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Citation for final published version:

Xu, Shen, Li, Zhixin, Zheng, Chen, Huang, Zhaojin, Tian, Jia, Lou, Yongqiang and Du, Hu ORCID: <https://orcid.org/0000-0002-1637-0626> 2021. A method of calculating urban-scale solar potential by evaluating and quantifying the relationship between urban block typology and occlusion coefficient: a case study of Wuhan in central China. *Sustainable Cities and Society* 64 , 102451. 10.1016/j.scs.2020.102451 file

Publishers page: <https://doi.org/10.1016/j.scs.2020.102451>  
<<https://doi.org/10.1016/j.scs.2020.102451>>

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1 **A method of calculating urban-scale solar potential by**  
2 **quantitating and evaluating the relationship between block**  
3 **typology and occlusion coefficient, a case study of a city in middle**  
4 **China**

5 **Abstract:**

6 The existing macro-city-scale solar roof utilization potential assessment method is not  
7 capable of considering the factor of mutual occlusion between urban buildings, and only  
8 makes use to one empirical value for the entire urban rooftop potential calculation. Relevant  
9 research shows that under different occlusion conditions, the potential of solar energy  
10 utilization varies greatly. This paper selects urban blocks with different morphological  
11 characteristics as the research objects, and analyses and quantifies the influencing factors of  
12 solar potential of urban roofing. To measure the overall solar potential of the city, it is  
13 necessary to quantify the occlusion caused by the urban environmental building roof. The  
14 urban blocks in different types and functions of buildings have different occlusions on the  
15 building roof. To quantify these differences, this paper uses typical high-density blocks.  
16 Taking Wuhan as an example, a large number of urban block examples were selected as  
17 research samples, a large number of urban block form indicators were counted, and data sets  
18 covering six types of morphological indicators such as building density, building height,  
19 floor-area ratio and orientation were established. The difference between the morphological  
20 indicators of the block was used to classify the urban blocks, and then the solar radiation  
21 simulation of the above blocks was modelled and simulated. The solar radiation values of  
22 different blocks were obtained and combined with their morphological parameters. Linear  
23 regression was used to obtain different roof solar occlusion factors for different block types.  
24 They are 0.099, 0.054, and 0.025, and the overall roof occlusion coefficient of the city is  
25 0.079.

26 **Keywords:**

27 Solar energy; Urban energy; Occlusion coefficient; K-means clustering algorithm

28

## 29 **1. Introduction**

### 30 **1.1 Expansion of solar energy utilization to urban scale**

31 The energy crisis and environmental pollution have always been major problems facing the  
32 world and are becoming increasingly serious. Urban energy consumption is an important part  
33 of global energy consumption evaluation. Related studies show that by 2030, 75% of energy  
34 consumption will come from cities (Cities and Climate Change, 2010). In order to meet  
35 people's growing demand for energy, renewable energy has become a hot topic for people to  
36 study. Compared with other renewable energy sources, such as wind energy and geothermal  
37 energy, solar energy is one of the few new energy sources that can be applied on a large scale  
38 in urban environments. The development and utilization of solar energy has received extensive  
39 attention and has been rapidly spread worldwide. Over the past decade, the global solar  
40 photovoltaic market has grown rapidly by 50%. The International Energy Agency (IEA)  
41 predicts that by 2050, the global share of electricity from photovoltaic (PV) systems will reach  
42 16%. At present, the application of solar energy in single buildings has been relatively mature  
43 (Aaditya & Mani, 2017; *Technology Roadmap: Solar Photovoltaic Energy*, 2010). Based on this,  
44 research on solar energy utilization in urban environments has also begun to develop in a  
45 continuous and large-scale manner. At the same time, research on the potential of urban solar  
46 photovoltaic utilization in the world is quite extensive and has gradually moved towards  
47 applications. Therefore, it is of great scientific significance and application value to carry out  
48 research on the impact of urban-scale photovoltaic power generation utilization potential.

### 49 **1.2 Existing problems in traditional methods of measuring solar photovoltaic utilisation** 50 **potential**

51 For the calculation of traditional solar photovoltaic potential, more software has been  
52 developed. Among these kinds of software, there is the Ladybug tool based on the Rhino and  
53 Grasshopper platform, and the CitySim software (D. Li et al., 2015; Ouria & Sevinc, 2018).

54 These kinds of software build the radiation model of the photovoltaic module (POA) by  
55 sunlight and accumulate the solar radiation over time to obtain the annual production capacity  
56 of the photovoltaic system. This type of method is called a method based on solar irradiance.  
57 However, for the calculation of solar energy potential at the city scale, the time-consuming  
58 accumulation method is too heavy and has little practical significance. For example, when  
59 determining the location of distributed solar energy in a city, methods at the city scale include  
60 the In My Backyard tool, the PVSITES project, and various GIS software-based methods  
61 (Anderson et al., 2010; Espeche et al., 2017). The PVSITES project is a large-scale  
62 photovoltaic installation and promotion project based on urban-scale solar potential  
63 distribution.

64 The estimation of urban-scale solar potential uses a top-down approach, which requires  
65 quantification of building roof area and urban environmental occlusion. Large-scale urban  
66 roof area information can be obtained using GIS data, neural network recognition methods  
67 for urban satellite images, and statistical methods for sampling estimation. A large number of  
68 studies have shown that neither the solar radiation distribution at the macro scale nor the  
69 quantification of roof area statistics is a problem (Araya-Muñoz et al., 2014; Bergamasco &  
70 Asinari, 2011; Kaynak et al., 2018; Y. Li et al., 2016; Wiginton et al., 2010). However, the  
71 quantification of urban environmental occlusion often lacks attention in the estimation of  
72 large-scale solar energy potential.

73 The quantification of the impact of dynamic shadow occlusion on solar energy between  
74 buildings is often not considered or only a unified empirical value is taken into consideration.  
75 The concept of occlusion and available roof area is used to introduce the concept of  
76 installation factors. Salvador Izquierdo et al. analyzed the roof installation factors of 17 types  
77 of buildings in Spain and found that the installation factor of roofs in Spain is about 0.78, but  
78 their research did not distinguish the types of buildings (Izquierdo et al., 2008); Luca

79 Bergamasco et al., in the photovoltaic utilization potential, classified the roof installation  
80 factors according to buildings, where the roof installation factors of residential and industrial  
81 plants were taken as 0.7 and 0.9, respectively (Bergamasco & Asinari, 2011). However, no  
82 systematic independent consideration of the impact of occlusion issues on solar potential has  
83 been accounted for. Considering that the city is a complex environment, the distribution of  
84 solar radiation affected by the occlusion problem is very uneven (Lobaccaro & Frontini,  
85 2014), and the determination of the occlusion factor in the traditional method lacks a certain  
86 science. The dynamic shadow occlusion of the building surface has a great impact on solar  
87 energy utilization, which makes it difficult for the traditional large-scale quantification  
88 method of solar radiation on the building surface to treat streets with different occlusion  
89 conditions fairly, so it is difficult to play a role in actual planning and utilization.

### 90 **1.3. Review of the research on the relationship between block morphology and block** 91 **solar energy shielding**

92 Occlusion is ignored because of the many influencing factors affecting the potential of solar  
93 photovoltaic utilization in cities. The environmental occlusion of a block is affected by the  
94 difference in weather conditions and the shape of the block, which is one of the most difficult  
95 factors to quantify. Among them, Taehoon Hong et al. studied the photovoltaic utilization  
96 potential of Gangnam District, Seoul, and estimated the photovoltaic utilization potential of  
97 the entire neighborhood. It was found that under the condition of real neighborhoods, the  
98 impact of blockages on photovoltaic utilization potential varies greatly. However, it is only  
99 described as an example (Hong et al., 2017). Kanters used the simulation software, Ecotect,  
100 to study the impact of urban density, land area, floor area ratio, and orientation on the use of  
101 shaded solar energy generated by the setting according to the two indicators of photovoltaic  
102 potential and power satisfaction rate. It is found that if the design is not reasonable, the solar

103 potential will decrease by 10% ~ 75% (Kanters, Wall, & Dubois, 2014; Kanters, Wall, &  
104 Kjellsson, 2014). These studies show that due to differences in climatic conditions, block  
105 shapes, density, and building spacing, the potential for solar energy caused by the mutual  
106 block between buildings in the blocks is significantly different. However, the occlusion of the  
107 block is not systematically analyzed according to the block type. Since the same types of city  
108 blocks have similar morphology, and the occlusion conditions caused by the morphology also  
109 have similarities, the typology classification of city blocks can be performed first, and the  
110 occlusion analysis for different types of blocks can be effective by simplifying calculations  
111 and making city data more accessible.

112 The clustering method is used to classify the blocks through the classification and calculation  
113 of the morphological parameters of different blocks in the city, and then carrying out a  
114 systematic research on each type of block, which can quickly and truly reflect the occlusion  
115 of the block in the city. Cluster analysis is an exploratory data analysis tool whose purpose is  
116 to organize a set of items (usually represented as a vector of quantitative values in a  
117 multidimensional space) into clusters to make the items in a given cluster highly similar (de  
118 Souza & de Carvalho, 2004), and belonging to different clusters has a high degree of  
119 similarity. In the study of urban air pollutants, Jing Zhang et al. used the K-means clustering  
120 algorithm to analyze the air pollutant types and proportion data, and obtained a cluster  
121 analysis of 74 cities in China (Zhang et al., 2016). Li Xinyi et al. combined the city's 2D  
122 satellite images and 3D building information and applied cluster analysis to the prototype  
123 classification of residential buildings to obtain the spatial distribution of different types of  
124 residential buildings in the city and the energy distribution characteristics of urban residential  
125 buildings (X. Li et al., 2018). The clustering method can classify a large amount of data with  
126 similarity and has high reliability.

127 It is necessary to quantify the occlusion impact according to the block type, and then quickly  
128 obtain the amount of solar radiation available on the building surface through the building  
129 surface area, and evaluate the power generation potential of distributed photovoltaic energy  
130 on urban buildings, which has an important role in improving energy efficiency and  
131 optimizing the energy structure of cities.

132 The purpose of this study is to solve the problem of mutual occlusion and neglect between the  
133 built environments in the calculation of urban-scale solar photovoltaic utilization potential.  
134 Based on the morphological characteristics of the city blocks, a clustering algorithm is used  
135 to classify them. The research can obtain the corresponding shielding coefficients and realize  
136 the problem of obtaining the spatial distribution characteristics of the solar photovoltaic  
137 utilization potential in the middle of the city through the shielding coefficients, and provide  
138 the basis for the overall solar building planning in the city.

## 139 **2. Dataset and Methods**

140 In this paper, the research on urban block occlusion is carried out in five steps [Fig.1].

141 The first step is to obtain real block sample data. At this stage, field surveys, satellite maps,  
142 and street view pictures are used to obtain multidimensional parameters of city blocks, and a  
143 database is established based on various block morphological index types.

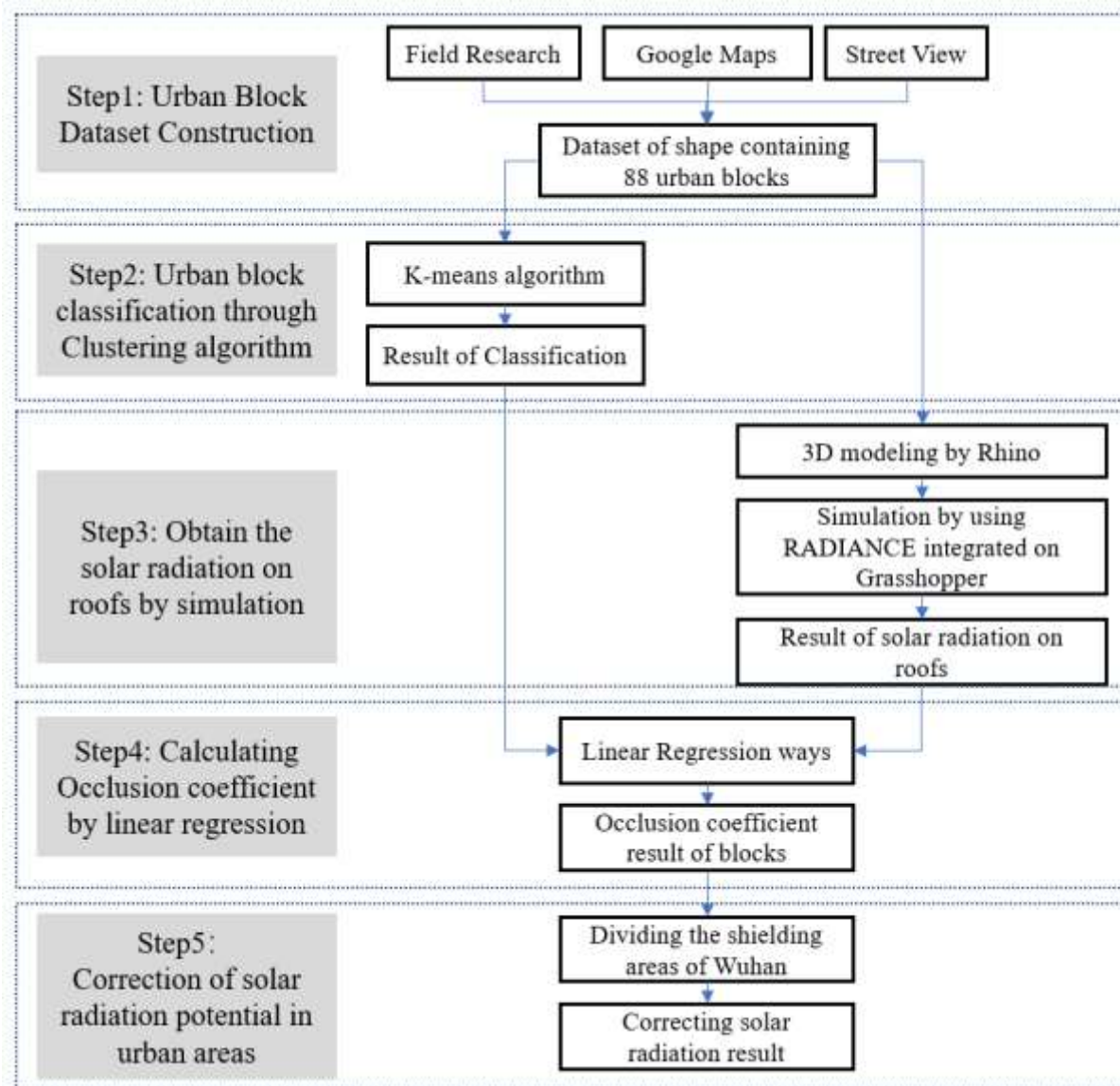
144 The second step is to classify the blocks. At this stage, the clustering algorithm is used to  
145 classify the blocks according to their morphological indicators, and the block types are  
146 analysed based on the classification results.

147 The third step is to calculate the solar radiation value of the above block. This step obtains  
148 data by using software simulation on the block model. The fourth step is to calculate and



149 analyse the average occlusion coefficient of different types of streets. This step uses a linear  
150 regression method.

151 The fifth step is to divide the shielding area of the central urban area of Wuhan according to  
152 the calculation results of Part 4, and modify the solar radiation potential value.



153

154 **Fig.1** Schematic of the analysis workflow.

155 **2.1 Acquisition of real block sample data**

156 ***2.1.1 Urban block data***

157 In this paper, within 88 selected districts with different morphological characteristics in  
158 Wuhan's electoral districts, the actual measurement and 3D buildings are used to obtain the  
159 real urban block. The case is to provide a data set for studying the urban roofing occlusion  
160 coefficient through research on representative cases. Therefore, the selection of urban block  
161 examples in this study follows three principles:

162 • Satisfy the diversity of block layout morphological characteristics: The diversity of block  
163 morphological characteristics includes the diversity of planar layout patterns and the diversity  
164 of height layout patterns. The selection on the diversity of the planar layout form includes  
165 determinants, courtyards, dislocations, etc. The diversity of the height layout form includes  
166 the bottom, multilayer, high-rise, and high-low staggered layout of urban blocks.

167 • Satisfy the diversity of urban area distribution: The selected urban blocks cover the central  
168 area of the city to the periphery of the city. The difference in urban spatial form caused by  
169 this urban area distribution is often reflected in the building density, such as the high density  
170 of the city centre, and low density in the suburbs.

171 • Satisfy the diversity of the architectural functions of the block: The function of a specific  
172 city block often determines the shape of the city block. This article covers the selection of  
173 city block cases, covering different types of functions such as industrial blocks, commercial  
174 blocks, residential blocks, schools, and institutions.

175

176

177 **2.1.2 Classification indicators of urban blocks**

178 In previous studies, the influencing factors that control the type characteristics of the block  
179 are: Site Area(SA), Gross Floor Area(GFA), Building Volume(BV), Building Footprint  
180 Area(BFA), Envelope Surface Area(ESA), Building Perimeter(BP), Number of Buildings,  
181 Building Orientation, Building Height(BH), Building Density(BD), BSA/BV, BP/BFA.

182 Comprehensively considering the land use indicators considered in the relevant literature and  
183 whether they are easy to obtain (Dekay & Brown, 2001; Montavon, 2010; Wei et al., 2015),  
184 this study considers the impact of 5 morphological index factors on the statistics of 88 block  
185 samples:

186 • Building height (BH): the vertical distance from the building roof to the ground. For the  
187 block, this study counts the average building height of the buildings in the block;

188 • Building density (BD): the ratio of the projected area of the building to the total area of the  
189 block;

190 • Building Surface area/Building Volume (BSA/BV): the ratio of the building's external  
191 surface area to the building's volume;

192 • Building Perimeter/ Building Footprint Area (BP/BFA): the ratio of the total length of the  
193 building's outer contour to the building's floor area;

194 • Floor area ratio (FAR): the ratio of the total area of all floors of a building to the total area  
195 of the block.

196 In this paper, a large number of blocks with different morphological characteristics are selected  
197 as samples in typical cities for actual measurement and 3D modelling, and a data set is  
198 established. [\[A1\]](#)

199 **2.2 Calculation method of solar radiation based on simulation**

200 Traditionally, the radiation measurement method is to obtain the total radiation sensor.

201 However, it is difficult to install sensors on a large scale on real urban street roofs.

202 Simultaneously, the actual measurement methods are difficult to carry out on a large scale.

203 Therefore, it is necessary to use simulation methods to measure the radiation in the real

204 environment. For the calculation of solar radiation on roofs in urban blocks, the key to

205 simulation is the setting of boundary parameters and whether the parameters are suitable for

206 the urban and meteorological environment of the study area. Therefore, the accuracy of the

207 simulation software needs to be verified.

208 Urban block solar simulation has three parts: urban block 3D modelling tool, solar simulation

209 tool and simulation results visualization tool. In this study, the 3D model of the urban block

210 model used was on Rhinoceros 6.0, and the solar simulation tool selected was the Radiance

211 radiation simulation software which is widely used. This software uses the Perez diffusion

212 radiation model (Perez et al., 1987, 1990) and has had many successful applications (Jakubiec

213 & Reinhart, 2013; Reinhart & Walkenhorst, 2001). Integrated into Rhinoceros 6.0, the

214 Ladybug & Honeybee plug-in of the Grasshopper visual programming platform built in

215 Rhinoceros 6.0 is used for the operation and visualization of measurement results.

216 **2.3 Clustering algorithm**

217 In this study, the K-means algorithm was used to perform a cluster analysis on five types of

218 morphological data and radiation per unit area of building roofs in 88 blocks, and the block

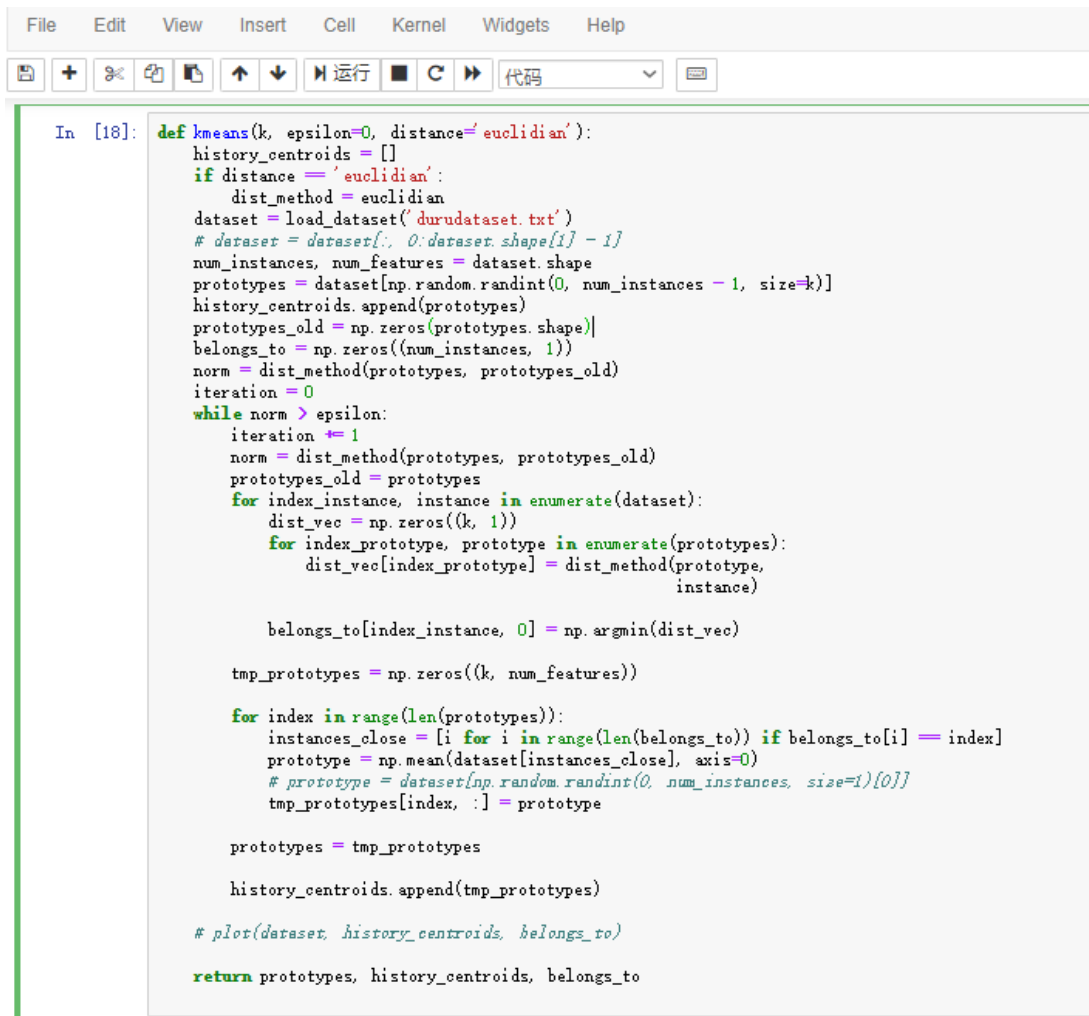
219 samples were divided into three block types.

220 Cluster analysis refers to the classification of samples based on individual characteristics, so

221 individuals in the same category will have a high degree of homogeneity, while individuals in

222 different categories will have a high degree of heterogeneity. Through this method, multiple  
223 classification of indicators, and the classification characteristics of samples can be expressed  
224 intuitively.

225 The Fig.2 shows the code implementation of the K-means algorithm used in this study.



```
In [18]: def kmeans(k, epsilon=0, distance='euclidian'):
history_centroids = []
if distance == 'euclidian':
    dist_method = euclidian
dataset = load_dataset('durudataset.txt')
# dataset = dataset[:, 0:dataset.shape[1] - 1]
num_instances, num_features = dataset.shape
prototypes = dataset[np.random.randint(0, num_instances - 1, size=k)]
history_centroids.append(prototypes)
prototypes_old = np.zeros(prototypes.shape)
belongs_to = np.zeros((num_instances, 1))
norm = dist_method(prototypes, prototypes_old)
iteration = 0
while norm > epsilon:
    iteration += 1
    norm = dist_method(prototypes, prototypes_old)
    prototypes_old = prototypes
    for index_instance, instance in enumerate(dataset):
        dist_vec = np.zeros((k, 1))
        for index_prototype, prototype in enumerate(prototypes):
            dist_vec[index_prototype] = dist_method(prototype,
                                                    instance)

        belongs_to[index_instance, 0] = np.argmin(dist_vec)

    tmp_prototypes = np.zeros((k, num_features))

    for index in range(len(prototypes)):
        instances_close = [i for i in range(len(belongs_to)) if belongs_to[i] == index]
        prototype = np.mean(dataset[instances_close], axis=0)
        # prototype = dataset[np.random.randint(0, num_instances, size=1)[0]]
        tmp_prototypes[index, :] = prototype

    prototypes = tmp_prototypes

    history_centroids.append(tmp_prototypes)

# plot(dataset, history_centroids, belongs_to)

return prototypes, history_centroids, belongs_to
```

226

227 **Fig.2 Clustering Algorithm Code**

## 228 2.4 Calculation method of solar occlusion coefficient

229 The total solar roof radiation in urban blocks is positively related to the building roof area in  
230 urban blocks. Therefore, a linear regression algorithm can be used to obtain a linear  
231 regression model of solar roof radiation in urban blocks. Since different types of streets have

232 different occlusions on the roof, the difference reflected in the linear regression model is the  
233 slope of the regression curve. Therefore, the slope of the regression curve can be used to  
234 calculate the solar occlusion coefficient of urban roofs.

235 A commonly used method for calculating solar radiation uses the three factors that affect the  
236 solar radiation on the roof to multiply by linear correlation. The calculation formula is as  
237 follows:

$$238 \quad R_{Total} = S_{roof} \times R_{Unit} \times (1 - \eta_{OF})$$

239 In this formula,  $R_{Total}$  is the available solar radiation on the roof of the block;  $S_{roof}$  is the  
240 available solar roof area on the block;  $R_{Unit}$  is the amount of solar radiation per unit area  
241 under unblocking conditions;  $\eta_{OF}$  is the block coefficient of the block, where the block  
242 coefficient  $\eta_{OF}$  is a measure of the coefficient of urban block environment on the occlusion  
243 of a building roof. The value ranges from 0 to 1, where the larger the value, the more severe  
244 the occlusion of the roof in this area.

245 In this study, in order to determine the occlusion coefficient value  $\eta_{OF}$  under different street  
246 types, a linear regression method was used. By performing linear regression on the  $R_{Total}$   
247 and  $S_{roof}$  values of the block samples, the occlusion coefficient  $\eta_{OF}$  of the block is  
248 calculated. The specific calculation formula is as follows:

$$249 \quad \eta_{OF} = 1 - B/B_{Origin}$$

250 In the formula,  $\eta_{OF}$  is the occlusion coefficient of the street,  $B$  is the slope of the curve after  
251 linear regression analysis, and  $B_{Origin}$  is the slope value of the curve under the condition of  
252 no occlusion, which is equivalent to  $R_{Unit}$  in value.

253 By analysing different block types, the occlusion coefficient  $\eta_{OF}$  of different block types can  
254 be obtained, and the regression analysis of all samples is capable of obtaining the average  
255 occlusion coefficient of the entire city.

256

257 **3. Results**

258 **3.1 City block classification based on clustering algorithm**

259 In this study, the Python scripting language was used to implement the clustering algorithm in  
260 the Jupyter Notebook development environment. After the 88 city block samples were  
261 classified according to the characteristics of the five indicators, three different differences in  
262 the urban form indicators were obtained. Clustering algorithm data results and visual  
263 classification results are shown in Fig.3 and Fig.4.

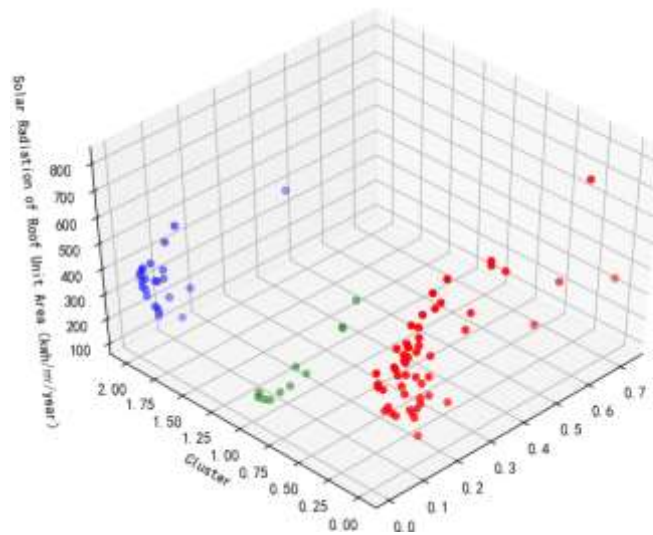


Fig.3 Cluster Results Visualization

264

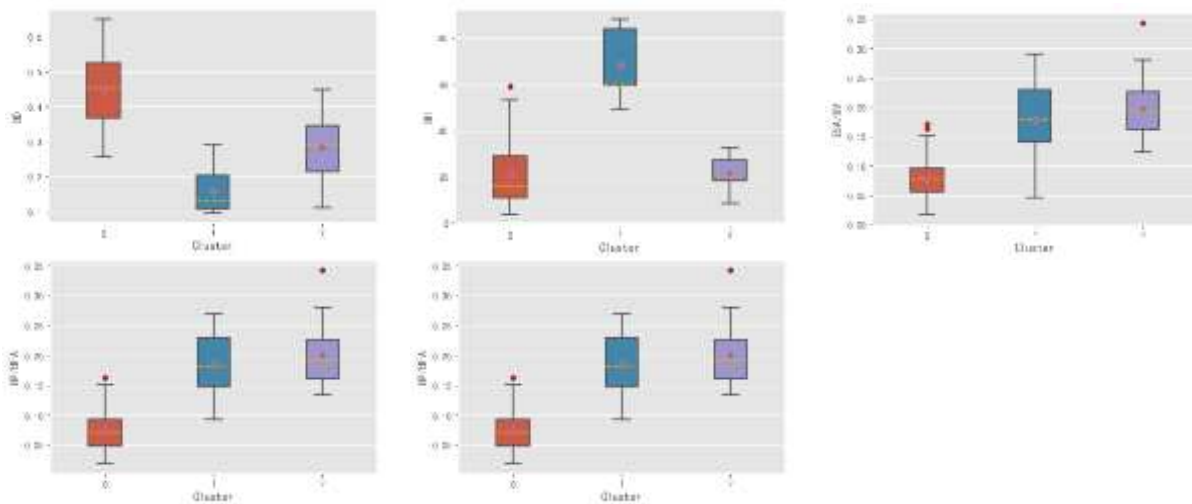


Fig.4 Cluster Algorithm Classification Result Indicator Distribution Characteristics

265



266 According to the classification results of the clustering algorithm, 88 urban block samples are  
 267 divided into 3 different types. By analysing the corresponding indicators of these three  
 268 categories, the corresponding three types of urban blocks are summarized (Table 2). The  
 269 characteristics are as follows:

**Table 2**  
 Cluster Algorithm Classification Result Statistics

Cluster Type	BH	BD	ESA/BV	BP/BFA	FAR
Cluster 0	Low & Middle	High	Low	Low	Middle
Cluster 1	High	Low	Middle	Middle	High
Cluster 2	Low	Middle	High	High	Low

271 Cluster0: low-rise or middle-rise, high-density blocks, represented by industrial plants and middle-high  
 272 rise residential areas( $24M < BH < 60M$ );

273 Cluster 1: high-rise, low-density block, represented by commercial complexes and office buildings;

274 Cluster 2: Low-rise, medium-density block, represented by multi-storey residential areas ( $BH < 24M$ ).

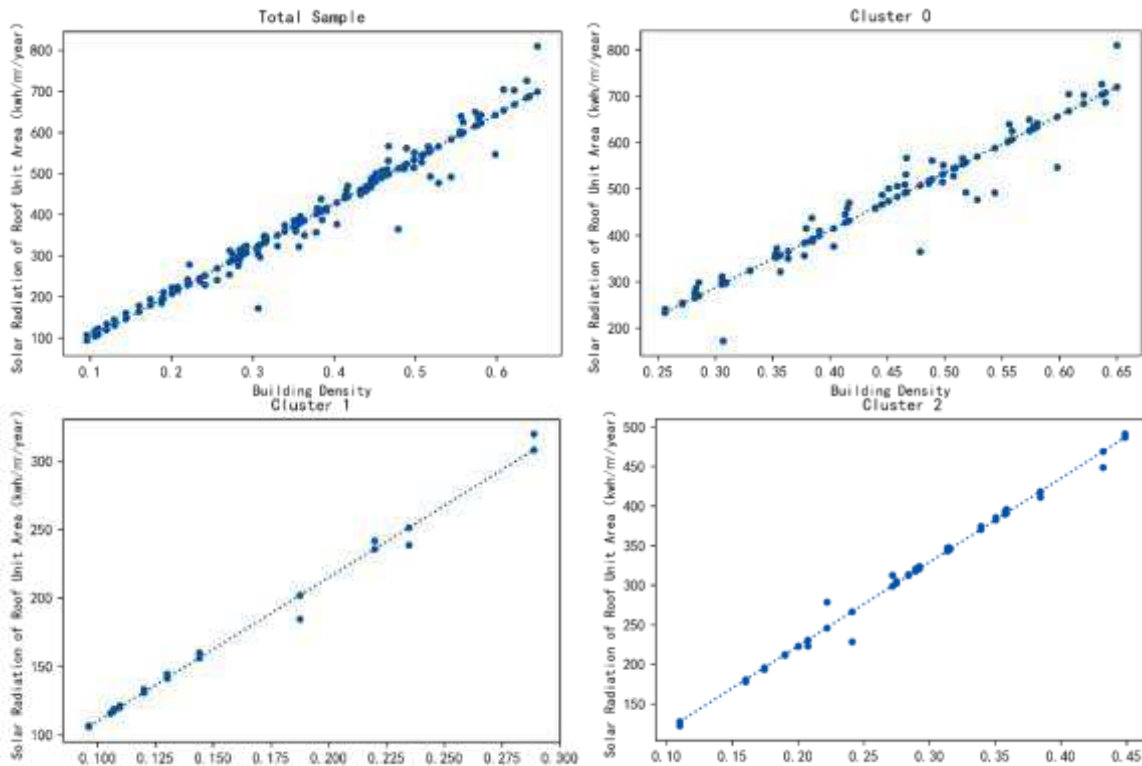
275 **3.2 Calculation of solar energy utilization potential occlusion coefficient in different**  
 276 **types of blocks**

277 Since different types of urban blocks have different potentials for solar energy utilization, after  
 278 classification of urban blocks, three different types have been obtained. This section separately  
 279 measures the amount of solar radiation from the roof of these three types of urban blocks, using  
 280 linear regression. The method obtains the roof solar radiation regression model of the  
 281 corresponding type of urban block, and finally calculates the roof solar occlusion coefficient  
 282 of the type of block.

283 **3.2.1 Linear regression analysis verification**

284 Through linear simulation of roof solar energy in 88 real urban blocks, and linear regression  
 285 calculation of solar radiation amount and block building density of roof unit area, linear  
 286 regression analysis was carried out for three different types of urban blocks, and the overall

287 linear regression analysis was carried out in 88 urban blocks. The overall regression curves and  
 288 correlation coefficients of the three types of blocks and urban blocks were obtained as follows  
 289 (Fig.5, Table 3).



290 **Fig.5** Linear Regression Curve

**Table 3**  
 Regression Curve and Correlation Coefficient Statistics

Type	Curve Slope	R <sup>2</sup>
Cluster 0	1235.8	0.8997
Cluster 1	1049.2	0.9856
Cluster 2	1061.2	0.9822
Total	1093.7	0.9437

291

292 The study found that in the three types of urban blocks, because the degree of occlusion of  
 293 different types of urban block roofs is different, the slope of the regression curve is different,  
 294 and the correlation R2 of the regression curve is about 0.9, so It is proved that the general linear  
 295 model is applicable to the regression analysis of solar radiation quantity and building density  
 296 of the roof unit area.

297 **3.2.2 Estimation of occlusion coefficient**

298 The solar occlusion coefficient is calculated by calculating the solar opacity coefficient of the  
 299 radiation amount and the building density regression curve of the roof unit area of three  
 300 different types of blocks and sample populations (Table 4). It is found that the difference of  
 301 roof solar occlusion coefficient of different types of blocks is obvious, for cluster 1, 2, and 3,  
 302 the roof solar occlusion coefficient averages are 0.099, 0.054, 0.025 for the city's overall 88  
 303 urban block samples, the calculated roof solar occlusion coefficient average is 0.079, that is,  
 304 the city's overall average. The roof will obstruct 8% of the solar energy, and the remaining 92%  
 305 of the solar energy will be used by roofing solar installations.

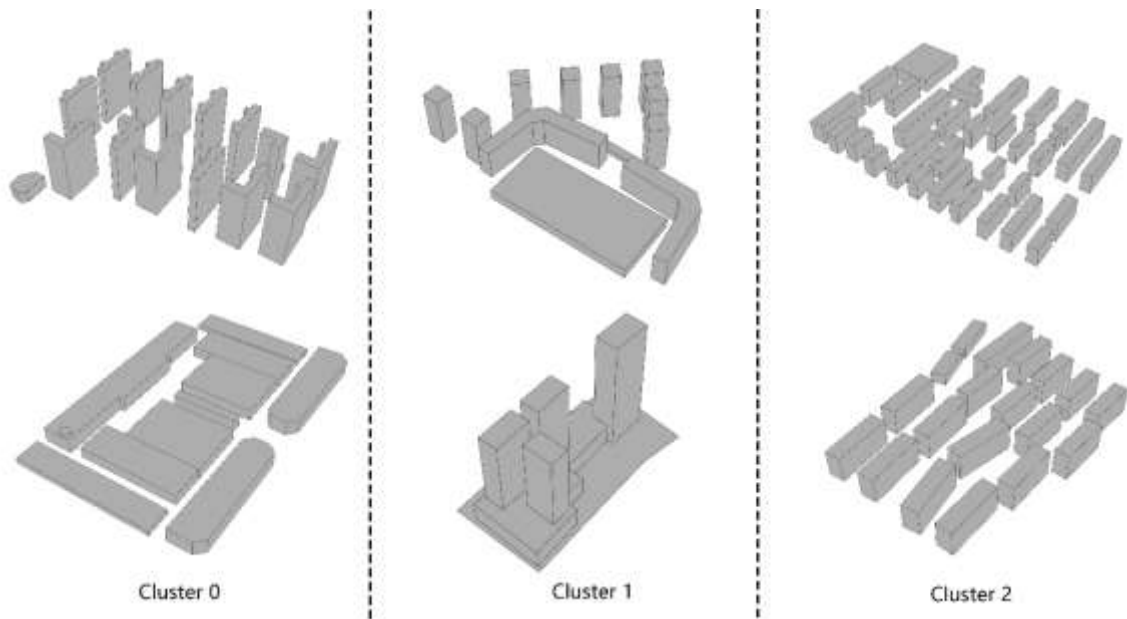
**Table 4**  
 Occlusion Coefficient with Block Type

Cluster Type	Feature	Curve Slope	Occlusion Coefficient	Block Type
Cluster 0	Middle and Low Rise; High Density	1235.8	0.099	Industrial Block; Middle-High rise residential Areas
Cluster 1	High Rise; Low Density	1049.2	0.054	Commercial Complexes; Office Buildings
Cluster 2	Low Rise; Middle Density	1061.2	0.025	Multi-storey Residential Areas
Total	-	1093.7	0.079	-

306  
 307 For the cluster 0 block, that is, the middle and low-rise high-density blocks represented by  
 308 industrial plants and middle-high rise residential areas(24M<BH<60M), the average occlusion  
 309 coefficient is 0.099;

310 For the cluster 1 block, that is, the high-rise low density represented by commercial complexes  
 311 and office buildings, the average occlusion coefficient is 0.054;

312 For the cluster 2 block, that is, a low-density medium-density block represented by multi-storey  
 313 residential areas (BH<24M), the average occlusion coefficient is 0.025; (Fig.6)



**Fig.6** Block Type Models of Clustering Results

314

315 In summary, the occlusion coefficient of the three types of blocks is less discrete, so when  
 316 calculating the solar energy application potential of the corresponding block, the average value  
 317 of the corresponding occlusion coefficient can be used for calculation.

318 For the city as a whole, the overall occlusion coefficient is close to the average level of 0.079,  
 319 but in the city scale measurement, when the roof occlusion coefficient needs to be simplified,  
 320 the value can be used to simplify the calculation.

321

### 322 **3.3 Calculate solar energy utilization potential at macro city scale based on occlusion** 323 **coefficient**

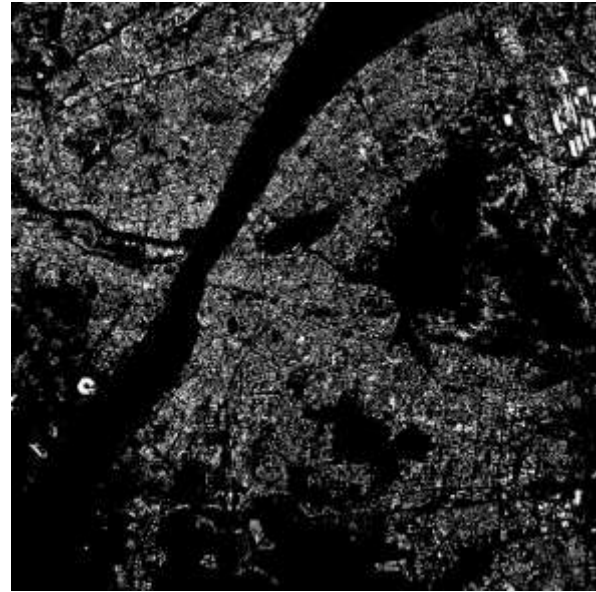
#### 324 ***3.3.1 Using open source channels to obtain the roof area of Hongshan District in Wuhan*** 325 ***City***

326 Taking Hongshan District in Wuhan as an example, this paper estimates the potential of  
 327 photovoltaic utilization in Hongshan District. The study area and recognition result are shown

328 in **Fig.7** and **Fig.8**



329 **Fig.7** The Range of Hongshan District



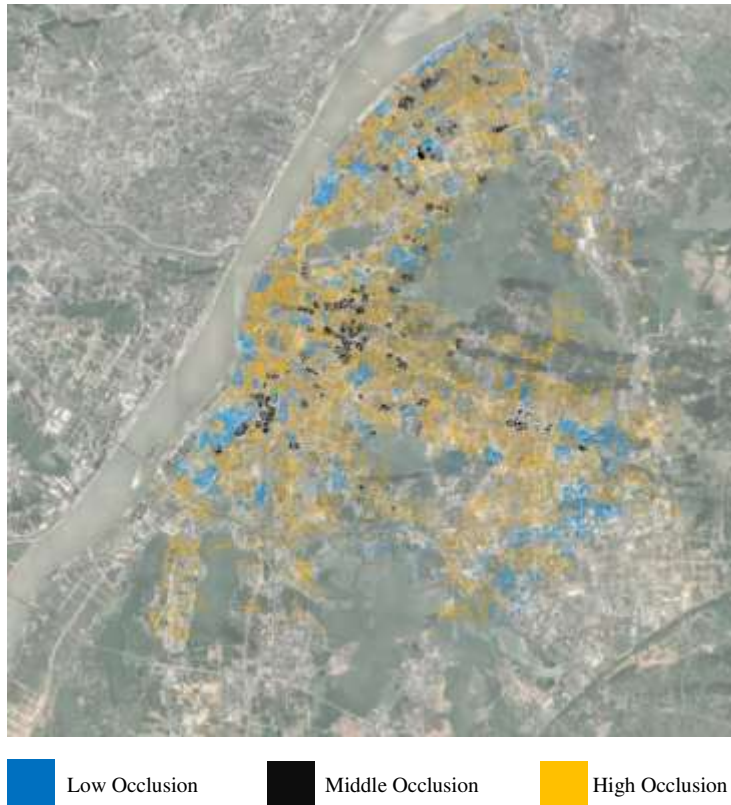
330 **Fig.8** Recognition Result of Study Area

331 The red line is the range of Hongshan District in Wuhan, which is defined by the Wuhan City  
332 Master Plan (2006-2020)(Wuhan Natural Resources and Planning Bureau, 2011). The urban  
333 area of Hongshan District is 480 square kilometres. Using the open source Wuhan GIS map  
334 file to calculate the roof area of Hongshan District, the total available roof area of Hongshan  
335 District is 41380900 m<sup>2</sup>.

### 336 ***3.3.2 Blocking the urban area of Hongshan District based on the obtained occlusion 337 coefficient***

338 Then the measured corresponding type roof occlusion coefficient was used to simplify the  
339 calculation of the overall occlusion of the city.

340 In the urban three-dimensional GIS file for different plots of the city, they were classified into  
341 different types of occlusion coefficients, and were assigned to different occlusion coefficients  
342 in calculating the overall solar photovoltaic utilization potential of the urban scale as shown in  
343 **Fig.9**.



343 **Fig.9** Occlusion Coefficient Visualization

344 Blue represents low occlusion (0.025), i.e. the cluster 2 block, whilst black represents medium  
 345 occlusion (0.054), i.e. the cluster 1 block, and orange represents severe occlusion (0.099), i.e.  
 346 the cluster 0 block, where the overall occlusion coefficient is 0.079. but in the city scale  
 347 measurement, when the roof occlusion coefficient needs to be simplified, the value can be used  
 348 to simplify the calculation.

### 349 ***3.3.3 Correcting the urban solar radiation according to the occlusion coefficient***

350 In this section, in the setting of the calculation parameters, the annual radiation per unit area of  
 351 Hongshan District is 1150 kWh/m<sup>2</sup>/year. After correcting, the total roof solar radiation in  
 352 Hongshan District is 45208.30 GWh/year.

353

354 **4. Applicable analysis and Theory**

355 **4.1. Occlusion coefficient applicability verification**

356 This study is based on the study of solar occlusion coefficient in real city blocks in Wuhan. It  
357 measures the solar occlusion coefficient of urban roofs for different types of blocks and cities.  
358 However, whether the roof occlusion coefficient measured in the urban environment of Wuhan  
359 is applicable to the whole world needs to be verified and analysed.

360 In terms of differences in urban meteorological conditions, the factors affecting the urban roof  
361 occlusion coefficient are mainly the solar elevation angle, that is, the solar elevation angle  
362 decreases with increasing latitude, and the roof solar occlusion coefficient decreases under the  
363 same urban form, in order to verify the urban roof due to differences in urban meteorological  
364 conditions. The influence of the solar occlusion coefficient is verified by the solar radiation  
365 simulation method in 11 major cities in the world. The verification model is selected from a  
366 typical urban block belongs to cluster 2 in Wuhan and is carried out under different  
367 meteorological conditions. The roof solar radiation simulation simulates and measures the roof  
368 solar occlusion coefficient. (Table 5)

**Table 5**  
Occlusion Coefficient Verifying Result Of 11 Main City in The World

Number	City Name	Latitude	Case Block Occlusion Number
1	Singapore	1.3	0.018073705
2	Bangkok	13.4	0.018194903
3	Mumbai	18.5	0.023502853
4	Beijing	39.9	0.045298833
5	Cairo	30	0.029726544
6	Shanghai	31.1	0.03294302
7	New York	40.4	0.037121775
8	Paris	48.5	0.037112789
9	London	51.3	0.044234758
10	Sydney	-33.8	0.014304145
11	Rio de Janeiro	-22.5	0.01363006

370 In this study, the occlusion coefficient is calculated for 11 major cities in different latitudes in  
371 the world (Fig.10). The calculated R-squared value is 0.8673, which indicates that in different  
372 latitude urban environments, it can be considered that the roof solar occlusion coefficient is  
373 linearly positively correlated by meteorological conditions. According to the calculation, in the  
374 same city form, the roof solar occlusion in the northern area will be higher than that in the south.  
375 The relationship between the meteorological and occlusion coefficients makes it possible to  
376 calculate other urban occlusions according to the Wuhan occlusion coefficient  
377 .

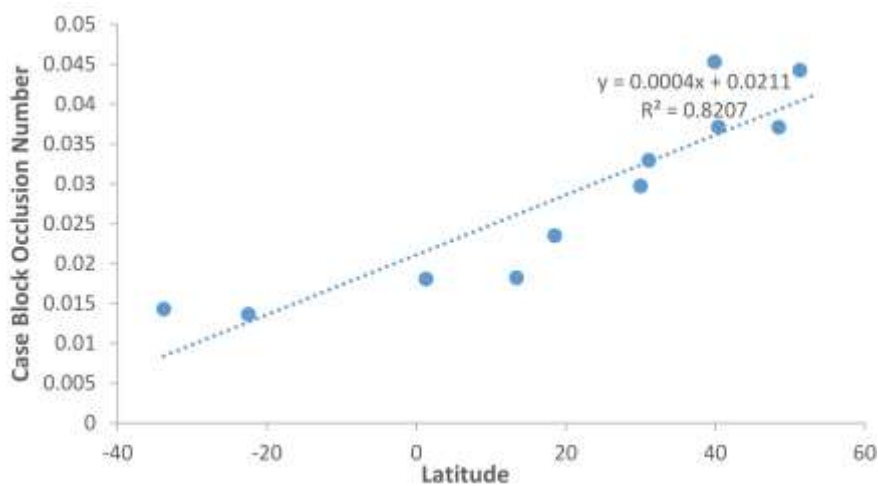


Fig.10 Linear Regression Curve

378

## 379 4.2 Conclusion

380 This paper proposes a method to quantify the problem of block occlusion in the use of solar energy.  
381 Then take Wuhan City as an example to use the obtained occlusion coefficient type to classify the  
382 relevant urban roofs and calculate the total solar energy potential of the city. Compared with occlusion,  
383 the city will produce 7% error, especially in the low-rise high-density block or the high-rise office block  
384 occlusion coefficient will cause 10% error.

385 In typical high-density cities, urban block types have commonalities, so the occlusion coefficients of  
386 different types of blocks proposed in this paper have certain applicability. There are differences in the



387 solar occlusion coefficients of different types of blocks. They are weak occlusion (0.01 occlusion  
388 coefficient) represented by industrial type blocks, middle occlusion (blocking coefficient 0.04)  
389 represented by middle and high-rise residential areas, and high occlusion represented by commercial  
390 type blocks (the occlusion factor is 0.13).

391 As far as the city as a whole is concerned, the urban block environment has different influences on the  
392 roofing of the city depending on the block. In different cities around the world, the roof solar occlusion  
393 coefficient is linearly positively correlated with the climatic conditions. The roof occlusion coefficient  
394 in Wuhan can be that it provides reference for the calculation of roof solar energy utilization in other  
395 cities around the world. This paper calculates in Wuhan area and provides reference for occlusion  
396 coefficient for solar energy measurement in other high-density cities.

397

398 Appendices:

A1  
88 Block Morphology Parameters

Number	Site Area(SA)	Gross Floor Area (GFA)	Building Volume (BV)	Building Footprint Area(GFA)	Envelope Surface Area(GSA)	Building Perimeter( BP)	Number of Buildings	Orientation	Building Height(M)	Building Density(BD)
1	38588.00	69847.00	907078.90	11841.00	33380.00	828.78	6	3	42.90	0.31
2	28203.00	91222.00	404033.48	12788.00	68850.00	1119.65	3	3	31.88	0.44
3	18423.00	40376.00	133078.40	4182.00	23720.00	659.47	3	2	32.70	0.27
4	96706.00	127882.00	333844.10	34823.00	41275.00	2867.00	12	2	35.90	0.28
5	46268.00	89415.00	434028.00	25120.00	30636.00	2316.00	9	2	36.90	0.42
6	33681.00	43866.00	138664.90	7544.00	31837.00	1717.00	20	4	38.50	0.23
7	187984.00	175834.00	1296490.00	83766.00	35389.00	6626.00	31	2	15.00	0.45
8	579573.00	369885.00	4367422.45	822319.00	71938.00	6960.00	12	2	13.57	0.26
9	128413.00	78411.00	366779.90	44521.00	30177.00	5653.00	31	5	9.90	0.30
10	106381.00	54334.00	238025.91	31060.00	24852.00	5162.00	25	4	4.99	0.49
11	45797.00	22262.00	100179.90	22262.00	4663.00	1796.00	6	5	4.58	0.49
12	53796.00	33984.00	231048.00	24690.00	32478.00	2514.00	12	6	8.90	0.47
13	168734.00	127188.00	693824.90	86978.00	43253.00	5596.00	17	3	8.96	0.32
14	87102.00	58522.00	284053.60	34054.00	31813.00	3602.00	11	3	8.40	0.39
15	45774.00	124425.00	323967.00	24682.00	42278.00	3630.00	15	4	14.20	0.54
16	34251.00	46116.00	129124.90	15372.00	22880.00	2796.00	18	8	8.48	0.43
17	238287.00	256298.00	724764.20	107726.90	68580.00	8519.00	34	1	8.78	0.45
18	228974.00	256311.00	1189897.58	89925.00	142518.00	9740.00	57	4	11.70	0.35
19	212311.00	101962.00	1696365.92	99862.00	40388.00	3462.00	10	2	36.28	0.47
20	223372.00	153379.00	1022490.48	101274.00	53262.00	7899.00	28	2	14.60	0.47
21	179978.00	505336.00	1338832.00	103236.00	29928.00	2394.00	3	4	12.00	0.37
22	202857.00	91823.00	1003643.40	74614.00	69293.00	3698.00	13	2	13.10	0.38
23	103775.00	71796.00	644826.90	81412.00	35336.00	3198.00	11	3	36.50	0.38
24	46742.00	39870.00	288913.40	28118.00	29326.00	2388.00	12	6	36.30	0.36
25	54259.00	35112.00	258998.80	24827.00	15412.00	1362.00	4	6	14.40	0.46
26	96963.00	70460.00	696328.80	40290.00	32865.00	2804.00	8	6	11.90	0.42
27	38121.00	21283.00	195470.40	28084.00	11315.00	990.90	2	6	9.46	0.55
28	28577.00	17267.00	138683.90	14551.00	15121.00	1228.00	7	2	10.90	0.51
29	27428.00	12726.00	207312.00	17276.00	10833.00	992.00	2	6	12.00	0.64
30	658941.00	389489.00	1428888.49	299468.00	234129.00	63838.00	45	4	1.84	0.43
31	349788.00	228224.00	805790.40	223828.00	121828.00	32848.00	23	1	1.46	0.64
32	83948.70	58211.42	732845.69	12214.00	134761.54	2246.00	11	4	60.00	0.13
33	31683.89	43048.78	190193.13	3089.78	40322.38	2838.00	13	3	20.00	0.17
34	48488.42	63888.66	215476.25	7095.58	41490.79	1481.00	9	2	28.00	0.16
35	27308.75	22555.19	90228.77	7318.00	18157.78	1694.00	13	2	12.00	0.27
36	24884.67	23795.01	125189.94	4827.88	27420.78	1288.00	10	4	28.00	0.20
37	28403.46	54634.00	232451.67	18624.00	50969.23	2484.00	27	4	20.00	0.28
38	38074.98	141558.00	566227.58	9437.13	181988.90	1899.00	9	2	66.00	0.10
39	48912.31	44012.90	178258.32	13712.18	38894.08	2859.00	19	2	13.00	0.29
40	96988.80	150269.00	625967.44	31250.37	144598.40	7086.00	65	3	26.00	0.32
41	86664.39	186793.00	726810.83	38843.63	138888.15	1570.00	14	5	82.00	0.11
42	71873.95	138099.00	554303.82	25195.40	166812.37	4833.00	41	3	22.00	0.25
43	44591.46	79238.00	289529.34	12328.99	54349.45	2875.00	16	3	19.00	0.34
44	111390.33	240778.21	982312.84	14608.55	154078.16	2567.00	16	3	60.00	0.14
45	38817.19	69932.90	249819.18	13878.34	34420.34	2885.00	33	3	18.00	0.36
46	82716.26	190274.00	744716.28	13701.04	215898.23	3718.00	26	4	54.00	0.22
47	83175.27	219638.65	878055.39	9983.67	216282.54	2457.60	15	3	88.00	0.12
48	87048.14	121611.00	487392.82	18038.99	81813.23	2794.00	22	2	27.00	0.21
49	62470.85	121188.00	1913141.22	18231.45	57898.95	2457.00	15	3	88.00	0.29
50	176860.47	276388.00	1111386.42	18827.66	265817.27	4492.00	27	4	58.00	0.14
51	113950.08	189023.00	981779.87	28282.22	126069.67	5798.80	40	4	27.00	0.31
52	47786.69	48365.96	185001.23	18233.65	64135.55	62708.00	72	2	10.20	0.38
53	76324.04	100272.00	398780.85	14499.67	93863.54	3394.00	32	4	27.50	0.19
54	125871.92	93297.00	370298.80	13886.67	89342.28	2448.00	19	3	26.70	0.11
55	103243.87	186652.00	823699.96	29878.71	121743.48	4484.00	31	3	27.50	0.29
56	58621.53	69165.96	333773.57	18425.71	56997.24	2879.00	20	2	19.20	0.31
57	162935.68	358824.00	1470388.83	17197.53	321518.23	2777.00	30	3	65.00	0.11
58	143202.94	228118.00	1101426.51	41251.93	144748.73	6774.00	41	4	26.70	0.28
59	78891.06	282938.00	1131720.00	42294.00	51222.00	798.31	1	5	27.00	0.60
60	6230.58	12412.00	49648.00	3183.00	4464.00	248.10	1	5	16.00	0.50
61	22718.58	34365.00	137490.00	11455.00	16791.00	1664.13	2	1	12.00	0.41
62	42674.74	198748.00	794984.60	24663.00	39807.00	614.86	1	0	32.00	0.32
63	89773.74	322329.00	1292280.00	40290.00	33498.00	2922.41	8	2	32.00	0.58
64	27383.43	190229.00	768118.60	13109.00	71929.99	1501.81	1	4	39.00	0.48
65	100740.87	306968.00	1227840.00	51160.00	73847.05	1801.81	5	1	28.00	0.51
66	81608.92	289211.00	1156844.00	31452.00	72899.08	1188.37	4	0	37.00	0.28
67	19191.03	18140.90	72260.80	6819.00	78070.99	994.60	3	0	11.00	0.30
68	18888.81	100997.00	403988.00	9991.00	31680.96	404.32	1	2	41.00	0.33
69	82485.95	229477.00	857909.00	34211.00	39483.95	1364.26	2	2	28.00	0.41
70	41844.27	217427.00	869708.00	31061.00	16307.95	723.52	1	2	28.00	0.63
71	42183.45	197388.00	789472.00	14874.00	62688.95	973.43	2	2	33.00	0.33
72	35918.51	167033.00	688122.00	17108.00	71226.95	1283.74	7	0	39.00	0.31
73	11058.89	23422.00	10728.00	3838.00	14668.95	1241.99	6	2	16.00	0.43
74	85538.39	159412.00	632648.00	25669.60	47786.24	1455.85	3	3	25.00	0.31
75	96438.47	254721.00	1018884.00	29796.79	72261.22	2104.01	5	2	34.00	0.31
76	94214.99	221969.00	887876.80	34233.53	69968.94	2565.42	5	2	26.00	0.36
77	68083.64	260171.00	1040684.00	16699.62	90846.12	1481.57	4	2	65.00	0.23
78	41206.17	81346.00	326184.00	12559.74	38239.31	1319.89	4	0	26.00	0.28
79	72875.00	167413.00	689632.00	13671.47	81367.22	3629.28	7	4	49.00	0.19
80	78891.51	275513.00	1102860.00	31043.66	83780.68	2055.02	4	2	35.00	0.40
81	110813.53	287803.00	1151720.00	41853.90	68188.23	2249.80	2	6	27.00	0.38
82	78117.50	212037.00	854228.00	26005.61	67361.39	2896.44	3	0	43.00	0.26
83	88883.17	108810.00	398440.00	19299.14	40669.97	1864.62	3	6	21.00	0.28
84	131121.03	234994.00	939618.00	42003.13	53884.78	2209.71	2	0	22.00	0.33
85	109408.11	186873.00	759692.00	22605.16	82735.88	2143.48	12	2	28.00	0.27
86	48862.94	116998.00	467600.90	16421.23	63811.70	2298.94	9	0	28.00	0.24
87	218760.83	367373.00	2269492.00	62451.49	198448.18	3201.32	12	2	36.00	0.29
88	158403.81	349522.00	1388398.00	89599.36	78841.63	3851.87	3	4	36.00	0.44

400 **Funding:**

401 This research was supported by the National Natural Science Foundation (No. 51678261), State  
402 Key Laboratory of Subtropical Building Science (No. 2017ZB08), and Wuhan Urban, Rural  
403 Construction Committee (No. 201726) and Fundamental Research Funds for the Central  
404 Universities (No.2019kfyXKJC029).

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