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## **A geospatial model of nature-based recreation for urban planning: Case study of Paris, France**

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1 **A geospatial model of nature-based recreation for urban planning: Case study of**  
2 **Paris, France**

3  
4 **Abstract**

5 Incorporating nature-based recreation into urban planning analyses requires  
6 understanding the accessibility, quality, and demand for urban greenspace (UGS)  
7 across a city. Here, we present a novel tool that lowers the barriers to such information  
8 by (i) providing a spatially-explicit assessment of recreational UGS supply and  
9 demand; (ii) differentiating results by population group or UGS type; and (iii) using  
10 an accessible open-source software platform that facilitates scenario comparison and  
11 communication. In a case study in Paris, France, we demonstrate how the tool helps  
12 address important urban planning questions. We show that between 42% and 55% of  
13 the population is currently below the UGS target of 10 m<sup>2</sup> per person, depending on  
14 the accessibility criteria used. Using revealed preference data, we demonstrate that  
15 older adults are disproportionately affected by the UGS deficit. Our assessment of  
16 future scenarios reveals that UGS targets set by public policies are largely insufficient  
17 (500 to 2800 ha are planned by 2030, while more than 4000 ha are needed to meet the  
18 policy target). By combining the strengths of established geospatial methods, the tool  
19 helps researchers and practitioners produce a more nuanced analysis of the recreation  
20 benefits of UGS implementation.

21  
22 **1 Introduction**

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23 Recreation in nature benefits people in many ways such as providing aesthetic  
24 experiences, enhancing people's physical and psychological health, and increasing  
25 social cohesion (Liu et al. 2020, WHO 2016, Keeler et al. 2019), thus representing an  
26 important category of ecosystem services (ES). Urban greenspace (UGS) such as  
27 parks, residential gardens, or sports and recreation areas, provides urban inhabitants  
28 with a major, if not only, opportunity for recreation, relaxation, socializing and  
29 interacting with plants and animals in cities (Soga and Gaston 2016). Despite the  
30 multiple benefits of nature experiences, people worldwide are spending less and less  
31 time in contact with nature (Soga and Gaston 2016). An important driver is the decline  
32 in accessible UGS as populations have rapidly concentrated into urban areas that are  
33 largely man-made and highly segregated from nature (Grimm et al. 2008, Turner et al.  
34 2004). As 68% of the global population will reside in cities in 2050 (United Nations,  
35 2019), it is crucial to ensure UGS provision in urban planning to secure the  
36 opportunity for natural-based recreation.

37 Advances in urban ES science are expected to fundamentally change decision-  
38 making (Cortinovis and Geneletti 2018a, Wilkerson et al. 2018, Hamel et al. 2021).  
39 Modelling tools can greatly propel this process by quantifying, mapping, and  
40 exploring the impacts of possible land use decisions (Guerry et al. 2015). Although  
41 recreation is far more studied than other cultural ecosystem services, modelling tools  
42 are still under-developed (Luederitz et al. 2015). One impediment is that modelling  
43 recreation requires information on population's diverse preferences and use regarding  
44 UGS (Bateman et al. 2014, De Valck et al. 2017), which is often unpractical or costly

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45 to collect for entire cities (Ives et al. 2017). Alternatively, recreation is modelled at the  
46 neighborhood or community level, relying on surveys of people's use of and  
47 preferences for different UGS types. Accessible and reproducible data are essential to  
48 develop practical modelling tools to integrate recreation in UGS planning, especially  
49 when the purpose is to serve a wide range of cities and decision contexts (Hamel et al.  
50 2021).

51 Both the quantity of UGS and recreational needs, i.e. where and what type of  
52 UGS people might use, should be considered in planning. Among simple approaches  
53 for modelling the recreation service, UGS standards—minimum targets for the  
54 amount of UGS that should be accessible (e.g., 10 m<sup>2</sup>/cap) (Byrne and Sipe 2010)—  
55 have been widely used (Maruani and Amit-Cohen 2007; González-García et al. 2020).  
56 However, UGS standards provide limited practical insights for urban planning since  
57 setting a UGS standard of 10 m<sup>2</sup>/hab does not indicate where and what type of UGS is  
58 needed the most (Badiu et al. 2016, Wilkerson et al. 2018). Needs-based approaches,  
59 relying on survey on residents' preferences and use of UGS, were developed to  
60 address diverse recreation preferences (Byrne and Sipe 2010) but they often concern  
61 smaller areas. Urban ES assessments provide a useful framework to provide spatial  
62 information on both UGS quantity and recreational needs (Baró et al. 2016, González-  
63 García et al. 2020, see Literature review). ES modelling tools that can translate UGS  
64 data into accessible and actionable information about where, how much and what type  
65 of UGS should be created will greatly help the implementation of UGS policies  
66 (Hamel et al. 2021).

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67 Here we present a software tool to assess recreational UGS supply and demand  
68 to facilitate the incorporation of recreation service in UGS planning. This tool is  
69 available on a web-platform and [is designed to be implemented as the “Urban Nature  
70 Access model” in InVEST](#) (Integrated Valuation of Ecosystem Services and  
71 Tradeoffs)—a free, open-source software suite that models multiple ES delivered by  
72 nature ([Hamel et al. 2021](#), [Sharp et al. 2020](#)). The model is easy to use and allows  
73 users to rapidly assess recreational UGS supply, demand and the supply-demand  
74 balance with flexible data requirements. [Based on our review of the literature \(Section  
75 2\), the tool application illustrated in this article](#) improves on existing options to  
76 support decision making in several ways: (i) it allows for rapid calculation of  
77 recreational UGS supply and demand to aid assessments based on commonly  
78 available data; (ii) it is compatible with both a “UGS standard” approach and needs-  
79 based UGS assessments; (iii) it is supported by an online calculation and visualization  
80 platform that facilitates comparison and communication of impacts of different UGS  
81 planning scenarios. After describing the new model in Section 3, we present a case  
82 study in the administrative region of Paris, France, to demonstrate how it supports  
83 UGS planning with different data requirement.

## 84 [2 Literature review](#)

### 85 [2.1 Recreational UGS supply assessment](#)

86 Recreation service supply is defined as the biophysical capacity of ecosystems to  
87 provide recreational opportunities ([Plieninger et al. 2015](#)). The biophysical UGS  
88 attributes including types, area, size, accessibility, configuration, facilities, safety,

---

89 maintenance, aesthetic, biodiversity, soundscape etc. have been considered as factors  
90 impacting recreation potential (Komossa et al. 2018, Paracchini et al. 2014). These  
91 factors can be broadly categorized according to availability and quality (La Rosa  
92 2014, Stessens et al. 2020, Stessens et al. 2017).

### 93 **2.1.1 UGS availability assessment**

94 UGS availability measures the quantity of UGS within a defined area or distance  
95 threshold (Tratalos et al. 2016). Such measures are aimed at quantifying how much  
96 UGS is accessible for the population from a given location, usually residential areas.  
97 A number of studies have shown that availability of UGS correlated with actual use  
98 for physical activity (WHO 2016). In particular, Schipperijn et al. (2010) reported that  
99 use of UGS in Denmark is determined by area and distance to home, along with other  
100 factors. Three types of UGS availability measurements have been studied.

101 First, cumulative opportunity indicators, such as UGS area per person, or the  
102 relative amount of green space (UGS area divided by total land area), within an area,  
103 often a predefined administrative boundary (Ekkel and de Vries 2017). For example,  
104 in UK's national ecosystem assessment, the percent of 17 types of environmental  
105 spaces within Local Authority District is mapped as culture ES availability indicator  
106 (Tratalos et al. 2016).

107 Second, proximity based indicators, i.e., presence of UGS of certain size within a  
108 distance threshold (termed as "accessibility" (Ekkel and de Vries 2017). The rationale  
109 behind this approach is that the size of a UGS determines the range of service the  
110 UGS is able to support (Stessens et al. 2017), and the UGS should be easily reachable

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111 for most of the nearby population. For example, the WHO Europe regional office  
112 recommends at least 0.5 ha UGS within 300 m linear distance from home (WHO  
113 2016).

114 More advanced, the gravity model conceptualizes the service provided by UGS  
115 as declining with “resistance” (often proxied by distance), which can be described by  
116 a decay function (Liu et al. 2020, Baró et al. 2016). Accessible UGS is calculated by  
117 summing up the UGS areas corrected by the decay function within an area served by a  
118 given UGS (Liu et al. 2020). The two step floating catchment area method (2SFCA)  
119 further modifies the gravity model by introducing “floating search radius” since  
120 different age, social status may be willing to travel different distances for different  
121 types of UGS (Luo 2004, Xing et al. 2018).

122 As with many ES, it is important to note that the majority of UGS availability  
123 literature is concentrated in the global North and developed cities in Asia with few  
124 case studies from the global South and less developed Asian cities, despite their high  
125 urbanization rates (Boulton et al. 2018). A wide range of UGS availability has been  
126 reported in that literature, ranging from very low supply, for example 2.65 m<sup>2</sup>/cap  
127 UGS in Hong Kong (public, collective and private UGS all included, (Jim and Chan  
128 2016)), 2.5 m<sup>2</sup>/cap in Schwerin, Germany (Wüstemann et al. 2016), and 4 m<sup>2</sup>/cap in  
129 Macedonia, Spain, and southern Italy, to very high with 200 m<sup>2</sup>/cap in some cities of  
130 German, Belgium and Austria (Fuller and Gaston 2009). Methodological studies  
131 found that data sources, UGS classification systems, distance thresholds, analysis  
132 techniques, and types of distance (network v.s. Euclidean distance) can greatly impact

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133 results (Mears and Brindley 2019). There is a call to develop standard ways to UGS  
134 quantification to interpret individual studies and understand differing results (Badiu et  
135 al. 2016, Mears and Brindley 2019).

136 Although there is no international standard for availability of UGS, the United  
137 Nations' objective is to provide universal access to safe, inclusive and accessible  
138 green and public space no less than 300 meters from each inhabitant residence by  
139 2030 (Sustainable Goal 11.7, United Nations Department of Economic and Social  
140 Affairs 2014). In the literature, distances between 300m and 800m are often used as  
141 UGS accessibility standards with most European cities using 300m or 500m (Boulton  
142 et al. 2018).

### 143 **2.1.2 Quality assessment**

144 UGS includes a varied range of ecosystems and is able to provide a diverse kind  
145 of “quality” and satisfy different recreational needs (Rupprecht et al. 2015). The  
146 concept of UGS “quality” is complex and multifold. It is challenging to assess UGS  
147 quality, especially when integrating user's preference with spatial information  
148 (Stessens et al. 2020). At the landscape level, indicators such as naturalness, land  
149 cover, presence of or distance to water, protection status, diversity of landscape, and  
150 view shed etc. are used to assess and map recreation quality (Komossa et al. 2018,  
151 Paracchini et al. 2014). Indicator selection is usually based on literature or  
152 assumptions with a few exceptions that are derived from user's preferences (De Valck  
153 et al. 2017, Tardieu and Tuffery 2019).

154 At a finer scale, in-situ observational evaluative indices are developed to assess

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155 UGS quality (Knobel et al. 2019). Generally, UGS size, recreational amenities such as  
156 water features or trails, facilities, and areas with organized recreational activities are  
157 common attributes associated with higher recreation quality (Donahue et al. 2018).  
158 However, these attributes are difficult to map at larger scales since some indicators  
159 (e.g., facilities or programming) rely on detailed and on-site investigation of  
160 individual UGS. New data sources, such as street view images, unmanned aerial  
161 vehicle images, and Google Earth images, are making such assessments possible.  
162 These data can be applied to delineate and classify urban environments at high  
163 accuracy and large scale (Pardo-García and Mérida-Rodríguez 2017). However, these  
164 approaches still constitute a research frontier, especially at larger scales.

## 165 **2.2 Recreational UGS demand assessment**

166 Understanding citizens' recreational needs is critical to design UGS that  
167 encourages urban dwellers to travel longer and spend more time to recreate (Byrne  
168 and Sipe 2010). There are significant differences in recreation preferences based on a  
169 number of demographic or social characteristics, such as age, gender, race, ethnicity,  
170 socioeconomic status (De Valck et al. 2017).

171 People's recreation preference and demand have been modelled using multiple  
172 approaches such as travel cost model (Binner et al. 2017, Tardieu and Tuffery 2019),  
173 discrete choice model (Vaara and Matero J 2011, De Valck et al. 2017, Ta et al. 2020)  
174 and hedonic pricing method (Loret de Mola et al. 2017, Sander and Haight 2012), and  
175 various data sources, many of which rely on surveys. Preference and visitation are  
176 collected through questionnaires, participatory mapping, or through on-site

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177 observations of usage of UGS (Bjerke et al. 2006, Polat and Akay 2015, Tardieu  
178 2017). Demand and preference can be determined by extracting statistical  
179 relationships between UGS characteristics, personal characteristics of respondents and  
180 visitation choices (Tardieu and Tuffery 2019). The merit of surveys is that multi-  
181 dimensional variables can be collected, allowing in-depth analysis of demands and  
182 preferences. The disadvantage is that they are resource intensive and difficult to apply  
183 at large scales, and local case studies use a variety of measurements and survey  
184 protocols which makes it difficult to synthesize findings and develop generic models.  
185 To our knowledge, only the UK, Finland and Denmark conducted national monitoring  
186 of UGS use which provide multiple dimensional recreation profiles of the citizens  
187 (Fish et al. 2016, Kenter et al. 2014, Schipperijn et al. 2010, Toftager et al. 2011,  
188 Vaara and Matero 2011). Comprehensive, long-term and large-scale research on  
189 recreational use of UGS is lacking which hinders the development of widely  
190 applicable models.

191 Another line of research relies on collecting data from a large group of  
192 population through social media. Flickr (Donahue et al. 2018), Instagram (Schwartz  
193 and Hochman 2014), Twitter (Hamstead et al. 2018) and STRAVA (Sun et al. 2017)  
194 have been used to explore the relative use of UGS. Recently machine learning  
195 algorithms have been jointly used with crowd-sourced images to detect the type of  
196 interaction with nature (Richards and Tunçer 2018). Scholars have emphasized new  
197 opportunities provided by large crowd-sourced data for images, videos, and other  
198 sources such as activity tracking applications. These data provide new potential

---

199 through near real-time monitoring, but also raise concerns regarding sampling bias,  
200 data structure and a lack of socio-economic information about visitors (Boyd and  
201 Crawford 2012).

### 202 **2.3 Existing recreation service modelling tools**

203 Multiple reviews on ES assessment tools have discussed recreation service  
204 modelling (Bagstad et al. 2013, Brown and Fagerholm 2015, Carter et al. 2012, Grêt-  
205 Regamey et al. 2017). Among the most popular models, Social Values for Ecosystem  
206 Services (SolVES) relies on a survey on public values and preference for locations to  
207 predict and map recreation value in landscape. SolVES can reveal heterogenous  
208 preferences for recreation but is problematic to transfer the results to unstudied area.  
209 The InVEST Recreation (“Visitation”) model approximates visitation using Flickr  
210 photos and builds a regression model with environmental attributes layer (Sharp et al.  
211 2020). However, the current InVEST recreation model (entitled “Visitation:  
212 Recreation and tourism”, v3.8) is not suitable for quantifying daily recreation in UGS,  
213 as it relies on a dataset with a bias towards highly attractive areas. For example, a  
214 leisure walk in a pocket park is unlikely to result in a post on Flickr. The Benefit  
215 Transfer Toolkit developed spreadsheets based on a meta-analysis of existing case  
216 studies (Loomis et al. 2018). It allows quantifying the economic benefits of the  
217 recreation service in unstudied area, but the limited sample cases lead to high  
218 uncertainty in the approach. The ESTIMAP recreation model calculates three  
219 indicators that can be used for a European assessment of nature-based recreation: the  
220 Recreation Potential (RP), the Recreation Opportunity Spectrum (ROS), and the share

---

221 of the population that can potentially profit from nearby nature for recreation  
222 purposes. RP is a composite indicator which estimates the capacity of sites to provide  
223 recreation services based on their naturalness, protection status and water component.  
224 ROS is derived by overlaying the RP index and a proximity index. RP and ROS are  
225 used to derive the third one through a zonal analysis with population raster (Zulian et  
226 al. 2013). Other existing “off-the-shelf” recreation service assessment tools include  
227 ROS developed by U.S. Department of Agriculture for managing forest recreation,  
228 Outdoor Recreation Valuation (ORVal) tool developed by the Land, Environment,  
229 Economics and Policy Institute of UK, Natural capital planning tool (NCTP)  
230 developed by Consultancy for Environmental Economics & Policy of the UK, and on-  
231 site evaluation tools such as Quality of Public Open Space Tool (POST) and  
232 Neighborhood Green Space Tool (NGST). They are reviewed and compared in  
233 [Supplementary Information A](#).

### 234 **3 Model description**

235 The following section describes the model algorithm. Our approach links  
236 recreation quality to different types of UGS in cities, in accordance with (Handley et  
237 al. 2002) and using a decay function to represent UGS availability. The interface of  
238 the online tool is described in [Supplementary Information B](#).

#### 239 **3.1 Recreational UGS supply modelling**

##### 240 **3.1.1 Default supply modelling**

241 We adopted the 2SFCA method to model recreation supply (Luo 2004). This  
242 approach relies on rasterized data for population and UGS and involves two steps

---

243 (Figure 1).

244 In the first step, for each UGS pixel  $j$  (green pixel in Figure 1a), the algorithm  
245 computes the greenspace to population ratio ( $R_j$ ) by dividing UGS area in pixel  $j$  ( $S_j$ )  
246 by population ( $p_k$ ) in the search radius. Since visitation on UGS declines with distance  
247 to residential areas, a decay function  $f(d_{kj})$  is applied to population values (Eq. 1).

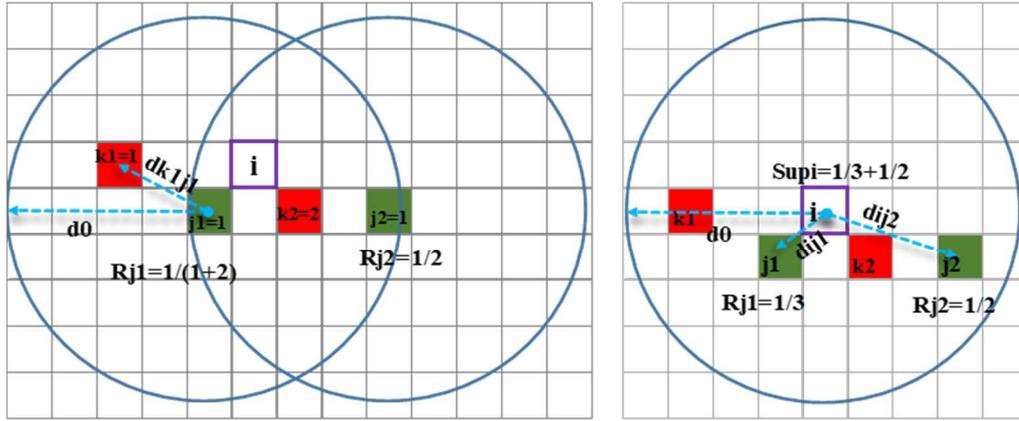
$$248 \quad R_j = \frac{S_j}{\sum_{k \in [d_{kj} \leq d_0]} p_k \times f(d_{kj})} \quad (1)$$

249 Where  $R_j$  is the UGS to population ratio of UGS pixel  $j$ ;  $S_j$  is the UGS area in  
250 pixel  $j$  ( $m^2$ );  $p_k$  is the population in pixel  $k$ ;  $d_{kj}$  is the Euclidean distance between pixel  
251  $k$  and  $j$ ;  $d_0$  is the search radius;  $f(d_{kj})$  is the decay function describing the decline of  
252 service against distance. Five different forms of decay functions are available to use in  
253 the software: Dichotomy, Power function, Gaussian function, Kernel density function,  
254 and Poisson regression function.

255 In the second step, for each pixel in the study area, the algorithm sums up  $R_j$   
256 values from UGS pixels within the search radius (Figure 1b). Thus, UGS supplied to  
257 pixel  $i$  ( $Sup_i$ ) is calculated as (Eq. 2) :

$$258 \quad Sup_i = \sum_{j \in [d_{ij} \leq d_0]} R_j * f(d_{ij}) \quad (2)$$

259 Where  $i$  is any pixel in the study area;  $Sup_i$  is the greenspace per capita supplied  
260 to pixel  $i$  ( $m^2/cap$ );  $R_j$  is the UGS-population ratio of a UGS pixel  $j$ ;  $d_{ij}$  is the  
261 Euclidean distance between pixel  $i$  and  $j$ ;  $d_0$  is the search radius.



(a) First step search

(b) Second step search

262

263

**Figure 1. Two-step floating catchment area (2SFCA) method to calculate urban greenspace**

264

**(UGS)-population ratio (a) and UGS supply (b).** Green pixels represent UGS, red pixels

265

represent inhabited pixels. Blue circles indicate the search radii around UGS pixels (step 1) and

266

then any pixel in the landscape (step 2).  $R_{j1}$  and  $R_{j2}$  are the UGS-population ratios for pixels  $j1$

267

and  $j2$ .  $D_{k1j1}$  is the distance between pixels  $j1$  and  $k1$ .  $Sup_i$  is the total UGS supply for pixel  $i$ .

268

The dichotomy function is used in this example.

269

### 270 3.1.2 Modeling supply of different UGS types

271

The model allows users to distinguish between different types of UGS, e.g.,

272

forest, municipal park, and community park, which will impact recreation differently

273

because of their qualities.

274

If  $r$  is the type of UGS and  $j$  is a UGS pixel of type  $r$ , and  $d_{0,r}$  is the search radius

275

for UGS of type  $r$ , the  $R_{r,j}$  is calculated by the area of UGS in pixel  $j$  divided by the

276

population within the radius. The recreation service supply of UGS type  $r$  to pixel  $i$

277

( $Sup_{r,i}$ ) is calculated by summing up the  $R_{r,j}$  of UGS type  $r$  within the radius. The total

278

UGS supplied to pixel  $i$  ( $Sup_i$ ) is calculated by summing up the  $Sup_{r,i}$  of all types of

279

UGS:

280

$$R_{r,j} = \frac{S_{r,j}}{\sum_{k \in [d_{kj} \leq d_{0,r}]} P_k * f(d_{kj})} \quad (3)$$

281

$$Sup_{r,i} = \sum_{j \in \{d_{ij} \leq d_{0,r}\}} R_{r,j} * f(d_{ij}) \quad (4)$$

---

282  $Sup_i = \sum_{r=1}^r Sup_{r,i} \quad (5)$

283

### 284 **3.1.3 Modeling UGS supply to different population groups**

285 The model can take into account the different search radii of subgroup  
 286 populations, which changes the supply of UGS.  $g$  represents the factors in which to  
 287 split the population (e.g., age group  $g_1, g_2, \dots, g_N$ ). Then the UGS supplied to  $g_n$  group  
 288 of people in pixel  $i$  can be calculated as:

289  $R_j$

290 
$$= \frac{S_j}{\sum_{k \in [d_{kj} \leq d_{0,g1}]} p_{k,g1} * f(d_{kj}) + \sum_{k \in [d_{kj} \leq d_{0,g2}]} p_{k,g2} * f(d_{kj}) + \dots + \sum_{k \in [d_{kj} \leq d_{0,gN}]} p_{k,gN} * f(d_{kj})}$$

291 
$$= \frac{S_j}{\sum_{n=1}^N \sum_{k \in [d_{kj} \leq d_{0,gN}]} p_{k,gN} * f(d_{kj})} \quad (6)$$

292 
$$Sup_{gn,i} = \sum_{j \in \{d_{ij} \leq d_{0,gn}\}} R_j \times f(d_{ij}) \quad (7)$$

293 Where  $Sup_{gn,i}$  is the UGS supplied to group  $g_n$  at pixel  $i$ ;  $p_{k,gn}$  is population of  
 294 group  $g_n$  at pixel  $k$ ;  $d_{0,gn}$  is the search radius for group  $g_n$ ;  $f(d_{kj})$  and  $f(d_{ij})$  is the decay  
 295 function.

### 296 **3.2 Recreational UGS demand modelling**

297 We define demand as *the amount of UGS per capita within proximity*, described  
 298 by two parameters: distance ( $d_0$ , in m) and amount ( $Dem_{cap}$ , in  $m^2/cap$ ). The  
 299 parameters can be calibrated by preferences from a survey, which represent  
 300 preferences for UGS area and proximity ( $d_0$  and  $D_{cap}$  can be differentiated according  
 301 to sub population groups' preferences for more accurate assessment). Alternatively,  
 302 users can define demand by applying a policy standard—for example, the Netherlands

---

303 set the target of a minimum greenspace provision of 60 m<sup>2</sup> per-capita within a 500 m  
304 radius around households (de Roo, 2011).

### 305 3.3 Supply-demand balance at multiple scales

306 The per-capita UGS supply-demand balance is defined for each pixel  $i$  by  
307 calculating the difference between per-capita UGS supply and demand ( $\text{Balance}_{\text{cap},i}$ )  
308 (Eq. 8).

$$309 \quad \text{Balance}_{\text{cap},i} = \text{Sup}_i - \text{Dem}_{\text{cap}} \quad (8)$$

310 To determine the balance for all people in pixel  $i$  ( $\text{Balance}_i$ ),  $\text{Balance}_{\text{cap},i}$  is  
311 multiplied with population at pixel  $i$  ( $p_i$ ), which indicates how much UGS is under-  
312 supplied or over-supplied at pixel  $i$ .

$$313 \quad \text{Balance}_i = \text{Balance}_{\text{cap},i} \times p_i \quad (9)$$

314 The administrative level supply-demand balance ( $\text{Balance}_{\text{adm}}$ ) is the sum of the  
315 pixel level supply-demand balance ( $\text{Balance}_i$ ) in an administrative unit (Eq. 10).  
316  $\text{Balance}_{\text{adm}}$  indicates how much UGS (m<sup>2</sup>) is under- or over-supplied in an  
317 administrative unit. Since the UGS surplus in one pixel cannot compensate for a  
318 deficit in other pixels due to inaccessibility,  $\text{Def}_{\text{adm}}$  is calculated as the sum of only  
319 deficit UGS values which indicate real shortage of UGS (Eq. 11).

$$320 \quad \text{Balance}_{\text{adm}} = \sum \text{Balance}_i \quad (10)$$

$$321 \quad \text{Def}_{\text{adm}} = \sum |\text{Balance}_i| \text{ if } \text{Balance}_i < 0 \quad (11)$$

322 If  $\text{Balance}_{\text{cap},i} < 0$ , it indicates that people in this pixel are under-supplied with  
323 UGS compared to the defined standard. Summing up population in these pixels within  
324 an administrative unit will provide the number of inhabitants with less than

---

325 recommended UGS in an administrative unit ( $pop_{\text{def,adm}}$ , Eq. 12).

$$326 \quad pop_{\text{def,adm}} = \begin{cases} \sum p_i, & \text{if } Balance_{cap,i} < 0 \\ 0, & \text{if } Balance_{cap,i} > 0 \end{cases} \quad (12)$$

## 327 **4 Application**

### 328 **4.1 Study area**

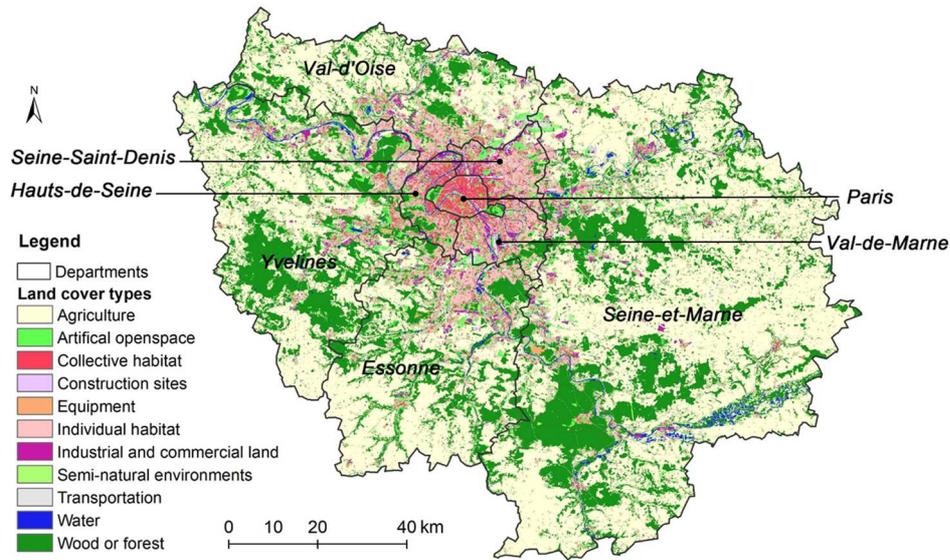
329 Our study focuses on Paris, France and the surrounding region of Île-de-France  
330 (France). The region has an area of 12,061 km<sup>2</sup> and is home to a population of about  
331 12 million people (Figure 2, Figure S5 in Supplementary Information, INSEE 2015).  
332 Since 2012, the amount of UGS has started increasing after a long period of decrease  
333 (Ta et al. 2020). However, the city of Paris remains a very densely populated area with  
334 a low amount of UGS per capita<sup>1</sup>. In 2013, the Île-de-France region adopted a  
335 masterplan that set a regulatory objective regarding UGS access, which should be  
336 achieved by 2030: supplying 10 m<sup>2</sup> of UGS per inhabitant in the region, giving  
337 priority to municipalities with less than 10% of open and natural areas (Institut Paris  
338 Région 2013). To reach this goal, the Green Plan (“Plan Vert”) aims to create 500ha of  
339 additional UGS (Region Ile de France 2017), and the regional master plan aims to  
340 create 2300ha of additional UGS (Institut Paris Région 2013).

341 In this context, our study addresses three questions: (1) Where is the policy target  
342 of 10 m<sup>2</sup>/cap met? (2) Which population groups are disproportionately affected by  
343 UGS deficits? (3) How would the implementation of planned UGS change the UGS

---

<sup>1</sup> According to the Green View Index (GVI) developed by the Massachusetts Institute of Technology, calculated using Google Street View panoramas, showing the percentage coverage of the canopy of a pixel: <http://senseable.mit.edu/treepedia/cities/paris>.

344 deficits?



345

346

**Figure 2. Land use map of Ile-de-France (based on MOS, 2017)**

347

## 348 4.2 Data processing

### 349 4.2.1 Urban greenspace

350

We derived UGS data from an existing dataset for 2017 with 81 land use types

351

(MOS 2017). UGS considered in the analysis include: (1) *forests* (MOS land cover

352

code 1-4, including wood or forests, sections or clearings in the forest, poplar, open

353

spaces with shrub or herbaceous vegetation); (2) *grassland* (MOS 7); (3) *water banks*

354

(MOS 5, banks of waterways without harbor or storage activities); (4) *public parks*

355

*and gardens* (MOS 13 and 25, parks and gardens, animal parks, zoos, amusement

356

parks); (5) *free slots for camping and caravanning* (MOS 24). We did not include

357

private gardens, outdoor sports fields, and golf course due to their restricted access.

358

The total UGS area is 3859 km<sup>2</sup>, equating to 31% of the study area.

359

### 4.2.2 Population

---

360 A disaggregation approach was used to produce a population grid at 100m  
361 resolution. We used IRIS level population census data collected by the National  
362 Institute of Statistics and Economic Studies in 2015 (vector, [INSEE 2015](#)). An IRIS  
363 unit is the smallest census unit available, which comprises between 1,800 and 5,000  
364 inhabitants, with an average area of 10 ha. The population census data also include  
365 sociodemographic characteristics such as age, median available income<sup>2</sup>, education  
366 etc. We projected the population from IRIS units based on the MOS land cover  
367 information (29 to 34, individual habitat, identical individual housing sets, rural  
368 habitat, continuous low habitat, continuous collective housing, discontinuous  
369 collective housing). The derived population map is as in [Supplementary information](#)  
370 [\(Figure S5\)](#).

### 371 **4.2.3 Future scenarios**

372 To illustrate the use of the model for urban planning, we have developed two  
373 spatial scenarios with additional UGS that represent alternative futures  
374 ([Supplementary information Figures S6-7](#)). First, we applied a scenario based on the  
375 Plan Vert that aims to create 500 ha of additional UGS by 2030 ([Région Ile de France](#)  
376 [2017](#)). Second, we applied a more ambitious scenario based on the regional master  
377 plan (“SDRIF”) with the objective to create 2800 ha of additional UGS by 2030  
378 ([Région Ile de France 2013](#)). The two scenarios provide insight into what is possible

---

<sup>2</sup> The IRIS perimeters are joined with socioeconomic data from a large dataset on localized social and tax file (FiLoSoFi) provided by the national statistics institute (INSEE). The median available income corresponds to the median income (among residents in the IRIS) actually available to a household to consume or save, that is the primary income + transfer income - compulsory taxes.

---

379 with various degrees of greening in the region.

380 To develop the spatial scenarios, we first extracted all deficient pixels from the  
381 supply-demand balance at pixel level ( $Balance_i$ ) for the current situation (i.e., with  
382 negative values). A 300m radius focal statistic analysis using ArcGIS was applied to  
383 this selection to incorporate all affected pixels in the subsequent selection steps.

384 For the 500ha new UGS scenario, we selected municipalities that were identified  
385 as *highly deficient* by the Plan Vert. Within these municipalities, 5557 pixels (about  
386 500ha) with the highest UGS deficiency values for land use types *vacant land* (MOS  
387 28), *open air parking* (MOS 75), and *quarries* (MOS 79) were converted to UGS to  
388 obtain the scenario map.

389 For the 2800ha new UGS scenario, we selected municipalities that were identified  
390 as *deficient* by the Plan Vert. Within these municipalities, 31111 pixels (2800ha) with  
391 the highest UGS deficiency values for land use types *vacant land* (MOS 28), *open air*  
392 *parking* (MOS 75), *quarries* (MOS 79), and *industry and business* (MOS 43-50 and  
393 52) were converted to UGS to obtain the scenario map. The *industry and business*  
394 land use types were applied in this scenario to include more highly deficient areas in  
395 the Paris inner city.

### 396 **4.3 Model set-up**

397 To reflect the objectives from the regional masterplan ([Région Ile de France](#)  
398 [2013](#)), we set the per capita UGS demand criterion ( $Dem_{cap}$ ) to 10 m<sup>2</sup> for all analyses.

#### 399 ***Model set-up for question (1): areas meeting the policy target***

400 To assess where the per capita demand was met by the existing UGS (question

---

401 (1)) and demonstrate model calibration using only the policy target set by the [SDRIF](#)  
402 for 2030 ([Région Ile de France 2013](#)) (i.e., 10 m<sup>2</sup>/capita), we used three distance  
403 thresholds ( $d_0$ ) in accordance with the UN's goal and literature (Section 2.1): 300 m,  
404 500 m and 800 m, which equal about 5, 10 and 15 min walking distances,  
405 respectively. The model was run without disaggregation of UGS or population groups  
406 and the dichotomy function was used ([Table 1](#)).

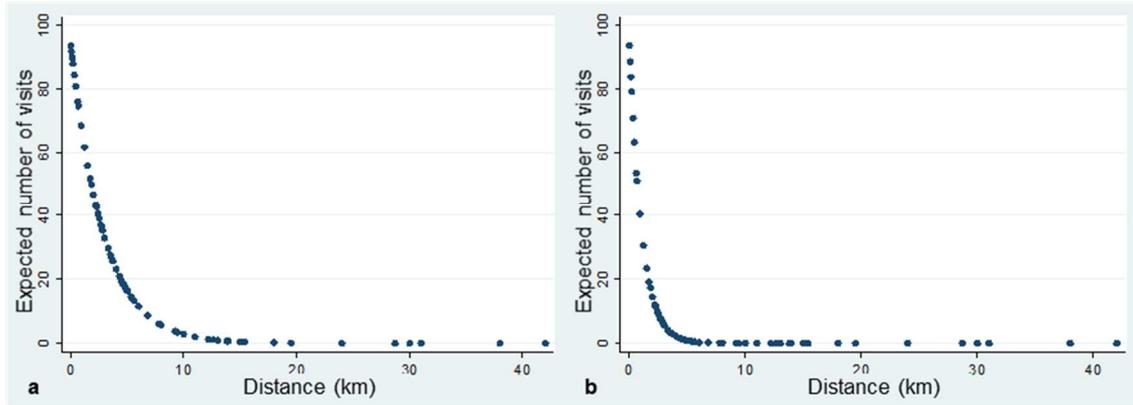
407 ***Model set-up for question (2): population groups disproportionately affected by UGS***  
408 ***deficits***

409 To assess which population groups are disproportionately affected by UGS  
410 deficits (question (2)) and demonstrate model calibration, we used a survey conducted  
411 in the region between April 15th and May 24th 2018. In total, 320 individuals have  
412 been face-to-face interviewed. They were asked to identify their residence, their most  
413 visited park during the year preceding the survey, their travel time to reach the UGS  
414 and the used travel mode. We also asked their number of visits in the park, and socio-  
415 demographic characteristics. The survey details and description of the sample can be  
416 found in [Ta et al. \(2020\)](#).

417 The travel distance between the most visited park and individuals' residence is  
418 calculated with Google maps, by calculating the distance between the respondent's  
419 municipality centroid and centroid of their most visited park. Distances were double-  
420 checked with the stated travel time declared by respondents. We assumed a 3.6 km/h  
421 speed by foot, 16 km/h by bike, and 60 km/h by car and public transport. To obtain the  
422 search radii for different age groups, a Poisson regression was applied to the stated

---

423 number of visits. The count data models such as the Poisson or negative binomial are  
424 commonly used to analyse visitation data, as this type of models is particularly  
425 accurate when the dependent variable is an integer that takes few different values,  
426 such as visitor trips to a destination site (Shaw, 1988, Englin and Shonkwiler, 1995,  
427 Baerenklau et al. 2010, Roussel et al. 2016, Tardieu and Tuffery, 2019). When plotting  
428 the data, we found that the Poisson function best described the decay of visitation  
429 against travelled distance to greenspace in our dataset. This is confirmed by likelihood  
430 ratio test on alpha, representing the dispersion parameter in our regression, which  
431 showed that our dataset was not overdispersed, justifying here the use of a Poisson  
432 model over a negative binomial model. Visits have been regressed according to age  
433 class (coded as a dummy variable 1 if older adult: above 60 and 0 if adult: 18-60), and  
434 distance. The regression results can be found in [Supplementary information Table S4](#).  
435 Accordingly to this Poisson regression, we derived the expected number of visits in a  
436 year and the expected distance traveled by the two age groups accordingly to the  
437 distance decay estimated for each group. Results showed that being older than 60  
438 years old increases the probability of visits compared to being younger but decreases  
439 the willingness to travel implying a search radius for older adults lower than the one  
440 for adults ([Figure 3](#)). The search radius for adults ( $d_{0, \text{adult}}$ ) has been estimated at  
441 2860m in average, and the search radius for older adults ( $d_{0, \text{elder}}$ ) at 1060m in average.  
442 We used the Poisson regression function as the decay function in the tool.



443

444 **Figure 3. Distance decay effect on the expected number of visits to UGS for population under**  
 445 **(a) and over (b) 60 years-old**

446

447 ***Model set-up for question (3): expected change in UGS deficits***

448 To assess how the scenarios would impact the UGS supply and demand (question  
 449 (3)), we used a search radius of 300 m and the “dichotomy” decay function. To  
 450 understand the impacts of the UGS planning scenarios on population subgroups, we  
 451 analyzed the income level of the population for whom UGS supply improved.

452

453 **Table 1. Input data and model settings for analyzing each UGS question (see text for**  
 454 **details)**

Input data	Question 1	Question 2	Question 3
Greenspace	MOS81 <sup>a</sup>	MOS81 <sup>a</sup>	Scenarios <sup>b</sup>
Population raster	100m raster <sup>c</sup>	100m raster <sup>c</sup>	100m raster <sup>c</sup>
Population structure	Census data <sup>c</sup>	Census data <sup>c</sup>	Census data <sup>c</sup>
Model expansion	Default	Split population	Default
Demand	10m <sup>2</sup> /cap <sup>d</sup>	10m <sup>2</sup> /cap <sup>d</sup>	10m <sup>2</sup> /cap <sup>d</sup>
Search radius(m)	300, 500, 800 <sup>d,e</sup>	Adult: 1060 <sup>f</sup> Older adult: 2860 <sup>f</sup>	300 <sup>d</sup>
Decay function	dichotomy <sup>d</sup>	Poisson <sup>f</sup>	dichotomy <sup>d</sup>
Data sources	<sup>a</sup> : MOS 81 categories for the year 2017, available upon convention with the Institut Paris Region. MOS 11 available at <a href="https://data.iledefrance.fr/explore/dataset/mode-occupation-du-sol-mos-en-11-postes-en-2017/information/">https://data.iledefrance.fr/explore/dataset/mode-occupation-du-sol-mos-en-11-postes-en-2017/information/</a> <sup>b</sup> : Scenarios developed as in section 4.2.3 <sup>c</sup> : iris population census data available at: <a href="https://www.insee.fr/fr/statistiques/3627376">https://www.insee.fr/fr/statistiques/3627376</a> <sup>d</sup> : policy target; <sup>e</sup> : literature <sup>f</sup> : survey in section 4.3 <i>Model calibration for question (2)</i>		

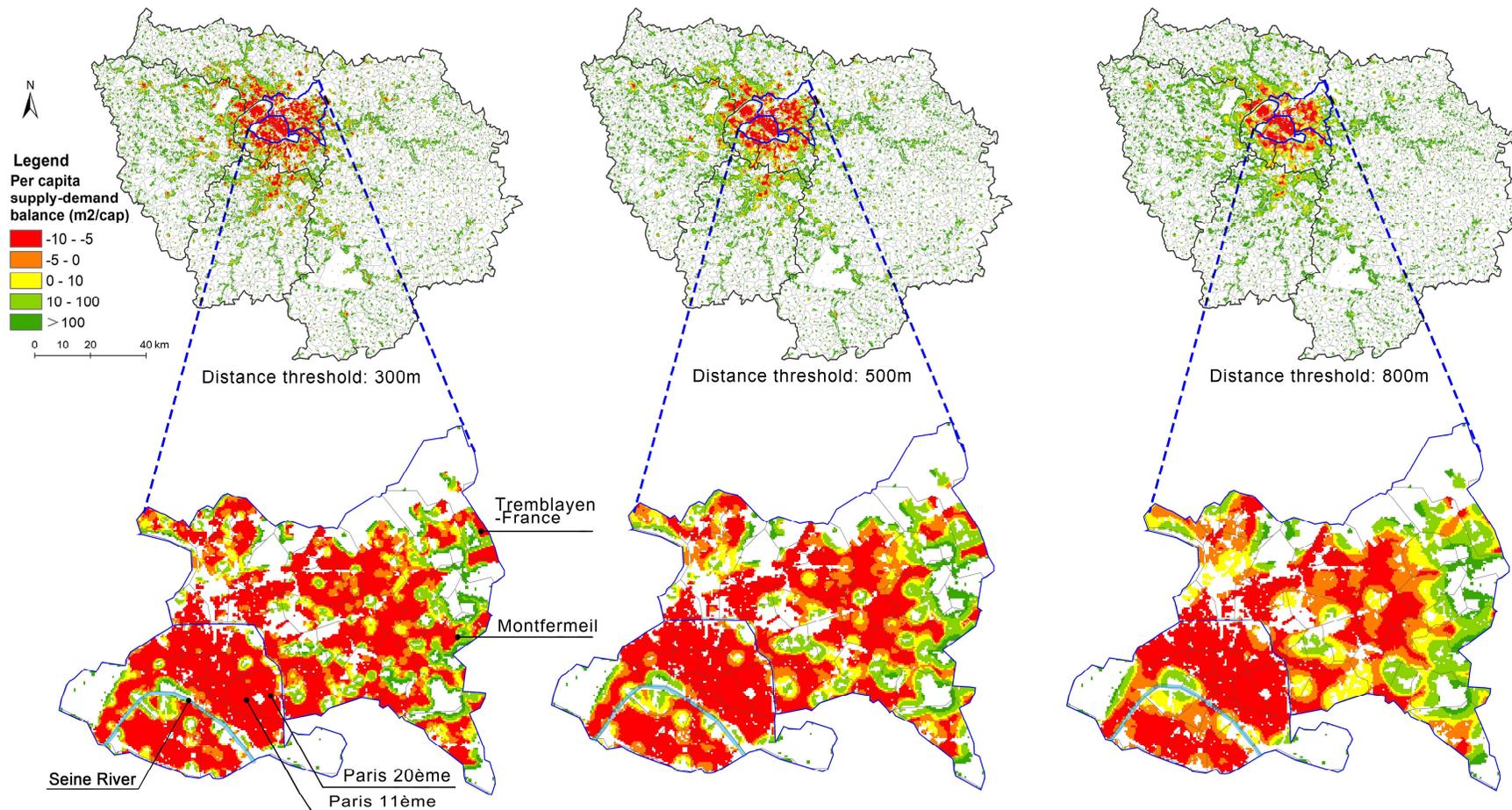
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## 455 4.4 Recreation service in Île-de-France

### 456 4.4.1 Recreational UGS supply-demand balance against policy standard

457 The per capita UGS balance at pixel level is shown in [Figure 4](#). Most deficit  
458 areas are located in the city center where population density is high. For the Paris city  
459 limits, the majority of people live in areas with a UGS deficit (300m threshold),  
460 although residential areas near large parks and along the Seine river have a UGS  
461 surplus. [For municipalities close to large UGS, the deficit decreased as the distance](#)  
462 [thresholds increased from 300m to 800m \(e.g., Montfermeil, Tremblay-en-France\).](#)  
463 [However, for municipalities in Paris limits, the deficit remains even distance](#)  
464 [thresholds increases \(e.g., Paris 11ème and Paris 20ème\).](#)

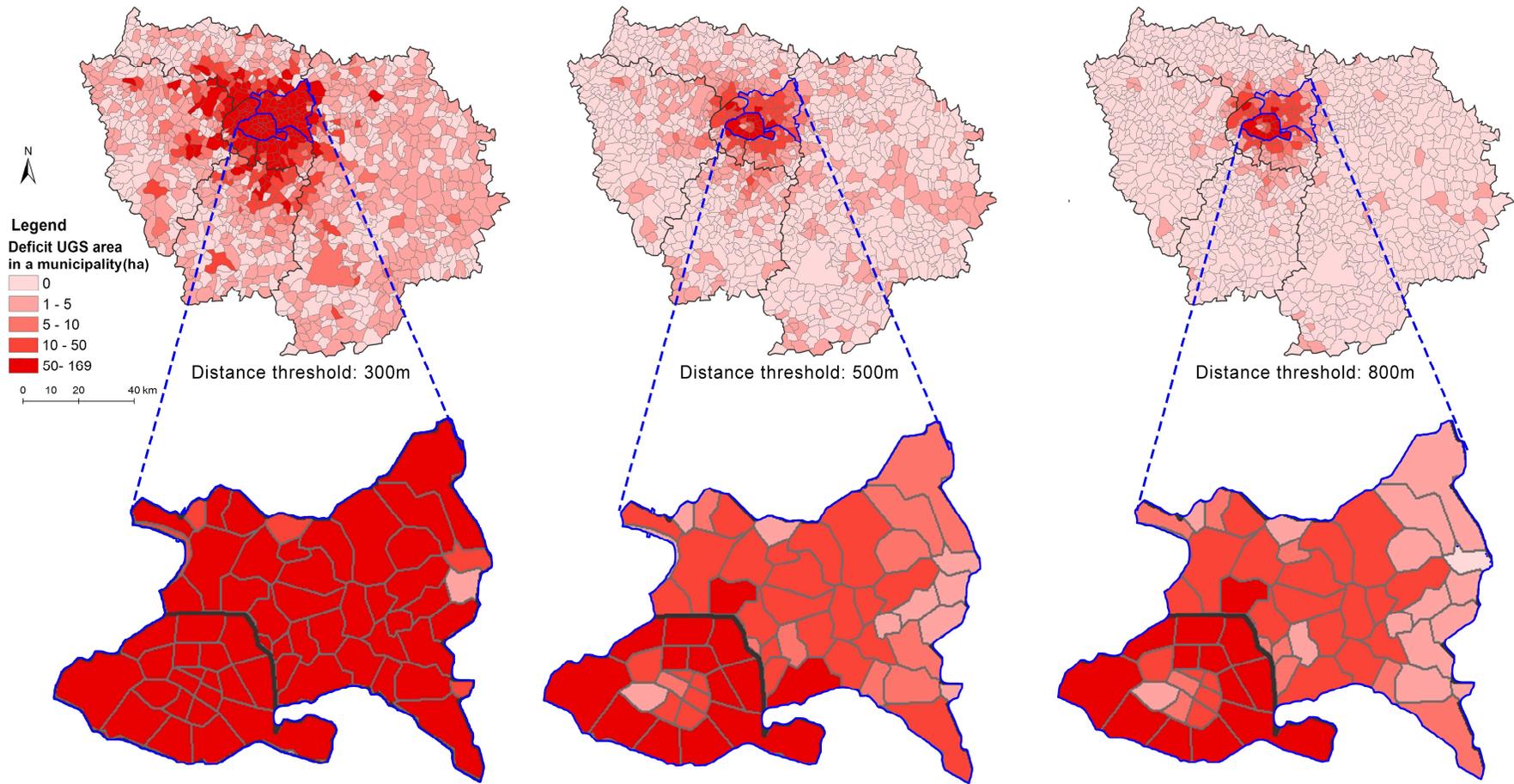
465 The UGS deficit area and percent of population under the recommended standard  
466 aggregated at the municipal level are shown in [Figures 5](#) and [6](#). In accordance with  
467 pixel level results, deficit municipalities are mainly concentrated in inner-city areas  
468 and their number decreased with increasing distance thresholds from 300m to 800m.  
469 Many municipalities have a small or no UGS deficit: 505 and 1084 out of 1300  
470 municipalities have no UGS deficit using 300m and 800m as search radii respectively  
471 [\(Table 2\)](#). However, at regional level, with the 300m radius, the total UGS area deficit  
472 is 4396 ha and the population with a UGS deficit accounts for 55% of the total  
473 population. With the 800m radius, the total UGS area deficit is 2810 ha and the  
474 population with a UGS deficit accounts for 42% of the total population.



475

476 **Figure 4. Recreation service balance (per capita UGS supply-demand balance,  $Balance_{cap,i}$ ) in Ile-de-France region for different distance thresholds (m<sup>2</sup>/cap).**

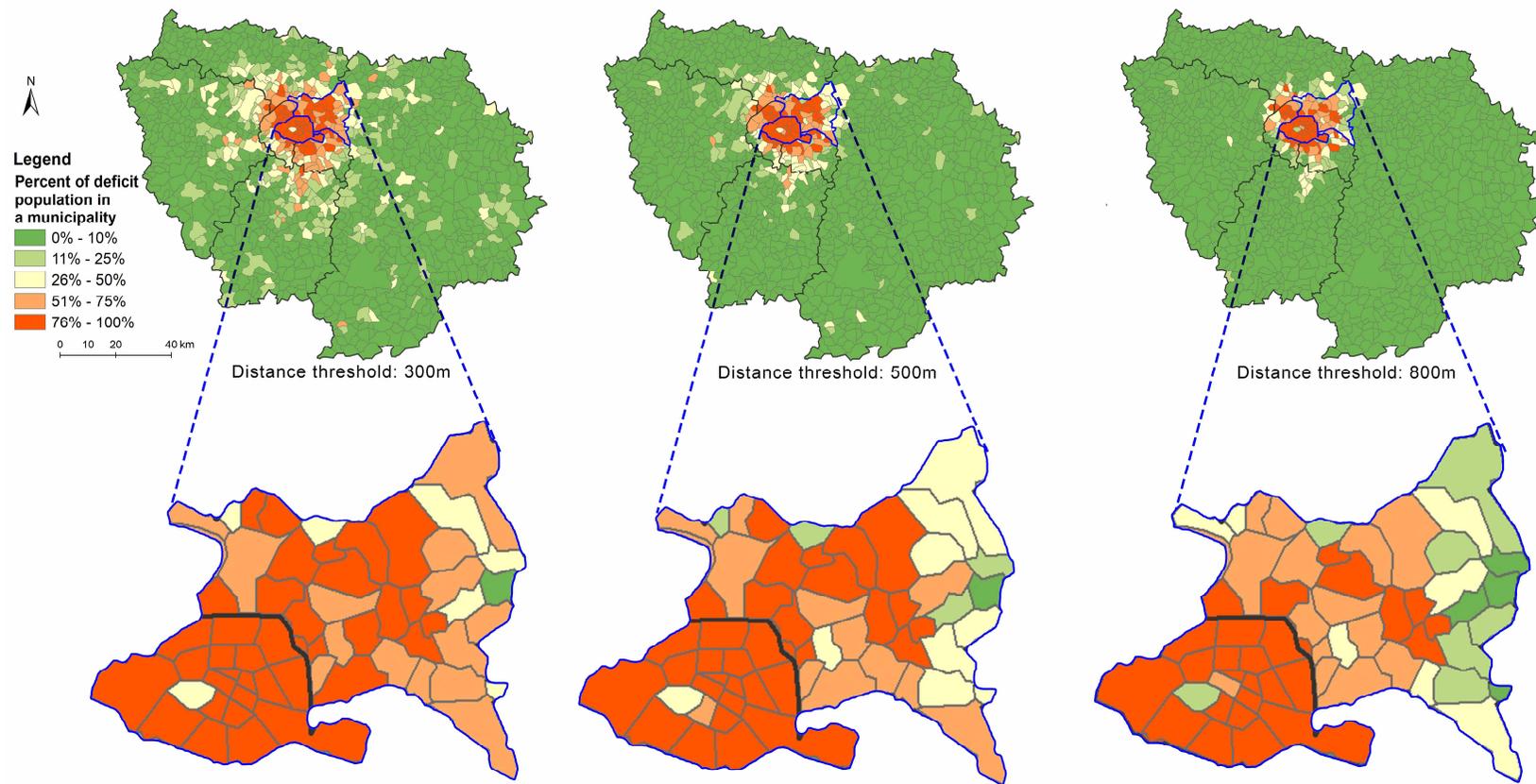
477 Blank areas mean there is no population on the pixel.



478

479

**Figure 5. Recreation service deficit ( $Def_{adm}$ ) in Ile-de-France region, for different distance thresholds. Policy target: 10 m<sup>2</sup>/capita**



480

481

**Figure 6. Percent of population below the policy target ( $pop_{def,adm}$ ) in Ile-de-France region, for different distance thresholds. Policy target: 10 m<sup>2</sup>/capita.**

482  
483

**Table 2. Number of municipalities associated with deficit UGS area and percent of deficit population using different distance thresholds**

Deficit indicator and levels		No. of municipalities in relation to UGS deficit levels		
		300m	500m	800m
Deficit UGS area (ha) in a municipality	0	505	886	1084
	0-5	639	291	128
	10	48	42	24
	10-50	90	64	50
	50-169	18	17	14
	Municipal mean	3.38	2.67	2.16
Region total		4396	3475	2810
Percent of population under UGS deficit in a municipality	0%-10%	901	1073	1147
	11%-25%	155	62	36
	26%-50%	100	64	36
	51%-75%	75	41	30
	76%-100%	69	60	51
	Region total	55%	48%	42%

484

Note: Total population: 12.08 million. Total number of municipalities: 1300

485

#### 4.4.2 Recreational UGS supply-demand balance among different age groups

487

There is a striking difference between the supply-demand balance between adults and older adults (Figures 4 and 5). The total number of older adults with a UGS deficit is 1,610,208 and number of adults with a deficit is 2,523,292. Adults with less than 10 m<sup>2</sup> UGS per capita are concentrated in a few inner-city municipalities, while the deficit among older adults is more widespread. For both adults and older adults, a higher percentage of people with a deficit are observed in and directly around Paris.

493

#### 4.4.3 Supply-demand balance in future scenarios

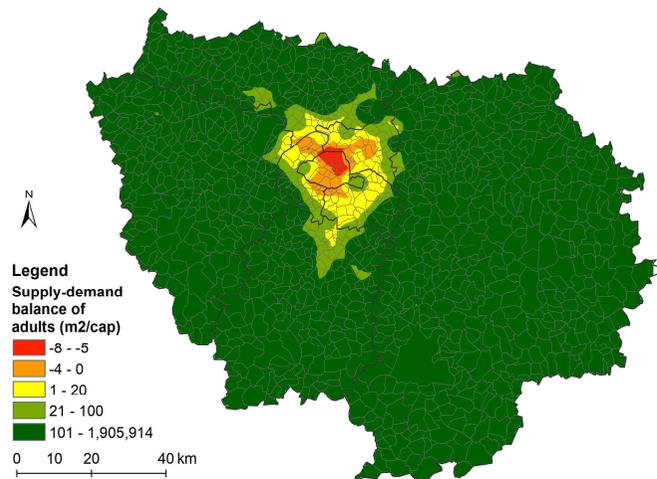
494

Scenario 1 (500ha additional UGS) reduced the UGS deficit by 360ha, accounting for 8% of total UGS area deficit. This scenario elevated 270,639 people's UGS access over the 10m<sup>2</sup> UGS per capita policy target, alleviating 4.1% of total deficit population. Scenario 2 (2800ha additional UGS) reduced the UGS area deficit

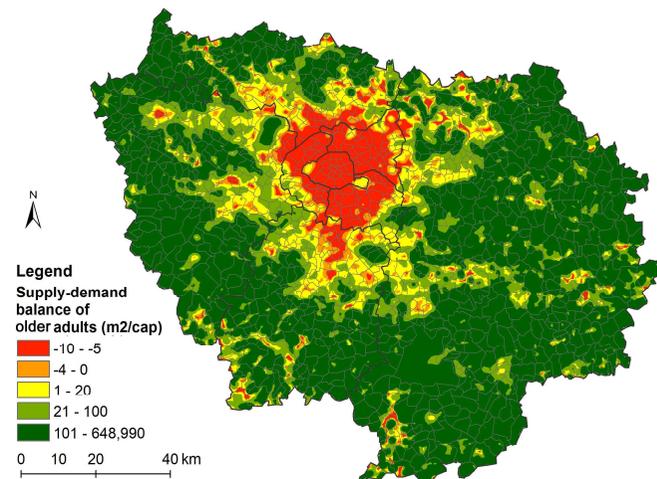
497

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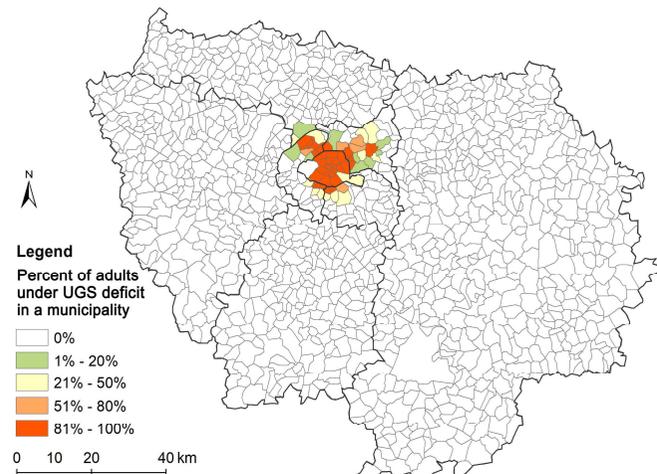
498 by 1582ha, accounting for 36% of the total UGS area deficit (Figure 8 a,c). This  
499 scenario reduced the number of people under UGS deficit by 1,381,591 accounting  
500 for 21% of the deficit population (Figure 8 b,d). Among the reduced deficit  
501 population, the majority were in the lowest income quantiles (64% and 80%  
502 respectively for Scenario 1 and 2) (Table 3).



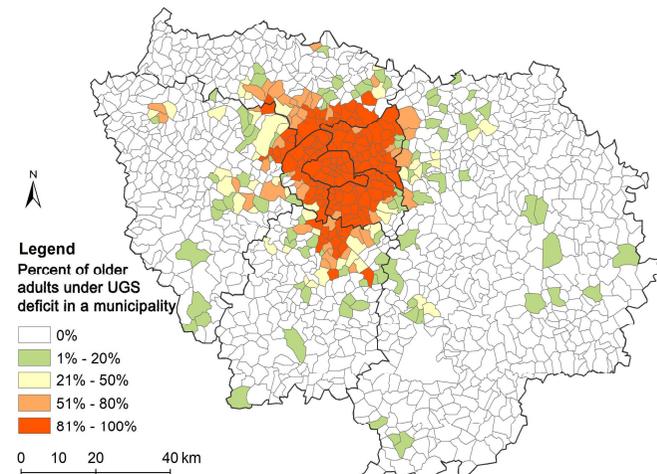
(a) Pixel level supply-demand balance of adults (m2/cap)



(b) Pixel level supply-demand balance of older adults (m2/cap)



(c) Percent of adults under deficit

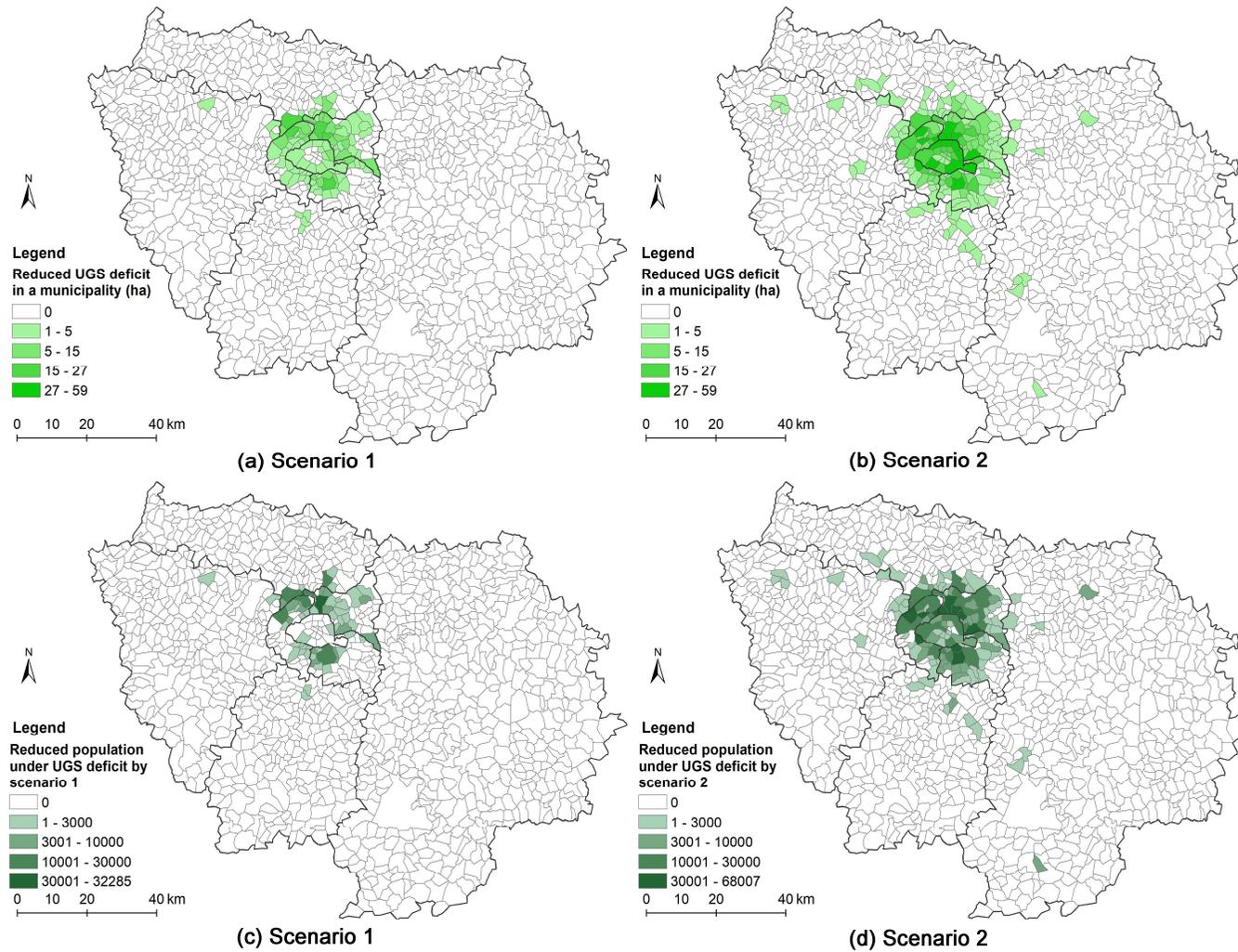


(d) Percent of older adults under deficit

**Figure 7. (a-b) Supply-demand balance , and (c-d) percent of population under UGS deficit, for different age groups. Policy target: 10 m<sup>2</sup>/capita**

503

504



505  
 506

**Figure 8. Reduced UGS deficit (top row) and population deficit (bottom row) in scenario 1 (maps a, c) and scenario 2 (maps b, d)**

507

**Table 3. Percent of reduced deficit population in each income quantile by two scenarios**

Income quantile	Percent of reduced deficit population in each income quantile	
	Scenario 1	Scenario 2
Lowest 25%	55.5%	40.5%
50%	25.2%	24.0%
75%	13.7%	16.7%
Highest 100%	5.6%	18.8%

508

## 509 **5 Discussion**

### 510 **5.1 Recreation service in Ile-de-France**

511 Although UGS accounts for 31% of land surface area in the Ile-de-France region,  
 512 55% of population have less UGS than the desired target. An additional 4396 ha is  
 513 required to meet the policy target for every inhabitant indicating that the master plan  
 514 and Plan Vert objectives are not ambitious enough with regard to this service.  
 515 Recreational UGS deficit showed a clear concentric pattern: high deficit areas are  
 516 located in a few high-density municipalities in and around the city center, while high  
 517 surplus areas are located in peripheric area, making the development of UGS in these  
 518 deficient municipalities even more difficult (Liotta et al. 2020). This is not unusual,  
 519 especially in large cities such as Paris, Guangzhou (Liu et al. 2020), or cities with  
 520 historic central neighborhoods such as Amsterdam (Paulin et al. 2020).

521 When including dwellers' preferences and use in the model, an important finding  
 522 emerges. The spatial difference in deficit in UGS between the general adult population  
 523 and older adults (Figure 7) is important and can be explained by the fact that elder  
 524 people are less likely to travel long distances to reach a UGS (represented by a

---

525 stronger distance decay than younger people), even though they are generally the most  
526 frequent visitors (Bateman et al. 2003). This has been observed in Ile-de-France  
527 through the revealed preference analysis conducted in this study (Supplementary  
528 information Table S4) and through the stated preferences obtained from a choice  
529 experiment (Ta et al. 2020). This suggests that older adults are disproportionately  
530 affected by the UGS deficit in Paris, having less opportunities to access UGS. Given  
531 the benefits of UGS for the ageing population, this finding could be used to promote  
532 UGS areas that respond to specific needs of this population group. In Ta et al. (2020),  
533 conducting a choice experiment study in the region, this population showed a clear  
534 preference for the walking transport mode on short distances (~1000 m), having  
535 access to UGS with trees no matter the size of the UGS. Thus for this population what  
536 matters is not a minimum surface of UGS but an easy access to wooded areas.

537       Although the 10m<sup>2</sup>/cap target is not very high compared with policy standards  
538 from other cities (Badiu et al. 2016), scenario analyses showed that in a densely  
539 populated city like Paris, achieving this goal is difficult due to the lack of available  
540 vacant land. In Ile de France, we found that most convertible land was located in areas  
541 with UGS surplus, and usually far from Paris. Conversely, in highly deficit areas there  
542 were not enough land to build UGS. Although converting business and commercial  
543 land (Scenario 2) would be costly, our results shows that it would be effective in  
544 changing the UGS supply-demand balance. This transformation is possible in urban  
545 renewal programs where old infrastrucutre, industrial or residential land can be  
546 converted. Building UGS in these area can bring significant accessbile recreation

---

547 opportunity to people along side other ES which should be considered to justify the  
548 cost (Song et al. 2019). Other options would involve retrofitting buildings with  
549 rooftop parks, greening courtyards and school yards, or altering street scapes to create  
550 greenways along roads, which would create additional greenspace for people to  
551 recreate (Manso et al. 2021).

552 Our scenario analyses also illustrate the importance of the accessibility criteria to  
553 identify priority areas for UGS investment. We used the Plan Vert to target our UGS  
554 implementation, where the municipalities were identified based on the criteria of  
555 access to greenspace as well as “attenuating or aggravating factors” such as the  
556 presence of other vegetation type (e.g., agricultural areas) or future urban  
557 densification plans. Targeting these municipalities while allowing UGS creation only  
558 in a few land use categories, meant that the amount of UGS added to the area (500  
559 and 2800 ha, respectively, for each scenario) is less than the reduction in deficit (360  
560 and 1582 ha, respectively). Although this study was conducted for illustrative  
561 purposes only, additional iterations with stakeholders could reveal more optimal  
562 scenarios based on commonly agreed UGS supply criteria (e.g., distance to UGS, type  
563 of UGS considered, and type of conversion allowed to increase UGS supply, etc.).

## 564 **5.2 Strengths of the geospatial tool**

565 Here we have presented and applied a UGS supply-demand assessment model  
566 that facilitates urban planning through a multi-scale approach. In previous models,  
567 recreation service is often measured by population with access to UGS within a  
568 certain distance (Geneletti et al. 2022, Cortinovis and Geneletti, 2018b, Sikorska et al.

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569 2020). Thus, these models obfuscate the differences between a crowded residence  
570 community that has access to a small UGS and an uncrowded residence community  
571 that has access to a large UGS. Our model takes these situations into account by  
572 measuring the recreation service using UGS area per inhabitant. Also, previous  
573 models typically assign weights to UGS quality indicators and produce a  
574 dimensionless composite indicator to represent recreation opportunity (Cortinovis and  
575 Geneletti, 2018, Stessens et al. 2017). Our model assigns different search radii and  
576 decay functions to different types of UGS and represents the corresponding recreation  
577 service using indicators with clear biophysical meaning (i.e., area of different types of  
578 UGS per person) which is easier for model users to understand. Our tool calculates the  
579 recreational supply-demand balance at the pixel and administrative levels. Pixel level  
580 supply-demand balance information can identify areas with highest deficiencies—  
581 where new UGS will most effectively mitigate a UGS deficit for recreation. The  
582 analysis at the administrative level supports a multifaceted analysis of UGS supply  
583 and demand by estimating the population under UGS deficit or surplus, differentiating  
584 between socio-demographic profiles. This information helps moving beyond  
585 “standards-based” approaches (Wilkerson et al. 2018), and allows model users to  
586 iterate and test different UGS planning scenarios. The model is currently available in  
587 an online visualization platform that facilitates comparing the impacts of different  
588 planning scenarios (Supplementary Information B). The advanced options of the  
589 model allows non-specialists to integrate information on citizen’s preferences and use,  
590 and to easily map the demand according to different distance decays and probabilities

---

591 of visit. This is, to our knowledge, the first online tool enabling these functions. The  
592 integration into InVEST as an open source model will allow users to run multiple  
593 ecosystem service models for a single study region ([Sharp et al. 2020](#)).

594 The Ile-de-France case study demonstrated how the model works with widely  
595 available data (land cover, population, and a policy target for UGS availability) to  
596 provide policy-relevant informations to urban planners. The flexible data requirement  
597 is an important feature, making the model applicable in cities with less data  
598 availability. Land cover and population data are available globally with increasingly  
599 high resolution ([GHSL 2019](#), [Urban Atlas 2018](#), [Worldpop 2017](#)). Therefore, the  
600 model can be particularly relevant in rapidly developing cities in the global South  
601 where UGS analyses have not been conducted routinely ([Rigolon et al. 2018](#)). The  
602 model can provide results sensitive to socio-demographic composition and allow to  
603 identify the beneficiaries of UGS investment. For example, in our case study we  
604 found that the scenario developed according to Plan Vert and SDRIF master plan  
605 predominantly benefitted people (IRIS) with the lowest median available income. The  
606 model also allows to implement more sophisticated assessment based on recreational  
607 surveys to consider individuals' preferences, widely hererogeneous regarding  
608 recreational activities.

### 609 **5.3 Limitations and potential improvements**

610 Despite its strengths, the tool may be not be appropriate for all recreational  
611 activities. For example, since the model provides a static picture of UGS and  
612 population locations, its usefulness is limited for activities such as running or cycling,

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613 where UGS users can cover long distances. Future improvements to the model could  
614 include different accessibility indicators for UGS and include road and pedestrian  
615 networks to better represent the idea of the “cognitive distance” for users to reach  
616 UGS (Montello 1991).

617 Another limitation of the model is that it expresses results in area per inhabitant  
618 and does not output economic or health and well-being indicators (although it can  
619 include preferences as an input). Future work could expand the indicators to facilitate  
620 economic valuation, at different scales. Revealed preferences as hedonic prices or  
621 stated preferences such as choice experiments approaches have been extensively used  
622 in urban areas to estimate the willingnesses to pay of dwellers for each visits  
623 (Choumert and Salanie 2008, Tu et al. 2016). As we also have expressed the  
624 “willingness to travel” of people in the Poisson regression (based in the travel cost  
625 technique intuitions), or in a choice experiment (Ta et al. 2020), our indicator of  
626 preference (distance or time) could be transformed into a monetary indicator for  
627 individuals. However their implementation typically varies with socio-economic and  
628 demographic context, making a standard approach and a standard evaluation difficult  
629 to implement in the tool.

## 630 **6 Conclusion**

631 We have developed a tool that supports the assessment of recreational supply and  
632 demand in urban environments. The tool’s main strengths are: (i) spatially explicit  
633 assessment of recreational UGS supply and demand based on commonly available  
634 data (land cover, population rasters); (ii) disaggregation of results by population group

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635 or UGS type; (iii) compatibility with simple quantitative and qualitative planning  
636 strategies (e.g., UGS per inhabitant standard, survey of population UGS preferences);  
637 and (iv) rapid and easily-accessible online implementation and visualization platform  
638 that facilitates comparison and communication of impacts of different UGS planning  
639 scenarios. A case study in Paris demonstrated the application of the tool to address  
640 questions such as: 1) Where is the policy target of 10 m<sup>2</sup>/cap met? (2) Which  
641 population groups are disproportionately affected by UGS deficits? (3) How do UGS  
642 implementation scenarios change the UGS deficits? We showed how older adults may  
643 be differently affected by UGS deficits, and how the criteria for UGS accessibility  
644 impacts policy recommendations in practice. This type of analysis helps nuance the  
645 assessment of UGS by providing more information on the beneficiaries of UGS  
646 implementation scenarios, thereby improving the integration of the UGS recreation  
647 service in ecosystem-based approaches to urban planning.

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