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## Satellite observations reveal a decreasing albedo trend of global urban cities over the past 35 years

Shengbiao Wu, Xingwen Lin, Zunjian Bian, Mathew Lipson, Raffaele Laforzezza, Qiang Liu, Sue Grimmond, Erik Velasco, Andreas Christen, Valéry Masson, et al.

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1 **Title:** Satellite observations reveal a decreasing albedo trend of global urban cities over the past  
2 35 years

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58  
59

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61

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64 Supporting materials: 20 figures, 2 table

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69 **Abstract**

70 Urban surface albedo is an essential biophysical variable in the surface energy balance across all  
71 scales, from micro-scale (materials) to global scale, changing with land cover and three-  
72 dimensional (3-D) structure over urban areas. Urban albedos are dynamics over space and time  
73 but have not yet been quantified over global scales due to the lack of high-resolution albedo  
74 datasets. Here, we combined the direct estimation approach and Landsat surface reflectance  
75 product to generate a 30-m-resolution annual surface albedo dataset for 3037 major cities (area >  
76 50 km<sup>2</sup>) worldwide for the period from 1986 to 2020, allowing spatial patterns and long-term  
77 temporal trends to be explored with possible causal drivers, and quantification of the surface  
78 radiative forcing from these albedo changes. Evaluation of this new albedo dataset using global  
79 urban flux tower-based measurements demonstrates its high accuracy with an overall bias and  
80 root-mean-square-error (RMSE) of 0.005 and 0.025, respectively. Analysis of the dataset reveals  
81 an overall trend of decreasing albedo for the 35-year evaluation period (1986-2020), which is  
82 robust accounting for a series of uncertainties from training sample representativeness, Landsat  
83 data uncertainty, seasonal variation, and snow-cover confounding impacts. Our results reveal that  
84 urban greening (measured by the Normalized Difference Vegetation Index (NDVI) trend) can well  
85 explain the total variances in the albedo trend for the 35-year period through two different  
86 pathways of tree planting and urban warming-enhanced vegetation growth. The decrease in urban  
87 albedo caused a warming effect indicated by positive surface radiative forcing, with a global city-  
88 level average surface radiative forcing of 2.76 W·m<sup>-2</sup>. These findings enhance our understanding  
89 of urbanization's impacts on albedo-related biophysical processes and can provide information to  
90 quantify urban surface radiation energy and design effective mitigation strategies to reduce urban  
91 warming (e.g., urban heat islands).

92 **Keywords:** Biophysical process; NDVI; Radiative forcing; Landsat; MODIS; Surface albedo

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## 98 **1. Introduction**

99 Urban areas represent the principal land cover that is most affected by intensive anthropogenic  
100 activities from replacing agricultural, forested or natural landscapes with impervious surfaces  
101 (Seto et al. 2012). Urbanization modifies the carbon exchange between the surface and atmosphere  
102 (e.g., anthropogenic emissions of carbon dioxide (CO<sub>2</sub>) from domestic heating, transport, industry  
103 and services, and electricity generation; Ribeiro et al. 2019; Wang et al. 2015), as well as changes  
104 surface radiative properties and energy partitioning (e.g., albedo and evapotranspiration; Cao et al.  
105 2016; Schwaab et al. 2021), and thus modifies biophysical variables (e.g., air temperature). This  
106 can result in nocturnal canopy air temperatures being warmer in urban areas than the surrounding  
107 non-urban areas, known as the canopy layer urban heat island (CL-UHI) (Estoque et al. 2020; Oke,  
108 1982). With a global urban population of 4.2 billion (around 55% of the total population in 2018)  
109 projected to increase to 9.7 billion (about 68% of the total population) by 2050 (UNDESA, 2019),  
110 the well-being of urban residents is at critical risk and simultaneously impact by urban-climate  
111 phenomena, such as the CL-UHI (Huang et al. 2020; Hsu et al. 2021). Improving our  
112 understanding of biophysical processes in cities can help to create more livable environments.

113

114 Surface albedo change can directly alter the biophysical processes of surface energy balance from  
115 micro (materials) to local and to global scales. Urbanization causes albedo changes by modifying  
116 surface materials and three-dimensional (3-D) structures (Shen et al. 2021). For example,  
117 anthropogenic land cover changes between 1700 and 2005 are estimated to have caused a 0.00106  
118 increase in global mean albedo, that is linked to a negative radiative forcing of  $-0.15 \pm 0.10 \text{ W}\cdot\text{m}^{-2}$   
119 (Ghimire et al. 2014; Myhre et al. 2014). For a long time, the use of highly reflective urban  
120 materials (e.g., white rooftops and light-colored pavements) has been actively encouraged as  
121 method to mitigate the surface-UHI (S-UHI) effect and improve human comfort (Morini et al.  
122 2016; Rosso et al. 2018). Numerous regional and global climate simulations have shown albedo-  
123 related impacts. A 0.1 increase in albedo in urban areas (e.g., rooftops and pavements) has been  
124 estimated to be able to reduce the global average surface temperature by 0.01-0.07 K, which is  
125 equivalent to a 25-150 billion ton offset in CO<sub>2</sub> emissions (Akbari et al. 2012; Menon et al. 2010;  
126 Xu et al. 2020).

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127  
128 Urbanization impacts on surface albedo are multifaceted. Initial urbanization, changing a natural  
129 vegetated surface (e.g., forest and grassland) to light colored short building may increase surface  
130 albedo (Kuang et al. 2019), but the same materials with denser 3-D urban morphology will  
131 generate more shadows, reducing the bulk surface albedo (Christen and Vogt, 2004; Groleau and  
132 Mestayer, 2013). The net surface albedo change depends on both urban cover materials and  
133 building arrangements (Falasca et al. 2019; Qin, 2015; Santamouris and Fiorito, 2021; Yang and  
134 Li, 2015). Satellite remote sensing can quantify these net effects with global coverage. Coarse-  
135 resolution satellites in previous studies based on the 500-m-resolution Moderate-Resolution  
136 Imaging Spectroradiometer (MODIS) and Global LAnd Surface Satellite (GLASS) albedo  
137 products were not able to accurately detect the fine-scale heterogeneity of urban albedo  
138 (Chrysoulakis et al. 2018; Hu et al. 2016; Tang et al. 2018). Use of higher-resolution satellite  
139 observations (e.g., 30-m Landsat and 10-m Sentinel-2) demonstrated their potential to monitor  
140 fine-scale urban albedo (Bonafoni and Sekertekin, 2020; Guo et al. 2022; Trlica et al. 2017).

141  
142 However, our spatiotemporal knowledge of urban albedo is limited for several reasons. First,  
143 existing satellite-based albedo studies are restricted to very few ( $\leq 11$ ) cities (Guo et al. 2022;  
144 Trlica et al. 2017), so the spatiotemporal trends may be city-specific. Second, the underlying  
145 drivers controlling the spatiotemporal patterns of surface albedo and their resulting climatic effects  
146 remain largely unclear. Urbanization are complex physical, socioeconomic, and cultural processes  
147 in 3-D space, involving extent expansion of new impervious areas (Liu et al. 2020; Zhang and Seto,  
148 2011) and increase in human modification on mature urban areas, such as building construction  
149 and greening activity (Theobald et al. 2020; Zhou et al. 2022). Previous studies attributed urban  
150 albedo variations to land cover change from natural lands to new urban structure by making the  
151 use of two-baseline-year datasets, without accounting for human modification activities (Ouyang  
152 et al. 2022). For example, large-scale tree planting in cities is a global agreement and effort to  
153 mitigate urban heat stress from climate warming and CL-UHI effects (Schwaab et al. 2021).  
154 Around 70% of cities worldwide witness urban greening phenomenon with increasing vegetation  
155 coverage (Sun et al. 2020; Zhang et al. 2021) and enhanced vegetation growth due to CO<sub>2</sub>  
156 fertilization and longer growing seasons (Hwang et al. 2022; Meng et al. 2020; Wang et al. 2019).

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157 These actions have substantially reshaped urban landscapes, but to what extent urban greening  
158 impacts the change of surface albedo and albedo-related climatic effects remains unknown.

159  
160 In such a context, the main objective of this study is to explore the spatiotemporal characteristics  
161 of albedo in cities globally and to decipher the underlying drivers of albedo change. By applying  
162 our previously developed direct estimation approach on the Google Earth Engine (GEE) cloud-  
163 computing platform, we construct an annual mean albedo dataset covering 35 years (1986-2020)  
164 for 3037 major global cities. Based on the novel dataset, we analyze the spatial and temporal  
165 patterns of urban albedo and assess the causes of albedo change linked to vegetation greening  
166 observed in Landsat-derived normalized difference vegetation index (NDVI) data. Lastly, we  
167 quantify the albedo-induced surface radiative forcing to model climatic responses from urban  
168 surface albedo change.

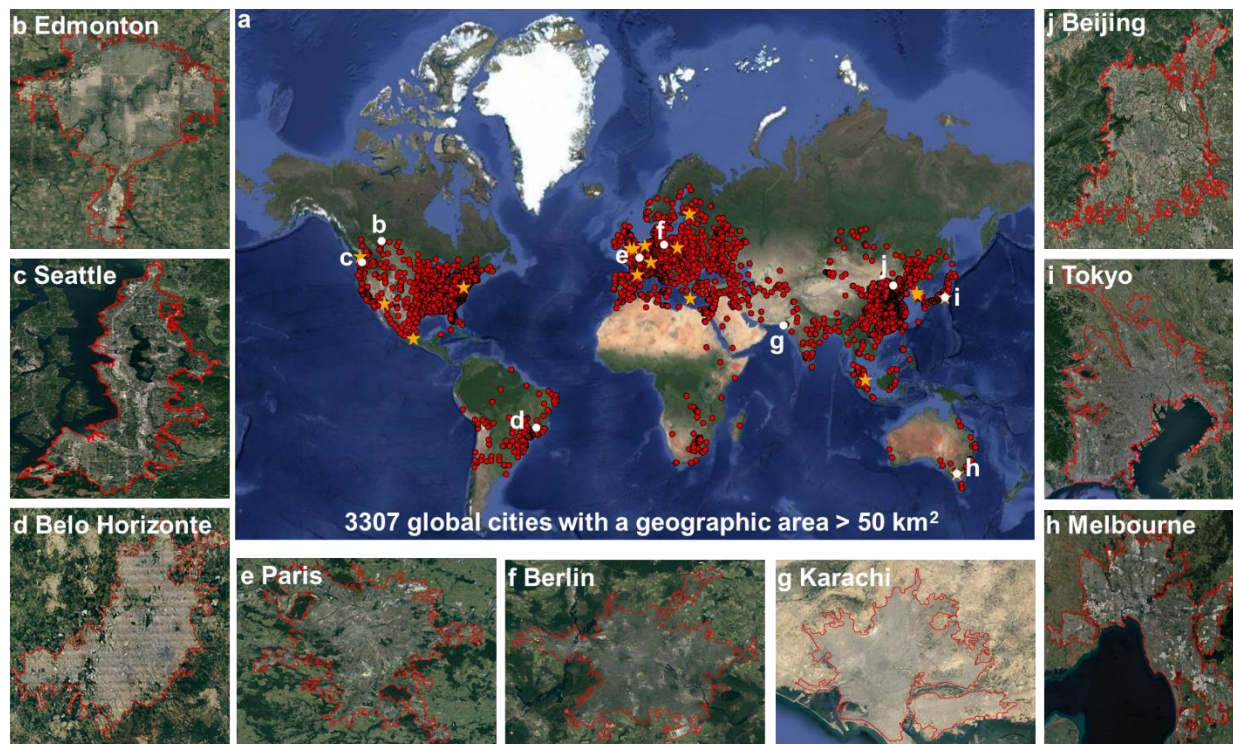
169

## 170 **2. Study area and materials**

### 171 **2.1. City areas**

172 The city areas were extracted from the 2018 Global Urban Boundary (GUB) product, which is  
173 based on 30-m-resolution global artificial impervious area product (GAIA; Li et al. 2020), using  
174 two criteria (Chen et al. 2022): (1) a spatial extent larger than 50 km<sup>2</sup>; and (2) availability of at  
175 least 30-year valid Landsat observations during the 35 evaluated years (1986-2020). A total of  
176 3037 urban areas globally (hereafter referred to as cities) satisfied these criteria and were selected  
177 (**Fig. 1**). Almost all cities have over 20 available Landsat images for each one-year cycle, with the  
178 annual average observation number ranging from 21 to 40 and a mean value of 30, indicating the  
179 capability to capture inter- and intra-year variations of urban surface albedo (**Figs. S1 and S2**).

180



181  
 182 **Fig. 1.** Urban areas (cities) used in this study. **(a)** City location globally (red dots), urban flux  
 183 towers (yellow pentagrams), and example of nine cities with boundaries (red polygons) as defined  
 184 by the Global Urban Boundary (GUB) product in 2018: **(b)** Edmonton, **(c)** Seattle, **(d)** Belo  
 185 Horizonte, **(e)** Paris, **(f)** Berlin, **(g)** Karachi, **(h)** Melbourne, **(i)** Tokyo, and **(j)** Beijing. The 3037  
 186 global cities are selected with an area extent larger than 50 km<sup>2</sup>. 21 worldwide urban flux tower  
 187 sites come from two collaborative projects: 19 flux sites from the Urban-PLUMBER multi-site  
 188 model evaluation project (Lipson et al. 2022a, 2022b) and 2 flux sites from the URBANFLUXES  
 189 project (Chrysoulakis et al. 2018; Feigenwinter et al. 2018). Background and city pictures are  
 190 extracted from the Basemap of Google Earth (Google. Inc).

191  
 192 **2.2. Datasets**

193 Five multi-source datasets are used in this study for different purposes: (1) surface reflectance data  
 194 (i.e., Landsat-5, Landsat-7, and Landsat-8 surface reflectance products; Gorelick et al. 2017); (2)  
 195 surface Bidirectional Reflectance Distribution Function (BRDF) data (i.e., MCD43A1; Wang et  
 196 al. 2018); (3) surface albedo data, (i.e., flux tower-based measurements and MCD43A3;  
 197 Feigenwinter et al. 2018; Lipson et al. 2022a, 2022b; Wang et al. 2018); (4) land cover type data  
 198 (i.e., European Space Agency (ESA) WorldCover and MCD12Q1; Sulla-Menashe et al. 2018;  
 199 Zanaga et al. 2021); and (5) downward solar radiation data, (i.e., the Bias-adjusted RAdiation  
 200 Dataset (BaRAD) product; Chakraborty and Lee, 2021). **Table 1** summarizes the ancillary  
 201 information of these datasets, including data category, dataset name, spatial coverage, ground



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202 resolution, observation period, usage description, and related references. **Table 2** provides detailed  
203 information for the 21 urban flux towers used for albedo validation.

204

### 205 **2.2.1. Landsat surface reflectance product**

206 We used 35-years (1986-2020) of the Landsat Level-2 surface reflectance (Collection 2, Tier 1)  
207 product with a 30-m spatial resolution derived from three Landsat satellites (i.e., Landsat-5 TM,  
208 Landsat-7 ETM+, and Landsat-8 OLI; Gorelick et al. 2017, **Table 1**). Landsat provides the longest  
209 high-quality global surface reflectance record available (Wulder et al. 2022). Landsat-5 TM and  
210 Landsat-7 ETM+ sensors have six spectral bands spanning three visible (i.e., blue, green, and red),  
211 one near-infrared (NIR), and two shortwave infrared (SWIR) bands, whereas Landsat-8 OLI has  
212 one additional ultra-blue spectral band. The pixel-level quality assurance (QA) auxiliary data for  
213 each surface reflectance dataset gives a bitmask metric indicating cloud, cloud shadow, snow, and  
214 ice conditions. To minimize the uncertainty caused by the Landsat-7 scan line off failure on albedo  
215 estimation (Qiu et al. 2021; Zhang and Roy, 2016), we primarily focused on the use of Landsat-5  
216 and Landsat-8 satellite data, with data availabilities of 26-year (1986-2011) Landsat-5 TM, 2-year  
217 (2012-2013) Landsat-7 ETM+, and 7-year (2014-2020) Landsat-8 OLI.

218

### 219 **2.2.2. MODIS BRDF/albedo product**

220 We used the 500-m spatial resolution MODIS BRDF product (MCD43A1, Collection 6; **Table 1**)  
221 in 2000-2020 to provide a high-quality surface BRDF/albedo training library (Wang et al. 2018).  
222 MCD41A1 is the most accurate satellite BRDF/albedo product and has been widely used for the  
223 training and calibration of the direct estimation approaches (Guo et al. 2022; Qu et al. 2013). In  
224 addition, the MCD43A3 albedo product was used for the spatiotemporal analysis of urban surface  
225 albedo for comparisons with Landsat albedo. MCD43A3 is derived from MCD43A1 and provides  
226 black-sky albedo (BSA) and white-sky albedo (WSA) data at local solar noon for MODIS seven  
227 spectral bands and three broadbands (i.e., visible, NIR, and shortwave).

228

### 229 **2.2.3. Land cover type products**

230 Two land cover type products are used (**Table 1**): 10-m ESA WorldCover for 2020, and 500-m  
231 MCD12Q1 products (Collection 6) from 2001 to 2020, for selecting training samples. WorldCover  
232 is generated from Sentinel-1 and Sentinel-2 data, with a similar algorithm framework for the

---

233 annual Copernicus Global Land Service Land Cover (CGLS-LC) product (Buchhorn et al., 2020).  
234 This dataset provides 11 land cover classes (i.e., tree cover, shrubland, grassland, cropland, built-  
235 up, bare/sparse vegetation, snow and ice, open water, herbaceous wetland, mangroves, and moss  
236 and lichen) with an overall global accuracy of 74.4% (Zanaga et al. 2020). It is freely accessible  
237 to the academic community (Zanaga et al. 2020). MCD12Q1 is generated by a supervised  
238 classification approach from MODIS reflectance with five legacy classification schemes (Sulla-  
239 Menashe and Friedl, 2018). We selected the International Geosphere-Biosphere Programme  
240 (IGBP) classification scheme for data analysis. The “built-up” definitions in these two land cover  
241 products have a slight difference. For WorldCover, “built-up” is defined as land covered by  
242 buildings, roads and other man-made structures, which excludes urban green areas (Zanaga et al.  
243 2020). For MCD12Q1, “urban and built-up lands” is defined as surface covered by at least 30%  
244 of impervious area, such as building materials, asphalt, and vehicles (Sulla-Menashe and Friedl,  
245 2018).

246

#### 247 **2.2.4. Surface downward solar radiation data**

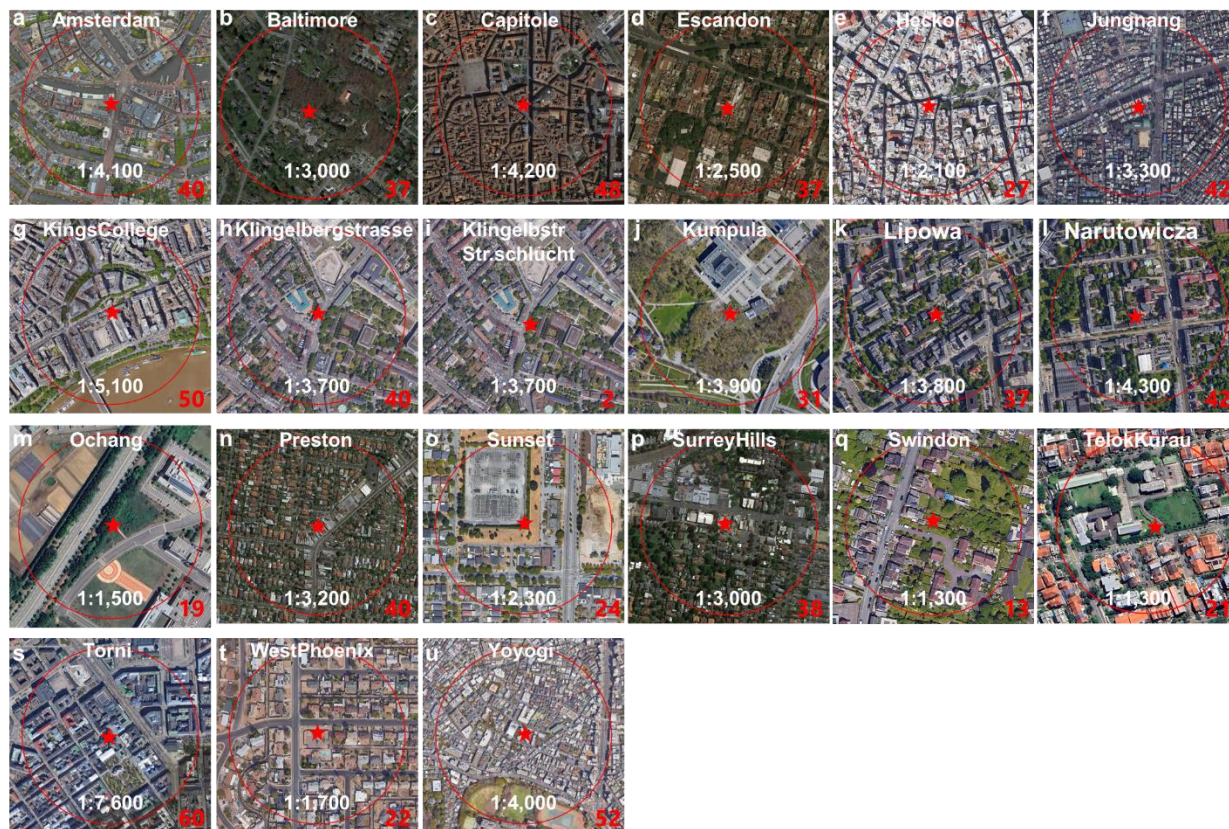
248 We used the 40-year (1980-2019)  $0.5^\circ \times 0.625^\circ$  monthly BaRAD solar radiation dataset (**Table 1**)  
249 owing to its temporal window overlapping with Landsat. BaRAD is generated from the Modern-  
250 Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) global reanalysis  
251 dataset using a bias-correction random forest algorithm, trained with Global Energy Balance  
252 Archive (GEBA) observations from 2500 worldwide ground stations (Wild et al. 2017). BaRAD  
253 is bias-adjusted (cf. MERRA-2) thus has high accuracy (Chakraborty and Lee, 2021). BaRAD  
254 provides three radiation components: total incoming shortwave, incoming direct beam, and  
255 incoming diffuse radiation. BaRAD data are used here to determine: (1) the fraction of diffuse  
256 radiation relative to the total incoming shortwave radiation, for the blue-sky albedo calculation  
257 (**Section 3.1**); and (2) the surface radiative forcing induced by albedo changes (**Section 3.5**).

258

#### 259 **2.2.5. Tower-based radiation flux measurements**

260 To evaluate the accuracy of our algorithm, we used downward and upward solar radiation  
261 measurements from 21 urban flux towers located throughout the world, including cities in Asia,  
262 Australia, Europe, and North America (**Fig. 1a**). The data collected by these towers were put  
263 together as part of two collaborative projects: Urban-PLUMBER (19 sites; Lipson et al. 2022a,

264 2022b) and URBANFLUXES (2 sites; Chrysoulakis et al. 2018; Feigenwinter et al. 2018). The  
 265 sensors on these towers are mounted at heights ranging from 2 to 60 meters above the ground, with  
 266 viewing footprints where impervious surfaces (i.e., buildings, roads, paved areas) cover between  
 267 31% and 97% of the plan area (**Fig. 2; Table 2**). The radiation flux measurements are used as  
 268 ground truths for assessing the accuracy of surface albedo estimates derived from Landsat satellites.



269  
 270 **Fig. 2.** Google Earth satellite images of flux sites (red pentagrams) and the associated radiation  
 271 footprint areas (red circles) for (a) Amsterdam, (b) Baltimore, (c) Capitole, (d) Escandon, (e)  
 272 Heckor, (f) Jungnang, (g) KingsCollege, (h) Klingelbergstrasse, (i) KlingelbstrStr.schlucht, (j)  
 273 Kumpula, (k) Lipowa, (l) Narutowicza, (m) Ochang, (n) Preston, (o) Sunset, (p) SurreyHills, (q)  
 274 Swindon, (r) TelokKurau, (s) Torni, (t) WestPhoenix, and (u) Yoyogi. The map scales and tower  
 275 heights (in meters) are shown at the bottom of each image in white and red, respectively. Note:  
 276 Footprint area (with a 25-m diameter) of the KlingelbstrStr.schlucht site in panel (i) is overlapped  
 277 by red pentagram symbol.  
 278

### 279 3. Methods

#### 280 3.1. Estimation of annual urban surface albedo from Landsat

281 We adopted our recently developed direct estimation approach to retrieve surface albedo from  
 282 Landsat satellites (Lin et al. 2022), with three key steps summarized as follows (**Fig. 3**):

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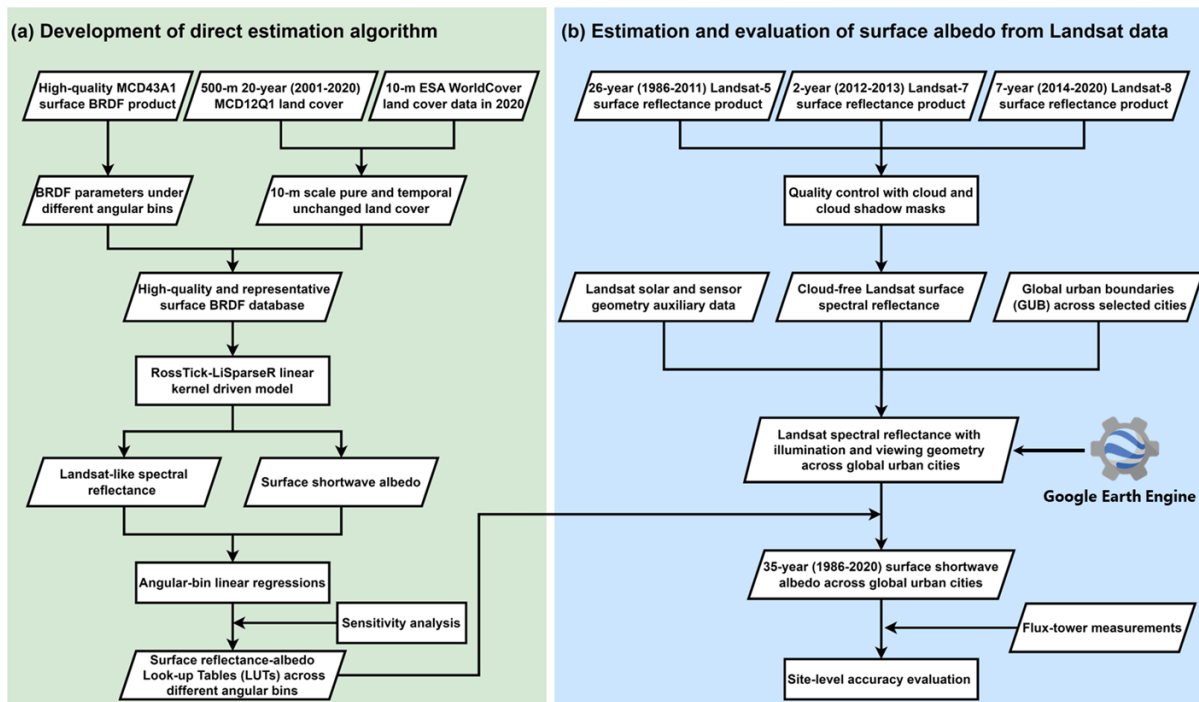
283  
284 **(1) Selection of high-quality surface BRDF/albedo datasets.** High-quality BRDF/albedo  
285 training datasets are the key to the direct estimation approach. To this end, we used the MCD43A1  
286 BRDF/albedo product with ESA WorldCover and MCD12Q1 land covers to screen the  
287 BRDF/albedo library that is representative at 30-m scale (Lin et al. 2022) with four criteria: (i)  
288 high assurance with the pixel-level QA of 0; (ii) homogeneous coverage (with the pixel-level land  
289 cover purity  $\geq 95\%$  indicated by the 10-m ESA WorldCover data); (iii) diverse land cover  
290 (including 16 dominant land types following the IGBP classification scheme); and (iv) reasonable  
291 data range (that refers to the pairs of reflectance and albedo within a physical range of 0-1). We  
292 considered this surface BRDF/albedo dataset from mixed land covers as a general scheme and  
293 compared it with the BRDF/albedo dataset from pure urban land cover (referred to as urban scheme)  
294 in the sensitivity analysis of algorithm development (**Section 5.1.1**), which shows a consistent  
295 performance.

296  
297 **(2) Generation of training and testing datasets.** Based on the selected BRDF/albedo library, we  
298 simulated Landsat-like surface reflectance in two steps. First, we simulated MODIS-like surface  
299 reflectance across its seven spectral bands using the linear RossThick-LiSparseR BRDF model  
300 (Lucht et al. 2000) with optimized angular settings (i.e., a  $2^\circ$  interval for solar zenith, viewing  
301 zenith, and local solar zenith angles; and a  $5^\circ$  interval for relative azimuth angle). Second, we  
302 converted the MODIS-like surface reflectance to the Landsat-like surface reflectance using band  
303 conversion coefficients derived using similar approaches to Qu et al. (2013). Considering the  
304 different spectral configurations for Landsat satellites (**Table S1**), we simulated surface reflectance  
305 datasets across six spectral bands for Landsat-5 TM and Landsat-7 ETM+, and across seven  
306 spectral bands for Landsat-8 OLI. We also simulated surface shortwave albedo from the MODIS  
307 BRDF/albedo library in two steps. First, we simulated spectral BSA and WSA datasets under clear-  
308 sky and perfectly diffuse illumination conditions, respectively. Second, we converted the spectral  
309 BSA and WSA albedo datasets to shortwave albedo using the regression coefficients proposed by  
310 Liang et al. (2002).

311  
312 **(3) Build-up of reflectance-to-albedo look-up-tables (LUTs).** With the pairs of simulated

313 Landsat-like surface reflectance and surface shortwave albedo, we created LUTs of reflectance-  
 314 to-albedo relations using the linear regression approach for each angular setting (He et al. 2018;  
 315 Qu et al. 2013). To minimize the potential impact from Landsat satellite orbital drifts (e.g.,  
 316 Landsat-5 drifted between 1995-2000 and 2003-2007, Landsat-7 drifted from 2017 to the present;  
 317 Qiu et al. 2021; Zhang and Roy, 2016), we trained spectral reflectance and shortwave albedo  
 318 relations for local solar noon (e.g., 12:00 p.m.) geometry that is independent from instantaneous  
 319 satellite observation time.

320



321

322 **Fig. 3.** Satellite-based direct estimation of surface albedo from Landsat, with two major steps: (a)  
 323 direct estimation algorithm development, and (b) surface albedo estimation and evaluation.

324

325 We applied our reflectance-to-albedo LUTs (BSA and WSA; Eq. 1) on the Google Earth Engine  
 326 (GEE, Gorelick et al. 2017) cloud-computing platform to estimate urban surface albedo for global  
 327 cities using four steps. First, we used the pixel-level QA auxiliary layer to exclude cloud, cloud  
 328 shadow, and snow contaminated pixels in Landsat surface reflectance. Second, we estimated BSA  
 329 and WSA from the quality-controlled Landsat surface, where the solar geometry is extracted from  
 330 metadata and sensor geometry is set as nadir due to small variations in Landsat sensor viewing ( $<$   
 331  $7.5^\circ$ ; Nagol et al. 2015). Third, we calculated annual blue-sky albedo from BSA and WSA by using  
 332 the diffuse fraction (i.e., fraction of diffuse radiation in total illumination radiation) from the

333 BaRAD dataset. Based on Landsat spectral reflectance, we also calculated the annual NDVI as an  
 334 indicator of vegetation cover. Finally, we stored Landsat-derived blue-sky albedo and NDVI as  
 335 two separate data layers for each city over 35 years. To verify the feasibility of the direct estimation  
 336 approach with training samples from mixed land covers over urban areas, we also compared the  
 337 algorithm with the training samples of pure urban cover in the discussion section.

$$338 \alpha = C_0(\theta_s, \theta_v, \varphi) + \sum_{i=1}^N C_i(\theta_s, \theta_v, \varphi) \times \rho_L(\lambda_i) \quad (1)$$

339 where  $\alpha$  is the surface shortwave albedo (BSA and WSA);  $\rho_L(\lambda_i)$  is the Landsat surface reflectance  
 340 at spectral band  $\lambda_i$  ( $i = 1, 2, 3, \dots, N$ ;  $N = 6, 6,$  and  $7$  for Landsat-5, Landsat-7, and Landsat-8,  
 341 respectively); and  $C_i(\theta_s, \theta_v, \varphi)$  denotes the regression coefficient at spectral band  $\lambda_i$  for solar zenith  
 342 angle  $\theta_s$ , view zenith angle  $\theta_v$ , and relative azimuth angle  $\varphi$ .

343

### 344 **3.2. Evaluation of urban albedo with radiation data from urban flux towers**

345 We evaluated the accuracy and uncertainty of Landsat blue-sky albedo using observed albedo  
 346 calculated from the incoming and outgoing shortwave radiation measured by 21 urban sites (**Table**  
 347 **2**). To match the Landsat-derived albedo at local solar noon and minimize diurnal variations  
 348 (Minnis et al. 1997), we used observations from 11:00 a.m. to 1:00 p.m. local standard time. As  
 349 the diffuse fraction ( $d$ ) is not recorded by these flux tower datasets and the BaRAD dataset is too  
 350 coarse for site-scale albedo calculation, we thus adopted a two-step strategy: (1) if the MODIS  
 351 Aerosol product (MOD08) has high-quality Aerosol Optical Depth (AOD) observation over the  
 352 target flux site, the radiative transfer simulation approach was applied (Wang et al. 2018); and (ii)  
 353 otherwise, we adopted an empirical approach shown in Eq. 2 to calculate diffuse fraction  $d$  (Stokes  
 354 and Schwartz, 1994):

355

$$356 d = 0.122 + 0.85 \times \exp(-4.8 \times \cos(\theta_s)) \quad (2)$$

357

358 We used the radiation flux footprint estimated from sensor height (**Table 2**; Román et al. 2009) to  
 359 crop the pixel-level Landsat blue-sky albedo image and calculate the corresponding albedo average,  
 360 and then compared this Landsat blue-sky albedo average with the tower-based albedo measured  
 361 on the same dates. For the accuracy assessment, four commonly used metrics were used: bias  
 362 (mean difference between Landsat-derived and tower-based albedo), root-mean-square-error  
 363 (RMSE), relative root-mean-square-error (rRMSE, the ratio between RMSE and the measured

---

364 albedo mean), and coefficient of determination ( $R^2$ ), with equations as follows:

365

366 
$$Bias = \frac{1}{N} \sum_{i=1}^N (\alpha_{Landsat,i} - \alpha_{ground,i}) \quad (3)$$

367 
$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\alpha_{Landsat,i} - \alpha_{ground,i})^2} \quad (4)$$

368 
$$rRMSE = \frac{RMSE}{\overline{\alpha_{ground}}} \times 100\% \quad (5)$$

369 
$$R^2 = \frac{\sum_{i=1}^N (\alpha_{Landsat,i} - \overline{\alpha_{Landsat}})(\alpha_{ground,i} - \overline{\alpha_{ground}})}{\sum_{i=1}^N (\alpha_{Landsat,i} - \overline{\alpha_{Landsat}})^2 \sum_{i=1}^N (\alpha_{ground,i} - \overline{\alpha_{ground}})^2} \quad (6)$$

370

371 where  $\alpha_{Landsat,i}$  and  $\alpha_{ground,i}$  are  $i$ th Landsat-derived and ground-measured albedo;  $\overline{\alpha_{Landsat}}$  and  
372  $\overline{\alpha_{ground}}$  are the average values of Landsat-derived and ground-measured albedo;  $N$  is the number  
373 of observations.

374

### 375 **3.3. Spatiotemporal characteristic analysis of surface albedo in global cities**

376 We calculated the 35-year city-scale blue-sky albedo mean from Landsat albedo time series to  
377 explore its spatial patterns. To further examine the temporal trends, we used the non-parametric  
378 Mann-Kendall statistic (Mann, 1945) and the non-parametric Theil–Sen slope estimator (Theil,  
379 1950) approaches, which do not require specific data distribution and are robust to outliers (Wang  
380 et al. 2019), to calculate the magnitude and direction of the pixel-level monotonic albedo trend at  
381 a statistical significance level of 0.05 (i.e.,  $p$ -value < 0.05). The city-scale albedo trend is calculated  
382 as the aggregation mean of all pixels that passed the significance test within the city area. The  
383 spatiotemporal patterns of Landsat blue-sky albedo are undertaken for two periods (1986-2020  
384 and 2001-2020). For comparison, we extracted 35-year city-scale spatiotemporal patterns of  
385 MODIS blue-sky albedo in 2001-2020, which is calculated from the integration of MODIS BSA,  
386 WSA, and BaRAD-derived diffuse fraction.

387

### 388 **3.4. Associations between urban greening and albedo change**

389 We explored the multifaceted associations between urban greening and albedo change in several  
390 steps. First, the spatiotemporal patterns of Landsat NDVI in the 1986-2020 and 2001-2020 time

---

391 periods were calculated and aggregated to city-level means. Second, the intra- and inter-city  
392 associations between urban albedo and NDVI trends were analyzed. Local examples in four typical  
393 cities: two rapid-urbanized Shenzhen city (22° 32' 29.4" N, 114° 3' 34.56" E), China and  
394 Birmingham city (52° 29' 10.47"N, 1° 53' 25.44"W), United Kingdom, together with two well-  
395 urbanized Milton city (30°37'49.0"N 87°02'47.0"W), Florida, and Pinehurst city (36° 41' 43" N,  
396 119° 0' 57" W), North Carolina, United States, were selected to showcase different pathways by  
397 which urban greening modulates surface albedo during the urbanization process. Lastly, the  
398 associations between urban albedo and vegetation in 2-D (measured by NDVI) and 3-D (measured  
399 by vegetation height from 10-m-resolution Sentinel-2; Lang et al. 2023) were investigated to  
400 elucidate the effects of urban greenery on surface albedo using data at the baseline year 2020.

401

### 402 **3.5. Urban surface radiative forcing induced by albedo change**

403 Changes in radiative forcing can be caused by natural and/or anthropogenic drivers (Shindell et al.  
404 2013). A positive radiative forcing occurs when there is more incoming than outgoing energy (i.e.,  
405 warming), whereas a negative radiative forcing (outgoing > incoming energy) results in a cooling  
406 effect. We quantified the urban surface radiative forcing (*RF*) from albedo changes (Chen et al.  
407 2015) using the following equation:

408

$$409 \quad RF = -K_{\downarrow} \times (\alpha_{t2} - \alpha_{t1}) \quad (7)$$

410

411 where  $K_{\downarrow}$  is the mean incoming or downward shortwave solar radiation between years  $t_1$  and year  
412  $t_2$ ; and  $\alpha_{t2} - \alpha_{t1}$  is the surface albedo difference between those years. We used BaRAD and Landsat-  
413 derived blue-sky albedo to derive pixel-scale RF (Eq. 7) and then calculated the city-scale RF from  
414 pixel-scale data. To minimize the impact of fluctuations in annual albedo, we used a 5-year average  
415 annual albedo for the RF calculation in 1986-2020. Namely, the mean surface albedo ( $\alpha_{t1}$ ) was  
416 estimated for the 1986-1990 period, and  $\alpha_{t2}$  for the 2016-2020 period, and  $K_{\downarrow}$  was estimated as the  
417 mean downward shortwave solar radiation between 1991 and 2015.

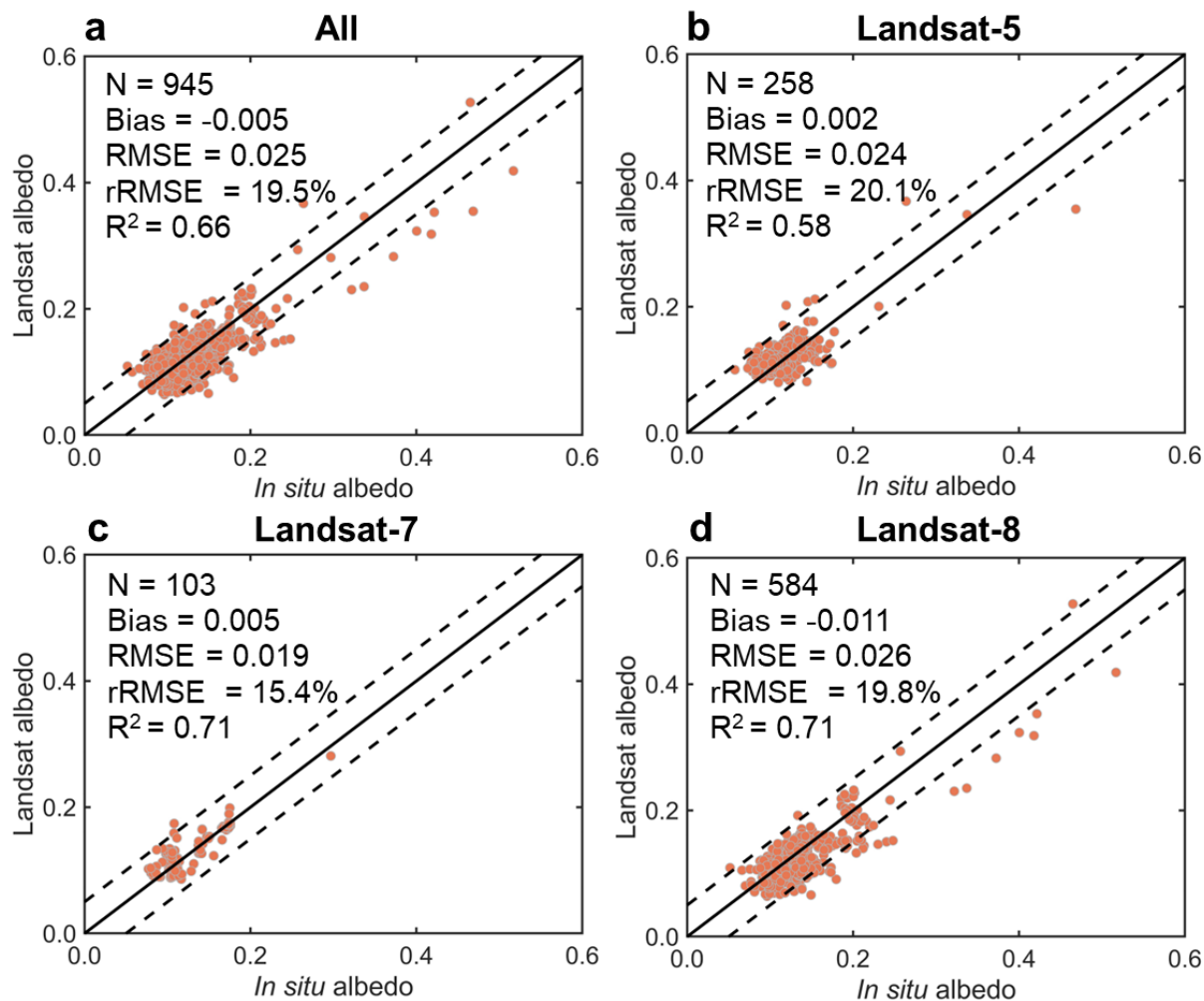
418

## 419 **4. Results**

### 420 **4.1. Accuracy assessment of Landsat urban albedo**



421 We assessed the accuracy of Landsat-derived surface albedo using the flux tower-based  
 422 observations (**Table 2**). Across the 21 flux tower sites, Landsat satellites individually achieve a  
 423 high albedo accuracy (bias = -0.011 - 0.005, RMSE = 0.019 - 0.026, rRMSE = 15.4% - 20.1%,  $R^2$   
 424 = 0.58 - 0.71; **Fig. 4b-d**). For all three Landsat satellites, the overall accuracy is also reliable (bias  
 425 = 0.005, RMSE = 0.025, rRMSE = 19.5%,  $R^2 = 0.66$ ; **Fig. 4a**). Temporal validation for individual  
 426 (**Fig. S3**) and combined (**Fig. S4**) years show similar accuracy patterns. These assessment results  
 427 suggest that the Landsat-derived albedo dataset is reliable and can be used to analyze the  
 428 spatiotemporal characteristics of surface albedo of cities globally.



429  
 430 **Fig. 4.** Evaluation of Landsat-derived albedo with flux-tower measurements for (a) all three  
 431 Landsat satellites, (b) Landsat-5, (c) Landsat-7, and (d) Landsat-8. The following comparison  
 432 statistics are calculated: N (number of Landsat data observed on the same date as flux-tower  
 433 measurements), bias (mean difference between Landsat-derived and tower-based albedo), RMSE  
 434 (root-mean-square-error), rRMSE (relative RMSE, ratio between RMSE and measured albedo  
 435 mean) and  $R^2$  (coefficient of determination), 1:1 line (solid line), error lines of -0.05 and 0.05

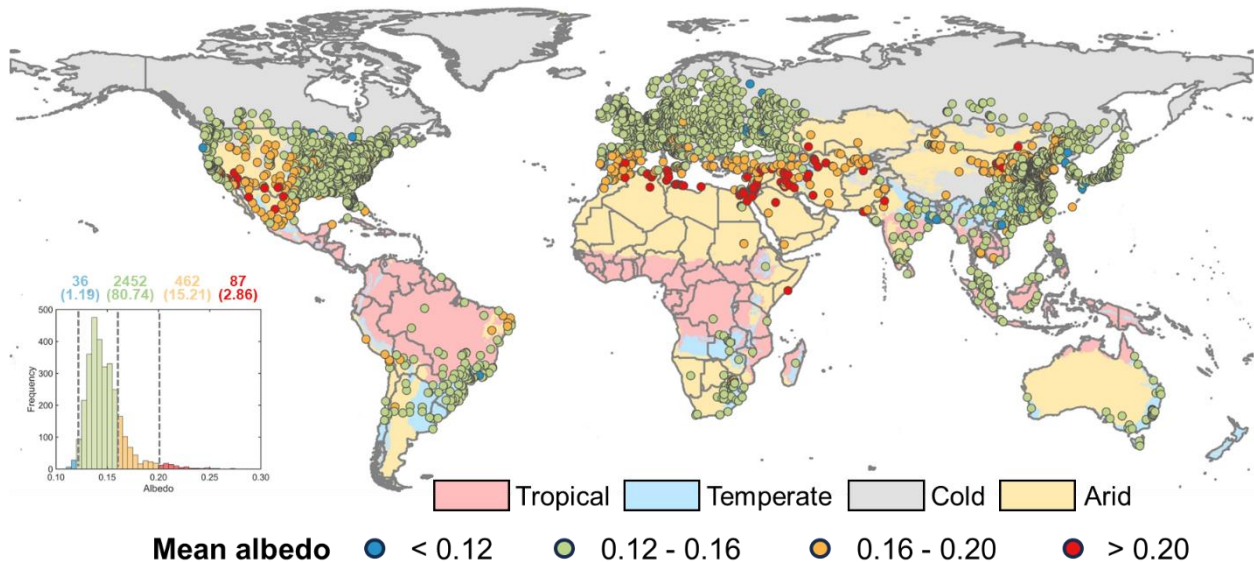
436 (dashed line).

437

## 438 4.2. Global variations of urban albedo

439 The 35-year (1986-2020), city-wide mean surface albedos for the 3037 global cities assessed here  
440 have clear spatial patterns (**Fig. 5**). Cities in temperate climates have the lowest mean albedo (0.143,  
441 N = 1340), followed by those in cold (0.144, N = 1073), tropical (0.145, N = 161), and arid (0.174,  
442 N= 463) regions. Cloud cover limits the number of tropical cities meeting the threshold of having  
443 35-year data. The albedo range for tropical cities (0.115-0.240) is in line with the range reported  
444 by Rechid et al (2009) (0.10-0.20). The urban albedo distribution is skewed, with most cities (2452)  
445 within the range of 0.12-0.16, followed by 462 cities within the range of 0.16-0.20, 87 cities with  
446 albedos > 0.2, and only 36 cities < 0.12. The 20-year (2001-2020) city-level annual mean albedo  
447 from the MODIS and Landsat datasets are close to those of the 35-year Landsat equivalence (**Fig.**  
448 **S5**), with the majority of cities within the range of 0.12-0.20 and very few presenting albedos <0.12  
449 or > 0.20.

450



451

452 **Fig. 5.** City-level average annual albedo (lower key) derived from 35-year (1986-2020) Landsat  
453 data for 3037 global cities mapped onto 1-km Köppen-Geiger climate (Beck et al. 2018) (upper  
454 key), with the number of cities (and the associated percentage in parentheses) given above the  
455 inserted histogram.

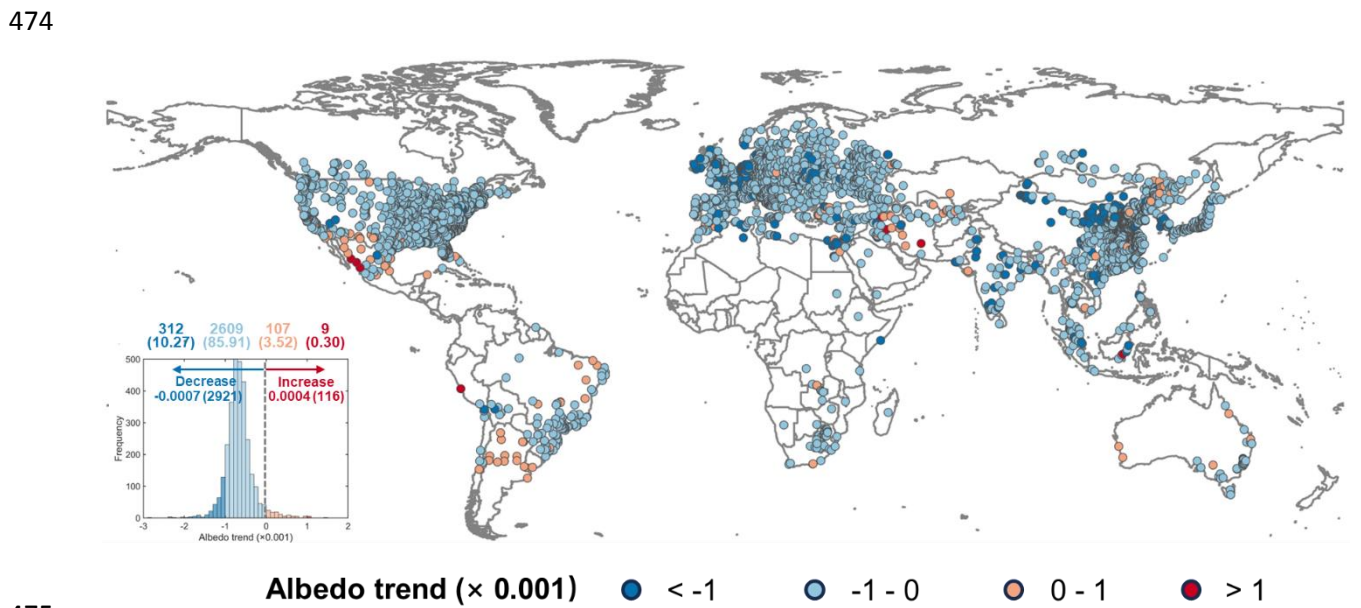
456

## 457 4.3. Global variations of urban albedo trend and driver attribution

### 458 4.3.1. Global temporal trends of urban albedo

459 The 35-year (1986-2020) trend of city-scale annual mean surface albedo depicts a negative slope  
 460 of  $-0.0007 \text{ yr}^{-1}$  (**Fig. 6**). When cities are subdivided by their mean trend, 2921 shows a decreasing  
 461 trend (mean trend =  $-0.0007 \text{ yr}^{-1}$ ) and 116 an increasing trend (mean trend =  $0.0004 \text{ yr}^{-1}$ ). Rapid  
 462 changes, lower than  $-0.001 \text{ yr}^{-1}$ , were observed in 312 cities across Europe, North America, East  
 463 Asia, and the Middle East. Most cities are in the  $-0.001 - 0.000 \text{ yr}^{-1}$  (2609) and  $0.000$  to  $0.001 \text{ yr}^{-1}$   
 464  $^{-1}$  (107) albedo change rate. Nine cities with a larger increasing albedo trend ( $> 0.001 \text{ yr}^{-1}$ ) were  
 465 observed in the Southwest region of the United States.

466  
 467 The 21-year (2000-2020) trends for MODIS and Landsat consistently decrease (**Figs. S6**), at rates  
 468 of  $-0.0003 \text{ yr}^{-1}$  and  $-0.0014 \text{ yr}^{-1}$ , respectively. Due to its inability to detect fine-scale urban  
 469 heterogeneity, the 500-m-resolution MODIS satellite returns a lower decreasing rate than the 30-  
 470 m-resolution Landsat (**Fig. S7**), supporting the necessity of using high-resolution satellite data to  
 471 monitor urban environments. The 21-year change rate ( $-0.0014 \text{ yr}^{-1}$ ) is twice as high as the 35-year  
 472 trend ( $-0.0007 \text{ yr}^{-1}$ ) for Landsat, indicating that the rate of worldwide urban albedo decrease has  
 473 grown.

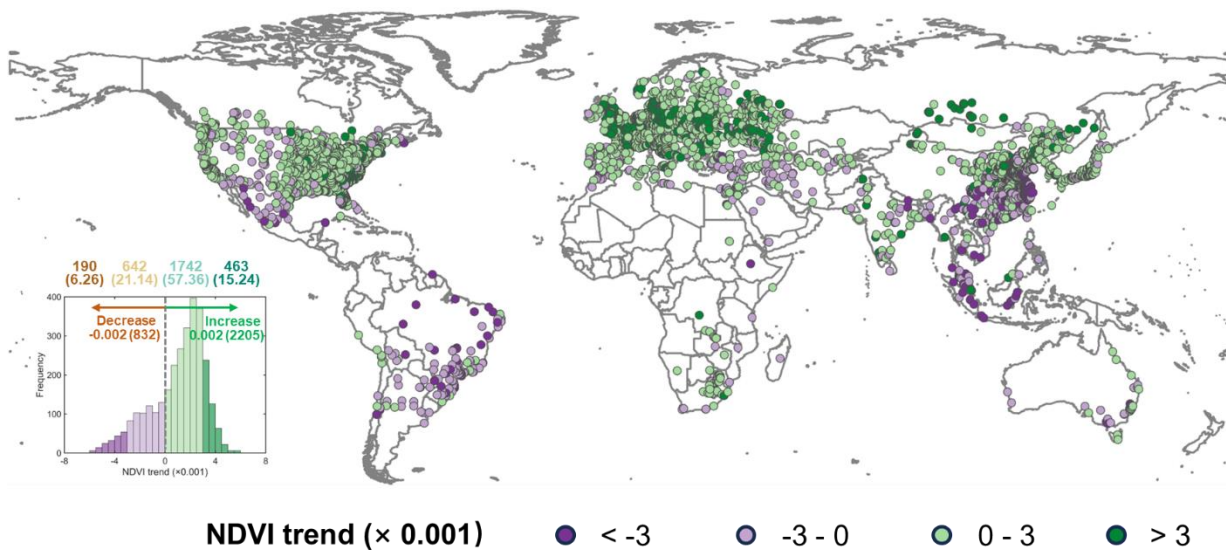


476 **Fig. 6.** Spatial patterns of the Landsat-derived city-level albedo trend for 3037 global cities over  
 477 35 years (1986-2020), with the albedo trend histogram and the number of cities (with the related  
 478 percentage in parentheses) given above the inserted histogram.

479  
 480 **4.3.2. Associations between urban albedo and greenness**

481 Greening activity is one potential driver influencing urban albedo change. Landsat NDVI has a  
 482 mean increase of  $0.001 \text{ yr}^{-1}$  for these 3037 cities during the same 35-year period, with 2205 cities  
 483 exhibiting an increase (i.e., greening) and 832 experiencing a decrease (i.e., browning, **Fig. 7**).  
 484 Most cities are in the  $0.000$  to  $0.003 \text{ yr}^{-1}$  (1742) and  $-0.003$  to  $0.000 \text{ yr}^{-1}$  (642) NDVI change range,  
 485 followed by 463 cities with an increasing NDVI trend  $> 0.003 \text{ yr}^{-1}$  and 190 cities with a decreasing  
 486 NDVI trend  $< -0.003 \text{ yr}^{-1}$ . Browning cities are predominantly found in East Asia, South America,  
 487 and the Southwest region of the United States.

488



489

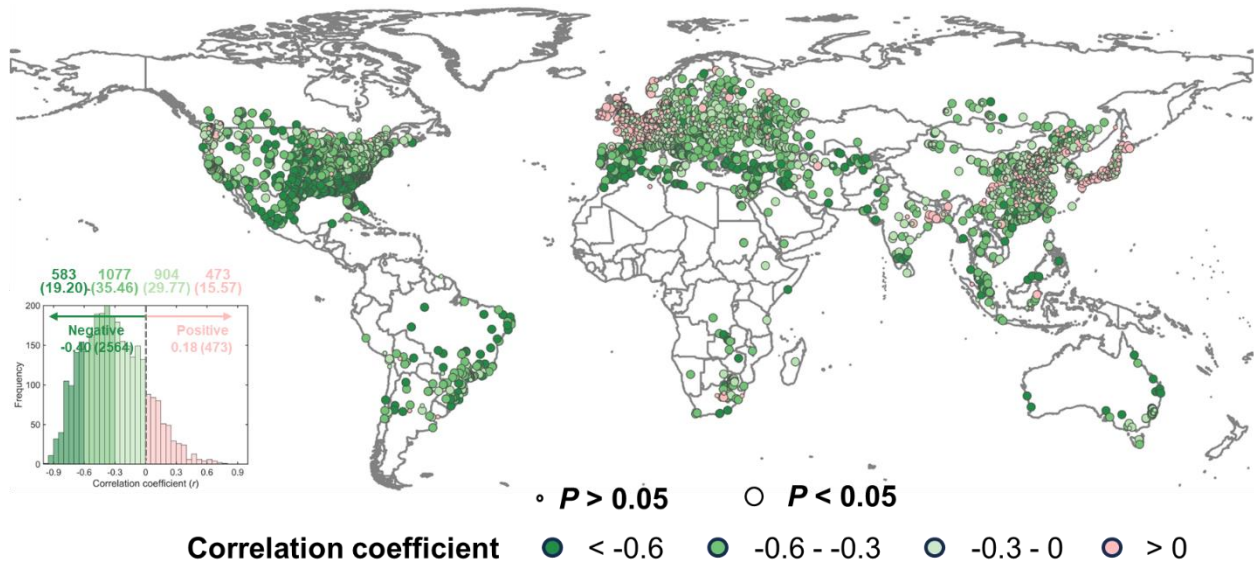
490 **Fig. 7.** Spatial patterns of the Landsat-derived city-level normalized difference vegetation index  
 491 (NDVI) trend for 3037 global cities over 35 years (1986-2020), with the NDVI trend histogram  
 492 and the number of cities (with the related percentage in parentheses) given above the inserted  
 493 histogram.

494

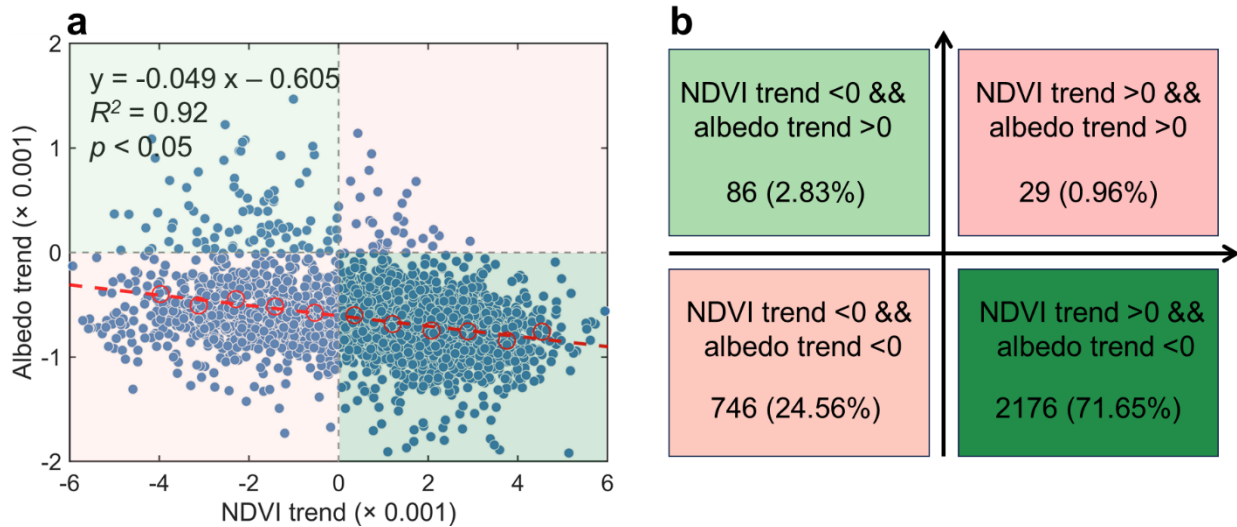
495 Intra-city associations (within cities) between urban NDVI and albedo trends show a total of 2564  
 496 cities are negatively correlated (**Fig. 8**), with 583, 1077, and 904 cities presenting correlation  
 497 coefficients  $< -0.6$ , within the  $-0.6$  to  $-0.3$ , and  $-0.3$  to  $0$  ranges, respectively. Only 291 of 473 cities  
 498 have statistically significant positive NDVI-albedo relationships, most of which are distributed in  
 499 Europe and East Asia. Inter-city associations (across cities) using the median albedo trends derived  
 500 from 10% NDVI bins show that the increase in NDVI trend (with a slope of  $-0.049$ ) coexists with  
 501 the decrease in albedo trend, which explains 92% of the total variance of the albedo binned trend  
 502 (**Fig. 9a**). Moreover, statistical results of NDVI and albedo trend consistency from the raw  
 503 observations show a decrease in albedo trend of 2176 (71.65%) cities in the opposite direction

504 with respect to the NDVI trend (**Fig. 9b**). As the greening trend is greater ( $0.004 \text{ yr}^{-1}$ ) for the past  
 505 21 years (**Fig. S8**), the intra- and inter-city associations between urban NDVI and albedo trends  
 506 become stronger, with more cities exhibiting negative NDVI-albedo correlation coefficients (**Figs.**  
 507 **S9 and S10**). These intra- and inter-city dominant negative associations reveal that urban greening  
 508 will lead to a decreasing albedo trend.

509  
 510



512 **Fig. 8.** Spatial patterns of the intra-city correlation between urban normalized difference vegetation  
 513 index (NDVI) and albedo trend for 3037 global cities over 35 years (1986-2020), with the  
 514 histogram (correlation coefficient key) of the city-level albedo trend and the number of cities (with  
 515 the associated percentage in parentheses) given above the inserted histogram. Large markers  
 516 represent a statistical significance level of 0.05 ( $p$ -value  $< 0.05$ ) and small markers represent a non-  
 517 significant trend with  $p$ -value  $> 0.05$ .



518

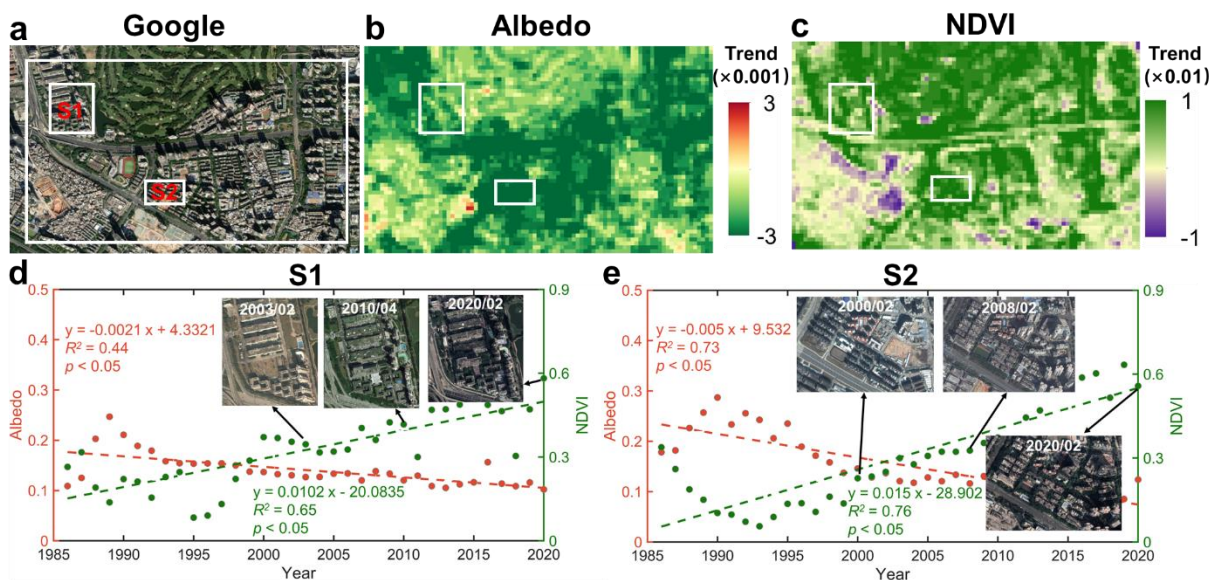
519 **Fig. 9.** Associations between city-level normalized difference vegetation index (NDVI) and  
 520 surface albedo trends for 3037 global cities over 35 years (1986-2020), with **(a)** scatter plot and  
 521 **(b)** statistics of NDVI and albedo trend consistency. In **(a)**, the city-level trends are averaged from  
 522 pixel-level trends that are statistically significant at a level of 0.05, using the non-parametric Mann-  
 523 Kendall and Theil–Sen slope estimator approaches. A zonal analysis is used to refine the  
 524 association results by averaging the NDVI and albedo trend pairs (red circles) within each 10%  
 525 NDVI interval for the linear regression (red dashed line).

526

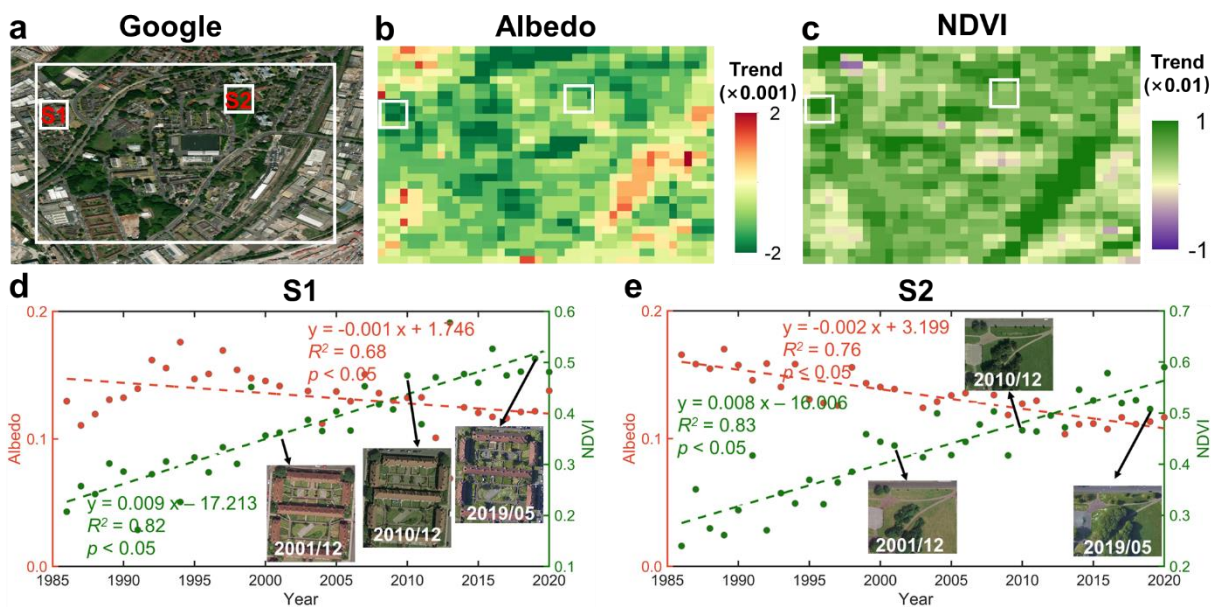
527

528 Four sample cities provide spatially explicit information on the decreasing trend of surface albedo  
 529 caused by different greening pathways: tree planting (Shenzhen, China and Birmingham, United  
 530 Kingdom) and urban warming-induced vegetation growth (Milton, Florida and Pinehurst, North  
 531 Carolina, United States). Shenzhen and Birmingham have experienced tremendous urbanization  
 532 during the past three decades, but they have also implemented tree planting programs in central  
 533 areas, as it can be observed through the NDVI trend maps and high-resolution Google Earth  
 534 satellite images (**Fig. 10a-c** and **Fig. 11a-c**). Two local sites in both Shenzhen and Birmingham  
 535 clearly show the opposite trends for the NDVI and albedo time series (**Fig. 10d-e** and **Fig. 11d-e**).  
 536 In comparison, Milton and Pinehurst are two well-urbanized cities without substantial impervious  
 537 area expansion in the urban fringe areas. Despite the absence of large-area tree planting activities,  
 538 greenness continues to increase in these two cities due to enhanced vegetation growth induced by  
 539 urban warming (**Figs. 12** and **13**). The significant negative correlation between surface albedo and  
 540 2-D (NDVI as vegetation coverage) and 3-D (vegetation height) vegetation structure metrics in the  
 541 baseline year 2020 further explains the multifaceted controls of urban greening on surface albedo  
 542 (**Fig. 14**). Besides urban greening, the other anthropogenic practices might influence surface

543 albedo variations. For example, as shown in **Figs. S11** and **S12**, building construction and rooftop  
 544 renewal with new light-color materials increase surface albedo. Nevertheless, the frequency and  
 545 intensity of building construction is lower than urban vegetation growth, which results in the  
 546 greening-dominated declining trend of urban surface albedo worldwide.  
 547

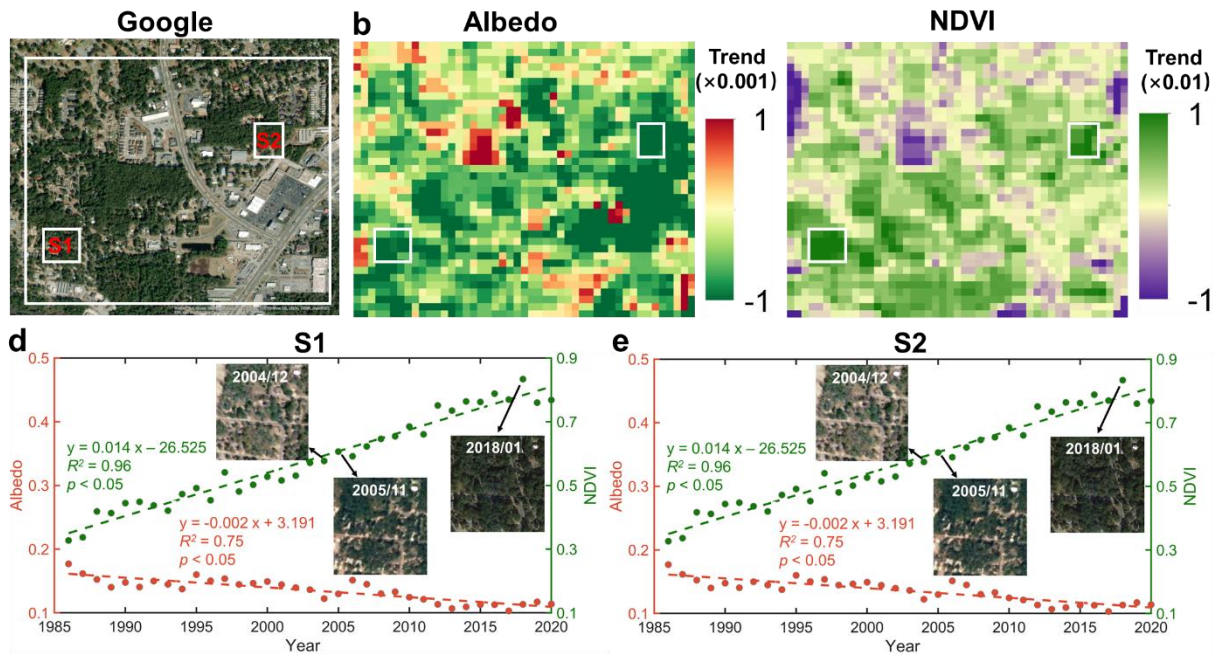


548 **Fig. 10.** Examples showing the close association between surface albedo and urban greening in  
 549 the Shenzhen city, China, based on the maps of (a) Google Earth satellite image, (b) albedo trend,  
 550 (c) NDVI trend, (d) time series of urban NDVI and albedo for S1 area in (a), and (e) time series  
 551 of urban NDVI and albedo for S2 area in (a).  
 552  
 553

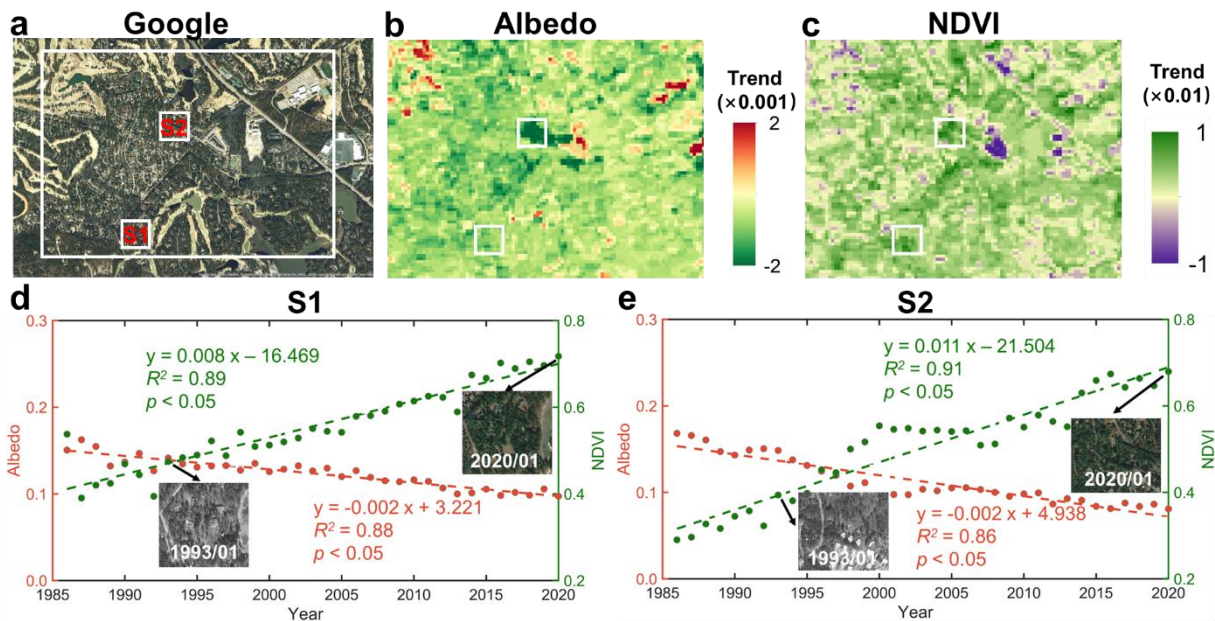


554

555 **Fig. 11.** Examples showing the close association between surface albedo and urban greening in the  
 556 Birmingham city, United Kingdom, based on the maps of (a) Google Earth satellite image, (b)  
 557 albedo trend, (c) NDVI trend, (d) time series of urban NDVI and albedo for S1 area in (a), and (e)  
 558 time series of urban NDVI and albedo for S2 area in (a).  
 559



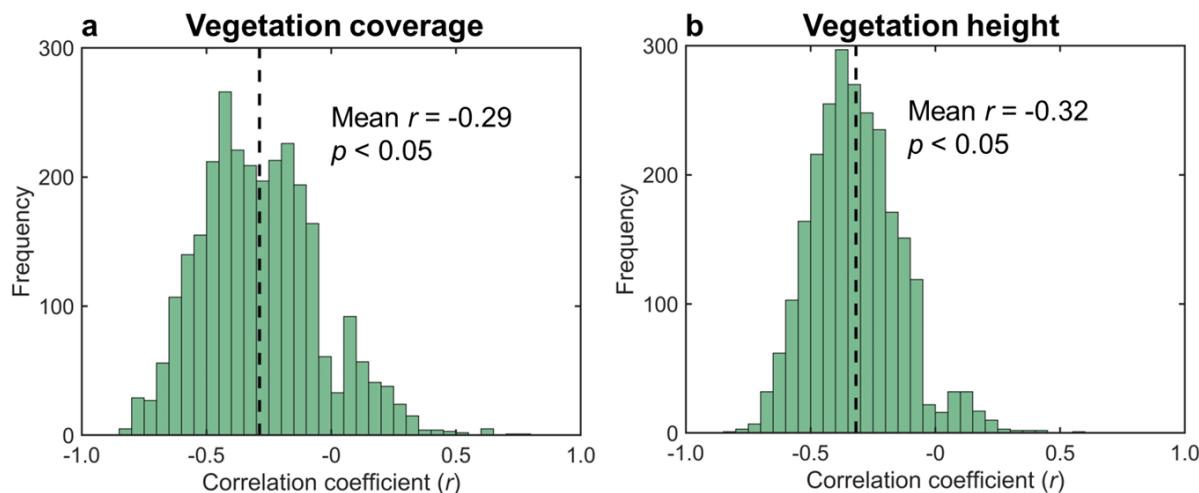
560  
 561 **Fig. 12.** Examples of close association between surface albedo and urban greening in the Milton  
 562 city, Florida, United States, based on the maps of (a) Google Earth satellite image, (b) albedo trend,  
 563 (c) NDVI trend, (d) time series of urban NDVI and albedo for the S1 area in (a), and (e) time series  
 564 of urban NDVI and albedo for the S2 area in (a).



565  
 23



566 **Fig. 13.** Examples of close association between surface albedo and urban greening in the Pinehurst  
 567 city, North Carolina, based on the maps of **(a)** Google Earth satellite image, **(b)** albedo trend, **(c)**  
 568 NDVI trend, **(d)** time series of urban NDVI and albedo for the **S1** area in **(a)**, and **(e)** time series  
 569 of urban NDVI and albedo for the **S2** area in **(a)**.  
 570

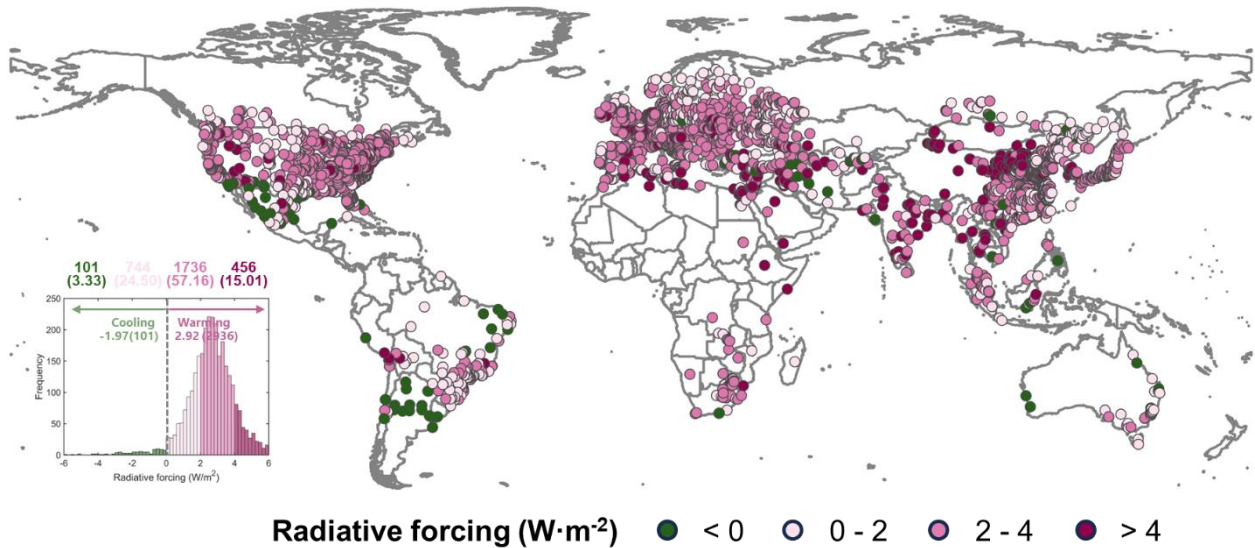


571  
 572 **Fig. 14.** Correlation between surface albedo and **(a)** 30-m-resolution Landsat normalized  
 573 difference vegetation index (NDVI, Gorelick et al. 2017), and **(b)** 10-m-resolution vegetation  
 574 height (Lang et al. 2023) of the baseline year 2020 for 3037 global cities.  
 575

#### 576 4.4. Global variations of albedo-induced urban surface radiative forcing

577 The 35-year change in surface albedo has caused a mean positive surface radiative forcing of 2.76  
 578  $\pm 1.92 \text{ W}\cdot\text{m}^{-2}$  for the 3037 global cities assessed in this study (**Fig. 15**), suggesting a net increase  
 579 in absorbed incoming solar energy at the urban surface. Large inter-city spatial variabilities are  
 580 observed, with values ranging from -10.75 to 23.34  $\text{W}\cdot\text{m}^{-2}$ . The 2936 cities with positive radiative  
 581 forcing (i.e., warming) have a mean value of 2.92  $\text{W}\cdot\text{m}^{-2}$ , while the 101 cities with negative  
 582 radiative forcing have a mean value of -1.97  $\text{W}\cdot\text{m}^{-2}$ . The mean magnitude of albedo-induced  
 583 radiative forcing also varies by regions: 3.14  $\text{W}\cdot\text{m}^{-2}$  for 1073 Asian cities; 3.09  $\text{W}\cdot\text{m}^{-2}$  for 92  
 584 African cities; 2.72  $\text{W}\cdot\text{m}^{-2}$  for 933 European cities; 2.60  $\text{W}\cdot\text{m}^{-2}$  for 789 North American cities; 1.23  
 585  $\text{W}\cdot\text{m}^{-2}$  for 31 Australian cities; and 0.85  $\text{W}\cdot\text{m}^{-2}$  for 119 South American cities.

586



587

588 **Fig. 15.** Spatial patterns of surface radiative forcing (RF,  $W \cdot m^{-2}$ ) from albedo change for 3037  
 589 global cities over 35 years (1986-2020), with the number of cities (and the associated percentage  
 590 in parentheses) given above the inserted histogram.

591

592

## 593 5. Discussion

594

### 595 5.1. Uncertainty analysis

596 Some influencing factors such as training sample representativeness, Landsat data uncertainty,  
 597 seasonal variation, building footprint, and snow event may mislead our findings. To examine their  
 598 impacts, we conducted sensitivity analyses and discussed the potential uncertainties associated  
 599 with each of these factors.

600

#### 601 5.1.1. Training sample representativeness

602 The representativeness of training samples, angular-bin size, and regression relationship between  
 603 reflectance and albedo are three factors that need to be considered for the successful application  
 604 of the direct estimation approach. Recent studies have thoroughly investigated the sensitivity to  
 605 the angular-bin size and the regression relationship between reflectance and albedo, verifying their  
 606 applicability to both natural and urban surfaces (Chen et al. 2023; Lin et al. 2022). Therefore,  
 607 training dataset representativeness has been highlighted as a key component for the application of  
 608 the direct estimation approach over urban areas. We conducted two sensitivity analyses using

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609 BRDF/albedo over mixed land covers (16 IGBP land covers used in this study, referred to as  
610 general scheme) and pure urban cover (referred to as urban scheme) to test the theoretical accuracy  
611 of this approach over urban areas. Results show that these two schemes have almost the same  
612 theoretical accuracy (0.0161 vs. 0.0156, **Fig. S13**), which is very close to the MODIS  
613 BRDF/albedo product accuracy (Wang et al. 2018). Based on the optimized BRDF/albedo training  
614 samples for the general scheme (7200 samples for 16 land covers with 450 samples per type) and  
615 urban scheme (3000 urban cover samples), we constructed one general and one urban reflectance-  
616 to-albedo LUT and validated their accuracy with global flux tower-based measurements.  
617 Validation results reveal that these two algorithms are highly accurate, suggesting that the direct  
618 estimation approach used in this study with the general training sample scheme is stable (**Fig. 4 vs.**  
619 **Fig. S14**).

620

### 621 **5.1.2. Landsat data uncertainty**

622 The uncertainty of Landsat data quality mainly stems from Landsat satellite orbital drifts and scan  
623 line corrector (SLC) failure in Landsat-7. On the one hand, Landsat satellite orbital drifts (e.g.,  
624 Landsat-5 drifted between 1995-2000 and 2003-2007, Landsat-7 drifted from 2017 to the present;  
625 Qiu et al. 2021; Zhang and Roy, 2016) alter local acquisition time, affecting solar-viewing  
626 geometry and surface reflectance, resulting in artificial impacts on surface albedo. To minimize  
627 such impacts, we trained the spectral reflectance with shortwave albedo at local solar noon (e.g.,  
628 12:00 p.m.) to construct reflectance-to-albedo LUTs, allowing us to compare predicted surface  
629 albedo across years (Guo et al. 2022). On the other hand, since Landsat-7 data covers only two  
630 years (2012-2013), the data gap impacts from this satellite on the main findings of this study are  
631 minor. Sensitivity analysis shows that the yearly mean and long-term temporal trend of global  
632 urban albedo are nearly the same, whether or not Landsat-7 satellite data are used (**Figs. 5-6 vs.**  
633 **Fig. S15**).

634

### 635 **5.1.3. Seasonal variation**

636 Seasonal impacts on urban albedo estimation and analysis come from two sources: seasonal  
637 vegetation growth and seasonal solar geometry change. On the one hand, Landsat satellite has a  
638 regular 16-day revisit cycle, which allows at least two observations per month to capture seasonal

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639 vegetation growth dynamics. On the other hand, our algorithm has normalized surface albedo to  
640 local solar noon and the solar position is relatively stable within a month, minimizing the  
641 interference from seasonal change of solar geometry. Sensitivity analysis results of the Landsat-  
642 derived albedo trends using time series from different seasons are very similar to those of the  
643 annual mean time series (**Fig. S16**), supporting the minor seasonal variation effects on the observed  
644 decreasing albedo trend of global urban cities in this study.

#### 645 **5.1.4. Building footprint**

646 Building footprint changes, such as those related to new construction or building renovations using  
647 different materials, might increase urban albedo (**Figs. S11 and S12**). To explore building footprint  
648 impacts on surface albedo, we used 30-m-resolution rasterized building footprint (i.e., total,  
649 average, minimum, and maximum building areas within a 30-m-resolution pixel) dataset for 242  
650 cities in the United States (Heris et al. 2020), and three building height datasets for China (120  
651 cities; Yang and Zhao et al. 2022), Germany (18 cities; Frantz et al. 2021), and the United States  
652 (372 cities; Falcone, 2016) to provide the horizontal and vertical building footprint metrics (**Table**  
653 **S2**). By conducting a bivariate relationship analysis between building footprint metrics and albedo,  
654 we found a positive correlation with mean correlation coefficients of 0.21, 0.21, 0.21, and 0.16 for  
655 maximum (i.e., area of the largest building intersecting each 30-m pixel), minimum (i.e., area of  
656 the smallest building intersecting each 30-m pixel), average (i.e., number of buildings that intersect  
657 each 30-m pixel), and total (i.e., total building footprint coverage per 30-m pixel) building areas,  
658 respectively (**Fig. S17**). We also observed a negative correlation between albedo and building  
659 height, with a mean correlation coefficient of -0.22 (**Fig. S18**), as shadowing and radiative trapping  
660 in canyons increase with building height. However, quantifying the contribution of the building  
661 landscape to albedo change remains a challenging task due to the lack of high-resolution urban  
662 building time-series products, which requires future investigation.

663

#### 664 **5.1.5. Snow cover impact**

665 Snow cover is another important confounding factor for the spatiotemporal analysis of global  
666 urban albedo due to its much higher reflectance than other urban materials. On one hand, because  
667 regular snow events only occur for short periods in the winter for high-latitude cities, they will  
668 have little impact on the general diminishing patterns of global urban albedo. Snow episodes, on

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669 the other hand, are rather regular across time, and their influence on long-term urban albedo is  
670 likely to be systematically linear, which will not modify the spatiotemporal trend analysis. Our  
671 sensitivity analysis results demonstrate that, with the exception of a few high-latitude Northern  
672 hemisphere cities, the overall decreasing trends of worldwide urban albedo are nearly the same  
673 whether snowy satellite pixels are excluded or not (**Fig. 6** and **S19**).

674

## 675 **5.2. Novelty and implication of this study**

676 This study makes several advances over past similar studies on methodological development. First,  
677 we investigated the direct estimation approach and validated its theoretical capability for retrieving  
678 surface albedo from Landsat over global urban areas. Our training sample representativeness  
679 sensitivity analyses indicate that more accurate urban BRDF/albedo training datasets beyond  
680 MODIS are one potential way to improve the algorithm accuracy, which should include fine-  
681 resolution 3-D radiative transfer model parameterization and global 3-D urban morphology  
682 datasets. Second, the absolute accuracy of the direct estimation approach for estimating urban  
683 albedo had not yet been properly evaluated. For the first time, this study used albedo data from  
684 incoming and outgoing shortwave radiation measured by synthesized global urban flux towers  
685 around the world as ground truth to assess the accuracy of the proposed algorithm. The results  
686 demonstrated that Landsat-derived urban albedo is reliable (**Fig. 4**).

687

688 The global 35-year, 30-m-resolution urban surface albedo dataset generated in this study is unique  
689 and valuable. Although many previous efforts have attempted to estimate surface albedo from  
690 high-resolution Sentinel-2 and Landsat satellite data (Guo et al. 2022; He et al. 2018; Lin et al.  
691 2022; Shuai et al. 2011; 2014), most of them were limited to individual locations, cities, or specific  
692 regions, and years, which hampered our understanding of the spatiotemporal patterns of global  
693 urban albedo throughout the past three decades of urbanization. Our albedo dataset of 3037 cities  
694 from around the world, including cities in the Global North and Global South, provides us a  
695 thorough picture of the dynamic spatiotemporal evolution of global urban albedo. This dataset can  
696 be incorporated as input data into urban canopy models (Ryu et al. 2016) for the monitoring and  
697 estimation of urban energy balance and other albedo-related studies.

698

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699 By comparing the results of the previous three decades with those of the previous two decades  
700 using the global 30-m resolution Landsat albedo dataset developed here, we found that global  
701 urban albedo is decreasing at an increasing rate, implying that the albedo-induced warming has  
702 been exacerbated. We also observed that the urban greening phenomenon is expanding around the  
703 globe. Since 1985, 72.60% of global cities (2205) have increased greening, and this proportion has  
704 increased to 89.20% (2709 cities) since 2001. This proportion is higher than the 70% reported in  
705 a previous study using coarse-resolution MODIS data (Zhang et al. 2021). Finally, our study  
706 demonstrates that urban greening regulates the decreasing trend of urban albedo through two  
707 different pathways: tree planting and urban warming-enhanced vegetation growth. These findings  
708 help to clarify recent controversial conclusions about worldwide urban albedo trend patterns (Guo  
709 et al. 2022; Ouyang et al. 2022). Guo et al. (2022) reported an increasing trend of urban albedo  
710 based on 30-m resolution Landsat-derived summer albedo across 11 Chinese megacities, without  
711 taking into account the various urbanization trends in other Chinese cities or around the world, as  
712 well as seasonal changes. By comparing the 1°-resolution albedo estimated from MODIS land  
713 cover types across two baseline years, 2018 and 2001, Ouyang et al. (2022) found a decreasing  
714 pattern in urban areas. This coarse-resolution and short-term data (since 2001) cannot detect fine-  
715 scale heterogeneity in the urbanization processes during the past three decades, such as tree  
716 planting and construction of new buildings and roads, as well as changes in existing artificial  
717 impervious surfaces. Using our 30-m resolution surface albedo and NDVI dataset covering 3037  
718 cities around the world, we determined that greening is the key controlling factor for the downward  
719 trend of urban albedo using multidimensional association analysis and further evidence from local  
720 cases.

721  
722 The strong relationship between urban greening and albedo has important implications. Planting  
723 trees, in conjunction with artificial albedo alterations (e.g., the use of high-reflective materials),  
724 have been recognized as two critical approaches to mitigate urban warming (Chen et al. 2022;  
725 Wong et al. 2021). However, albedo-induced warming effects of urban greening have received  
726 little attention. Recent vegetation greening research at regional and global scales have found that  
727 albedo is a key component in the greening-induced change in the Earth's energy budget and might  
728 potentially offset cooling benefits, causing local and global warming (Lian et al. 2022; Piao et al.  
729 2020). This study provides empirical evidence of the warming effect triggered by changes in urban

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730 albedo caused by increased vegetation, a phenomenon that must be taken into account when  
731 evaluating the effectiveness of greening-based cooling solutions by incorporating such fine-scale  
732 datasets with 3-D microclimate models (e.g., SOLWEIG; Lindberg et al. 2008).

733

### 734 **5.3. Limitations and future perspectives**

735 It is important to recognize and resolve various limitations and uncertainties in this study for future  
736 research. Topography is an essential factor in estimating albedo, although it has seldom been taken  
737 into account when mapping surface albedo on a wide scale using satellite data. In this study, we  
738 do not include topography, as the majority of the cities investigated exhibit minimal variations in  
739 elevation (mean slope =  $3.3^\circ$ , **Fig. S20**). But some cities have large slopes, and their surface albedo  
740 retrieval may still require accounting for topographic impacts (Wu et al. 2018, 2019).

741

742 Another critical issue to address is 3-D urban morphology, which requires significantly higher  
743 resolution data (e.g.,  $\sim 1$  m) for both the satellite surface reflectance and morphology datasets. The  
744 impact of urban geometry, such as the density of buildings, the sky view factor, and the aspect  
745 ratio of buildings, on surface albedo, and in turn on air temperature close to the surface is widely  
746 recognized (Xu et al. 2020; Yang and Li, 2015). The increasing availability of high-resolution  
747 Digital Surface Model data (e.g., Scott et al. 2022) and 3-D building data (e.g., Zhou et al. 2022)  
748 will strengthen interpretation of higher-resolution satellite observations beyond Landsat (e.g., 10-  
749 m Sentinel-2 with  $\sim 5$ -day revisit; 3-m PlanetScope with daily revisit; Drusch et al. 2012; Planet  
750 Team, 2022) to improve albedo estimates at urban facet scale (e.g., road, roof, and wall).

751

752 Although fine-scale albedo trends have been studied, Landsat data remains a mixed signal that  
753 cannot effectively segregate individual contributions from different urban elements (e.g., building,  
754 tree, and grassland) to the overall spatiotemporal trend of urban albedo. Furthermore, the  
755 individual contributions of tree planting and urban warming-enhanced vegetation growth to  
756 greening-induced urban albedo modification are still unknown. An integration of fine-resolution  
757 land-cover datasets of different urban elements and high-resolution albedo datasets are expected  
758 to be used for isolating and assessing the individual contributions of particular urban features.  
759 Finally, this study did not take into account the detailed spatial and temporal variations associated  
760 with land cover changes, which can be analyzed by combining our Landsat albedo data with the

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761 appropriate high-resolution annual land cover map data. This will be helpful for city climate  
762 change management to address mitigation, adaptation, and forecasting because it directly affects  
763 surface energy balance (Duveiller et al. 2018; Oke 1982).

764

## 765 **6. Conclusions**

766 The spatial and temporal features of urban surface albedo in cities around the world and their  
767 underlying drivers are still not well understood due to a lack of high-resolution albedo observations.  
768 In this study, we generated a 35-year, 30-m resolution annual albedo dataset for 3037 worldwide  
769 cities. We demonstrated the accuracy and reliability of the albedo dataset by comparing it to albedo  
770 data derived from flux tower-based measurements. We investigated the spatial and temporal  
771 patterns and trends of urban albedo using this dataset and found that most cities had a decreasing  
772 albedo trend as a consequence of increased greenness. Cities with this decrease in albedo are  
773 expected to experience more (positive) surface radiative forcing.

774

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787

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**Table 1.** Datasets used in this study by type.

Usage type	Dataset	Spatial extent	Resolution (m)	Frequency	Period	Purpose description	Reference
Surface reflectance	Landsat-5 SR	Global cities	30	16-day	1986-2011	Surface albedo & vegetation cover	Gorelick et al. 2017
	Landsat-7 SR	Global cities	30	16-day	2012-2013	Surface albedo & vegetation cover	Gorelick et al. 2017
	Landsat-8 SR	Global cities	30	16-day	2014-2020	Surface albedo & vegetation cover	Gorelick et al. 2017
Surface BRDF	MCD43A1	Global	500	Daily	2000-2020	BRDF database for LUT training	Gorelick et al. 2017; Wang et al. 2018
Surface albedo	Tower-based measurements	Table 2	-	10-30 min	Table 2	Albedo evaluation	Lipson et al. 2022a,b
	MCD43A3	Global	500	Daily	2000-2020	Albedo spatiotemporal analysis	Wang et al. 2018
Land cover type	ESA WorldCover	Global	10	Annual	2020	BRDF training sample selection	Zanaga et al. 2021
	MCD12Q1	Global	500	Annual	2001-2020	BRDF training sample selection	Gorelick et al. 2017; Wang et al. 2018
Solar radiation	BaRAD	Global	0.5° x 0.625°	Monthly	1980-2019	1) Diffuse skylight ratio estimate 2) Surface radiative forcing estimate	Chakraborty and Lee, 2021

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**Table 2.** Flux sites used for albedo evaluation, Tower height and impervious area fraction are available from Lipson et al.(2022a) and <https://mcr.unibas.ch/dev/sqlldb/index.php?nav=dbplot>. Footprint diameter (D) of tower measurement ( $D = 2H \cdot \tan(\text{FOV}/2)$ ) is calculated from tower height (H) and sensor’s field of view (FOV) according to Román et al. 2009.

Site name	City	Country	Latitude (°)	Longitude (°)	Tower height (m)	Footprint diameter (m)	Impervious area fraction	Observation year (s)	Reference
Amsterdam	Amsterdam	The Netherlands	52.367	4.893	40	505	0.68	2019-2020	-
Baltimore	Baltimore	United States	39.413	-76.522	37	467	0.31	2002-2006	Crawford et al. 2011
Capitole	Toulouse	France	43.604	1.445	48	606	0.90	2004-2005	Goret et al. 2019
Escandon	Mexico	Mexico	19.404	-99.176	37	467	0.94	2011-2012	Velasco et al. 2014
Heckor	Heraklion	Greece	35.336	25.133	27	341	0.92	2019-2020	Stagakis et al. 2019
Jungnang	Seoul	South Korea	37.591	127.079	42	524	0.97	2017-2019	Hong et al. 2020
KingsCollege	London	United Kingdom	51.512	-0.117	50	631	0.79	2012-2013	Bjorkegren et al. 2015
Klingelbergstrasse	Basel	Switzerland	47.562	7.581	40	505	0.79	2003-2021	Feigenwinter et al. 2018
KlingelbstrStr.schlucht	Basel	Switzerland	47.561	7.581	2	25	0.79	2014-2020	Feigenwinter et al. 2018
Kumpula	Helsinki	Finland	60.203	24.961	31	391	0.46	2011-2021	Karsisto et al. 2016
Lipowa	Łódź	Poland	51.763	19.445	37	467	0.76	2008-2012	Fortuniak et al. 2013
Narutowicza	Łódź	Poland	51.773	19.481	42	530	0.65	2008-2012	Fortuniak et al. 2013
Ochang	Ochang	South Korea	36.720	127.434	19	240	0.47	2015-2017	Hong et al. 2020
Preston	Melbourne	Australia	-37.731	145.015	40	505	0.62	2003-2004	Coutts et al. 2007
Sunset	Vancouver	Canada	49.226	-123.078	24	303	0.68	2012-2016	Crawford and Christen, 2015
SurreyHills	Melbourne	Australia	-37.827	145.099	38	480	0.54	2004-2004	Coutts et al. 2007
Swindon	Swindon	United Kingdom	51.585	-1.798	13	158	0.49	2011-2013	Ward et al. 2013
TelokKurau	Singapore	Singapore	1.314	103.911	21	253	0.85	2006-2007	Roth et al. 2017
Torni	Helsinki	Finland	60.168	24.939	60	758	0.77	2011-2013	Järvi et al. 2018
WestPhoenix	Arizona	United States	33.484	-112.143	22	278	0.48	2011-2012	Chow, 2017
Yoyogi	Tokyo	Japan	35.665	139.685	52	657	0.92	2016-2020	Ishidoya et al. 2020

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Note: The KlingelbstrStr.schlucht site with a 2-m tower height observes the fluxes of grassland in urban environment.