terms	**Term**	**edf**	**Ref.df**	**F**	**p-value**
	s(total_green)	1.280	1.516	143.223	<0.001
	s(log(total_blue)	1.909	2.438	6.785	<0.001
	s(simpsons)	7.184	7.799	11.580	<0.001
	Latitude	4.380	5.344	20.255	<0.001
	GCV = 1.8161	Scale est. = 1.7503	n = 435		

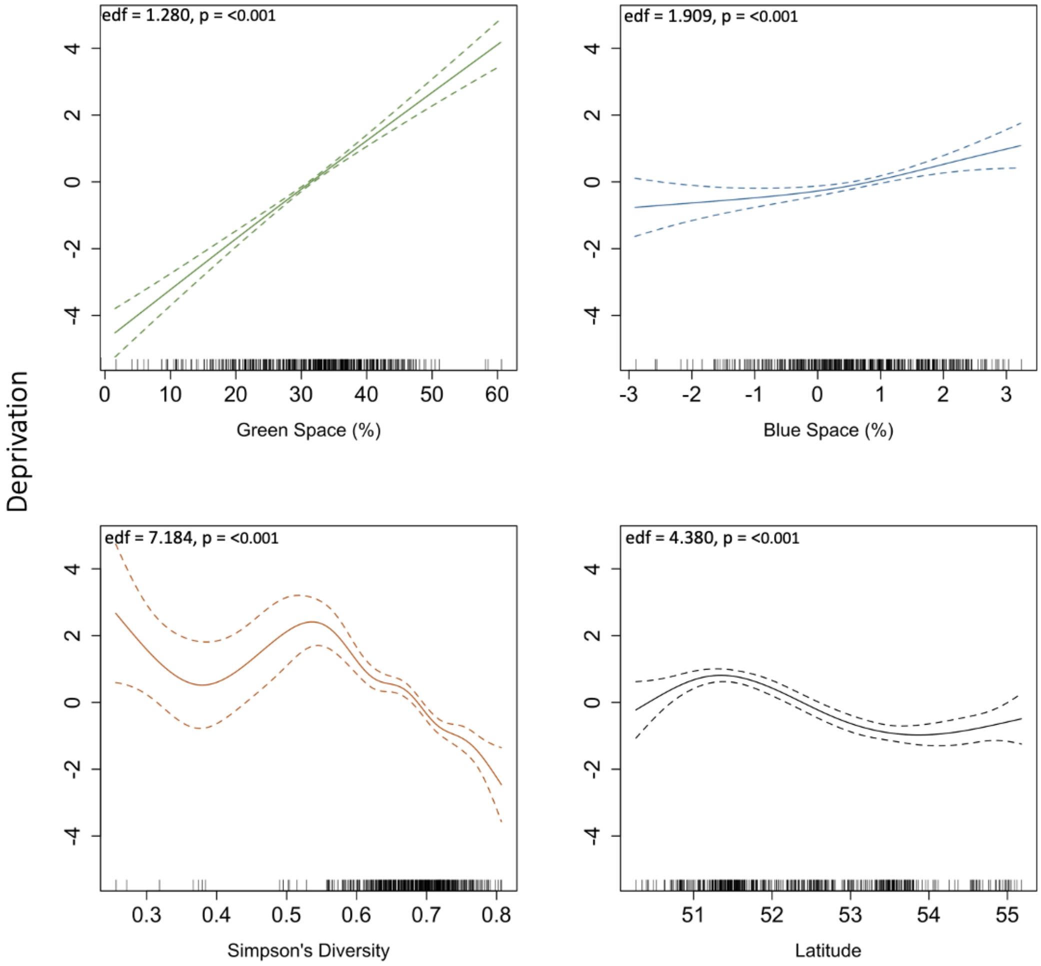


Fig. 7. Effects of four significant predictors of deprivation: green space (top left), blue space (top right), Simpson's Diversity Index (bottom left) and latitude (bottom right), as produced by the GAM smooth terms (thin plate splines, k = 9). Estimated effects are shown by the solid lines with 95% confidence intervals within dashed lines. The y-axis represents the deprivation index, where higher values indicate lower deprivation.

Discussion

Here, we developed a comprehensive method to quantify urban blue spaces at scale across GB, including freshwater and marine environments, and explored urban land use patterns from ecological and social perspectives. We found that blue spaces are more prominent in coastal and estuarine cities than in inland cities, but remain a minority land cover type compared with grey and green spaces. However, unlike green space coverage, which has strong associations with socioeconomic deprivation, blue space coverage remains comparatively even across deprivation gradients. Our results also indicate that the most deprived cities tend to have the greatest land-cover diversity, suggesting urban ecosystems could be simplified during regeneration. Collectively, our findings address current knowledge gaps in urban blue space baselines and offer new perspectives on blue, green, and grey space land cover patterns, vital for creating sustainable, equitable cities.

We created a highly detailed composite map of blue space by integrating land cover and land use datasets, addressing the underrepresentation of certain blue spaces in their original formats. This method particularly improved the representation of small waterbodies, commonly missed by 10 m resolution land cover data[49], while retaining important blue space habitats which are only available from these datasets (e.g., saltmarsh). Overall, our urban land cover results aligned with previous assessments, indicating that approximately 30% of urban areas are made up of natural cover (grass, trees, water, etc.)[50]. But our study included a 200 m extension to urban boundaries, offering a 'doorstep scale' perspective[47] of blue and green spaces which surround cities.

By assessing land beyond standardised urban geometries and incorporating highly relevant coastal blue spaces (including the sea), which are not always included in existing blue space maps, we provide a more realistic and holistic assessment of accessible urban blue spaces. Our integrated approach captures habitats that are often overlooked, such as intertidal areas, beaches, and saltmarshes, which are highly relevant to both biodiversity [51] and social well-being [22]. We recommend that future blue space assessments adopt a holistic framework, combining land use and land cover data to encompass all habitats that can reasonably be classified as blue space, as demonstrated here.

Overall, coastal cities and seaside towns had the highest proportion of blue space, reflecting their proximity to marine environments. However, unlike inland areas, the relative blue space of coastal urban areas decreased as factors of urbanisation increased (e.g., the size and population of a city), with larger coastal urban areas having proportionately less blue space than smaller ones. This decrease could be linked to landward urban expansion, driven by coastal erosion [52], the provision of setback zones [53], or coastal squeeze [54]. If this is the case, any urban development in coastal areas which does not involve the coastline would reduce the relative land-water interface and therefore decrease the proportionate blue space in that urban area. Seaward expansion via land reclamation could also share a similar effect, unless artificial bays, marinas and lagoons suitable for beachgoers are created, such as those in the UAE[55]. In contrast, blue space coverage showed a slight positive relationship with city area and population size in inland cities. This unexpected pattern may reflect the influence of man-made blue spaces, such as park lakes and reservoirs[56], which can substantially increase blue space proportions in inland cities. For example, Staines-upon-Thames had high blue space cover due to nearby reservoirs, which were created as part of London's water infrastructure[57]. Therefore, in some circumstances, blue spaces could remain stable and even increase during urbanisation and utilitarian water management.

We found estuarine cities had more blue space than inland cities, but less than coastal cities, reflecting their natural role as transitional zones between land and sea. We also found evidence for estuarine cities having high grey space coverage and restricted blue space accessibility, primarily due to heavy industrialisation. In our sample, 10 of the 14 urban boundaries that required modification to exclude completely inaccessible and non-residential zones (e.g., refineries and cargo ports) were estuarine, suggesting that industrial land use in estuarine cities constrains blue space accessibility. These urban patterns are consistent with wider evidence that estuarine habitats have faced substantial declines as a result of sprawling coastal developments[58] and land reclamation of wetlands[38]. However, Ghomeshi and Walczak[59] highlight the potential for blue space regeneration in post-industrial cities, while Burda and Nyka[60], advocate waterfront renewal in areas where port and shipyard industries have withdrawn from city centres. Examples include Kingston Upon Hull, which has multiple access points to the Humber Estuary, and docks that have been converted into commercial hubs[61].

Our results show that blue space cover is heavily dependent on the location of the urban area, with geographic biases having a strong influence on blue space extent, and that the effect of urbanisation on blue space availability can be highly varied across different regions. Furthermore, we show that blue spaces are less abundant than green spaces, presented here at scale and in a previous case study on Bristol, England[40]. The scarcity of urban wetlands, particularly inland freshwater systems, makes them disproportionately vulnerable to land-cover change during urbanisation, highlighting the importance of prioritising their preservation. We also observed a trade-off between green and blue space cover in urban areas, finding that as green and blue space replace one another, grey space remains relatively stable. This can be seen in coastal cities, which have less green space cover than inland cities, but no difference in grey space cover. Previous research exploring low green space within coastal cities highlights that environmental conditions on exposed coasts, including strong winds and sea salt aerosol[62], can create challenging conditions for trees, resulting in stunted growth, increased dieback, and less amenity value[63]. In addition, trees can block desirable views of water bodies, and can be removed or opposed by communities[63], indicating that the presence of a blue space can indirectly affect green space cover in urban areas.

By examining social data, we found that blue space cover remains comparatively stable across levels of socioeconomic deprivation, whereas green space cover typically declines with increasing deprivation, as shown here and in previous studies[21,64]. We also found levels of deprivation were lower in the south of England, as shown in previous studies [65], suggesting the trends captured in our model are reliable. Our findings highlight that blue space inequity is less pronounced than for green spaces, building on the growing interest in the role of blue spaces in mitigating environmental inequalities across deprived communities[66]. However, the equitable distribution of blue space does not necessarily equate to use or quality, as social and cultural factors can shape who actually benefits from these environments[67]. Many urban waterways and coastal margins remain inaccessible due to private ownership, infrastructure barriers, or safety concerns, and water quality issues, such as pollution, can limit their ecological and social value[68]. Future assessments should therefore consider accessibility, connectivity, and environmental conditions as key indicators alongside spatial coverage. The stability of blue space cover could be explained by their geographic and physical constraints, often being fixed features of the landscape (e.g., a river or coastline) which do not necessarily increase with urban expansion or regeneration. In contrast, green spaces, which can be more easily introduced or expanded, are commonly provided for in urban design. In addition, we found that general land-cover diversity increases with increasing deprivation, suggesting that the most deprived communities occupy areas with a more heterogeneous mix of land-cover types, potentially reflecting a more complex urban form and higher habitat diversity.

These findings suggest that urban regeneration, typically associated with increasing wealth, may drive physical homogenisation through simplification of land cover, alongside more commonly studied forms of cultural and social homogenisation[69–71]. For example, brownfield sites, including previously developed, derelict, and contaminated land, can provide valuable refuges for urban biodiversity[72], but are often removed during regeneration, reducing the diversity and extent of urban habitats[73]. These areas frequently host a mosaic of early-successional habitats, such as bare ground, ruderal vegetation, and ephemeral wetlands, which support pioneer plants and invertebrates[74]. In contrast, large stretches of improved grassland, commonly provided during development, offer limited habitat diversity that is further constrained by intensive management regimes[75,76]. Therefore, without careful habitat management, regeneration may simplify urban habitats and undermine ecological resilience.

Nevertheless, regeneration and urban redevelopment also present opportunities to enhance blue infrastructure through the adoption of water-sensitive and ecologically informed design principles, for example, Sustainable Drainage Systems[77,78]. Integrating blue space creation or restoration, such as daylighting culverted rivers, constructing urban wetlands, or re-naturalising watercourse banks, can simultaneously improve biodiversity, water management, and social amenity[23,79,80]. Ensuring that blue-green infrastructure is embedded in urban planning frameworks and incorporated into concepts such as the '15-minute city'[81], as proposed by Kabisch and Egerer[82], is therefore essential to mitigate the homogenising effects of regeneration while enhancing urban resilience.

To conclude, this study presents a novel, integrated approach for mapping and analysing urban blue space across GB, incorporating inland, estuarine, and coastal settings to capture spatial variation within cities. As interest in creating accessible natural spaces in cities increases, a comprehensive perspective on land cover is essential if urban planners are to address both ecological and social demands of urban environments. Here, we found that blue spaces are ubiquitous with urbanisation, much like green space, but have far less cover, particularly across inland areas. We also provide a robust baseline for urban blue space cover, suitable for comparison in future studies. Furthermore, in addition to reaffirming known patterns of socioeconomic deprivation and green space, we provide new land-cover perspectives, which show that blue space remains relatively stable across levels of deprivation, but the diversity of land cover increases with deprivation. This suggests that urban land cover may become homogenised with urban regeneration, thus having counteractive effects on biodiversity and sustainability goals. Collectively, our results highlight the need to incorporate blue spaces, alongside green spaces, into holistic ecological perspectives of the urban environment to better understand landscape-scale land-use patterns. If all blue-green spaces are accounted for within both social and ecological contexts, future urban development has the potential to be more sustainable, inclusive, and responsive to growing urban pressures.

Methods

Study area

Great Britain (GB), made up of England, Wales and Scotland, is the ninth largest island in the world and home to over 65 million people[83]. The population is highly urbanised, with 83% (56 million) of England's population living in built-up areas[84]. Across all three countries, the composition, location and size of built-up areas are highly varied, ranging from small coastal towns to extensive urban agglomerations.

Data sources

Five GB datasets were used to gather geospatial, ecological, and socioeconomic perspectives: (1) a layer detailing built up area boundaries provided by the Office of National Statistics[85], (2) a 10 m resolution land cover map detailing 21 habitats, created by the Centre for Ecology and Hydrology[86], (3) Ordnance Survey Vector Map land-use boundaries[87], (4) UK Government population census results[83], and (5) UK Government Index of Multiple Deprivation Indices[88].

Data handling

Built-up urban areas were identified from the Built-Up Areas layer (n=8545), and sub-sampled into the 500 largest by area using the QGIS field calculator. Original geometries were then extended by 200 m using the QGIS buffer tool to include highly accessible spaces (either visually or physically) falling outside of the original geometries but relevant to the area. For example, the sea, accessible in most coastal regions, will always fall outside of statistical zonations, meaning original geometries would introduce strong boundary effects in assessments of blue space cover. An evaluation of general accessibility was carried out for all coastal and estuarine regions using satellite imagery and Google Street View. This process consisted of checking for access points and identifying disconnected built-up areas, which were part of an urban agglomeration, but not residential or publicly accessible (see Supplementary Fig. 1). In total, 14 urban areas were modified to remove disconnected (no public roads or paths) and inaccessible industrial zones, including refineries and ports (see Supplementary Table 5).

Land cover types within urban areas were quantified with CEH land cover data[86] and OS land use data[87]. Although very accurate (82.6% overall), the primary focus of the CEH land cover map was terrestrial cover, meaning coastal and intertidal zones have lower accuracy[86]. Similarly, smaller water bodies (<0.5 ha or <40 m wide) have less accuracy when compared to large water bodies[86], meaning narrow but notable blue spaces (such as rivers and canals) are often missing. As blue space was our focus, we assessed other cartographical resources to improve accuracy, retaining the CEH land cover for all other habitats. Three highly accurate OS land use layers (~ 1 m resolution) were identified for blue space improvements, consisting of Tidal water, Surface water and Foreshore (delineated by low and high tide water marks). CEH and OS data sets were then combined following the workflow below.

Compiling land cover and land use data for blue spaces

Land cover data were downloaded from the Digimap Portal at 10 m resolution in raster format (.tif) and processed using QGIS (v.3.36) as batches using five steps: (1) clip original file to extended BUA boundaries (*processing toolbox* > *clip raster by extent tools*), (2) convert raster data to polygons maintaining resolution (*processing toolbox* > *vector creation* > *raster pixels to polygons*), (3) merge land-cover polygons by shared attributes (*processing toolbox* > *vector geometry* > *dissolve*), (4) assign location names to new shapes (*processing toolbox* > *vector general* > *join attributes by location*), and (5) calculate areas of land cover (*field calculator* > *geometry* > *$area*).

Land use data were downloaded from the OS Data Hub within a GB Local District Data package. The three layers of interest were then processed individually in QGIS, following these steps: (1) merge data (*edit* > *merge selected features*), (2) clip with extended BUA geometries (*vector* > *geoprocessing tools* > *clip*), (3) assign names, (4) calculate area (methods for steps 3-4 were the same as for steps 4–5 above).

Overlap between land cover and land use layers was resolved using geoprocessing tools. First, OS Tidal water and Surface water layers were used to replace CEH land cover classifications when overlap occurred (*vector* > *geoprocessing* > *difference*). Second, CEH littoral layers (isolated layers) replaced OS foreshore cover when overlap occurred (as before). To retain ecological classifications, land use data were reclassified as follows: Tidal water to Saltwater, Surface water to Freshwater, and Foreshore to Littoral Sediment (see Supplementary Fig. 2 and Fig. 3 for examples). The accuracy of the new dataset was checked using the Topology Checker plugin, and by summing the area of all newly classified geometries and comparing them with the unclassified extended BUA.

Defining blue, green and grey space

When defining blue spaces, we adopted the definition of Grellier et al.[18], "Outdoor environments either natural or man-made that prominently feature water and are accessible to humans either proximally (being in, on or near water) or distally/virtually (being able to see hear or other-wise sense water)".This definition acknowledges that blue spaces can be experienced with or without direct contact[89]. Based on this, we assumed that all blue land covers listed in Fig. 2 and falling within our extended urban areas have the potential to offer some form of physical or sensory exposure, and therefore qualify as blue spaces.

To define green spaces, we grouped all non-blue natural habitats found within urban areas listed in Fig. 2, acknowledging the fact that people experience greenness across an entire built-up area and not just in designated Open Green Spaces[90]. As with blue space, either visual or physical accessibility was assumed for all land falling within urban areas. Grey spaces, areas of land characterised by impervious surfaces, were defined by combining *Suburban* and *Urban* land cover data.

Defining habitat diversity

Habitat diversity metrics, based on all 21 land-cover classifications, were calculated using the Shannon Diversity Index and Simpson's Diversity Index, both commonly used as proxies for habitat heterogeneity[91,92].

Built-up area geographic categorisation

During the conception of the study and data preparation, it was noted that many of the selected urban areas were from distinct geographic regions. These were classified into three geographic categories: coastal, when facing seawards; estuarine, when located along an estuary; and inland, when not connected to any major tidal systems.

Ranking built-up areas by blue space

Built-up areas were ranked by proportionate blue space cover (1-495) and grouped into deciles (n = 50) to characterise and describe "the bluest areas", and to understand how blue space compares with other types of urban land cover (namely grey and green space).

Social data

Deprivation assessments were restricted to England due to variability in deprivation calculations between England, Wales, and Scotland. Our analyses used the Indices of Multiple Deprivation (IMD), which are calculated from multiple socioeconomic indicators at a national level[88]. The IMD uses a decile ranking system (IMDD), with 1 being the most deprived and 10 being the least. To calculate the overall deprivation scores of the urban areas used in this study, we used the original BUA layer (not extended) and followed these steps: (1) IMD datasets were downloaded from government portals as statistical parcels aggregated to Lower-layer Super Output Areas (LSOAs); (2) statistical parcels containing IMDD information were then refitted into the original BUAs using a cookie cutter approach (*vector > geoprocessing > clip*); (3) names of each bounding BUA were assigned to new shapes (*processing toolbox > vector general > join attributes by location*); and (4) a weighted average per urban area was calculated by multiplying the area of each land parcel by its IMDD score (decile), summing these values, and dividing by the total area of that built-up area.

Statistical analysis and visualisations

All statistical analyses were carried out in R Studio[93], using base R version 4.2.2[94] unless otherwise specified. Before analysis, data distribution and normality were assessed visually using histograms, box plots, and quantile-quantile plots. Parametric and non-parametric methods were used based on the data distribution. Kruskal-Wallis and Dunn's test were used to test differences between blue, green and grey space cover across geographic categorisation. Spearman's rank correlation coefficient was used to test associations between blue space cover and the size of a built-up area, population counts, grey space and green space. Land-cover diversity was calculated in R package *vegan* [95]. Data manipulation and plots were created with R package *tidyverse*[96].

A Generalised Additive Model (GAM) from the *mgcv* R package[97] was used to test the predictive power of environmental variables for deprivation. The GAM was chosen for its flexibility in handling non-linear relationships between predictors and the response variable. To address multicollinearity, we assessed correlations between predictor variables using a correlation matrix[98], with a threshold of >0.8 indicating significant collinearity (see Supplementary Fig. 4). This analysis revealed strong correlations between grey space and green space, and between population size and urban area size. Specifically, grey space and green space were inversely correlated, while population size and urban area size were positively correlated, meaning variables omitted based on collinearity could be reasonably inferred based on those retained (see Supplementary Fig. 5). Our final model used a Gaussian family with an identity link function, appropriate for continuous response variables. Smoothing splines were applied to account for non-linearity among predictors, with the best smoothing parameters and variables selected via a stepwise approach (see Supplementary Table 6). To preserve model interpretability and maximise stability, grey space and population size were omitted. We used the gam.check() function within *mgcv* to assess model fit by examining residual plots and k-index values, confirming that the model was appropriate and that the smoothing terms were correctly specified, with no indications of overfitting or other major issues.

Data and code availability

All data and code used in this study are accessible on github (https://github.com/MCMorgan06/Bluest_Cities_UK) and zenodo (**10.5281/zenodo.16038672**).

Competing Interests and conflicts

The authors (Matthew Morgan, Rodney Forster, Charlotte Hopkins, and Africa Gómez) declare no competing interests.

Author contribution Statement

M.M., R.F., C.H., and A.G. contributed to the conceptualisation of the study. M.M. was responsible for all data handling, processing, analysis, and visualisation, and led all writing and formatting. M.M., R.F., C.H., and A.G. reviewed the manuscript. All authors have read and approved the final manuscript.

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Figure titles (bold) and legends

Fig. 1: Schematic overview of the study design

Summary of research questions, data inputs, spatial processing workflow, and statistical analyses. See Methods for full dataset descriptions and procedures.

Fig. 2: Classification and grouping of land-cover types across urban areas

a Original BUA boundaries for Plymouth (top and middle) and the same area after applying the 200 m extension (bottom). **b** UKCEH land-cover classification (legend shown in panel D). **c** Blue-space layers from Ordnance Survey. **d** Harmonisation of UKCEH classes into green, grey, and blue groupings. **e** Composite map showing the combined classifications.

Fig. 3: Percentage land-cover types across urban areas

a Total percentage coverage (y-axis) of each land-cover type (x-axis, *n* = 21) across all urban areas (*n* = 495), with overlap removed. **b** Boxplot showing the percentage coverage (y-axis) of each land-cover type (x-axis) within individual urban areas.

Fig. 4: Blue space cover in urbn aras

a Distribution of inland (*n* = 397), estuarine (*n* = 27), and coastal (*n* = 71) urban areas included in the study. **b** Composition of inland, estuarine, and coastal urban areas within each decile ranked by of blue space cover. **c** Mean cover of grey space, green space, and blue space per blue space decile. Dashed lines indicate overall means: grey space = 64.6% (top), green space = 31.8% (middle), and blue space = 3.6% (bottom). **d** Urban areas colour-coded by their percentage of blue space cover.

Fig. 5: Land-cover composition across coastal, estuarine, and inland urban areas

Percentages of blue space (left), green space (middle), and grey space (right) are shown for all urban areas, grouped by region: coastal (*n* = 71), estuarine (*n* = 27), and inland (*n* = 397). Significant differences identified by Dunn's test are indicated (*$p < 0.05$, **$p < 0.001$, ***$p < 0.0001$).

Fig. 6: Relationship between blue space cover and city size

Scatter plots showing associations between blue space cover (%) and city area (m^2) across coastal (left), inland (middle), and estuarine cities (right). Spearman's rank correlation coefficients (RHO) and p-values are shown above each plot. Inland and estuarine data are displayed on a log scale.

Fig. 7: Predictors of deprivation

Effects of four significant predictors of deprivation: green space (top left), blue space (top right), Simpson's Diversity Index (bottom left) and latitude (bottom right), as produced by the GAM smooth terms (thin plate splines, $k = 9$). Estimated effects are shown by the solid lines with 95% confidence intervals within dashed lines. The y-axes represent the deprivation index, where higher values indicate lower deprivation.